A Novel Multisensoric System Recording and Analyzing Human Biometric Features for Biometric and Biomedical Applications

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1 Introduction

This thesis is focused on the biometric input device and the assessment of the acquired behavioral biometric signals for biometrics and biomedical applications. The recording and the study of the human handwriting features especially those involved in the handwriting movements are the fundamental parts of both behavioral biometrics and biomedical research studies. One way to study the dynamics of human motor functions of fingers, hand and wrist movements is to investigate the features of handwriting, drawing or hand gestures. Because of handiness of using a pen, the recording of such dynamics with a pen is useful in:

(i) Behavioral biometrics: person authentication or handwritten object recognition
(ii) Human computer interactions: input to the computer system
(iii) Home care and medical applications: numerous other purposes including experimental psychology and neuroscience for therapy and disease diagnostics.

The features recorded during handwriting can be used for the determination of: “what is being written”, “who is the writer” and “what is the health condition of the writer” as illustrated in Figure 1.1.

Features of handwriting movements determine

What?	Who?	Condition?
Handwritten items	**Persons**	**Dysfunctions**
Handwritten object recognition	Person authentication	Disease or medication diagnosis

Figure 1.1: Handwriting features can be used to determine a handwritten object, to recognize a person or to detect the health condition of a writer.

With the growth of developments in information technology, more secure and reliable person authentication is becoming increasingly important in the control of access to resources or data. Although traditional authentication methods are still extensively deployed in practice, they are based on the knowledge (Password or PIN code) or the possessions (keys or cards) or a combination of both (cards with PIN numbers). But they do not comply with present security requirements. Unlike traditional authentication systems, in the biometrics-based systems, personal authentication is carried out by using human build-in (private) biological (e.g., fingerprints, iris, face) or behavioral traits (e.g. handwriting, gesture). Therefore, biometric authentication systems are expected to provide better security and prevent unauthorized access

to resources or personal data. Among the behavioral methods, the authentication by handwriting signatures is promising because of a long history of using handwritten signatures, a wide acceptance in public domain and the intimacy of writing with a ballpoint pen.
Furthermore, handwriting skills are developed in early life of individuals. Everybody has his private handwriting and own signatures, often used for traditional authentication. Handwriting process is characterized by the actions of the human hand and fingers motion pre-determined by brain and muscle activity reflecting neuro-motor characteristics of the person [34]. Handwriting sequences (e.g., single characters, words or signatures) and its related process of motion are considered as private to an individual, the latter being invisible to potential forgers. Therefore, an online biometric system which uses handwriting dynamics is expected to generate more efficient, reliable and secure solution for person authentication.
However, current online biometric signature authentication still has to be improved because of its lower user acceptance, non-handiness of the input device, low efficient sensors and low accuracy of the classifiers.
The dynamic features of handwriting are commonly captured by pen based graphic tablets or pads. In such devices x-y position coordinates, tip pressures on the surface and pen tilt are measured. In some other pen-based approaches, refill pressures with tilt angles are employed for the data sampling. Very rarely grip forces of the fingers holding the pen are used. In practice, most of the systems based on the devices mentioned above have serious disadvantages, especially in data acquisition. Because they are intrusive, uncomfortable to use, costly, have low performance with respect to error rates, may be suited only for limited populations or show poor mobility or protection against imitation.

1.1 Biometric Smart Pen BiSP for the Assessment of Human Hand Movements

For more comprehensive assessment of handwriting movements, a novel multisensoric ballpoint pen named Biometric Smart Pen (BiSP) has been developed in order to record and analyze the handwriting, drawing and gesturing movements during handwriting on paper pad or free in space [1].

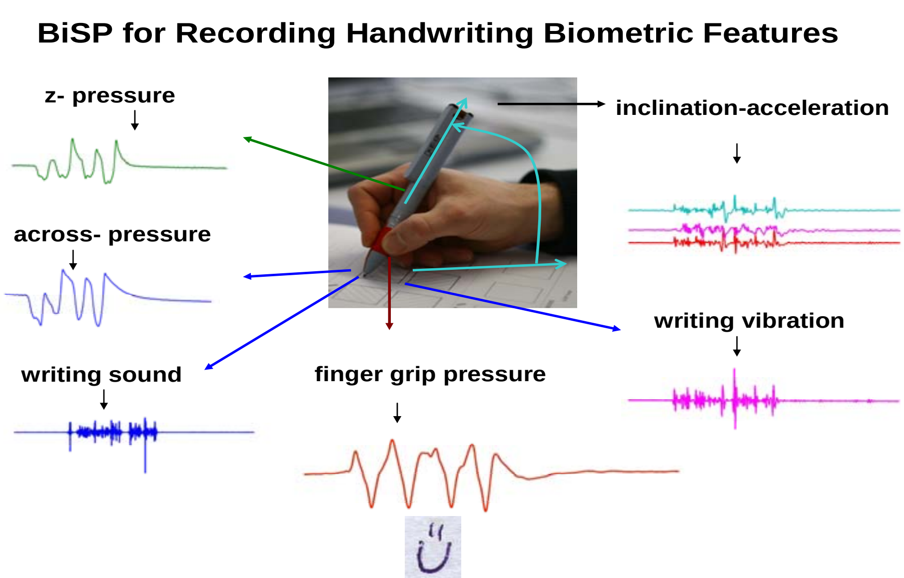


Figure 1.2: Illustrates BiSP and the recorded handwriting signals obtained from a handwritten single character "Ü".

Because of its sensors and dimensions making it appear like a commonly used pen, it has the ability to measure more natural dynamics of the fingers and hand movements in terms of pen refill pressures, finger grip pressures holding the pen, vibration (writing sounds) of refill generated during writing on pad, and pen inclination and tilts during handwriting.
The grip sensing of BiSP is unique and provides excellent dynamics of the fine motor skills of a writer. It also makes its debut in the acquisition device. Handwriting features recorded with BiSP in terms of refill pressures, vibrations and writing sound signals, finger grip pressures and inclination signals obtained from a handwritten single character "Ü" on paper pad are shown in the Figure 1.2. They are the result of a complex and a highly practiced task and involve human fine motor skills. It is well known that there are certain diseases, e.g., Parkinson's disease (PD) which cause deficits in the motor performance and has a distinct impact on human fine motor skills. Therefore, symptoms of neuro-motor dysfunctions can seriously influence handwriting or its extracted features. The writing of the Parkinsonian patients is often found distorted and smaller because of the tremors, slowness and reduction of the movement amplitudes. One possibility to register and analyze the dysfunctions of the hand, fingers and wrist movements is to record and study the kinematics and dynamics of handwriting, drawing or gesturing movements by using the BiSP system. The features recorded by BiSP and used for biometric and medical applications are named biometric and neuro-motoric features, respectively.

1.1.1 BiSP Modes of Operation

The BiSP device is used for the online record of handwritten characters and words, drawings, and gesture traits. Due to the diversity of the sensors installed in the BiSP device, especially the acceleration-tilt and finger grip sensors, it is possible to record signals during handwriting, drawing or gesturing not only on pad but also for the movements performed exclusively in air in this thesis. The acquisition of the movements performed in air is often referred to as handwriting in air (off pad). Hence, for the acquisition of handwriting or gesturing movements the BiSP system can be applied in two modes: (1) on paper pad and (2) free in air (off pad) as shown in Figure 1.3.

On pad   Off pad (In air)

BiSP modes of operation

Figure 1.3: Illustrates the different modes of operation of the BiSP device.

The properties of the recorded features (signals) are not only determined by the human biometric traits and object specific features but also by the modality of writing—on pad or in air.

1.1.2 BiSP Operation and its Application Potential

As shown in the Figure 1.4, the operation steps of the BiSP system in biometrics or biomedical application starts with the recording of features provided by handwriting movements. In the next stage, the biometric or neuro-motoric features are extracted from the recorded data. Finally, decision is made after the features are classified by feature comparison. The biometric and neuro-motoric features recorded with BiSP can be analyzed for the following applications:

- Biometrics—person authentication including verification and identification
- Medicine—diagnosis and therapy
- Computer input—handwritten character or hand gesture recognition

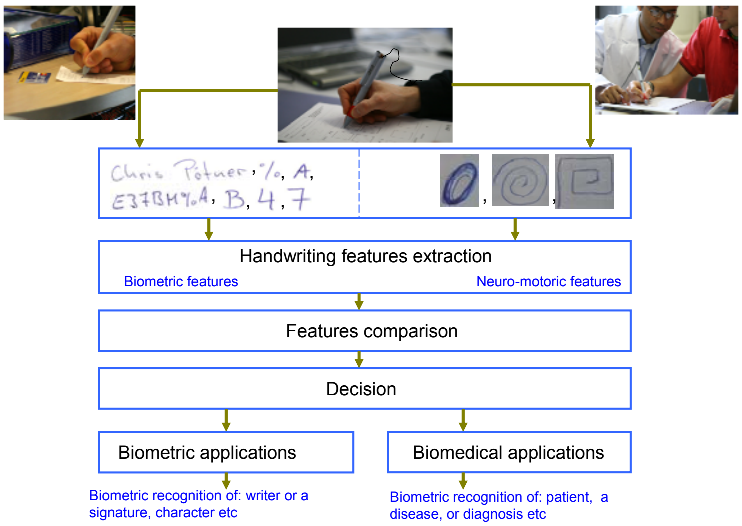


Figure 1.4: Illustrates BiSP recognition system operations: data acquisition, features extraction and classification, and decision in: (1) biometrics (2) biomedical diagnostics.

1.1.3 Key Benefits of the BiSP System

BiSP is ergonomic, non-invasive and provides a comfortable feeling while writing.
Key benefits of BiSP system are:

- High potential for use in multiple applications
- Little infrastructure
- Mobility and online usage
- Ergonomic handling
- High acceptance
- Low-cost system

1.2 Goals and Structure of the Thesis

1.2.1 Goals and Objectives

It is a challenge to study the dynamics of handwriting, drawing or hand gesture movements due to the complexity of data acquisition and processing demand for diverse applications. The major difficulties are the acquisition of high quality data and the characterization of the acquired data accurately and efficiently. Research and development work in the framework of the BiSP project has been done for some years at the University of Applied Sciences, Regensburg [1]. The sensor techniques and software methods for classification implemented in the BiSP system are need to be improved. So, the current statistical method—SigID [50] used for features extraction and classification has to be enhanced or enlarged by further software techniques. Because the major problems in software are (i) automatic selection of the right features, (ii) lower classification accuracy for short inputs like single characters and (iii) manual procedure for performance score calculation. In addition, the sensor technique still is not optimized for a comprehensive sensing of handwriting movement and the ergonomics (size and easy handling) of device must be improved for higher user acceptance. Finally, further study work is needed to evaluate the application potential of BiSP in health care.

So, the aim of this thesis is first to design and develop a new multisensoric pen device which leads to an increase in user acceptance and acquires high quality data from the user. The second goal is to develop data analysis methods capable of improving the overall reliability and accuracy of the classification based on BiSP data. A further goal is to evaluate the enhance BiSP system used for analyzing symptoms of Parkinson disease.

The improvements of the old BiSP system are addressed to implement: (i) novel sensor techniques in the BiSP device (ii) new data acquisition and analysis methods—enhanced pre-processing of time series data (iii) new classifiers based on DTW for accurate and robust classification of data and (iv) a new operation mode of BiSP that is data acquisition during writing in air.

In biometrics, the objectives are to improve the performance of person authentication or handwritten object recognition by using a new designed BiSP system. Therefore, the thesis deals with the instrumentation, measurement aspects, and the implementation of biometrics based on handwriting on pad or free in air. The software method to be developed is based on a biometric two factor authentication (TFA) which makes use of both behavioral biometrics and knowledge simultaneously gained from a PIN word handwritten on paper pad or alternatively in air by using BiSP.

For medical application, the focus is to develop software methods to measure neuro-motoric features obtained from handwriting, drawing or gesturing movement. The objective is to analyze personal neuro-motoric features in order to characterize Parkinson’s disease or to control medication by recorded data obtained from diverse hand, fingers and wrist movement tasks.

Many data processing techniques including enhanced pre-processing and dimension reduction methods as well as feature extraction and classification techniques have to be implemented and tested. For this purpose, the Dynamic Time Warping (DTW) together with its variants and Support Vector Machine (SVM) techniques are established and evaluated for data analysis.

In brief, the essential aims of the thesis are to develop sensor techniques and software methods to determine the feasibility of the BiSP system in order to register and to analyze human fine motor features in multiple applications. To achieve this, several experiments have been performed with the advanced BiSP system to analyze: (1) biometric person authentication (2) biometric handwritten object recognition (3) features of writer with Parkinson disease in relation to healthy controls—biomedical applications.

The main experimental objectives in biometrics are:

- Applying the novel BiSP device to record biometric features while used in on pad or in air modes of operation for the following movement tasks:
  - Signatures—handwriting on pad
  - PIN words—handwriting or drawing on pad and in air
  - Characters—handwriting or drawing on pad and in air
- Developing a DTW based method for handwritten objects recognition.
- Developing a DTW based method for biometric person authentication by using hand-written PIN words and handwritten signatures.
- Evaluation of biometric performance based on the enhanced BiSP system.
- Evaluation of recognition performances while x-y position coordinates and finger grip pressure signals provided by the enhanced pen device are analyzed.
- Comparison of person authentication performance while using handwritten PIN words and handwritten signatures.

- Comparison of person authentication performance while using handwritten private PIN words and handwritten public PIN words.
- Evaluation and comparison of biometric person authentication while handwriting or drawing in two modalities: (1) on pad and (2) In air (off pad).
- Design and evaluation of the biometric two-factor authentication method.

The main experimental objectives in biomedical data analysis are:

- To register with BiSP the neuro-motoric features of the hand, fingers, and wrist during the following movement tasks:
  - Circles in air: hand gesture movements
  - Circles, spirals and meanders on pad: handwriting or drawing movements
  - Finger-taps: gesture movements
  - Diadochokinese (hand-wrist): hand gesture movements
- To develop software methods to:
  - Study the dysfunction of handwriting, drawing or gesturing movements
  - Distinguish between PD patients and healthy persons automatically

1.2.2 Structure of the Thesis

This thesis is divided into eight chapters. **Chapter 1** defines the scope, applications and introduces the thesis topic. **Chapter 2** presents essential fundamentals and definitions encountered in biometrics. **Chapter 3** first introduces basics of handwriting generation and recognition processes. Next, gives a brief overview of common handwriting acquisition devices and then of the BiSP devices developed and used for the input of handwriting, drawing or hand gesture movements. **Chapter 4** presents methods and data analysis procedures. It gives data collection and data pre-processing techniques. Then theoretical background of features extraction, dimension reduction and classification techniques is given. Finally, the techniques of performance evaluation developed in the thesis are described. **Chapter 5** presents the Dynamic Time Warping DTW classifier for BiSP data. Initially, it introduces related work on DTW based classifier and then proposes DTW based techniques used in the thesis. In the chapter, several proposed techniques for the representation of time series data such as piecewise area approximation, reduced univariate approximation, area bound approximation, bio-reference level assigned approximation etc are described. Finally, two types of extension to the symbolic aggregate approximation are suggested.

Chapter 6 illustrates the BiSP system for biometric applications. It describes experiments and results in the context of biometrics for person authentication, handwriting recognition and Two Factor Authentication TFA. It begins with the experiments for the biometric person and single character recognition and shows competitive performance results obtained for handwritten PIN words and signatures. The performance evaluation of the enhanced BiSP system, described for the recognition of handwritten PIN words, is also discussed. Next, experimental results for several proposed representations of data and advanced pre-processing techniques applied to the time series data are given. Finally, security enhancement experiments based on TFA method and results for handwriting on pad and in air are discussed.

Chapter 7 presents the BiSP system for medical applications. It describes experiments and the results in the context of neuro-motor features registration with the BiSP system. The developed data analysis methods and the classifiers for characterizing the Parkinson's disease are described. It begins with the introduction of PD and its effects on handwriting. In this chapter, handwriting, drawing and hand gesture movements involved in the predefined tasks are considered. Furthermore, the methods for special movement tasks such as the hand-wrist and finger-taps movements are described. It shows classification results of data in the framework of Parkinson's disease diagnosis. **Chapter 8** finally summarizes the major findings and highlights the prospects of future work and application.

2 Fundamentals and Definitions

Traditionally, people recognize others because of their face, eyes, ears, and voices that are somehow already stored in their brain. During communication or interaction with other people, humans are identified, as simply as, by their names or, by their body characteristics such as gait, voice etc for long time. The use of fingerprints or of handwritten signatures during commercial and/or financial interactions to determine the identity of a person is a common approach now.

Nowadays, the demand of person authentication has essentially increased in order to access a resource or a facility [5]. With more and more interaction of people using modern information technology, an automatic reliable person authentication system is essentially required for security reasons or personalization requirements. This chapter first, gives traditional and common authentication methods. Further, it presents the essential fundamentals and definitions encountered in biometrics. The conclusion of this chapter also defines the problems associated with the biometric systems.

2.1 Traditional Authentication

Traditional authentication procedures based on knowledge (PIN codes or passwords) and possession (keys or cards) are still used because they have the following advantages:

- Familiar to use
- Easy to handle
- High acceptance
- Little or no user training is needed

Therefore, to some extents these systems are assumed functional so far.

But traditional authentication procedures do not provide sufficient security standards with the increasing human-resource interactions and have some more drawbacks. As passwords or PIN codes can be forgotten or lost and keys or cards can be misplaced. This can have potential threats to be used by an un-authorized person. Therefore, traditional authentication methods, do not comply well with the present and growing future security requirements. Some of the limitations associated with traditional "password" based authentication are discussed in detail in [6]. To face future demands in person authentication, the methods based on biometrics are needed to improve the security [5-6].

2.2 Biometrics

The term Biometrics is stemmed from bios (life) and metrics (measure). Therefore, biometrics is a collection of techniques used to measure human's physiological characteristics or behavioral traits in order to recognize them for person identification or verification. Physiological characteristics of humans are the biological features such as face, fingerprint, iris etc. While, on the other hand behavioral traits are the actions or the behaviors of humans e.g. keystroke dynamics, voice, gesture, gait, signature and handwriting dynamics.

Biometrics based methods have several advantages over the traditional authentications methods and offer higher security standards. They are more reliable because the biometric features cannot be lost or forgotten and it is difficult to copy or forge them.

Thus, biometric authentication systems are expected to be a promising and powerful alternative to the traditional authentication methods [2-10].

Biometric System Operation

A biometric system attempts to solve a complex-pattern-recognition problem by using human build-in biometric characteristics to determine the identity of a user.

As shown in the Figure 2.1, its operation begins with acquisition of raw biometric signal data from an individual user. The data is processed to extract a set of useful features. Then this feature set is compared against the person specific template already stored in the database. Finally, it either validates a claimed identity or determines the identity associated with the signal [5-6].

Basic Modules of a Biometric System

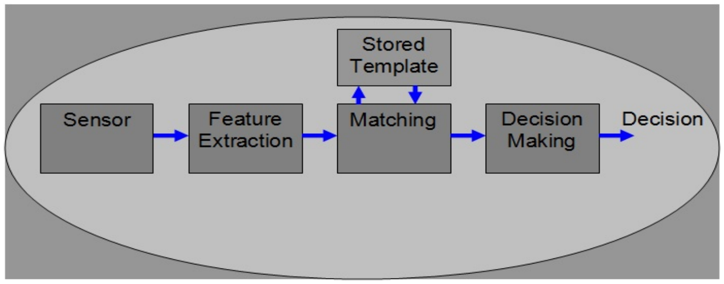


Figure 2.1: Biometric system modules

A biometric system consists of the following four basic modules:

- Sensor module
- Feature extraction module
- Matching module
- Decision-making module,

Biometric system or person authentication operates in verification or identification modes.

In **verification**, the system accepts (or rejects) a claim of identity of an individual based on a one-to-one test comparison of biometric patterns (sample) of the person in order to confirm the claimed identity.

Identification is a process of one-to-all test comparisons. It involves comparisons of a sample pattern to all reference patterns of all enrolled individuals in the database. The system attempts to establish identity of a person in the database.

According to Jain et al, [5] any human biological measurement (physiological or behavioral) can be considered as optimal biometric trait to be used for recognition that satisfy the following requirements.

- Universality or availability: every person should possess the characteristic
- Uniqueness: each person should have private biometric characteristic (distinctiveness)
- Permanence: characteristic should not change over time
- Collectability: the characteristic should be easily acquirable.

Single Biometric Methods

There are diverse single biometric methods based on physiological or behavioral features of human that can be used for person recognition.

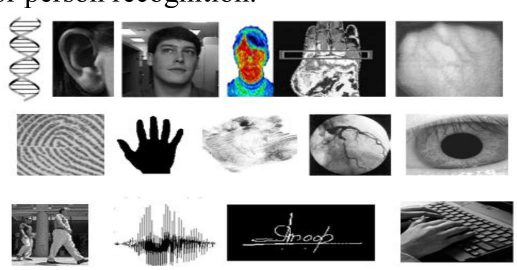


Figure 2.2: Examples of biometric characteristics (adopted from [5-6]).

Figure 2.2 illustrates some examples of biometric methods based on (1) physiological characteristics: DNA, ear, face, facial thermo-gram, hand thermo-gram, hand vein, fingerprint, hand geometry, palm print, retina, and iris, and (2) behavioral characteristics: gait, voice, handwriting and keystroke dynamics.

The applicability of a biometric technique depends heavily on the requirements of the application domain [4-9].

The following requirements should be considered in a practical biometric system [5-6]:

Storage: the system should be able to store data efficiently.

Performance: is the level of accuracy of biometric system. It also refers to all the factors that influence the accuracy, efficiency, robustness, computational speed and resource requirements of a biometric system.

Acceptability: indicates the extent to which people are willing to accept that a particular biometric characteristic should be used for their recognition.

Circumvention: reflects how easily the system can be fooled using fraudulent methods. The system should be able to resist against potential spoof attacks.

A comparison on various biometrics and their limitations is given in [5].

Problems and limitations of Biometric Systems

Biometric systems are expected to show the following desirable properties:

High intra-class similarity—the biometric features recorded for a particular user should be similar in distinct enrolments or in different sessions.

High inter-class variability—the biometric features recorded for one user should be distinct from those of all other users in the database.

Early research in biometric system development was mainly devoted to design, develop and test the novel biometric systems and algorithms. Therefore, numerous biometric techniques and large number of classifier algorithms are being developed. Now research on further improvements in terms of reliability and accuracy is advancing in all above-mentioned areas.

Recent research has shown that human factors (physical, behavioral and social) and sensor interface affect significantly performance of the overall biometric system [2-3]. Hence, the following factors should be considered in this regards:

High intra-class variation is a serious concern in biometry. This variation may occur in different enrolment sessions due to typical un-wanted behavior of the user who is incorrectly interacting with the sensor or on account for sensor malfunction or modification. For detail on the sensor interoperability problems see [2].

Physical environment and psychological condition of the user is another concern that might result in high intra-class variation at various time instances [5]. Users may be uncertain about where or how to position themselves or an object to the biometric sensor to get a valid reading. They may have concerns about using biometric device for a certain application and in a certain context.

User training and instruction is necessary if people are not familiar with a biometric device which is to be used.

Although biometric authentication systems have been applied in commercial (i.e., electronic data security), government (i.e., border control) and forensic (i.e., criminal investigation) applications, the reliable biometric person identification has still need to be improved. One way of improvement of biometric systems that use a single biometric trait (uni-modal biometrics) is to address the following limitations associated with them [4-6].

1) Distortion or noise in biometric data
2) Intra-class variations: Due to noise or distortions in data at different enrolments from a single user, high intra-class variations may exist in the acquired biometric data. This high variation may cause a genuine user being incorrectly rejected by the biometric systems.

3) Distinctiveness: It is expected for a biometric trait to vary significantly across the population.
4) Non-universality: it may not be possible to extract distinguishable feature sets of an individual.
5) Spoof attacks: A biometric system must be capable to distinguish the imposter's spooling attempts.
6) Speed or recognition time: it is not expected that a user is waiting for several minutes for an identification decision. Therefore, a biometric authentication system should be fast to result authentication decision.

In conclusion each biometric technique has its strengths and weaknesses and therefore there is no 'single biometric' that is 'optimal' at present. A comparison on various biometrics and their limitations that operate on single biometric trait (uni-modal biometric) are listed in [3-6]. One possibility to improve conventional authentication systems (that are based on knowledge or possession) is to use them in multiple levels based on knowledge-possession combinations. In spite of little improvement, there is still a potential threat of traditional authentication system being used by un-authorized person. The limitations associated with traditional authentication systems are detailed in [5-6].
On the other hand, fortunately biometric authentication systems provide a high degree of security [5] because, they are based on human build-in possessions (e.g., face or fingerprint) or actions (e.g., behaviors i.e., signature or gaits). Further, it is not required to remember biometrics so it is convenient to use a biometric system in this sense.

2.3 Multimodal Biometric Systems

Some of the problems or limitations which may occur in biometric person authentication applications are described in the previous section. The systems that use more than one uni-modal biometric systems in combinations or use multiple authentication levels are known as multimodal biometric systems. Being able to authenticate users at multiple levels, these systems will be more reliable and robust and are expected to meet the performance requirements in the existing and emerging future authentication applications. The limitations imposed on uni-modal biometric systems can be overcome by making use of multimodal biometric systems. These systems overcome some of the problems by taking into account the advantages obtained from different sources. These sources may include the following [5-7]:
1) Multiple sensors for the same biometric e.g., use of x-y positions coordinates of pen or horizontal and vertical pressures of pen for signature data or alternatively pressures of finger grip and inclinations of pen for signature data during handwriting with BiSP.
2) Multiple instances of the same biometric e.g., fingerprints from different fingers of a person or using handwritten PIN and signature recorded with a pen from a person.
3) Multiple representations and matching algorithms for the same biometric trait e.g., multiple matching software like DTW and SVM.
4) Multiple biometric traits e.g., face and fingerprint or handwritten signature and fingerprint.

The problem of noisy sensor data can be solved by using multiple sensors. The use of multiple instances of the same biometric can ensure the physical presence of a user. The multiple matching algorithms for the same biometric may also be used to improve the recognition performance of the system [7].

Fusion of Information

In order to reduce complexity, the information fusion (combination) can be made at any stage of the biometric system modules as described above. For example the Figure 2.3, illustrates different levels of information fusion when a combination of two uni-modal biometrics e.g., face and fingerprint is used for person identification. It comprises:

- Sensor level fusion
- Feature level fusion
- Match score level fusion
- Decision level fusion

A fusion technique applied at an early stage (i.e., feature extraction level) is considered as more effective that gives improvement in results than that of one applied at a later stage (i.e., matching scores level). However, a combination at feature level is more difficult [5].

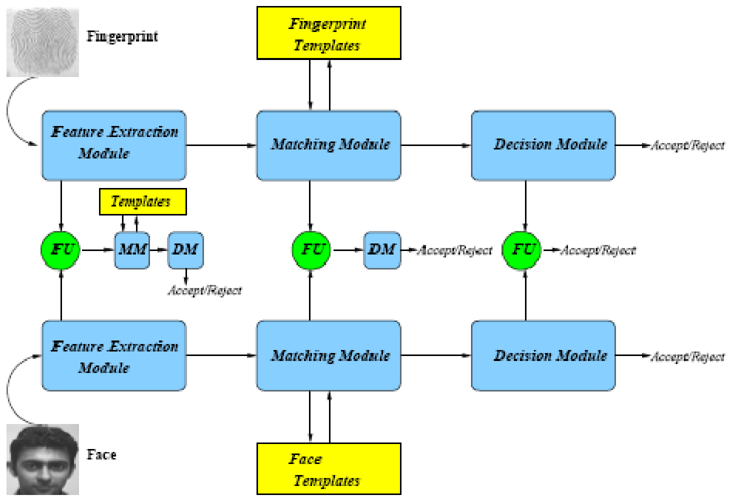


Figure 2.3: Levels of fusion in a multimodal biometric system [8].

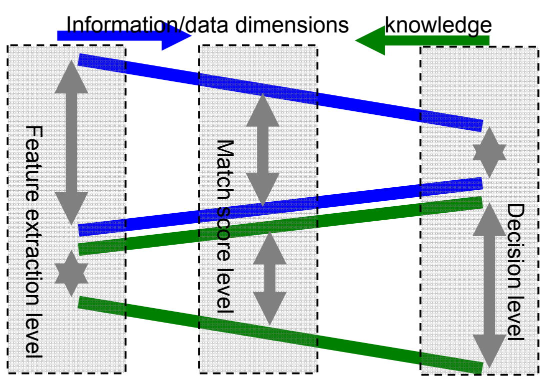


Figure 2.4: Relation of Information, knowledge and data-dimension.

Figure 2.4 illustrates the relation between information-content (or data dimensions) and knowledge at different fusion levels. At sensor or feature extraction level, the data exists in very high dimensions with richest information compared to the data at a later fusion stage. Data exists in low dimensions but it has more knowledge about the identity associated with the data at a later stage of fusion. The relation between information and the knowledge of the evidence goes opposite when going from left to right (i.e., information and data dimensions go on decrease with increase in knowledge) or contrary relation is accounted when going from right to left as shown in the Figure 2.4.

Disadvantages

In multimodal biometrics, the information from multiple sources can be used in different possible ways in multiple levels of authentication [4-8]. This authentications based on multiple sources of information in multimodal biometrics can essentially increase the accuracy and reliability of the system. But this improvement in the system will be at the cost of:

i) inconvenience to the user in providing multiple clues (e.g., face/finger print)
ii) more user training
iii) longer acquisition time
iv) more complex data processing
v) more infrastructure and higher technical complexity

The above-mentioned concerns encourage us to develop a biometric system that should be familiar to the users. The biometric authentication by handwriting signatures or PIN words is promising because of long history of signatures, wide acceptance in public domain and the intimacy of writing with a pen. If we attempt to provide a biometric two factor person authentication system based on single biometric trait (handwriting) then it is expected that it can outperform the personal authentication with—high recognition accuracy, more effectiveness and more convenient to the users. The biometric two-factor authentication procedure is described in section 6.6.

3 Biometric Measurement Systems for Handwriting

This chapter first, defines the field of handwriting biometrics and introduces handwriting generation and recognition processes. Then it discusses the online and offline recognition systems as well as local and global approaches for handwriting recognition. Later it gives a brief overview of handwriting acquisition devices, and then finally presents the BiSP devices developed and used in the study work for the input of handwriting, drawing or hand gesture movements.

3.1 Human Handwriting

Unlike physiological biometrics where the physical characteristics of a person (e.g., fingerprints) are recorded and used for person recognition, behavioral biometrics uses the records of handwriting movements for that. Person authentication by means of handwriting is one of the wide researched subjects in behavioral biometrics. Handwriting studies have been long used not only for person verification and document authentication but also in numerous other applications including neurological disorder quantification, experimental psychology, neuroscience, engineering, computer science or forensic science etc [31].

The handwriting features associated with the measurements of hand and finger movements involved in handwriting can be categorized as:

(i) Object specific features
(ii) Biometric features and
(iii) Neuro-motoric features.

This division of handwriting features is because of the fact that they are extracted and analyzed for three major applications associated with:

- Handwritten object recognition
- Person identification and/or verification and
- Disease diagnosis

For this, the handwriting attributes are recorded in terms of kinematics and dynamics of hand and finger movements.

3.1.1 Handwriting Process

Handwriting is a process determined by brain and muscle activity reflecting neuro-motor characteristics of the person [34]. Handwriting is a demonstration of one of the intelligent, skilled and practiced actions of human hand and finger motions. These movements are called ballistic motions because they do not necessarily involve sensory feedback. In handwriting, the individual muscle forces are not essentially determined by simple feedback but rather pre-determined by brain activity. The corresponding motor control or motion can be learned so that results in similar samples of handwritten texts. Therefore, handwriting of a person may not change significantly on paper, credit card or on a blackboard [33-35] or even in air. Handwriting and the related process are considered as private to an individual and the latter is invisible to potential forgers. Such handwriting information given by a word or signature has been widely researched for personal verification in behavioral biometrics. It is known that the complex handwriting process can be influenced by environment and mental conditions or the modification of physical writing [36]. In spite of this, traditional person identity verification is still accepted by means of handwritten signatures and is a topic of present research. The handwriting recognition systems can be divided into two groups depending on which data acquisition and analysis method is used: **offline** and **online** systems.

3.1.2 Offline and Online Handwriting Recognition Systems

In offline recognition, a word or signature first handwritten on a document and then its image is digitized after scan. The offline handwriting recognition is regarded as static recognition because it deals with digitization of already handwritten text. The image (shape) information obtained from the handwritten object is used in data analysis for personal verification.
In online recognition, a special pen or input device such as a pressure sensitive tablet is used for handwriting to record not only the shape but also the dynamics of handwriting in real time that are used for verification. Online recognition is regarded as dynamic because the temporal and dynamic handwriting features in terms of timing parameters like x-y positions coordinates or pressures, speeds, accelerations etc are also recorded and analyzed. This online method is more popular and reliable for person authentication because a potential forger can mimic the shape of a signature for instance but it is much more difficult for him to copy the dynamics of signing. Offline systems are less accurate than the online systems, because the temporal and dynamic information of handwriting are not available [33][37-39][41]. A detailed comparison on offline and online recognition systems can be found in [32].

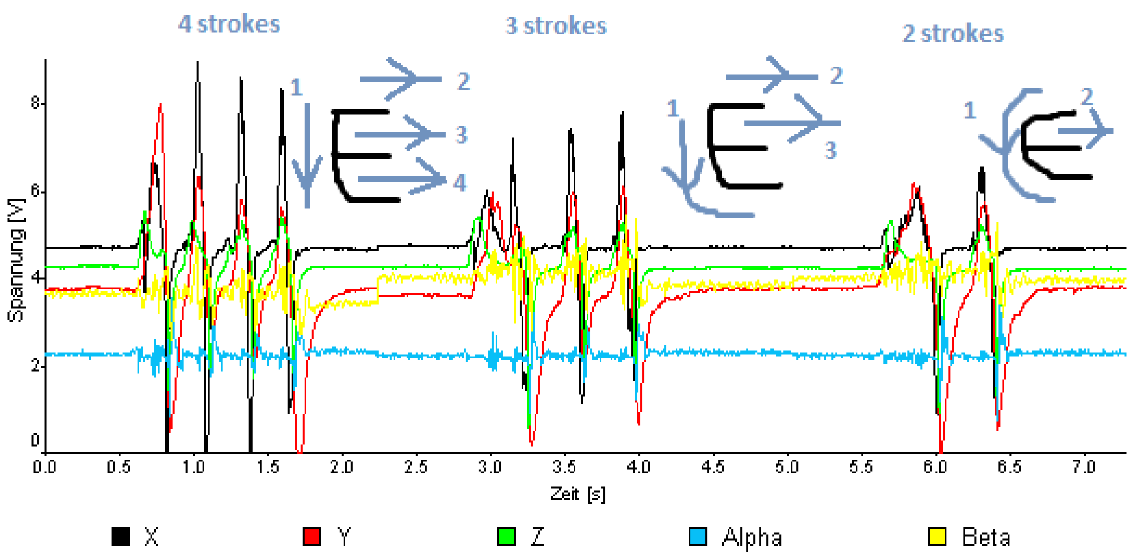


Figure 3.1: Same person's signals recorded with BiSP for online handwritten character "E" with different numbers and ordering of strokes.

As illustrated in the Figure 3.1, a handwritten object "E" can be drawn by different numbers and orders of strokes resulting in different patterns in the signals even when the whole image of "E" looks similar. In offline recognition, the representation of the image is often insensitive to the variations in the strokes ordering. This is not the case for dynamics of writing resulting in different patterns in an online signal even when the same object is handwritten by the same person (see Figure 3.1) making online handwriting recognition more complex. But at the same time, for a person authentication task, the handwriting style of an individual is an advantage and could be treated as a discriminating or private feature of a person for recognition. The curves in Figure 3.1 reflect sensor signals of BiSP (for details of BiSP and signals see section 3.3).
Consequently, two approaches can be applied on different application scenarios, such as online recognition systems can be used for credit card purchases, computer login or for accessing sensitive data (or resources), while offline systems can be used to authorize a document or to verify a signature (offline) on a bank check [33].

3.1.3 Global and Local Approaches

Online signature verification methods can be categorized into two approaches: global (parametric) approach and local (functional) approach. In the global approach, only the parameters or feature sets extracted from the complete signals are used for data analysis. Examples of global measurements include the total writing time, number of strokes, or average writing speed etc. Generally, the numbers of features are equal for all samples. This makes the comparison of samples simple. Because of the higher level of data abstraction, these approaches are very fast. But sometimes it is difficult to select the correct parameters [52]. On the other hand, functional approaches use the complete signals as features set in terms of time functions (time series) that essentially contains more signing information, and hence provide similarity results that are more accurate [38][39]. Though the dynamic nature of handwriting is clearly more involved and the feature selection is simpler in the local approach, it has some serious drawbacks. It includes the comparison of samples of unequal length. In addition, it needs longer computing time and still suffers more from intra-class variation problems. To overcome partly these problems dynamic time warping (DTW) based classifiers have been applied for several decades (see Chapter 5.)

3.2 Handwriting Acquisition Devices

With the technological advancement, numerous handwriting acquisition devices have been developed and used for the input of handwriting. The acquisition devices, such as pressure sensitive graphic tablet and/or pen based input devices, are used to record static and/or dynamic information related to handwriting. In this section, first we will give a brief overview of handwriting input devices that are used in offline and online data acquisition. Then in the following section, we will describe the proposed pen based acquisition devices termed as Novel Biometric Smart Pen BiSP.

Three major trends can be observed in handwriting data acquisition devices [31]:

1. *Scanner-based acquisition devices—mainly used in offline recognition systems*
2. *Tablet-based acquisition devices—mainly used in off-line and online recognition systems*
3. *Digital Pen-based acquisition devices—mainly used in online recognition systems*

This thesis deals with the on online handwriting data acquisition and analysis.

3.2.1 Scanner-based Acquisition Devices

Traditional table scanners or cameras are the familiar acquisition devices in offline handwriting acquisition. An interesting option is the handy scanner C-Pen of C Technologies shown in the Figure 3.2.

Figure 3.2: A handy scanner C-Pen [31].

A C-Pen consists of a digital camera inside the pen that captures and saves the offline captured handwritten text or signature into memory as a document. The data is then transferred to a PC, PDA or mobile phone using cable or infrared (IR) communication. The detail on such sensors is omitted here.

3.2.2 Tablet-based Acquisition Devices

Digital tablets are among the oldest and most commonly used online acquisition devices used with computers. They are also known as pressure sensitive graphic tablets or pads. A large number of systems use two cooperating devices for data acquisition—a tablet or touch screen and a plastic pen as shown in the Figure 3.3. These are most popular devices and many papers have reported on such devices being used for online data acquisition [32][36-39][75]. A digitizer provides an interface between the pen and the tablet and recognizes the motion made with the pen, stylus or human finger and passes it to the tablet. The basic purpose of the digitizer in a pen tablet is to transform the position of the pen into x and y coordinates. The captured sample data is represented by time functions of different signals as:

—Pen-tip x-/y position coordinates and/or normal pressure
—Angles of the pen (pen azimuth & pen altitude)

A detailed overview on these technologies underlying the tablet based pen system, potential advantages and disadvantages of these technologies are given in [31, 45].

Figure 3.3: Tablet and pen systems for data acquisition from WACOM (Graphire2, Intuos2, and Clintiq) and ePen tablet [31].

The WACOM acquisition instrument will be described in more detail below in section 3.4.

3.2.3 Pen-based Acquisition Devices

Pen-based systems for the on-line handwriting acquisition are available on the market or are being improved by research institutes [31]. Its online data acquisition is sometimes different to that of tablet-based acquisition. The pen based input device generally captures more comprehensive signals:

—Pen-tip x-/y position coordinates and/or normal pressure and/or
—Forces/pressures on Pen-tip in three directions
—Two (three) angles (accelerations) of the pen-shaft in two (three) dimensions, relative to the writing surface

The **N-scribe** (by Digital Ink) as shown in Figure 3.4 and described in [45] uses a GPS-like measurement system and converts handwritten text into a digital code. The pen does not require any special pad or paper.

Figure 3.4: N-scribe [45]

Anoto Pen (by Anoto AB Company) consists of a digital pen and digital paper. The pen contains a camera, a pressure sensor, and ordinary ink cartridge. The needed special digital paper is conventional paper with a special *Anoto pattern* printed on it (Figure 3.5).

Figure 3.5: Anoto Pen, Anoto patterns and Anoto Pen.

The digital pen looks like an ordinary ballpoint pen. The pen uses the camera to take digital snapshots of the pattern so that the pen can calculate its position in the entire Anoto pattern. Infrared light is used to make the dots of the Anoto pattern visible to the digital camera. The Anoto pattern is printed with carbon-based black ink and the infrared light interacts with the carbon-based dots. A small number of dots uniquely define the position in the full pattern. The pattern consists of small dots that are barely visible to the eye, it is perceived as a slightly off-white color. The ink from the pen is not visible to the camera; its function only is to make the written text visible to the human eyes [31].

Force Sensitive Tablet (F-Tablet)

F-Tablet [47] is capable of capturing both the dynamic handwriting force information and static trajectory of the pen-tip during writing. With the core part of the sensor, the F-Tablet can capture the two torques and three perpendicular forces between the pen and the tablet. Figure 3.6 shows the tablet frame (1) with processing circuits (2), force/torque sensor (3) and the active input tablet area (60 x 60mm^2) (4) for handwriting.

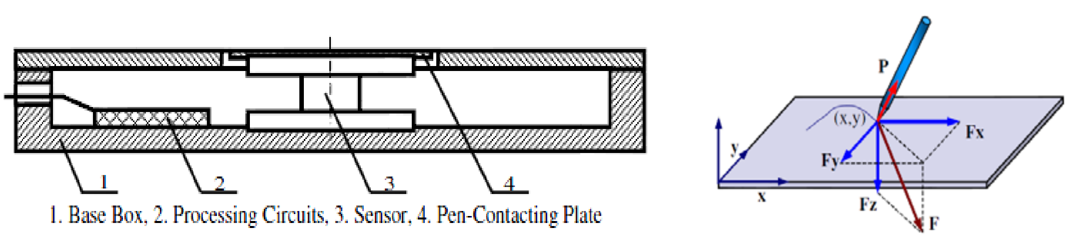


Figure 3.6: Frame diagram of the tablet and schematic diagram of force action [47]

The working principle can be observed from Figure 3.6. The F-Tablet is designed to measure forces between 0~10N, to digitize with a 12bit AD converter and to sample each channel data at the frequency of 100Hz. For details on F-Tablet, see [47].

3.2.4 Other Pen based Input Systems

The handwriting features are commonly captured by pen based graphic tablets or pads. In such devices x-y position coordinates, tip pressures on the surface and pen tilt are measured.

In some other pen-based approaches, refill pressures with tilt angles are employed for the data sampling. Several pen based acquisition systems are reported in [47-49].
The above-mentioned acquisition devices are most extensively used for handwriting acquisition. The obvious disadvantage and difficulty in the use are more complex techniques, limited mobility, high cost, uncomfortable or unnatural in use, intrusive and low performance. Hence, a pen device system which is more comfortable, nonintrusive and natural in use is required. Such a device is expected to produce handwriting sequences (personal signatures) with low perturbations resulting in less intra-class variations in handwriting movements for an individual.

3.3 Novel Biometric Smart Pen (BiSP) Device

3.3.1 Related Work

The ***Bi**ometric **S**mart **P**en* (BiSP) project team at the University of Applied Sciences, Regensburg, Germany has configured several smart ballpoint pen prototypes during the last decade [1].
In this section, a brief overview is presented for two former BiSP prototypes termed MechPen & MicPen. Novel BiSP pen base data acquisition systems used in the thesis will be described in detail in the following sections.

Figure 3.7: BiSP MechPen with cover in action and electronics

BiSP MechPen. This special pen-prototype was built at the University of Applied Sciences in Regensburg during the year 2002 (Figure 3.7). The pen consists of two pairs of mechanical sensors which measure the forces or pressures resulting from the horizontal and vertical movements of the pen-refill. The pen produces a total of three signals: the normal pressure signal (longitudinal axis of the pen) and two signals corresponding to the horizontal and vertical movements of the pen. Four strain gauge sensors which measure the horizontal and vertical movements of the pen are located near the pen nib and they are placed orthogonally to each other. The signal produced by the horizontal pair of sensors is called **x** and the one produced by the vertical sensors is **y**. Each pair of sensors is connected to the Wheatstone bridge. Therefore, there is only one output signal corresponding to the horizontal movement of the pen (**x**) and one corresponding to the vertical movement (**y**).
BiSP MicPen. Another BiSP prototype of a pen-based device was a microphone based BiSP device (MicPen). Audio signals generated at the pen tip due to the movements of the pen during handwriting on a paper pad are measured by a microphone mounted inside the pen and in contact to the refill (Figure 3.8).

Figure 3.8: BiSP MicPen without cover.

The MicPen is additionally equipped with a pressure sensor in order to record normal pressure on refill. For detailed description and information on BiSP MechPen and MicPen see [31][50-51].

3.3.2 Novel Multisensoric BiSP

Numerous person authentication systems base on several handwriting acquisition devices using a range of signature verification systems have been proposed. In practice, most of the systems mentioned above have serious disadvantages, especially in data acquisition. Because they are intrusive, uncomfortable to use, costly, have low performance with respect to error rates, may be suited only for limited populations or show poor mobility or protection against imitation. In BiSP project, a unique multisensoric ballpoint pen based system has been developed which is superior in many respects to current pen based human computer input devices [1]. The ability to measure miscellaneous biometric patterns from the same biometric trait (handwriting) at the same time is the main benefit of the New BiSP device. Different to previous versions of BiSP—**MechPen** or **MicPen**, new BiSP device contains (i) novel sensor techniques including grip sensing of fingers holding the pen, (ii) size of the pen is very similar to the commonly used ballpoint pen and (iii) all sensors and electronics parts are now installed inside the pen. The BiSP device is for the acquisition and analysis of human hand and fingers movements while handwriting, drawing or gesturing on any paper pad or free in air. It is equipped with a diversity of sensors for monitoring:

- Dynamics of pressures transferred in x,-y dimensions from the refill to the pressure sensors
- Normal pressures of refill during writing
- Dynamics of pressures of fingers grip holding the pen
- Acoustic and vibration signals generated by pen-tip
- Inclination-acceleration of the pen in three dimensions

Together with common and newly developed classifiers, the BiSP pen system is expected as an innovative system for following uses:

- Biometrics for highly secure human identification/verification based on handwriting biometric features
- An essential part of a desktop computing relating to electronic recognition of handwriting and gesturing. For an example to transfer handwriting notes or drawing from common paper pad, or handwriting or gesturing free in air to the computer
- In life sciences for computer aided diagnostics, therapy and training tasks in medicine, physiology and education using biometric data corresponding to neuro motor behavioral traits of human hand and finger movements during drawing or gesturing on paper pad or free in air. The BiSP based system is preferably well suited for the classification and quantification of hand-motor dysfunctions (e.g., due to Parkinson's disease) and the analysis of the fine motor movements of patients under drug treatment.

As a result, new trends incorporated in this thesis towards the development of BiSP acquisition devices are based on the following dynamic measurements:

—Pen-tip x-/y position coordinates
—Pressures on Pen-tip in three directions
—Pressures of fingers grip holding the pen during writing
—Acoustic signals generated by the refill during writing
—Acceleration and tilt of the pen in three dimensions

3.3.2.1 Multi-sensor BiSP Device

The sensors implemented in the BiSP device employed in the experiments are shown in Figure 3.9.

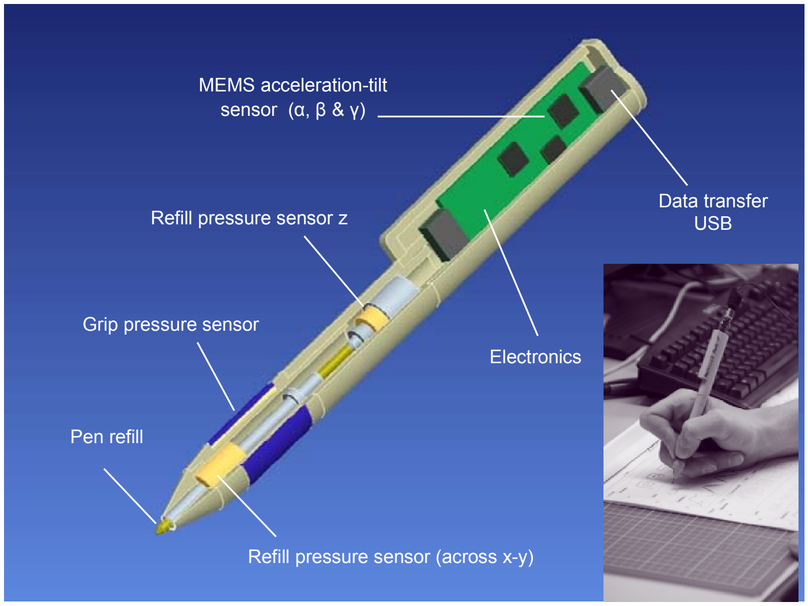


Figure 3.9: Novel BiSP Pen design for monitoring handwriting movements.

The change of forces resulting from handwriting on paper pad and transferred by the refill is monitored by three piezoelectric film (PEF) based pressure sensors—two pen-refill and one grip pressure sensor. There is a micro-electro-mechanical sensor (MEMS) located at the electronic part of the pen which can measure acceleration and inclination of the pen in three directions. Therefore, handwritten objects are represented by multivariate time series data provided by the diverse sensor techniques as described in the following.

Piezoelectric Film (PEF)

Piezoelectric materials produce an electric charge when subjected to mechanical deformation and conversely, undergo deformation when subjected to an electric field. Basically, electrical charge produced in piezoelectric materials results from the displacement of an electric dipole. Hence, piezoelectric materials generate an electrical charge proportional to applied pressure. Piezoelectric properties have been found in several ceramic and plastic materials. Piezoelectric films such as polarized fluoropolymers (polyvinylidene fluoride (PVDF) exhibit high piezoelectric effect. For details on piezoelectric sensors see [68, 69].
PEF is flexible, lightweight material with high mechanical strength and stability. It is possible to transform PEF into different sizes and shapes making it easy to fabricate as a pressure sensor. A PEF is responsive to a changing stress and the dynamic forces or pressures like those generated by the fingers on the pen during handwriting. Consequently, PEF based pressure sensors are a good choice for the dynamic handwriting pressure sensing in the BiSP. For this study work, the PEF sensors were fabricated by using commercial piezoelectric films of MSI sensors [60].
The connection wires are soldered to tiny cut pieces of copper foils which are then glued onto the PEF for lead attachments. A further silicone rubber layer of about 1mm thickness is coated on both sides of the film for protection and improved sensitivity.

3.3.2.2 *Refill across Pressure Sensor*

Changes in force due to handwriting on any paper, transferred by the pen-tip (refill) is monitored as across sensor (x-channel) with the help of PEF foil placed close to the front part of the refill (pen tip). PEF is wrapped around the refill holder at the nearby pen tip inside the pen holder as shown in the Figure 3.10. The across(t) sensor measures the change of forces resulting from handwriting pressures along the x-y axes of the pen-tip movements and generates a single time series signal of accumulative pressures along x-y dimensions during handwriting.

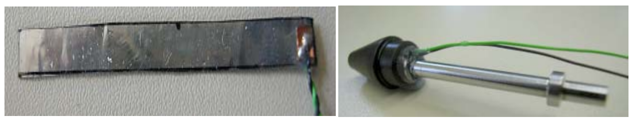


Figure 3.10: PEF with copper terminal connections and installed as across sensor

3.3.2.3 *Refill z Pressure Sensor*

PEF is wrapped around a solid cone which is placed in the housing. The cone is directly attached to the refill at the opposite end of the pen tip. A silicone rubber pushes back the refill through a solid cone which serves as an elastic spring. The z-sensor (z-channel) measures the normal (longitudinal to refill axis) pressures of hand and fingers exerted on the pen-tip transferred by the refill during handwriting. A PEF with copper terminal connections and installed as z-sensor is shown in Figure 3.11.

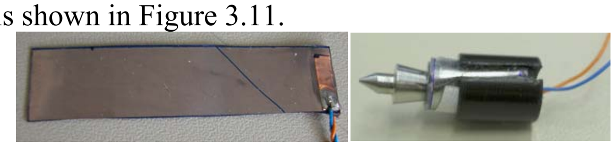


Figure 3.11: PEF with copper terminal connections and installed as z-sensor.

3.3.2.4 *Finger Grip Pressure Sensor*

The grip pressure of the fingers holding the pen during handwriting is detected by a PEF based finger grip sensor. This kind of grip sensing is unique and provides excellent dynamics of fine motor skills of a writer during handwriting with the BiSP. The configuration and the principle of function of the PEF based finger grip sensing technique is shown in Figure 3.12.

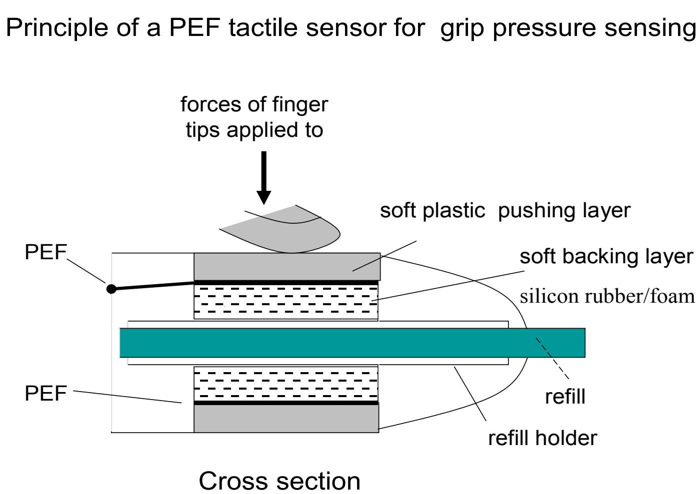


Figure 3.12: The principle of finger grip sensing technique.

PEF is wrapped around the case of pen near the gripping area. Further, silicone rubber housing around the PEF layer act as pushing and backing layer.

Figure 3.13: Fabricated PEF finger grip sensor

Figure 3.13 illustrates the fabricated PEF finger pressure sensor. Silicone rubber coated on both sides is for protection and efficient use of the PEF.

3.3.2.5 Inclination-acceleration Sensor

A micro electro mechanical (MEMS) seismic sensor is also installed inside the pen on the circuit unit. It measures the acceleration-tilt of the pen device in three directions. With the change of acceleration or tilt of the pen, the seismic mass is deflected by the inert and gravity effect, respectively. The shift from its neutral position results in a change of capacitance. This change is detected and is evaluated by the sensor chip in conjunction with a microcontroller. The output signal from the sensor is a superposition of both the acceleration and gravitation effect. In the case of handwriting on a paper pad, the sensor ultimately captures the tilt of the pen. The tilt itself is characterized by the angles α, β and γ measured in the x, y and z directions.

A three-axis MEMS accelerometer from VTI technologies—SCA3000 and its installation inside the pen is shown in Figure 3.14.

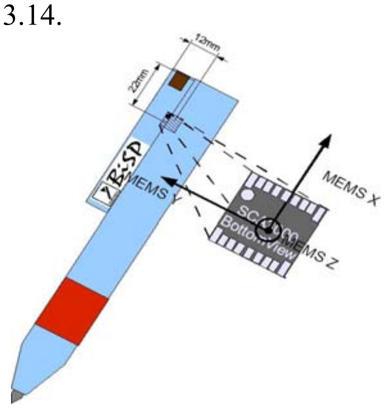


Figure 3.14: The principle of MEMS tilt installation.

Electronics:

Figure 3.15 shows the block diagram of the electronics implemented inside BiSP device. The block diagram of Figure 3.15 indicates the basic components of the electronics operations and signal flow in the BiSP device. It consists of PEF pressure sensors connector to corresponding amplifiers, MEMS accelerometer and a microcontroller with USB functionality.

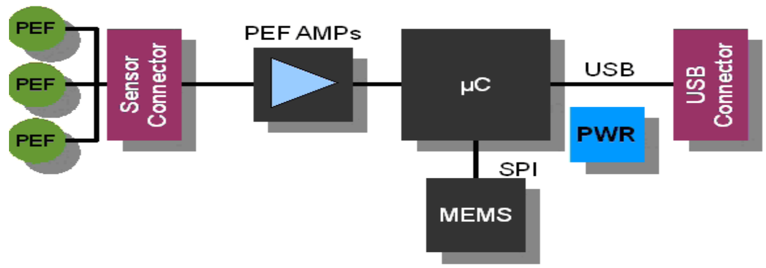


Figure 3.15: The schematic of BiSP electronics.

Figure 3.16: A compact BiSP device with refill & finger-grip pressure sensors, inclination sensor and electronics.

The response of PEF and MEMS sensors is different at different grip positions and orientations of the pen. Therefore, the pen is used with a specified starting grip position marked on the pen.

Altogether, the pen device provides up to six signal channels. These are low pass filtered and digitized by a 10-bit A/D converter at a sampling frequency of 500Hz. The data is transferred to a computer by a wired (HID-USB) interface.

3.3.2.6 Sensor Signals of BiSP

Typical sensor signals recorded with BiSP during handwriting single character “ü” twice are shown in the Figure 3.17.

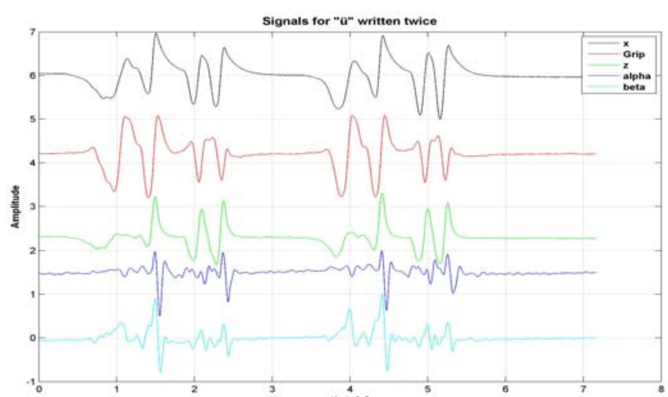


Figure 3.17: Typical time series recorded with BiSP for handwriting single character “ü” twice.

The handwritten object is represented by data provided by five sensor channels: (1) horizontal x(t) and (2) vertical z(t) refill pressure, (3) finger grip pressure Grip(t), (4) longitudinal alpha(t) and (5) vertical beta(t) angles.

3.4 Other Developed Pen Systems

3.4.1 WACOM's Enhanced Pen System

Human fine motor skills of hand and finger movements can be measured by recording the dynamics of handwriting. It includes pen tip position, pen pressure, and pen inclination, velocity and acceleration measured during handwriting. These measurements are not only attractive to researchers in biometrics for personal authentication but also in areas such as medical diagnosis or therapy [53-57]. In these regards, the dynamic features of handwriting are widely captured by pen based graphic tablets or pads which sample the x-y position coordinates and in addition, pen tilt and tip pressures on the surface. Grip forces of fingers holding the pen are not used in graphic tablets. A comparison of the WACOM's graphic tablet with a prior version of BiSP—**MechPen** (a pen without grip sensor) has revealed different strengths of both devices for analysis of human fine motor skills [53].
Initially, in this section, the WACOM's graphic tablet is introduced and then an enhanced version based on a biometric pen based writing system is described. The pen device of the widely used WACOM's graphic tablet [46] (see Figure 3.18) is additionally equipped with a finger grip pressure and inclination-acceleration sensors which are commonly used in BiSP (see section 3.3.2). The evaluation results of such enhanced writing system are presented in section 6.2.

Figure 3.18: The WACOM's graphic tablet pen system.

3.4.1.1 WACOM Graphic Tablet

WACOM Intuos 3 graphic tablet pen system [46] used to develop the enhanced handwriting input system records the trace of the pen tip (x-/y-coordinate sequence), as well as the pressure of the pen tip on the surface and two different angles of the pen relative to the tablet. The x-/y-position of the pen are measured with an accuracy of ± 0.25 mm. The pressure of the pen on the tablet is recorded with 10 bit resolution (i.e., 1024 pressure levels) and the inclination angle of the pen relative to the axis of gravitation are measured with a resolution of about 1^{o}. All signals are recorded at a sampling frequency of 200Hz. The Intuos 3 Pen (named as Grip Pen) *is equipped with a rubberised grip area that reduces writing fatigue but there is no grip pressure sensor installed*. Experiments have shown that the resolution of inclination and pen tip pressure data provided by the used WACOM system do not meet high demands of biometrics and medical application.

3.4.1.2 Enhanced Graphic Tablet Device

In comparison, the BiSP device is much better suited for studying fine motor skills of a person. While, the graphic tablet system is superior if precision of a traced figure or the hand-eye-

coordination have to be analyzed and rated. But the graphic tablet needs more infrastructures that are a tablet for tracing handwriting movements.
The aim of our development work is to combine essential advantages of both input devices in a new enhanced WACOM pen system. The enhanced acquisition system is for the assessment of handwriting dynamics where grip pressure sensing is also involved.
Therefore WACOM Intuos 3 Grip Pen is *actually equipped with a finger grip pressure* as well as inclination-acceleration sensing techniques commonly used in the BiSP system. As shown in the sketch of Figure 3.19, the finger grip sensor (3) is mounted beneath the rubber cover (2) of the WACOM Intuos 3 pen device (1). Based on a piezoelectric thin film technique, the sensor (3) measures the change of finger grip pressure generated in the tactile area.

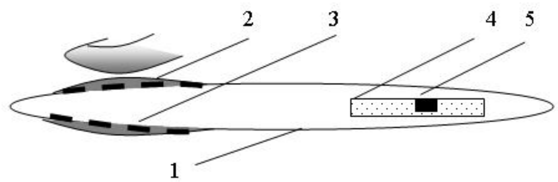


Figure 3.19: The sketch of enhanced WACOM's graphic tablet pen system.

Figure 3.19 illustrates the sketch of a WACOM pen device (1) enhanced by a finger grip based on piezoelectric thin film (3) embedded under a rubber cover (2). On the electronic board (4) a MEMS acceleration & tilt sensor (5) is integrated.
The passive piezoelectric sensor and its electronic conditioning are designed for low power consumption (about 2mW). The electronic board (4) includes a current amplifier, analogue to digital converter, an integrated MEMS acceleration-inclination sensor (5) and a USB (HID) interface. In the fast prototyped version, the circuit is mounted onto the case of the WACOM pen device as shown in Figure 3.20.
By this arrangement, the enhanced device could be realized without high technical effort.
The data-sampling rate of the BiSP sensors is 500Hz while the graphic tablet has a rate of 200Hz. The sampling rate of the graphic tablet system is artificially enhanced up to 500Hz in such a way that the output data is appropriately duplicated in order to achieve data sets of same length for all channels during online data acquisition. Using this input device, the handwriting dynamics are recorded in terms of time series of position coordinates x(t), y(t), finger grip pressure grip(t) and three axes of acceleration-inclination signals. For the evaluation work, in this thesis, only x-/y positions and grip pressure data are investigated (see section 6.2).

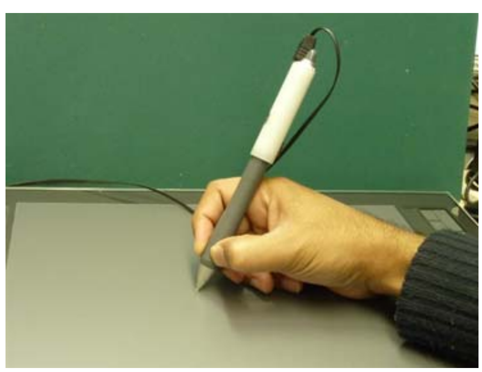


Figure 3.20: Prototype of enhanced WACOM Intuos 3 graphic tablet pen system for monitoring handwriting movements.

3.4.2 A Touch Screen and Tactile Pen based System

Figure 3.21 shows copper lead attachments, the connections of wires and transparent silicon protecting layer in the PEF sensor preparation stage. Silicon layers were coated as protecting and backing layers on the piezoelectric film in the pre-preparation phase of piezoelectric film based pressure sensors as describe in section 3.3.2.1.

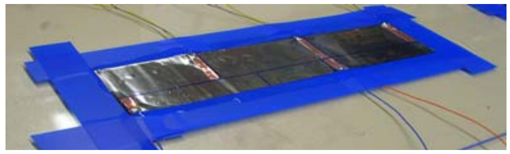


Figure 3.21: PEF foil with terminal connections and silicon layer in the preparation stage.

During this preparation phase, a novel tactile and pressure sensitive pad has been developed which can be used with any ballpoint pen in combination with paper for the online input of handwritten characters or signatures. The tactile writing pad is constructed using PEF foil installed beneath the writing area of the plastic writing pad. The schematic diagram of writing pad is shown in Figure 3.22.

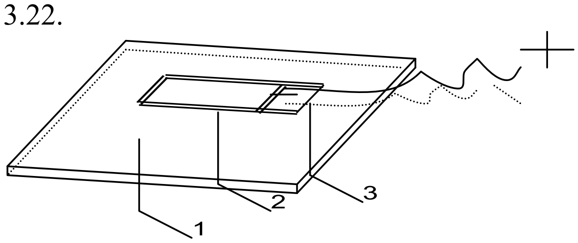


Figure 3.22: Schematic diagram of tactile and pressure sensitive writing pad

It illustrates three main parts. A plastic pad (1) works as writing pad for the input of handwriting sequences on a common paper that is placed on the pad by using any ballpoint pen. The PEF foil (2) which serves as a pressure and tactile sensor embedded beneath the pad which makes the writing surface a touch and pressure-sensing element. Part 3 shows the positive and negative terminals of PEF foil which are attached to the amplifier.
The dynamics of handwriting sequences are recorded in terms of capturing the tactile effects and pressures of pen tip on such a novel writing pad (input device). The ability to measure miscellaneous pressures, lift off & retouch of pen tip and writing surface with respect to the time axis are the key biometric features which can be recorded and are the main potential of the input device (for details on experiments and results see section 6.5).

3.5 Other Hand Movement Measurement Systems

Other human body motions have also been investigated in human behavioral biometrics related to gait or gestures including movement of fingers, hand and arm. The recognition of such motions has been applied to personalized motions or gestures in biometrics, human computer interaction (HCI) & robotics and in medicine (rehabilitation). Human gesture is the neuromuscular activity to express oneself and interact with others. In HCI, free hand gestures allow the users to interact with the computer directly and easily in a natural way.
The most extensively used gesture recognition systems are based on computer vision and use cameras to capture and process visual data. In Vision Wand, cameras capture hand movements. In Wii remote, the movement of hand is detected by cameras constituting a gesture recognition system. Though the visual gesture-data based techniques are more popular, they have high cost and computational load and need more infrastructure and resources. Smart gloves have been used for signature verification. They have also been employed to capture or recognize very fine gestures and finger movements. Though wearable gloves use multiple sensors to capture the motion of fingers and hand, these are inadequate for use in many

applications such as in mobile units or PDA's because of the constraints of high cost and computational demands. Accelerometer based gesture recognition systems are becoming more popular. The MEMS 3-axis accelerometers are inexpensive, consume little power and make the design of a mobile gesture recognition system possible. They have been used for human motion and gesture recognition and HCI. The dual or 3-axis accelerometers have been used to detect and quantify human motions of hand, lower/upper limb or in remote monitoring of gesture performance in home care applications. Examples include tele-rehabilitation systems needed to quantify the progress of patients recovering from pathological dysfunctions, and in the study of tremor and balance [61-66].

Hence, a number of techniques based on several different types of sensor have been proposed for human motion recognition under behavioral biometrics. The proposed methods are essentially associated with the recognition of human motions required in biometric and medical applications.

3.5.1 The Benefit of BiSP for Hand Movement Measurements

Contrary to state of the art diverse sensing techniques and systems, the BiSP pen benefits essentially from the use of a MEMS 3-axis accelerometer, a finger grip sensor together with other sensors in a single unit. Consequently, it allows the recording of the dynamics of hand and finger movements during handwriting and gesturing on a paper (on pad) or in free space (off pad). This thesis deals with the recording and analysis of handwriting, drawing and gesturing motions with BiSP device. The recorded features have been analyzed for applications in biometric recognition of a person, recognition of handwritten object and/or of a disease diagnosis.

4 Methods of Data Analysis

A biometrics based system measures and analyzes physiological or behavioral characteristics (traits) of humans. The online handwriting measuring system (i.e., BiSP device) naturally records time series data that is behaviorally influenced during the process of handwriting. The recognition system is expected to classify handwriting data that is unlike physiological biometric data (e.g., iris), contains temporal shifts due to fluctuations in handwriting even in two similar sequences (e.g., characters, signatures or PIN words) from the same writer. A generic biometric authentication system (see Figure 2.1) consists of several data processing steps: data acquisition, data pre-processing, data classification and the decision such as for the authentication. For the acquisition of handwriting data, several different types of data acquisition devices have been employed (section 3.2). After data collection, several data analysis methods can be used for classification where several feature extraction procedures can be applied.

For the recognition of handwriting data obtained by BiSP, several methods have been tested for feature extraction and classification: Neural Networks NNW, Hidden Markov Models HMM, Support Vector Machines SVM and its combination [52][76], statistical methods [50][51], discrete Wavelet Transformation DWT and Dynamic Time Warping DTW with its variants [30][31][40-44]. Since even two signatures from the same person may vary due to the small intra-class variation of a person resulting in a comparison of signature feature vectors of unequal lengths, therefore the comparison method that involves dynamic distance measures such as DTW is expected to be very successful in generating accurate results [87]. This chapter describes data collection and data pre-processing procedures, as well as performance evaluation methods designed in the thesis. Further, a brief overview of the feature extraction and classification methods used in person authentication domain is also given.

4.1 Data Collection

A novel pen (BiSP) is used for the online input of handwritten characters and words, drawings and gesture movements. The BiSP device used in the experiments is for the acquisition and analysis of human hand and fingers movements while handwriting or gesturing on any paper pad or free in air as shown in the Figure 1.3. The data sheet used for the input of handwritten PIN words, signatures and single characters is shown in the Figure 4.1.

The handwriting sample data (see Figure 6.2) obtained from handwriting on pad in terms of multivariate time series has six columns:

- across(t)—refill pressures along x-y dimensions
- y(t)—grip pressures of fingers holding the pen
- z(t)—normal pressures of refill
- α(t)—alpha: inclination 1
- β(t)—beta: inclination 2
- γ(t)—gamma: inclination 3

For most of the recognition tasks, the gamma channel is not used in on pad handwriting mode. Therefore, five columns of multivariate time series data are analyzed for on pad mode of recognition. For person authentication or handwritten object recognition, BiSP data is acquired of single characters, symbols, PIN words and signatures handwritten on pad and free in air.

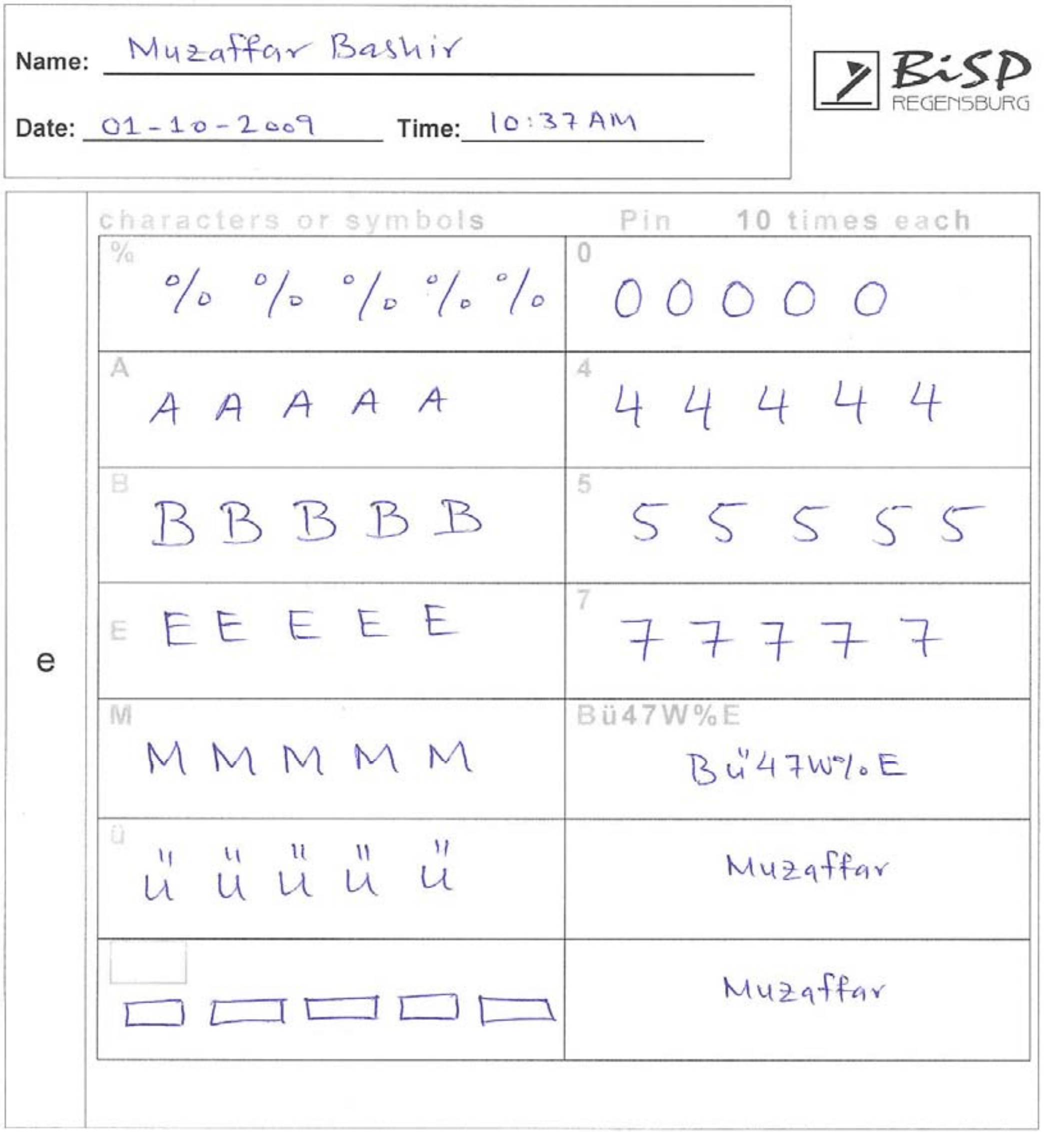


Figure 4.1: The data sheet used for the enrollment of handwriting of writers.

4.1.1 Database

In order to perform different recognition experiments, several datasets have been collected such as of handwritten “single characters”, “PIN words” and “signatures”. The BiSP data is collected in two modes of operations: (1) on pad and (2) in air (off pad). All databases contain samples from different writers including men, women, right-/left-handed persons with diverse handwriting styles. Majority of the enrolled persons are students at University of Applied Sciences Regensburg, Germany. All writers were volunteers and out of all enrolled persons, the majority of them were available for the data acquisition tasks in a single session while others were invited in more than one session for enrollments. Each handwritten object was recorded 10 times separately and timely spaced in a sequence. Therefore, data acquisition is considered as collected under nearly optimal similar conditions that keep intra-class variability low.

4.1.1.1 Single Characters

The database used for single character recognition was collected with the BiSP device while handwriting on paper pad as well as in air. The set of items (objects) that is later used in data analysis is denoted as "single characters". This set consists of eleven single characters: {letters—A, B, E, M, ü, digits—0, 4, 5, 7, two symbols—%, ▭ (rectangle)}.

4.1.1.2 Private PIN words and Signatures

All writers wrote a PIN word (Personal Identification Number unique for each writer) and their private signatures with BiSP pen. The PIN word is a sequence of seven unique single characters which were handwritten by the owner of the PIN (e.g., "7MBA5%E").

4.1.1.3 Public PIN words

All writers wrote a public PIN word (same for each writer). The PIN word "A7405B%" is a sequence of seven unique single characters handwritten by each writer.
Although the same group of people contributed to all databases, however each dataset was used for the person authentication task independently. The recognition procedure for handwritten PIN words is same as that of private signatures.

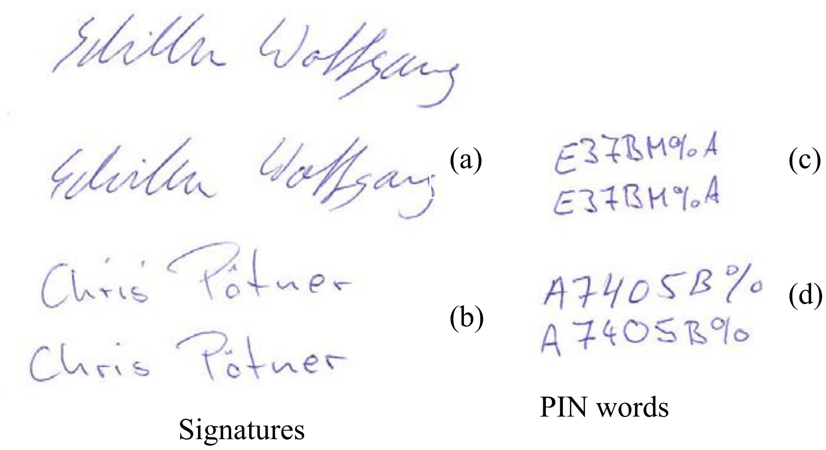


Figure 4.2: Shows image of signatures and PIN words (a) two complex signatures, (b) two relatively simple signatures, (c) two private PIN words of a writer and (d) public PIN words from different writers.

Figure 4.2 illustrates that the personal handwriting styles are included in the handwriting sequences. Two images of (a) complex signatures, (b) simple signatures, (c) and private PIN words of a person and (d) two public PIN words obtained from different writers are shown.

4.1.1.4 PIN words and Single Characters Handwritten in Air

For writing in air, the elbow is resting on a desk in order to exclude (almost) arm and shoulder movements. Writing in air enables the items handwritten in a small frame of space at the same position. Therefore, the collected samples were affected considerably neither by a displacement and rotation of the instrument (pen) nor by repositioning or extra movements of the involved arm and wrist. The procedure for handwriting mode in air is shown in Figure 4.3.

Figure 4.3: Procedure for monitoring handwriting movements in air mode

The handwritten PIN words, single characters or signatures were used for person authentication or handwriting recognition.
For recognition, the first stage is collection of multivariate time series data using BiSP. Then data is pre-processed.

4.2 Data Pre-processing

Real world biometric data may contain some amount of noise. Therefore, the data is generally preprocessed in order to reduce sensor noise and redundant data. This pre-processing of data may reduce database size and improve signal quality, too. Therefore, the data is smoothed and detrended to remove sensor noise and linear detrend. Further, amplitude normalization of all sensor channels is done to make them comparable and to minimize (partially) large variations of the time series in the amplitude domain. The sum of all channels is for the dimension reduction leading to decrease computational loads. As described in section 6.1.1, there are enough specific biometric and object related information in the time series even when they are obtained from the sum of all channels. Hence, the summed signal depicts a high reproducibility and distinctiveness. Therefore, multivariate time series data are converted to univariate time series by sum in some of the experiments in this thesis. Further, time series are down-sampled to reduce the complexity of DTW classifier further. For classification, DTW similarity match is performed on length normalized time series (i.e. time series is re-sampled to equal lengths). All together data is pre-processed by smoothing, detrending, normalizing amplitude, converting dimension to univariate, down-sampling and normalizing the length of data.

4.2.1 Segmentation of Data

Segmentation is used to select meaningful part of the signal that actually belongs to handwriting for classification. Segmentation determines the beginning and the ending of the signals of handwritten objects. A further segmentation of handwriting data is sometimes carried out essentially to divide data to: (i) individual segments that correspond to individual characters or (ii) different strokes in a sample of a sequence. The latter is used to calculate features (segment length, number of segments etc) for authentication purposes. It is common that the data is segmented with fixed sized time frames or into fixed number of segments [31]. As the BiSP handwriting data was captured separately therefore no separate segmentation of signals is performed in the study work in general. The segment length of sequences depends on the nature of the handwritten object and the writer. There are two types of segmentations involved in feature extraction stage used in this study. The data is segmented by using (1) static frame size (section 5.2) or (2) dynamic frame size. In the former, data is divided into number of equal sized frames. In the latter approach, dynamic frame lengths are selected by considering local peaks and zero line crossing points (section 5.5).

4.2.2 Smoothing of Data

It is done in order to remove undesirable spikes and noises from the input data. Smoothing of handwriting sequence-data (e.g., signature) is generally carried out by a simple moving average or spline smoothing techniques to eliminate noise. Smoothing of BiSP data is done by local regression using weighted linear least squares and a 2nd degree polynomial model. It is used to eliminate the potential sensor noise. Each smoothed data point value is determined by the neighboring data points defined within the predefined span based on a regression weight function. The regression weight for each data point in the span is given by the tri-cube function as shown in the equation (4.1).

$$\omega_i = \left(1 - \left|\frac{x - x_i}{d(x)}\right|^3\right)^3 \tag{4.1}$$

where x is the predictor value associated with the response value to be smoothed, x_i are the nearest neighbors of x defined in the span and d(x) is the distance along the abscissa from the x to the most distant predictor value within the span. Span is the number of data points used to compute each element. For more details, see [12].

4.2.3 Detrending of Data

Detrend process removes the mean value or linear trend from a time series. Detrend computes the least squares fit of a straight line to the data and subtracts the resulting function from the data. Therefore, linear trends in terms of best least squares straight-line fit are removed from the data before smoothing. The Figures 6.12 and 6.18 illustrate the smoothing and detrending procedures applied on time series data.

4.2.4 Normalization of Data

In order to partially compensate large personal variations of time series in the amplitude domain, normalization of the time series is done in such a way that data is normalized more often to [-1,1] or alternatively sometimes to other ranges such as [0, 1] or z-score (for details see section 6.3). Normalization of handwriting sequences minimizes personal variation in the handwriting data resulting in lower intra-class variations. However, in only a few examples in the literature, normalization of handwriting data is not performed where personal variations are used as a personal feature by the system for the person verification task. As we focused on time series data analysis using DTW and its variants based classifiers, therefore generally recommended time series length and amplitude normalization procedures are applied [37],[49],[52],[59]. For evaluation, the performance calculated of different normalization procedures are compared (see section 6.3).

4.2.5 Down-sampling of Data

In order to compensate the complexity of DTW, the low pass filtered time series are down-sampled to reduce the sampling rate or, the size of the database. Filtering of data is performed by an eight-order low-pass Chebyshev Type I filter. It filters time series effectively by doubling the filter order in both the forward and reverse directions in order to remove all phase distortions.

Figure 4.4 shows the time series for handwriting single-character “B” recorded by BiSP device (sampling frequency 500Hz) in original and reduced number of data points (i.e., 1100-183-110) at down-sampling rates of M=6;10. It indicates the global and local curves are preserved in the time series represented by a reduced number of data points with the help of the down-sampling procedure.

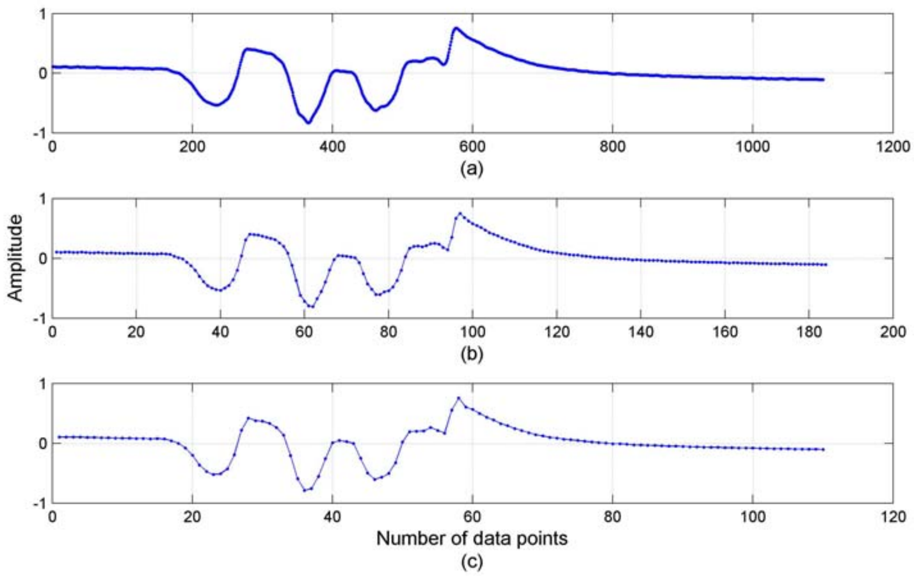


Figure 4.4: Illustrates the effect of down sampling a pressure signal of handwriting single-character "B": (a) original number of data points, (b) data down-sampled by M=6 and (c) data down-sampled by M=10.

4.2.6 Generating Query and Sample Data

Several field studies have been performed for data collection, to (1) recognize a—handwritten signature, PIN word or single character for a person authentication and (2) to recognize a handwritten item for handwriting recognition task. For evaluation of a given task of classification, the dataset is subdivided into query (test-sample) and reference (prototype-reference) samples due to the "leave-one-out" mechanism. It means one out of all samples is repeatedly selected as a query and matched against the remaining samples.

4.3 Features Extraction and Dimension Reduction

The features extraction stage is next stage after data acquisition and pre-processing in a biometric authentication system. At this stage, a large number of global and/or local features can be calculated from biometric data. Generally, redundant data elements are removed in such a way that the two qualities of: distinctiveness and reproducibility are preserved that is the required properties of the biometric signals [13] to use for recognition. Feature extraction procedures reduce the size of the data (dimensionality) that essentially benefit in lowering the problems of large data size and computation time. Generally, in online recognition procedures, the features can be divided into two types: global or local features (see section 3.1.3). The global features are the parameters or features sets extracted from the whole signals, such as total writing time, number of strokes or average writing speed etc. Hence, the numbers of features are equal in a sample and reference sequence data. Because of the higher level of data abstraction, the approaches used for classification are generally simple and very fast. But it is difficult to select correct parameters and also these approaches have low performance. On the other hand, the local features based approaches especially the use of complete signals as features set in terms of time series essentially contains more dynamic information, and hence provide results that are more accurate [38-39].

Multidimensional Data

Feature extraction or alternatively dimension reduction techniques ideally transform high dimensional data into a meaningful representation of reduced dimensionality [21]. The sample data acquired by the BiSP device during handwriting or signing has a high dimensionality because of high sampling rate and several numbers of variables (channels). A typical example of BiSP signals during handwriting is shown in Figure 3.17 & 6.2 Dimensionality reduction of BiSP data is necessarily important for the recognition of online data where the analysis of multi-dimensional time series data is involved.

Several statistical features, such as signal length, maximum, minimum, mean width, skewness, total writing time, number of strokes or average writing speed etc are calculated from handwriting signals. As many numbers of features can be extracted from a handwriting signal, it is obviously difficult to select correct parameters for classification [52].

Another research trend in features extraction is to combine systems based on fusion of local and global features [14]. A large number of features to discriminate genuine and forged signatures have been proposed in the literature and the consistency and discriminative power of features are evaluated in [15].

Diverse dimension reduction procedures based on linear and non-linear dimension reduction techniques have been proposed in recent years. A detailed and comparative review on state-of-the-art dimension reduction techniques can be found in [16-23]. A briefed introduction of few dimension reduction techniques is described in the following section, more details can be found in [16-23],[66].

4.3.1 Singular Value Decomposition

Singular Value Decomposition (SVD) is a core least squares computation based dimension or feature reduction technique that can be applied on matrix data (multivariate time series data). SVD is a global transformation technique. A real world data such as BiSP data of handwritten sequence pattern can be a matrix M(m x n) of m sensor channels (variables) and of n samples. Due to redundancies and covariance in natural data, SVD technique is a good candidate for dimension/feature reduction. The Singular Value Decomposition of matrix M can be given by the equation.

$$M_{mxn} = U_{mxm}\, S_{mxn}\, V^{t}_{nxn} \tag{4.2}$$

where

- U_{mxm} is an m x n orthogonal matrix($U^tU= I$)
- V_{mxm} is also orthogonal
- S has diagonal with non-negative elements in descending order, with the highest singular value in the upper left index of the S matrix, and are called singular values of M.

The columns ui and vi of U and V are known as left and right singular vectors of matrix M respectively. S = diag(s1,s2,….., smin(m,n) and s1>= s2>=….>=smin(m,n)>=0= sn-1=sn. The singular values of a matrix M are unique. SVD attempts to represent a high dimensional data approximately into fewer dimensions. The dataset is examined and then rotated such that the first axis has the maximum variance, the second axis has the second maximum variance orthogonal to the first, the third axis has the maximum possible variance orthogonal to the first two, etc. Further detailed treatment on SVD can be found in [16][22][66]. The SVD based procedure implemented in the thesis is described in Chapter 7.

4.3.2 Spectral Decomposition (Discrete Fourier Transformation)

In spectral decomposition, the time series data is transformed from time domain to frequency domain. There are number of advantages for time series representation in frequency domain including dimension reduction, noise removal and feature selection etc. The key idea of

Discrete Fourier Transformation (DFT) is that a time series (signal) can be represented by the superposition of a finite number of sine and/or cosine waves. Each of these waves is represented by a complex number known as a Fourier coefficient. In DFT procedure, a time series (signal) of length n can be decomposed into n sine/cosine waves that can be used to reconstruct the original signal. The dimension reduction of original data is achieved by discarding low amplitude coefficients in the reconstruction of signal that may have very little impact on information loss [23][30].

4.3.3 Wavelet Decomposition

Discrete Wavelet Transformation (DWT) represents data in terms of the sum and difference of a prototype function known as mother wavelet. Unlike DFT where it accounts for global contribution for transformation, in DWT the wavelets are localized in time and it is possible to account contribution in the transformation from wavelet coefficients that represent small and local subsections of the data being studied. Therefore, DWT allows multi-scale resolution analysis of the data. The data compression is done by using the first few coefficients to generate reduced approximation of the original data. More additional coefficients can be used to transform data with more high detail resolution [23].

4.3.4 Non-negative Matrix Factorization (NNMF)

Non-negative Matrix Factorization (NNMF) is a useful matrix decomposition technique for multivariate data. NNMF factors the non-negative matrix data subject to non-negativity constraints. These constraints lead to a part-based representation of data because they allow only additive combinations of original data. For a given Matrix V (nxm) of n dimensional data vectors of m sensor channels (variables), it is possible to determine non-negative factors W and H in order to approximate the original matrix V such that:

$$V \approx W\,H \tag{4.3}$$

The matrix V is factorized into nonnegative factors matrix W (nxr) and matrix H (rxm). The factorization is not exact because W H is a lower-rank approximation to the original matrix V. The resulting dimension reduction is obtained by choosing r smaller than n or m. Each column of matrix W contains basis vectors while each column of H contains the weights. Alternatively, each data vector (column of V) is approximated by a linear combination of the columns of W, weighted by the components of h. Therefore, W contains optimized basis for the linear approximation of the data in V. Since relatively few basis vectors are used to represent many data vectors, good approximation can only be achieved if the basis vectors discover structure that is latent in the data [25][26][27]. The NNMF based procedure implemented in the thesis is given in Chapter 7.

4.4 Classification Methods

After extracting features from the handwriting signals, next stage is classification. Classification of data can be static or dynamic depending on the techniques used in features extraction and classification. A large number of classification methods have been employed in online signature authentication domain. Here, the techniques used in the thesis are described.

4.4.1 Support Vector Machine

Here, we will provide a brief introduction to support vector machine (SVM). For more details, see [11]. SVM is a new and promising pattern classification technique based on statistical learning theory developed by Vapnik. The basic idea of SVM is to map either linearly or nonlinearly the input space into a higher dimensional feature space. The kernel function used decides for the mapping. The SVM constructs separating hyper-planes in the new feature space that are optimal keeping the classes separated with the largest margin and with minimum classification error. SVM has a good performance even under conditions of small training dataset [49],[73]. The SVM based procedure implemented in the thesis is described in Chapter 7.

4.4.2 Nearest Neighbour Classifier

For multi-class classification, the frequently used methods are 1-nearest neighbour (1-NN) and the k-nearest neighbour (k-NN) methods.

Let P= $\{ \vec{p}_i \}_1^n$ be a set of n points (representative class number (single pattern)) in a k-dimensional space (feature space) and let $\vec{q}$ be a query point. A statement of the Nearest Neighbour problem is:

Determine the point $\vec{p}_c$ in P which is the minimum distance from $\vec{q}$, i.e.

$$\|\vec{q} - \vec{p}_c\| \leq \|\vec{q} - \vec{p}_i\| \ \forall \ \vec{p}_i \in P$$

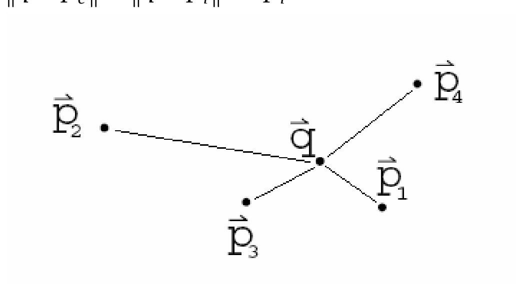


Figure 4.5: Representative classes feature vectors $\vec{p}_1$ .... $\vec{p}_4$, and query feature vector $\vec{q}$ which is classified depending on the distance from each class [31].

This is a classical problem of computational geometry that may appear in computer vision, image processing or in general pattern recognition. It is assumed that $\vec{p}_c$ is unique and also that the distance metric is based on Euclidean distance denoted by $D_{ij}=\|p_i - q_j\|$. Note that the acceleration method is applied to any metric that satisfies the triangle inequality. For more details on the method, see [31].

4.4.3 Hierarchical Clustering

Data clustering based on statistical data analysis is a common technique in pattern recognition domain. Data clustering is considered as unsupervised learning in machine learning problems. Clustering is the classification of dataset into subsets called clusters so that the data in each subset (ideally) share some common feature—often proximity according to some defined distance measure.

In hierarchical clustering (HC), commonly used distance measure is Euclidean distance. Another distance measure is DTW distance also used in character recognition [31]. In HC, the data is grouped at different scales by creating a cluster tree also known as dendrogram. The cluster tree is not a single set of clusters, but rather a multilevel hierarchy comprising clusters at one level are joined as clusters to the next level. In HC, the following procedure is performed:

- As a first step, the similarity (or dissimilarity) between every pair of objects in the data set is determined. For similarity, generally the distance (Euclidean or DTW) between objects is calculated.

- The objects are grouped into a binary hierarchical cluster tree. Using the distance information obtained in the above step, the proximity of objects to each other is determined and the pairs of objects that are in close proximity are linked. The newly formed clusters are grouped into larger clusters until a hierarchical tree is formed.
- Next step is to determine clusters in the hierarchical tree. This step creates a partition of the data by detecting natural groupings in the hierarchical tree [12].

In the thesis, the DTW distance used in HC method is a measure of similarity between two handwriting sequences.

For illustration, an artificially formulated example adopted from [12] is presented. Consider for example a dataset P, made of five objects (suppose data is for five different writers) where an object is shown by x, y coordinates as O1= (1,2), O2= (2.5,4.5), O3= (2,2), O4= (4,1.5), O5= (4,2.5). All objects represent data obtained from normal control writers except data of the object 2 (O2) which belongs to a Parkinson's disease PD writer.

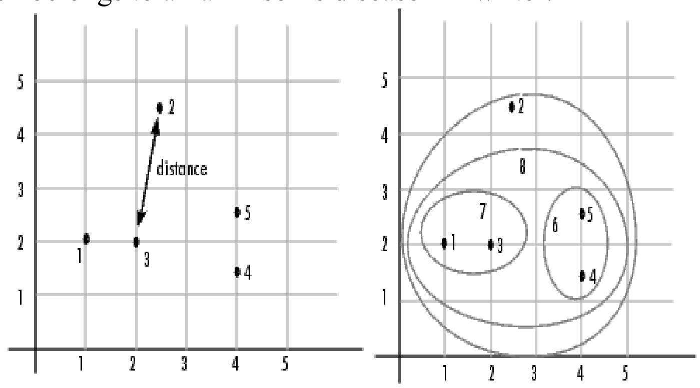


Figure 4.6: Illustrates (left) plot of five objects and objects in hierarchy of clusters (right) [12].

The distances between all the pairs are calculated and a vector Q of distance information is created where each element of Q contains the distance between a pair of objects, given by Q= {2.91, 1.0, 3.04, 3.04, 2.54, 3.35, 2.5, 2.06, 2.06, 1.0}. The first element of Q (2.91) represents the distance between O1 and O2, similarly the second element (1.0) shows the distance between O1 and O3, and so on. The proximity between objects in the data set is calculated using distance information. The pairs of objects that are close together are linked into binary clusters. Further, bigger clusters are formed using newly formed clusters in order to generate a hierarchical cluster tree. The figure above illustrates graphically the linkage of groups of objects into a hierarchy of clusters. The object 6 is a newly created cluster formed by grouping objects O4 and O5 which are closest with a distance value of 1.0. Similarly cluster 7 is formed by grouping objects O1 and O3, which also have distance value=1.0. Next, the object 8 forms a new cluster by grouping objects 6 and 7. Finally, the object 8 is grouped with object 2 from the original data set. Further, the hierarchical binary cluster tree created by the MATLAB tools—linkage and dendrogram function is shown in the Figure 4.7.

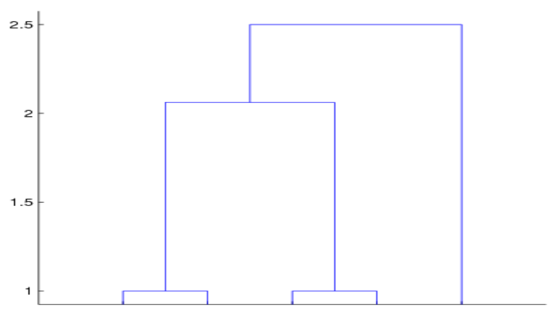


Figure 4.7: Dendrogram plot of hierarchical binary cluster tree.

Figure 4.7 shows dendrogram plot of dataset for five subjects. The x-axis shows objects and the height indicates the distance between them. In the above example the object 2 (PD writer's data) is grouped into a different cluster. For details on dendrogram, see [12]. The HC based procedure implemented in the thesis is given in Chapter 7.

4.4.4 Classification Based on Similarity Distance Measures

The similarity between two similar sequences of handwritten objects (signatures or single characters) can be determined by calculating distance between them. Two popular distance measures in this regard are: (i) simple Euclidean distance (ii) dynamic time warping DTW distance. As described earlier, in parametric (global features) based approaches, generally equal number of global features are extracted from the samples and simple distance such as Euclidean distance measure can be used to compare two handwriting sequences. Here, simple Euclidean distance can be used to compute similarity between time series very fast. The simple Euclidean distance function for two time series (Q, C) of equal lengths is given by the following equation:

$$D(Q,C)=\sum_{i=1}^{n}(\mathrm{q}_{\mathrm{i}}-c_i)^2 \tag{4.6}$$

However, this point-to-point comparison can be extremely unrealistic for comparison of time series obtained from handwriting because it fails to control small distortions in the time axis. The second alternative is functional (dynamic or local features) based approaches where the complete signals as functions of time (time series) can be used for comparison of unequal sequences. So the method which is able to accommodate the non-linear spatial and temporal shifts in time series such DTW is used [49]. Figure 5.1 illustrates comparisons of time series using simple Euclidean distance and DTW distance based matching techniques. The details on DTW based classification methods are given in Chapter 5. The classification of BiSP data based on similarity distance (Euclidean distance) measures implemented in the thesis is given in section 6.4.

4.5 Evaluation of System Performance

The last stage in a biometric authentication system (see Figure 2.1) following by classification of data is the decision of the recognition which determines the performance of a biometric system. This recognition is made due to the match score between sample (e.g., input signature) and reference (template stored in the database) of handwritten objects. A handwriting identification system decides on the match score a decision of two types: (1) a sample is genuine (comes from the same writer) or (2) imposter (belonging to the different writer). The higher the score, the more certain is the decision that the two samples come from the same writer as well as the same handwritten object.

For the system performance evaluation, two types of error rates are calculated: (1) false acceptance rate—mistaking biometric samples from two different writers as from the same person (also called false match rate) (2) false rejection rate—mistaking two biometric samples from the same writer as from two different writers (also called false non-match rate).

False acceptance rate (FAR) and false rejection rate (FRR) are used to express the security of the biometric system.

A user of the system can set a threshold for FAR and FRR. However, there is a tradeoff between FAR and FRR in every biometric system because these two values are inversely related, increasing one by setting a different threshold often results in lowering the other. For example, if a lower threshold is fixed, the system becomes more tolerant to input variations and noise, and then FAR increases with the decrease in FRR. On the other hand if a higher

threshold is fixed to make the system more secure, then contrary applies to FAR and FRR values.
There are additional performance parameters that better express the identification accuracy and performance of the biometric system such as the equal error rate (EER) and the receiving operating characteristic (ROC) curve. The EER is a point where FAR equals FRR. The system performance at all the operating points (threshold values) can be depicted in the graph of a ROC curve. A ROC curve is a plot of FAR as a function of FRR.
Further details on the parameters FAR, FRR, EER and ROC can be found in [5][31][49][93].

4.5.1 Proposed System Performance Parameters

In order to evaluate the performance of the person or handwritten object recognition, the following criteria is established:
(a) the score of recognition denoted by SR, (b) the certainty of best match denoted by CM, (c) the Error Rate (ER), (d) the runtime and, (e) the receiver operating characteristic ROC curve, which is frequently used for the evaluation of biometric person recognition.

4.5.1.1 Score of Recognition (SR)

Person Recognition
For person authentication based on handwritten PIN words or signatures, the score SR (%) is defined as follows:

$$SR = \frac{G - falscount}{G} \times 100 \quad \text{with} \quad G = P \cdot R \cdot (P - 1) \tag{4.6}$$

where G is the number of all classification tests, P is the number of persons enrolled, R is the number of references for an item written by one person. The total number of false classifications " *falscount* " is given by:

$$falscount = \sum_{k=1}^{P} falscount_k \tag{4.7}$$

where "$falscount_k$" is the number of false classifications of writer 'k' among the persons and is determined by:

$$falscount_k = \sum_{j=1}^{R} \sum_{i=1}^{P} f(d_{k,j}, d_{i,j}), \forall (i \neq k) \tag{4.8}$$

where the DTW distance value $d_{k,j}$ stays for the top best match of writer 'k' and the distance $d_{i,j}$ for the other writers ($i \neq k$).
The classification function f(,) used above is defined as:

$$f(a,b) = \begin{cases} 0 & if \quad a < b \\ 1 & \quad\;\; a \geq b \end{cases} \tag{4.9}$$

Where 'a' and 'b' are two DTW distance values.
Note: the DTW distances $\{d_{u,v}\}$ of writer 'k' comes from queries (of writer 'k') matched to all references of all writers. The indices 'u' and 'v' refer to writers and queries, respectively. Further the term "false classification" means the query sample and the top best matching reference sample do not represent the same writer.

Character Recognition

For the recognition of a single character among the population of number of enrolled characters C from one writer, we replace P—number of persons in equation 4.6-8 by C—number of characters.

4.5.1.2 Certainty of Best Match (CM)

The certainty of best match CM is defined by:

$$CM = 100 \times (d_d - d_t) / d_t \tag{4.10}$$

where 'd_t' stays for the DTW distance between the query and a reference sample with the top best match representing the same writer and item, while 'd_d' is the distance of the best match between query and a reference representing different writers. A high value of CM means a high certainty of classification. The higher the CM, the more certain is the decision that the two samples come from the same writer.

4.5.1.3 Error Rate (ER)

The classification accuracy of sequences in terms of Error Rate is defined as:

$$ER = 100 - SR \tag{4.11}$$

4.5.1.4 Run Time

The run time is a critical parameter in real time recognition system. It is defined by the time taken by the system to recognize one sample. The run time will essentially increase with the increasing numbers of writers and/or handwritten objects.

4.5.1.5 Area under ROC Curve

Receiver Operating Characteristic ROC of a biometric classification system is a graphical depiction of the relationship between the False Rejection Rate FRR and False Acceptance Rate FAR as a function of the decision threshold's value. The area under the ROC curve AUC with ≤ 1 is a well-suited measure to evaluate the performance of recognition. The better the performance, the greater the area under the ROC curve. For more details of ROC in biometric person recognition, see [93].

The aim of the biometric system is to recognize handwritten items (PIN words, signatures or single characters) with high SR, CM, and AUC values and while with low ER values.

Further, the aim is to minimize the computing time for the recognition without degrading SR and CM significantly.

5 Dynamic Time Warping Based Classifier for BiSP Data

Part-I Background and Introduction

5.1 DTW an Intuitive Way of Time Series Matching

5.1.1 Real World Data and DTW

A time series data is a collection of observations occurring in time order in virtually every scientific discipline and business applications [70]. Numbers of online measurement or monitoring systems naturally generate time series data. There have been a number of algorithms proposed to classify or cluster large time series datasets. The problem associated with the similarity search of high dimensional data is generally solved by first performing dimension reduction on the data [23] (see section 4.3). The methods used to classify time series data often compute the similarity between them. Euclidean distance is typically calculated very efficiently for this. For real world data of behavioral biometrics such as two similar sequences of time series obtained from handwriting, there subsists temporal shifts in the time axis. So, simple point-to-point comparison can be extremely unrealistic and generate brittle distance measure. The reason is that simple point-to-point comparisons fail to control small distortions in the time axis. On the other hand, elastic distance measuring method known as Dynamic Time Warping (DTW) is based on dynamic programming. It accommodates non-linear shifting of the time axis in similar sequences which are out of phase to detect similarities [58],[70]. Due to its ability to accommodate nonlinear distortions in the time axis for alignment and recognition, DTW is one of the most practical approaches. In particular, it is very important to apply DTW on the time series data obtained from handwriting. DTW is a more intuitive way to recognize handwriting or gesture patterns because it is able to compare two sequences (curves) of time series in a way that makes sense to humans as visualized in the Figure 5.1.

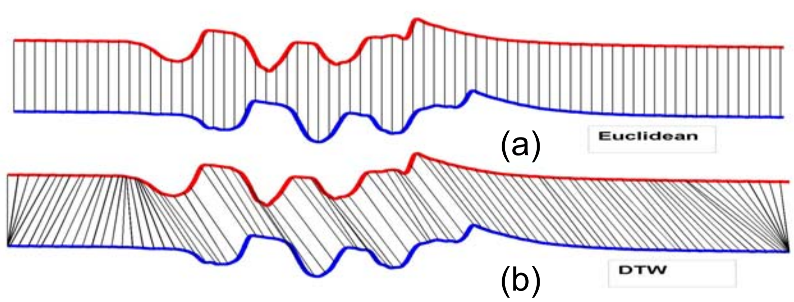


Figure 5.1: Two sequences of pressure signals obtained from handwriting the letter “B” two times by the same writer.

The sequences have an overall similar shape, but they are out of phase over time axis. a) Euclidean distance based on simple point-to-point alignment will produce a pessimistic dissimilarity measure. The nonlinear DTW alignment in (b) produces a more intuitive distance measure to be calculated.

In [89], it was reported that the results obtained for handwriting recognition based on DTW-algorithm are more “intuitive” to humans than the results of other recognizers. Therefore, DTW based classification approach is expected to improve the user acceptance of the handwriting recognition systems.

5.1.2 BiSP Data: multivariate time series

The BiSP data has a high dimensionality due to the high sampling rate and several numbers of variables (sensor channels). The data is also affected by the natural variation of behavioral biometrics. Therefore, real world BiSP data obtained from handwriting is necessarily multivariate time series data which includes temporal shifts in the time axis for even two genuine handwritten sequences (e.g., signatures).

5.2 DTW-Related Work

DTW has been used in various time series classifications and pattern recognition applications such as biometrics, data mining, computer vision, etc., [58][82]. But classic DTW is well known for its slow computations. Several techniques have been proposed to improve DTW by modified warping techniques or reduced computational complexity.
As a simple solution to address the two issues, local and global path constraints are used. To speed up DTW, there are some modified techniques which operate on a higher-level abstraction of data, such as piece wise aggregate approximation PAA of time series (PDTW) [70], data down-sampling [24][40],[83-84], reduced numbers of data point comparisons as in extreme points warping, segment to segment matching, dynamic positional warping (DPW), dynamic programming matching (DPM), stroke point warping (SPW) and lower bounding techniques [38-39][58][85-88]. In the following, first a brief review of classic DTW and of Piecewise DTW (PDTW) is given. Finally, modified DTW techniques implemented and used in the thesis are discussed.

5.2.1 Review of Classic DTW

Suppose we have two time series Q and C of unequal lengths of n and m respectively.

$$Q = q_1, q_2, ..., q_i, ..., q_n \tag{5.1}$$

$$C = c_1, c_2, ..., c_j, ..., c_m \tag{5.2}$$

To align two sequences using DTW, we construct an n-by-m matrix where the (i^{th}, j^{th}) element of the matrix contains the distance $d(q_i, c_j)$ (generally Euclidean distance is used) between the two points q_i and c_j given by the equation:

$$d(q_i, c_j) = (q_i - c_j)^2 \tag{5.3}$$

or alternatively given in equation 5.17 for multivariate time series. Each matrix element (i, j) corresponds to the alignment between the points q_i and c_j which is illustrated in Figure 5.2. A warping path W is a contiguous set of matrix elements that defines a mapping between Q and C. The kth element of W is defined as $w_k = (i \ , j \ )_k$ so we have:

$$W = w_1, w_2, ..., w_k, ..., w_K \quad \max(m, n) \le K < m + n - 1 \tag{5.4}$$

The warping path is typically subjected to several constraints.

- **Boundary conditions:** $w_1 = (1,1)$ and $w_K = (m, n)$, this requires the warping path to start and finish in the diagonally opposite corner cells of the matrix

- **Continuity:** Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a - a' \le 1$ and $b - b' \le 1$. This restricts the allowable steps in the warping path to adjacent cells (including diagonally adjacent cells).
- **Monotonicity:** Given $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a - a' \ge 0$ and $b - b' \ge 0$. This forces the points in W to be monotonically spaced in time.

Exponentially many warping paths satisfy the above conditions, however we are interested only in the path that minimizes the warping cost:

$$DTW(Q,C) = \min\left\{ \sqrt{\sum_{k=1}^{K} w_k} \middle/ K \right. \tag{5.5}$$

The K in the denominator is used to compensate for the fact that warping paths may have different lengths [24].

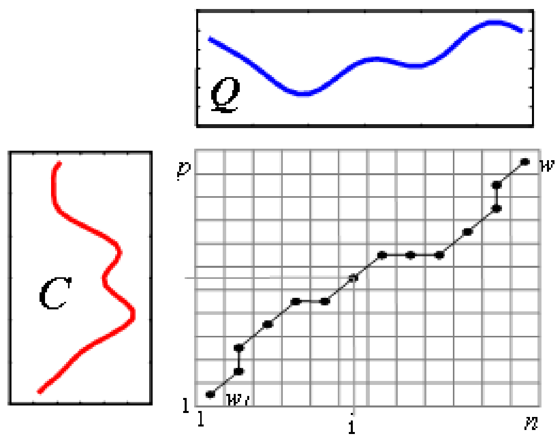


Figure 5.2: An example-warping path [24].

5.2.1.1 Local Constrains on Time Warping

This path can be found very efficiently using dynamic programming under global and local constraints. A local constraint is used to evaluate the following recurrence which defines the cumulative distance $\gamma(i,j)$ as the distance $d(i,j)$ found in the current cell and the minimum of the cumulative distances of the adjacent elements. The two popular options are the following:

$$\gamma(i,j) = d(q_i, c_j) + \min\{\gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1)\} \tag{5.6}$$

$$\gamma(i,j) = d(q_i, c_j) + \min\{\gamma(i-1,j-1), \gamma(i-1,j-2), \gamma(i-2,j-1)\} \tag{5.7}$$

Several other options and graphical interpretation can be found in [58],[85]. The basic idea behind such constraints is to limit the permissible warping paths by imposing local restrictions on the set of alternative steps considered. For example, the above equations can be viewed as admissible step patterns. It forces the warping path to move one diagonal step for each step parallel to an axis [58]. From experience learned through trial and error, the local constraint of equation 5.7 provides more accurate similarity results than that of equation 5.6. Hence, it is used for the work presented in this thesis.

The simple Euclidean distance between two sequences can be seen as a special case of DTW where the k^{th} element of W is constrained such that $w_k = (i,j)_k$, $i = j = k$. Note that it is only defined in the special case where the two sequences have the same length. The time and space complexity of DTW is O (nm) and discussed in [24].

This review of DTW is necessarily brief [24] we refer the interested reader to [90] for a more detailed treatment.

5.2.1.2 Global Constraints on Time Warping

In addition to the constraints listed above, a global constraint is also used as shown in the Figure 5.3[58]. Figure 5.3 illustrates the two of the most frequently used global constraints namely the Sakoe-Chiba Band and the Itakura Parallelogram. The advantage of such constraints is twofold: they are not only used to prevent pathological warping, where a relatively small section of one sequence maps onto a relatively large section of another but also they slightly speed up the DTW distance calculation because a subset of the warping path matrix (warping window) is allowed to visit. The obvious advantage is the improved computational speed. However it may result in misalignments as shown in [58][83].

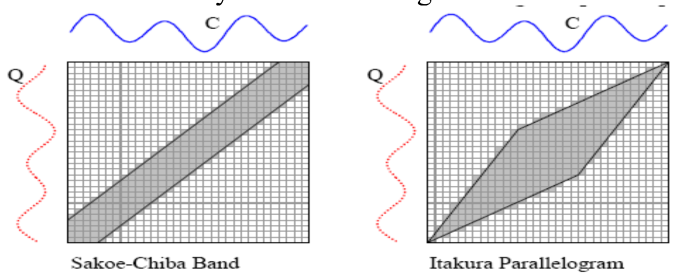


Figure 5.3: Illustrates two of the most frequently used global constraints that restrict the warping paths to the gray areas.

For illustration, data sequences obtained from handwriting the character "B" by the same writer, their DTW alignment and optimal warping path are shown in the Figure 5.4.

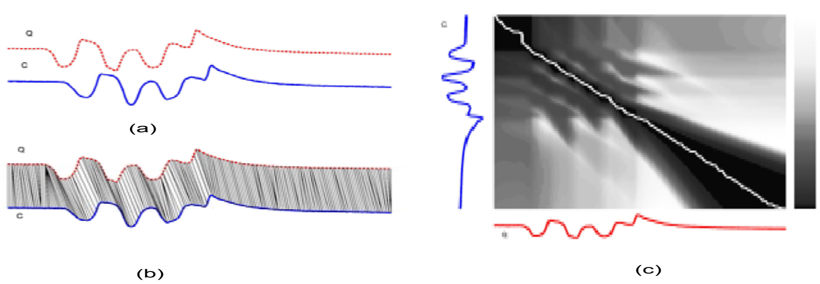


Figure 5.4: a) Two sequences Q and C obtained from handwriting "B" two times by the same writer. The two sequences are out of phase. b) DTW alignment. c) To align two handwriting sequences the optimal warping path is shown.

5.2.2 Piecewise Dynamic Time Warping (PDTW) of Time Series

Classic DTW has computing time and memory space problems, especially in online signature or handwriting recognition. To speed up computations, there are some modified techniques which operate on higher-level abstraction of data or operate by reducing the number of data point comparisons. Therefore, the two main approaches to speed up DTW are based on:

1) Data or dimension reduction
2) Reduction of the number of data points comparisons

The focus in this work is on (1) which naturally also encapsulates the second one.
The classification of time series data of handwriting is complex. Therefore, dimensionality reduction techniques are used not only for effective representation of the time series data but also to reduce computational complexity of the classic DTW. In the following section, a brief

review of Piecewise Aggregate Approximation (PAA) is given and then the proposed speed-up techniques are presented.

5.2.2.1 Piecewise Dynamic Time Warping (PDTW)

In [70], E. Keogh et al. introduced a modified DTW algorithm applied on piecewise aggregate approximation PAA of the time series. PDTW takes advantage of the fact that approximation of most time series by the PAA (see below) can be computed more efficiently as standard DTW.

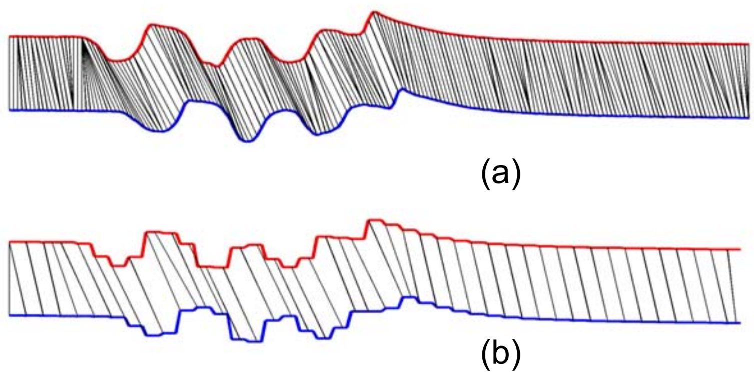


Figure 5.5: The alignment between two similar time series obtained from handwriting "B" discovered by (a) standard DTW and (b) by PDTW

The alignment between two time series as discovered by (a) DTW and (b) PDTW for the same time series in their PAA representation is shown in the Figure 5.5. This presents strong visual evidence that PDTW finds approximately the same warping as DTW. The details on the algorithm and background of PDTW reproduced here for completeness can be found in [23], [58], [70].

5.2.2.2 Piecewise Aggregate Approximation (PAA)

Suppose a time series $C = c_1, c_2, ..., c_n$, of length n. Then PAA representation of C in N dimension $(1 \le N \le n)$ is given by a vector $\overline{C} = \overline{c}_1, \overline{c}_2, ..., \overline{c}_N$. For convenience, N is a factor of n. It is not a requirement but it does simplify notation. The i^{th} element of $\overline{C}$ is calculated by the following equation:

$$\overline{c}_i = \frac{N}{n} \sum_{j=\frac{n}{N}(i-1)+1}^{\frac{n}{N}i} c_j \tag{5.8}$$

Simply stated, to reduce the data from n to N dimensions, the data is divided into N equal sized "frames". The mean value of the data within a frame is calculated and a vector of these values becomes the reduced data representation. The equation 5.8 divides a sequence into the correct number and size of frames.

5.2.2.3 Warping with PAA Representation

To align two sequences Q and C using reduced dimensionally representation of $\overline{Q}$ and $\overline{C}$, Piecewise Dynamic Time Warping (PDTW) is used. Therefore an N-by-M matrix is constructed where the (i^{th}, j^{th}) element of the matrix contains the distance $d(\overline{Q}_i, \overline{C}_j)$ between the two elements $\overline{Q}_i$ and $\overline{C}_j$. The distance between two elements is defined as the square of the distance between them:

$$d(\overline{Q}_i, \overline{C}_j) = (\overline{Q}_i, \overline{C}_j)^2 \tag{5.9}$$

Apart from this modification, the matrix-searching algorithm is essentially unaltered. Equation 5.6 is modified to reflect the new distance measure:

$$\gamma(i, j) = d(\overline{Q}_i, \overline{C}_j) + \min\{\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)\} \tag{5.10}$$

To compensate PDTW distance measure to be measured in the same units as DTW, the square root of the compression rate c is used. Therefore, the equation 5.5 can be rewritten as:

$$PDTW(\overline{Q}_i, \overline{C}_j) = \min\left\{ \sqrt{\sum_{k=1}^{K} w_k} \middle/ \sqrt{c} \right. \tag{5.11}$$

Because the length of the warping path is measured in the same units as DTW, we have:

$$PDTW(\overline{Q}_i, \overline{C}_j) \cong DTW(Q, C) \tag{5.12}$$

The time complexity of original DTW algorithm is O(nm), where the time complexity for a PDTW is O(NM), with M=m/c and N=n/c. So the speedup obtained by PDTW should be O(nm)/O(NM) which is O(c^2).
In the following section, the proposed speed-up techniques are described.

Part-II Proposed Methods

5.3 Piecewise Area Approximation based DTW

5.3.1 Motivation for Piecewise Area Approximation

One limitation of PDTW is that the compression ratio must be specified carefully. A lower compression rate will obviously produce a fine approximation resulting in slow computations. In contrast, a higher compression rate results in a coarse approximation, which leads to an increase in false dismissals. The motivation of PAA is based on the assumption that consecutive data-points are correlated with their neighbors generally, therefore in PAA representation a 'neighborhood' of data-points is approximated by its mean value [23][24]. PAA is one of the most popular methods for the dimensionality reduction of time series. However, this minimization using (1) equal frames size and (2) mean values may generate a high possibility to miss some important patterns in some time series (see Figure 5.7). These limiting factors are the main motivation of the "*proposed piecewise area approximation*" of time series. In the literature there are some improved PAA representation techniques such as piecewise linear aggregate approximation PLAA [91], a qualitative approximation of time series [79-81], [92].

5.3.2 Piecewise Area Approximation (PArA)

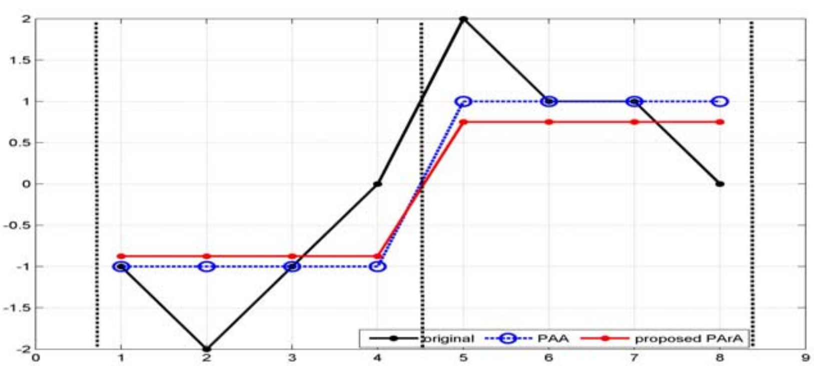
In classic PAA, each data value is represented by a mean value of segment in a frame of static size while in proposed piecewise area approximation denoted "proposed PArA", a segment of curve falling in a frame is represented by its area.

Piecewise Area Approximation by Static Frame Size

A time series $C = c_1, c_2, ..., c_n$ of length n is approximated by PArA representation and is given by a vector $\overline{A} = \overline{a}_1, \overline{a}_2, ..., \overline{a}_N$. The i^{th} element of $\overline{A}$ is calculated by rewriting equation 5.8 as:

$$\overline{a}_i = \frac{N}{n} \int_{j=\frac{n}{N}(i-1)+1}^{k=\frac{n}{N}i} c_{(j:k)}\, dt \qquad (5.13)$$

The data is divided into N equal-sized frames as given by equation 5.13 and is based on "static frame size". Therefore, simply stating static and fix-sized frames are used. Dynamic frame sizing is described in section 5.5.1.



C= (-1, -2, 1, 0, 2, 1, 1, 0) n= |C| = 8

Case I (PAA)

$\overline{C}$ = (mean (-1,-2,-1, 0), mean (2, 1, 1, 0)), $\overline{C}$ = (-1, 1), N= |$\overline{C}$| = 2

Case II (Propose PAA)

s_1= (-1,-2,-1, 0), s_2= (2, 1, 1, 0),

$\overline{A} = \left(\frac{1}{4}\int_1^4 s_1 dt, \frac{1}{4}\int_5^8 s_2 dt \right)$, $\overline{A}$ = (-0.875, 0.750), N= |$\overline{A}$|=2

Figure 5.6: An illustration of data reduction by PAA and proposed-PArA

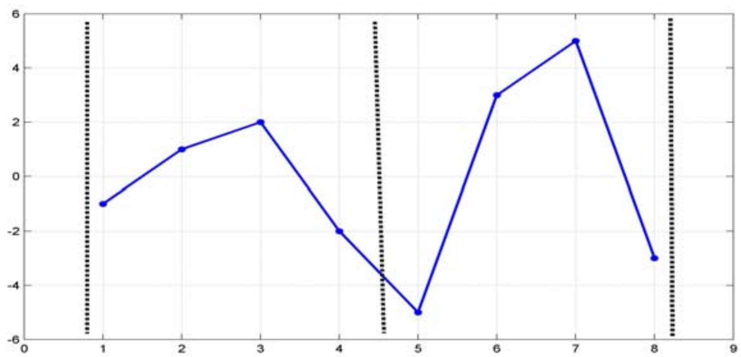
Figure 5.6 illustrates a data reduction of a time series (of n=8) by using both PAA and proposed PArA. Time series is divided into N=2 frames and the values in the frames are reduced by (i) mean and (ii) area under the curve in PAA and PArA respectively. The ratio of the length of the original time series to the length of its PAA or PArA representation is called compression rate $c = n / N$.

5.3.3 Warping with Proposed Piecewise Area Approximation

The same algorithm and procedures described in PDTW can also be used for proposed piecewise area approximation based DTW (PADTW). However, the equation 5.13 is used in place of equation 5.8. Note: The compression rate c used in equation 5.11 is ignored in PADTW. Hence DTW algorithm is applied on PArA representation of time series.

5.3.4 Piecewise Aggregate Approximation vs. Proposed Piecewise Area Approximation

This section demonstrates that "proposed PArA" is similar and competitive to PAA and has a potential of improvement in the representation of time series data.
One expected limitation of PAA is the representation of "*equal numbers with opposite signs*" resulting in zero mean values while on the other hand PArA may not always give zero values for the same data points as shown in the Figure 5.7.



Case I (PAA)
C= (-1, 1, 2, -2, -5, 3, 5 -3) n= |C| = 8

$\overline{C}$ = (mean (-1, 1, 2, -2), mean (-5, 3, 5,-3)), $\overline{C}$ = (0, 0), N= $|\overline{C}|$ = 2

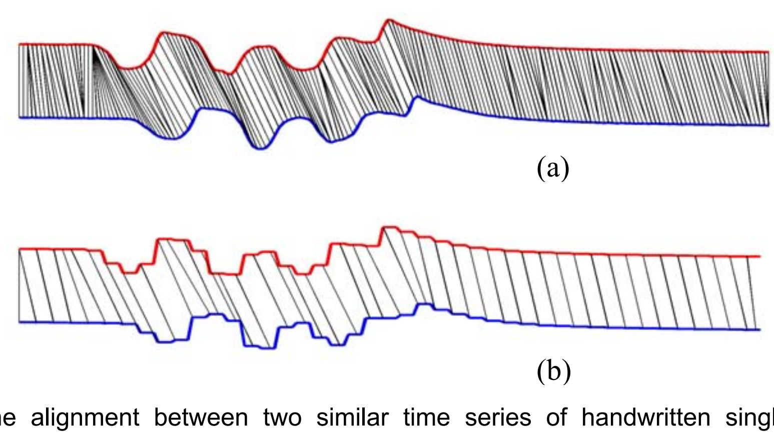
Case II (Proposed PArA)

s_1= (-1, 1, 2,-2), s_2= (-5, 3, 5,-3),

$$\overline{A} = \left(\tfrac{1}{4}\int_1^4 s_1 dt, \tfrac{1}{4}\int_5^8 s_2 dt \right), \quad \overline{A} = (0.375, 1), \ N = |\overline{A}| = 2$$

Figure 5.7: A time series with equal numbers of opposite signed numbers used for representation of PAA and proposed PArA

Figure 5.7 shows a time series of n=8 points and its reduced data representation in two cases. The time series is divided into two frames and each frame has equal numbers of opposite signed numbers. The mean of each frame is zero in PAA representation contrary to non-zero values provided by the integrals of the segments in the frames in PArA method.



(a)

(b)

Figure 5.8: The alignment between two similar time series of handwritten single character "B" discovered (a) by standard DTW and (b) by proposed PADTW

In Figure 5.8, the alignment between two similar time series is shown for (a) DTW (b) PADTW. This presents strong visual evidence that PADTW finds approximately similar warping as found in PDTW (see Figure 5.5).

5.4 DTW on Down-sampled Time Series

Data down-sampling is another method to reduce number of data points in the time series obtained from handwriting and hence the size of the database. The computational complexity for the classification of handwriting data is reduced by applying DTW on down-sampled time series data (section 4.2.5).
The local and global features included in the time series of handwritten signature at different down-sampling rates are shown in the Figure 5.9. The wave segments do not loose relevant information for DTW match.

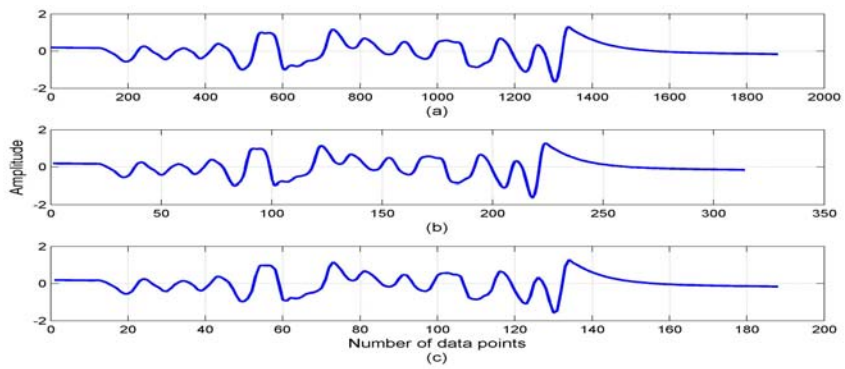


Figure 5.9: Time series of a signature at down-sampling rate: a) M=1 (original), b) M=6 and c) M=10.

In conclusion, by approximation of time series with some compression method and then performing DTW on the new representation essentially reduce computational complexity and memory requirement. Figure 5.10 [24] shows DTW warping path: for (1) original and (2) reduced representation of time series.

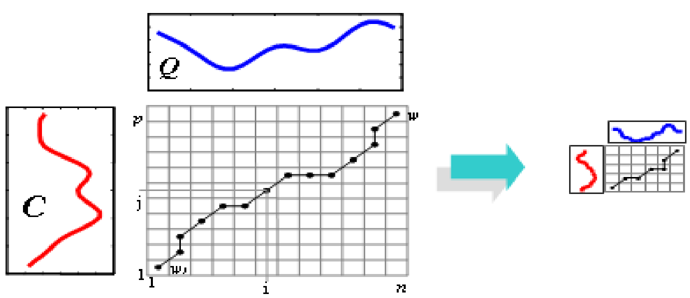


Figure 5.10: Example of warping path with DTW and PDTW.

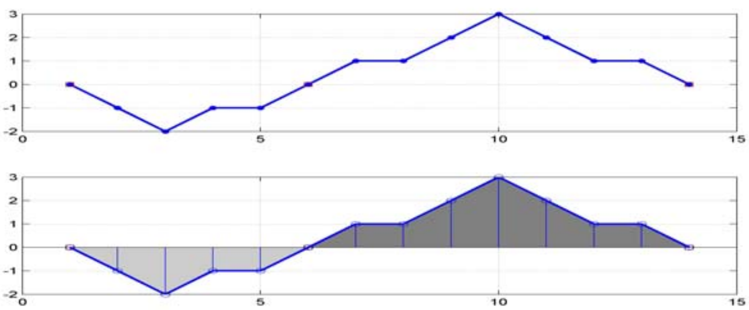
5.5 Proposed Area Bound Dynamic Time Warping (AB_DTW)

There are two problems suggested for the most popular PAA presentation of the time series: (1) static frames size and (2) the use of mean values of data in a frame. In the PArA method, the problem (2) is addressed by using an integral value of a curve (area) in the frame. Further, in Iterative Deepening DTW (IDDTW) [24], Iterative Multi-Scale DTW (IMDTW) [83] and Fast-DTW [84] there are some improvements suggested for PDTW algorithm where the basic idea is to iteratively exploit the DTW at different resolutions to improve warping. In some cases, it is required for a user to prove the quality of the similarity search result [24].

To face with the problems, here in the thesis a novel approach called "Area Bound Approximation" (ABA) of time series is presented. It is the proposed PArA (section 5.3) implemented with a dynamic frame size. The strategy is to combine two ideas:

- Dynamic frames: Divide time series into frames of different sizes
- Calculate area of curve in a frame

The proposed warping method is called Area Bound Dynamic Time Warping (AB_DTW). As the name suggests, the technique warps areas bounded by the local regions of sequences.
The procedure described in DTW algorithm is also applied for the proposed AB_DTW method with a difference of the fact that DTW is applied on ABA representation of time series. The work of [38-39], [70], [73] inspire the method presented in this section. Its procedure is illustrated in the Figure 5.11.



Case I: 1D

Time index= (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,14)

$R = (0,-1,-2,-1,-1, 0, 1, 1, 2, 3, 2, 1, 1, 0)$ $\quad$ $n = |R| = 14$

zc = (1, 6, 14)

$S_1 = (0,-1,-2,-1,-1, 0)$, $S_2 = (0, 1, 1, 2, 3, 2, 1, 1, 0)$

$$\overline{R} = \left(\tfrac{1}{6}\int_{1}^{6} s_1 dt, \tfrac{1}{9}\int_{6}^{14} s_2 dt \right) = (-0.833, 1.222) \qquad N = |\overline{R}| = 2$$

Case II: 2D

$$\overline{R} = \begin{pmatrix} 3 & 10 \\ -0.833 & 1.222 \end{pmatrix} \qquad N = |\overline{R}| = 2$$

Case II: 2DN

$$\overline{R} = \begin{pmatrix} 0.300 & 1 \\ -0.833 & 1.222 \end{pmatrix} \qquad N = |\overline{R}| = 2$$

Figure 5.11: Examples of proposed Area Bound representation

The curve in (a) stands for a time series R of fourteen (n) points and three zero-crossing (ZC) points marked at (1, 6 and 14). In (b) the time series is divided into two (N=zc-1) unequal frames. A vector of normalized area values calculated in each frame becomes the ABA representation. Equations below the curves demonstrate the calculation of the area of the curve in each frame.

5.5.1 Area Bound Approximation of Time Series using Dynamic Frame Size

In ABA approach, the size of the frames is not necessarily uniform and fixed. Therefore, different sized frames are selected automatically based on consecutive zero-crossings ZC and the selected points falling into a frame are abstracted by calculating the area of the curves in the dynamic frames (see Table 5.1). A vector of these normalized area values becomes the data reduced data representation of the original time series as shown in Figure 5.11. The focus of the thesis work is on the data reduction and therefore a local data reduction based approach that allows overall heavy data reduction is introduced.

5.5.1.1 One dimensional case (1D)

In the one-dimensional case, each calculated area is represented by a single point in a vector of reduced time series. As shown in Figure 5.11, two area values are calculated for segments from time index 1 to 6 and from 6 to 14 respectively. Therefore an original sequence with three zero-crossings is transformed into two area values “-0.833” and “1.222” represented by a vector in 1D case.

5.5.1.2 Two dimensional cases (2D)

In 2D, the same calculated area is represented by two data points—time index and the calculated area values. Therefore, the time series is transformed into a 2 dimensional vector of mean time index values approximated as “$3.5 \approx 3$” and “10” and calculated area values of “-0.833” and “1.222” respectively. The mean of the time index value is rounded to integer. In another case denoted by “2DN”, the obtained time index values are normalized to [0 1] as illustrated in the Figure 5.11.

5.5.2 AB_DTW Warping Process

The AB_DTW warping process consists of the following steps:

- Positive peaks (PK+) and Negative peaks (PK-) determination
- Zero-Crossing (ZC) determination
- Bounded Areas Calculations
- Bounded Area Matching

The extreme points of peaks and valleys (local extremes) are treated as PK+ and PK-. The zero-crossing ZC points are defined as the points of signal crossing zero line (or a certain value) while signal values are moving with respect to time:

(a) From baseline towards zero
(b) From peak (PK+) towards zero
(c) From peak (PK-) towards zero.

Note: For each time series, a straight-line fit is removed before determination of zero crossing points (section 4.2.3). In this study, the mean of time series is considered as zero crossing line.

5.5.2.1 Bounded Area Calculation

A time series R of length n is given by

$$R = r_1, r_2, \ldots\ldots, r_n \tag{5.14}$$

If the points $zc_1, zc_2, zc_3, \ldots\ldots, zc_k$ are the zero crossing points such that $|zc| = k$, the number of segments s_j of the original sequence R will be zc-1 (i.e. equal to |k-1|).

Now the time series $\overline{R}$ represented by ABA is given by:

$$\overline{R} = \frac{1}{|1+zc_2-zc_1|}\int_{zc_1}^{zc_2} s_1 dt, \frac{1}{|1+zc_3-zc_2|}\int_{zc_2}^{zc_3} s_2 dt, \ldots\ldots, \frac{1}{|1+zc_k-zc_{k-1}|}\int_{zc_{k-1}}^{zc_k} s_{k-1} dt \tag{5.15}$$

Each calculated area is divided by the number of data point in the segment. Therefore, a time series of length (n) with the number of zero-crossings zc is transformed into a vector (reduced time series) of areas of length N such that N = zc-1. Note: If no zero crossing point is determined then the ends of the sequence will be treated as zero crossing points i.e. |zc| >=2 or N>=1. This special case did not occur in this study work. The area bounded by the local wave of the signal is calculated as area+ and area-. The area+ is the area bounded by the sub-sequence (above ZC) for two consecutive ZC points. It includes positive peaks (PK+). Similarly, area- is the area bounded by the sub-sequence (below ZC). A middle ZC point is contributing to two consecutive areas. Each area can contain one or more peaks and the area is actually determined for a segment of all points enclosed by two consecutive ZC points. Very small ripples are not considered as peaks (PK±). Therefore, if area (area±) is less than a certain threshold then the area is considered as coming from ripples or noise called “RN area”. RN areas are omitted. RN areas are adjusted in the adjacent areas. The area contribution of segment of two consecutive ZC is omitted if the segment does not contain any peak (PK+ or PK-). Or similarly one very small-calculated area is not neglected if the adjacent area contributions are greater than a certain threshold value. Normalized area± are calculated by trapezoidal rule with the help of MATLAB tools [12]. The flow of steps for area bound calculation based on peaks and zero-crossing detection algorithm is shown in Table 5.1.

Table 5.1: Area bound calculation using peaks and zero-crossings

Step 1	Define threshold_1 for peak detection
Step 2	Define threshold_2 for zero crossing determination
Step 3	Find values and index points of peaks (local maxima and minima) > = threshold_1
Step 4	Find an array ZC of zero-crossing index values using threshold_2
Step 5	Initialize first zero-crossing index point out of ZC array
Step 6	Initialize an array index ind
Step 7	Begin loop (until end of ZC array)
Step 8	Select next zero-crossing index point out of ZC array
Step 9	Find number of peaks PK between first and next zero-crossing index
Step 10	If PK is zero go to step 8, else go to next step
Step 11	Find segment of signal from first to next zero-crossing index points
Step 12	Calculate area enclosed by the segment and find normalized area value (divide area by length of segment)
Step 13	Put area value into an array A using index ind
Step 14	If two dimension case then put mean of first and next into an array of time T using index ind, else go to next step

5.5.2.2 Bounded Area Matching

For the comparison of reference and sample time series converted into corresponding ABA representations, the DTW algorithm is used to carry out the optimal similarity match of two sequences. For 2D area bound representations, the elements of the reference and sample sequences can be expressed as two-dimensional data— $q(t_i, v_i)$ and $c(t_j, v_j)$ respectively, where “t_i” and “v_i” are the averaged time index and the value of calculated area respectively. The local distance (d(,)) shown in equation 5.3 can be expressed in 2D case as:

$$d(q_i, c_j) = (q_i - c_j)^2 = \sum_{k=1}^{2} (\mathrm{q}_{\mathrm{i,k}} - c_{j,k})^2 \tag{5.16}$$

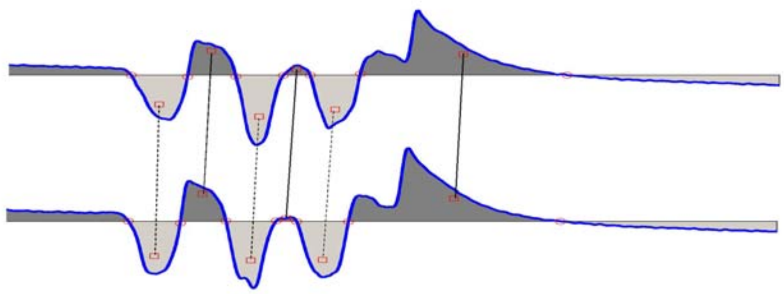


Figure 5.12: The alignment between two similar time series as discovered by AB_DTW is shown.

The curves illustrate two sequences of handwriting "B" from the same writer and their ABA representation. The different shaded areas are in different shads above and below zero-crossing line. The alignment between two similar time series as discovered by AB_DTW is shown in the Figure 5.12. DTW based warping procedure for AB_DTW is demonstrated in section 6.4.2.

5.5.3 Segmentation of Data Required in AB_DTW

One important aspect of the time series data analysis is the evaluation and comparison of the DTW and AB_DTW based classification methods when applied on the time series and its area bound representations respectively. As for the evaluation of the AB_DTW method, the baselines at both ends of the time series are ignored (see Figure 5.12 & Figure 6.18) therefore to account for a similar treatment in the DTW method, the time series are exclusively segmented.

Table 5.2: Segmentation using peaks and zero-crossings

Step 1	Divide original signal into two signals. $Signal_1$ represents the first half and $signal_2$ is the reversal of the second half of original
Step 2	Find $threshold_1$ using 1/4th of STD of $signal_1$
Step 3	Find values and index points of peaks (local maxima and minima) > = $threshold_1$
Step 4	Find index value of first peak PKID
Step 5	Find $threshold_2$ for zero-crossing using MEAN of $signal_1$
Step 6	Find zero-crossing index values ZC_1 using $threshold_2$
Step 7	Find zero-crossing index values ZC_2 < PKID
Step 8	If ZC_2 is zero then take negative of the $signal_1$ i.e., $signal_1 = signal_1*(-1)$ and go to step 2, else go to next step
Step 9	Find last index of ZC_2 as a first point of segmentation seg_1
Step 10	Repeat step 2 to step 9 for $signal_2$
Step 11	Find last point of segmentation seg_2 using seg_1 of $signal_2$ by using equation: $seg_2 =$ length(signal)-seg_1
Step 12	Find segmented signal using index point seg_1 of $signal_1$ and seg_2

This is done in order to select similar segments of time series for the DTW method as used in the AB_DTW method or alternatively to select more closely the signal parts that actually belong to the handwriting. The latter is also helpful in the detection of zero crossing points near the ends of a time series. The detection of these points is crucial in the pre-processing of data in case of AB_DTW methods. Therefore, the segmentation of handwriting signals is done based on "peak and zero-crossing determination algorithm". The flow of steps for segmentation algorithm is shown in Table 5.2.

5.6 Dynamic Time Warping for Multivariate Time Series (MDTW)

In section 5.2, two time series Q and C are univariate time series. That is, the elements of Q and C are scalar: $c_i, q_j \in R$, where Q and C are given by the equation 5.1-2. This thesis deals with the analysis of multivariate time series signals obtained from handwriting by using multichannel sensors pen. Therefore, Q and C are multivariate time series: $c_i, q_j \in R^l$, where l is an integer constant representing number of channels ($l \geq 1$). The *p*-th dimension of a time series element is represented by $c_{i,p}$. For l =1 the multivariate time series of Q and C reduce to univariate time series [59].

Local Distance Measure for Multivariate Time Series

To align two sequences using DTW a local distance is calculated as given in equation 5.3. For comparing multivariate time series components, we can rewrite local distance for multivariate time series as:

$$d(q_i, c_j) = (q_i, c_j)^2 = \sum_{p=1}^{l} (\mathrm{q_{i,p}} - c_{j,p})^2 \text{, (where } l \text{ is number of channels)} \tag{5.17}$$

Each dimension (channel) of c_i and q_j contributes an equal amount to the total error in this distance measure, because the ranges of all dimensions of C and Q are normalized to make them comparable. The DTW algorithm is now used to find a warping path, which aligns corresponding locations of indices i and j in the two time series C and Q [59].

Note the following consideration: **(1)** in MDTW, indirectly, the fusion of all dimensions (channels) is carried out as a part of its algorithm using equation 5.17 which is no doubt also an essential part of multivariate time series comparison. Further **(2)** this also involves handling and manipulation of high dimensional data (e.g., Q is "$n \times l$" dimensional matrix)—storage, subtraction, square etc as part of the algorithm.

5.7 Single Channel Dynamic Time Warping (SDTW)

In Single channel DTW method denoted by SDTW, the DTW distance is calculated for each dimension (channel) of two multivariate time series channel by channel. Therefore, DTW must run for each channel of two multivariate time series separately and the average DTW distance is used for comparison. So, SDTW match provides an averaged distance $SDTW(Q,C)$ which is obtained by algebraic mean of $DTW(Q,C)_l$ distances of all channels, given by:

$$SDTW(Q,C) = \frac{1}{l} \sum_{p=1}^{l} DTW(Q,C)_p \quad \text{, (where } l \text{ is number of channels)} \tag{5.18}$$

5.8 Reduced Dynamic Time Warping (RDTW)

The proposed DTW method called Reduced Dynamic Time Warping (RDTW) is applied on reduced dimension of multivariate time series. In the following section, the reduced approximation technique is described.

Reduced Univariate Approximation of Multivariate Time Series

For two multivariate time series Q and C, the elements of Q and C are multidimensional which increases the complexity of data analysis. In order to reduce the complexity of DTW especially on multivariate time series, the latter are reduced to univariate time series by the direct sum of all sensor channel signals. Therefore, the elements q_i and c_j of Q and C in the reduced univariate approximation are given by:

$$q_i = \frac{1}{L}\sum_{p=1}^{l}(\mathrm{q}_{\mathrm{i,p}}) \tag{5.19}$$

$$c_j = \frac{1}{M}\sum_{p=1}^{m}(\mathrm{c}_{\mathrm{j,p}}) \tag{5.20}$$

Where l and m are the number of channels and L & M are the averaging constants. In this study work, the number of channels are equal (i.e. l=m) and the denominators are taken as unity (L = M=1).

Sum of Multivariate Time Series: In this dimension reduction by the sum of all variables, each dimension of q_i and c_j contributes an equal amount to the obtained reduced univariate time series. In the channel abstraction process, the ranges of all dimensions (channels) of the original C and Q are normalized to make them comparable. Different channel normalization procedures [10][33][52][59] are described in section 6.3. In order to increase the influence of each channel in the summed signal, the averaging constants L and M are taken as unity. The reproducibility and distinctiveness of converted univariate time series are illustrated in the section 6.1.

Note that unlike MDTW where the channel fusion is dealt as a part of the DTW algorithm, in RDTW the channel fusion is carried out as a part of the pre-processing stage and therefore, the RDTW matching algorithm is reduced to that used for univariate time series (i.e. DTW).

5.9 Bio-Reference Level Assigned Dynamic Time Warping

The proposed warping method is called Bio-Reference Level Assigned Dynamic Time Warping (denoted by Bio-DTW). Here, the DTW algorithm is applied on time series after a data pre-processing where biometric reference levels are assigned to the time series obtained from handwriting signals.

The bio-reference level assigned approximation of time series is a process of conversion of multivariate time series into univariate time series by using the personal biometric reference level, as described in the following section.

Bio-reference Level Assigned Approximation

In DTW based classifiers, generally the time series are normalized in time and amplitude domains. However, a special treatment for a shift in amplitude of the univariate time series that is derived from multivariate time series data is proposed. A person specific so-called bio-reference level is added to the corresponding univariate time series. Consequently, amplitude values are shifted to new base levels.

The focus of this study work is to determine an individual reference level of a writer, because it is found that the reference level is valuable information for a writer (section 6.3). This reference level essentially determines the accumulative temporal behavior of a writer in terms of refill pressure and inclination of the pen (see equation 5.21 & 6.4). Standard deviation (STD) values are calculated for each channel of the original multivariate time series and different combinations of these values are tested for best performance of recognition. The best reference level value determined for the accuracy of person identification termed as “bio-reference level (BRL)” is given by the equation 5.21-22.

A multivariate time series of a sample is converted to one dimensional univariate time series by direct sum in such a way that data is normalized before conversion. Further, the bio-reference levels are added to the corresponding univariate time series. Hence the elements q_i and c_i of the transformed time series Q and C are given by:

$$q_i = \frac{1}{L}\sum_{p=1}^{l}(\mathrm{q}_{\mathrm{i,p}}) + \frac{1}{2}\sum_{j=4(j-1)+1}^{2} STD(q_{\forall i,j}) \tag{5.21}$$

$$c_i = \frac{1}{M}\sum_{p=1}^{m}(\mathrm{c}_{\mathrm{i,p}}) + \frac{1}{2}\sum_{j=4(j-1)+1}^{2} STD(c_{\forall i,j}) \tag{5.22}$$

Where l and m are the number of channels, the averaging constants L and M are taken as unity and the second term in the equations shows the component BRL.
STD is standard deviation. For a time series s(t) of N data points, STD(s) is given by:

$$STD(s) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(s_i - \bar{s})^2} \quad \text{with} \quad \bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i \tag{5.23}$$

Note the second term in equation 5.21-22 is another form of representation of equation 6.4.

5.10 DTW on Symbolic Representation of Time Series

Many symbolic representations of time series have been proposed over the past couple of decades. The transformation of real world data (time series) into symbolic representation has a great potential of improvements such as in reducing the complexity of data analysis. Further advantages are:
(1) In the connection of lot of on-going developing research and methods to represent time series data into an efficient and abstract format which is also useful for classification.
(2) To allow researchers to avail of the wealth of data structures and algorithms from the text processing and bioinformatics [78].
A symbolic representation of time series that allows dimensionality reduction was introduced in [78-79]. The method described there allows a very good dimensionality reduction, conversion to symbols and distance measures to be defined on symbolic representation. In this section, a short review on "Symbolic Aggregate Approximation" SAX representation of time series is given, and then symbolic representation procedures as proposed in the thesis are described.

5.10.1 Symbolic Aggregate Approximation (SAX)

In [78], a new approximation—a symbolic representation of time series is introduced called as "**S**ymbolic **A**ggregate Appro**x**imation" (SAX). SAX allows reduced approximation of time series of arbitrary length n to a string of symbols of arbitrary length w, typically w<<n. The discretization procedure used is unique in that it uses an intermediate representation between the raw time series and the symbolic strings. The two transformation steps are:
i) transform the data to Piecewise Aggregate Approximation (PAA)
ii) then symbolize the PAA representation into a discrete string
There are two important advantages to doing this [70],[77-78]:
- Dimensionality Reduction by using PAA
- Lower bounding of the distance measure.

The PAA technique is reviewed in section 5.2 and an example of PAA & SAX approximation is shown in the Figure 5.13 [78]. PAA representation is transformed using symbols {a, b, c} to form a word "baabccbc". Therefore, the SAX is defined where PAA representation is a necessary intermediate step. Review of the SAX is necessarily briefed here, for details on SAX and its distance measures see [78-81].

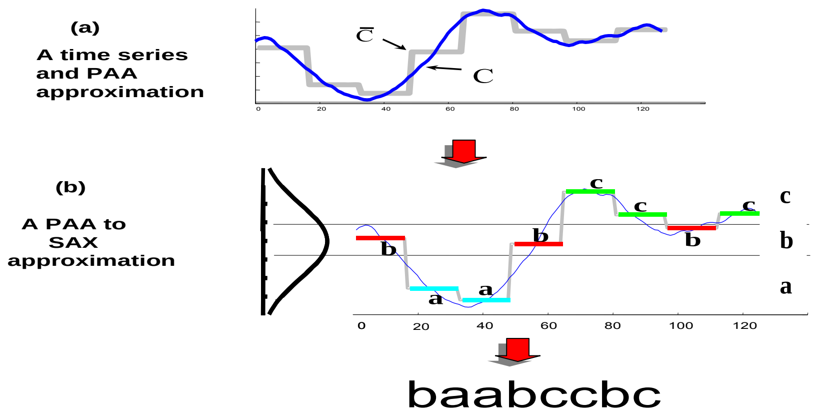


Figure 5.13: An example of a time series, its PAA and SAX approximations

5.10.2 Extension of SAX

In SAX, the discretization procedure is based on PAA representation as an intermediate representation between raw time series and symbolic string. As noted in the previous section 5.2, the PAA approach minimizes dimensionality by the mean values of part of the time series falling within equal sized frames. However, the PAA has the drawback of possibly missing important patterns in some datasets as shown in the Figure 5.7. There are some extensions to SAX technique as described in [80-81] where a modification in PAA (intermediate step) is suggested to face with this problem.

Previous sections in part are dedicated to show the strengths and weakness of PAA representation and in the section 5.3, 5.5, the competitive ability of the proposed dimension reduction techniques is shown. The improvement expected in the proposed quality of SAX based similarity search method is based on improvements suggested for the intermediate representation (i.e., in PAA). In the following section, modified SAX techniques are described.

5.10.2.1 SAX using Piecewise Area Approximation

In **S**ymbolic **Ar**ea appro**x**imation (SArX), the SAX based pattern matching is supplemented with a change in the pre-processing step. In the approach, the intermediate PAA representation is replaced by piecewise area approximation PArA. The PArA approach minimizes dimensionality by calculating area of the subsection of time series falling within equal sized (static) frames (see section 5.3). The same algorithm and distance measures described in original SAX pattern matching technique [78] can also be used for proposed SArX method.

5.10.2.2 SAX using Area Bound Approximation

In **s**ymbolic **Ar**ea **b**ound appro**x**imation (SAbX), the SAX based pattern matching is supplemented with a change in pre-processing step. Therefore, the intermediate PAA representation of SAX based procedure is replaced by area bound approximation of time series using frames of dynamic sizes (see section 5.5).

The same procedures and distance measure described in original DTW pattern matching technique can also be used for proposed SAbX representation.

5.10.3 SAX using PAA and Proposed Approximations Methods

Traditional SAX based representation of time series data has shown its superiority to other representations because of its capabilities to be used in dimensionality reduction, lower bounding and streaming symbolic approach. Because of the discrete nature of SAX, it is possible to use this technique in emerging tasks such as anomaly detection and motif discovery [78].

As a great similarity between PAA and proposed PArA (for example) is shown even with a further improvement in the representation, therefore it is expecting that the extended SAX techniques are superior to or competitive with the traditional SAX technique.

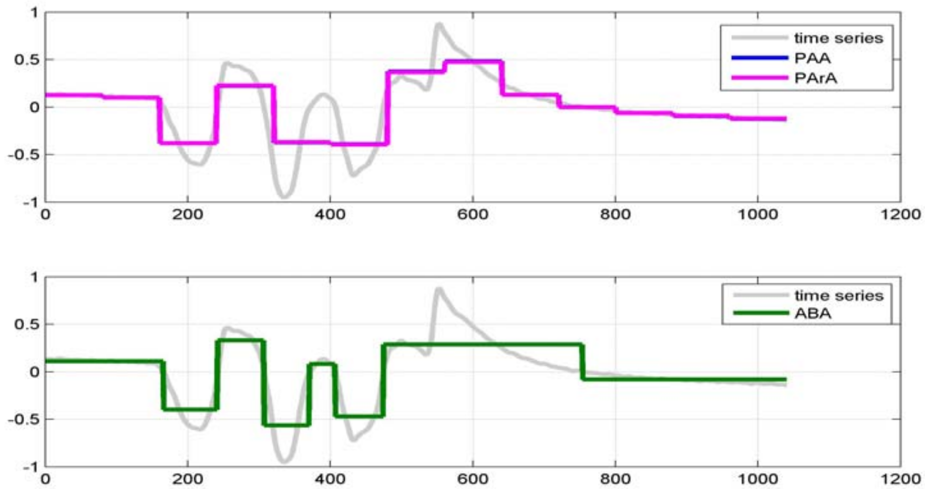


Figure 5.14: An example of a time series of single character "B", its discretization by PAA, proposed-PArA and proposed-ABA approximations.

Figure 5.14 shows an example of PAA & proposed approximations of a time series obtained from handwriting single character "B". Both the PAA and PArA show similar representations while area bound approximation ABA is more intuitive.

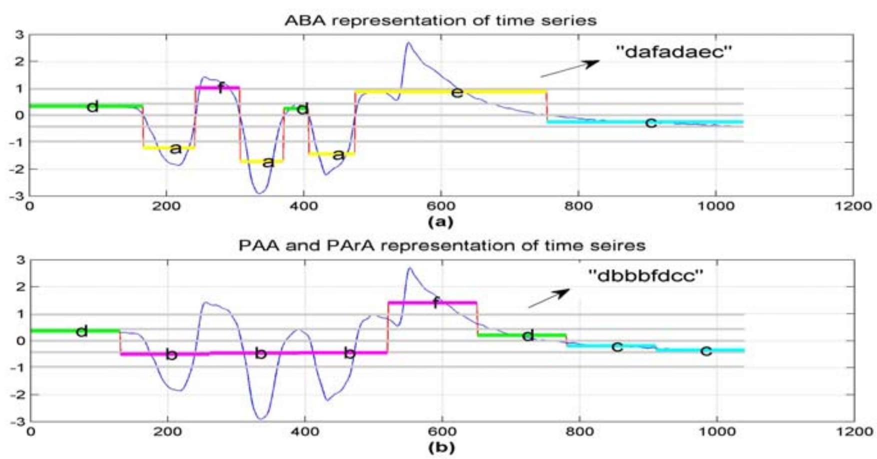


Figure 5.15: A time series mapped to word (symbols) by (a) SAbX and (b) SAX & SArX

A time series discretized by (a) ABA, (b) PAA and PArA approximations as well is shown in the Figure 5.15. The time series is mapped to the words (symbols) "dafadaec" and "dbbbfdcc" respectively. Area bound approximation (ABA) transforms time series to the word "dafadaec" which is a more intuitive transformation.

In summary, like SAX, the proposed extended SAX techniques—SArX or SAbX are equally well potential candidates for adopting ideas, definitions, algorithms and data structures commonly used in the bioinformatics domain.

6 BiSP System for Biometric Applications

The aim of the thesis is to apply the multisensoric pen (BiSP) which is designed to record and analyze human fine motor features for biometrics (this chapter) and medical applications (see chapter 7). The following sections present experiments and results for biometric person authentication or handwritten object recognition which are still partly published in [40-44] (section 6.1-5).

6.1 Biometric Person and Handwritten Object Recognition

The BiSP is a ballpoint pen like device for the online input of handwritten characters and words, drawings and gestures movements. The BiSP device used in different experiments is shown in the Figure 6.1.

Figure 6.1: BiSP device in action.

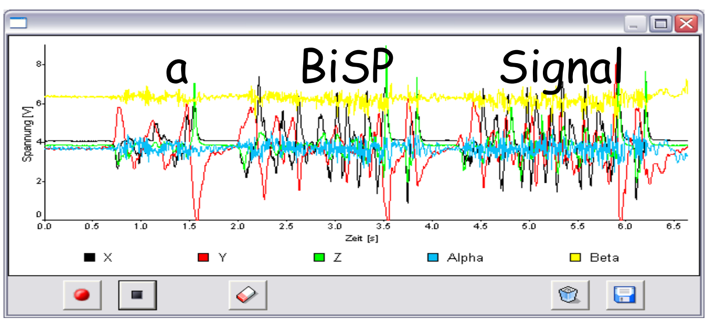


Figure 6.2: Typical signals obtained from handwriting the sentence “a BiSP Signal” on pad.

The multivariate time sample data obtained by the BiSP system during handwriting the sentence “a BiSP Signal” on pad is shown in the Figure 6.2.
The change of forces resulting from handwriting on pad and transferred by the refill is monitored in terms of multivariate time series data as: (i) pressures (at pen-tip) across refill in x-y direction, (ii) pressures of finger grip of fingers holding the pen, (iii) pressures longitudinal (z) to refill axis and (iv & v) acceleration-tilt of the pen in two directions. For details on multi-channel-sensors, data see section 3.3.

This section deals with the BiSP system applied for the recording and recognition of:

1) Signatures
2) PIN words and
3) Single characters

6.1.1 Methods and Data Analysis

For classification, DTW and its variants are applied on BiSP multivariate time series data (multichannel) generated during handwriting on paper pad. DTW is known to be useful for classifying handwritten signatures, single characters or words based on an elastic similarity match of time series. For details on DTW based classifier see chapter 5.

The computing time and memory space problems associated with DTW are overcome by confining DTW match to: **(i)** a few single characters handwritten by a small group of persons, **(ii)** down-sampled time series data and **(iii)** the sum of the multivariate time series (section 5.8). The DTW match was performed after an adequate pre-processing of original data (section 4.2). For each handwritten item (signature, PIN word or single character) the BiSP device provides multivariate time series corresponding to five sensor channels.

For clarity, the DTW algorithm is termed as “Single DTW” (denoted as SDTW) when applied to the multivariate time series channel by channel and “reduced DTW” (denoted as RDTW), when applied to the univariate time series given by the sum of all sensor channels (section 5.8). Thus the SDTW match provides five distance values “d_k” and the algebraic mean of these distance values is used to evaluate the comparison of multivariate time series. The aim is to compare the performance of recognition based on RDTW and SDTW. The drawback of SDTW is its large computing time. The recognition time of a written item can significantly be reduced by a factor of about five using RDTW in this regard.

Reproducibility and Distinctiveness of Time Series

Figure 6.3 illustrates reproducibility and distinctiveness for the time series obtained by the sum of all sensor channels. The signals are from the items ‘A’, ‘ü’, ‘4’ and a PIN ‘E37BM%A’ written by the same or two different persons. It shows a high reproducibility and distinctiveness of the univariate time series (added channel signals) even though the dynamic attributes of all individual channels are included. It is obvious that enough specific biometric and object related information is embedded in even a time series of short length (single characters) or in a time series of longer strings (PIN words or signatures), in order to discriminate between various handwritten objects or human individuals.

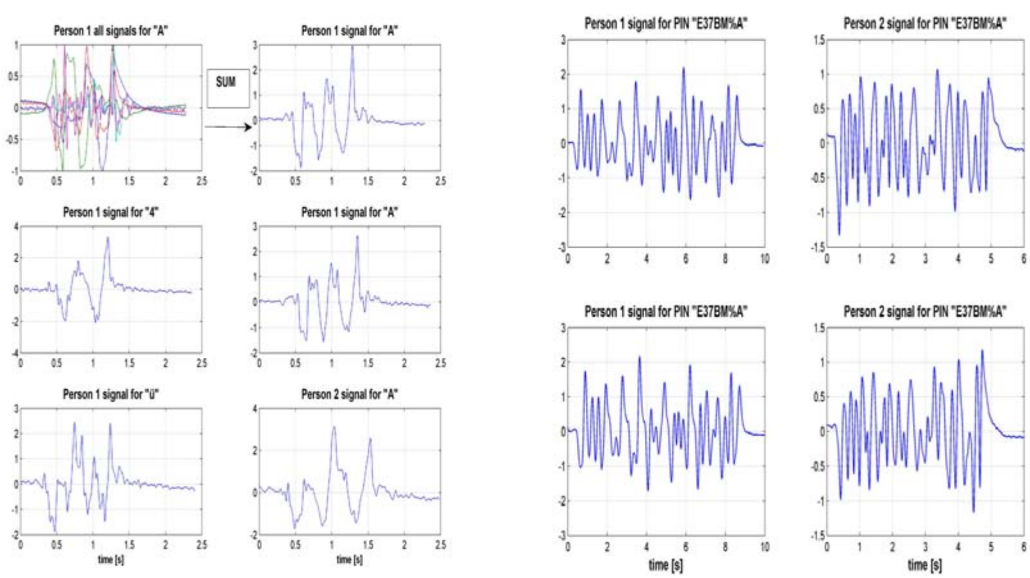


Figure 6.3: Reproducibility and distinctiveness of time series obtained by the sum of all sensor channels.

6.1.2 Experiments and Results

The main objective of the experiments was a critical validation of the biometric person or handwritten object recognition based on RDTW and SDTW applied on time series data. For evaluation tasks, the database is divided into query and reference samples and leave-one-out mechanism is used for data analysis. The performance of recognition is evaluated in terms of runtime, score of recognition SR, certainty of best match CM and the receiver operating characteristic ROC curves, which is a commonly used method for the evaluation of biometric person recognition. For detailed treatment on these parameters, see section 4.5.1.

6.1.2.1 Single Character Recognition

For demonstration of reproducibility or similarity, a RDTW match of two time series of the item "E" handwritten by a person is shown in the Figure 6.4. It indicates that equal items written by the same person in several copies are matched very well (reproducibility), i.e., the RDTW-distance is very low. Similarly, it was also shown that different items written by the same person or equal items written by different persons are sufficiently dissimilar (uniqueness) and have obvious larger RDTW-distance.

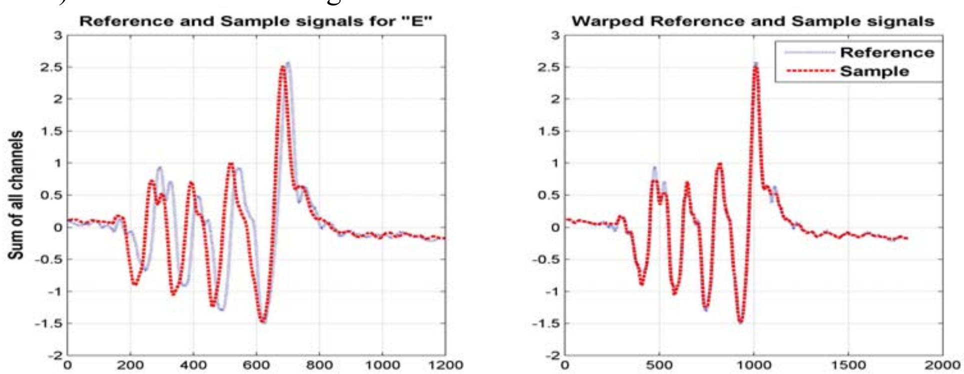


Figure 6.4: Two time series of letter "E" written by one person before and after RDTW.

For single character recognition, an intra-individual match was accomplished and the averaged is determined for all enrolled persons. One query sample out of all reference samples is repeatedly selected corresponding to one of all characters written 10 times by the same person and is compared against the remaining set of all samples. Based on the SDTW and RDTW similarity match, the performance parameters are calculated for the single character recognition as shown in the Table 6.1. The values are averaged over all enrolled writers (writer independent) and the data is down-sampled by M=10.

Table 6.1: Writer independent performance of single character recognition for SDTW and RDTW match of down sampled data (M=10)

items	Score of recognition SR		Certainty of best match CM		Runtime (s)	
	SDTW	RDTW	SDTW	RDTW	SDTW	RDTW
Avg	99.72	99.22	41.39	49.58	1.94	0.39

The score SR is slightly higher (on average 0.5%) when SDTW is applied however, RDTW provides a higher CM (about 20%). Another benefit of RDTW is its lower computing time, which is about fifth part of the SDTW's time. The performance of the RDTW method complies very well with the claims of an online single character recognition system. If RDTW is applied to BiSP-data down-sampled by M=10, single characters handwritten by the same person can be recognized at an excellent score (SR $\geq$ 99%) with a response time (< 0.5 second). It indicates that the short length of a single character encodes an amazing amount of person and handwritten object specific information.

Biometric person authentication is also evaluated using single characters based on leave-one-out mechanism applied on time series obtained from 11 single characters. The performance parameters based on SDTW and RDTW matched 11 single characters, and the mean (avg) for person recognition are shown in the Figure 6.5.

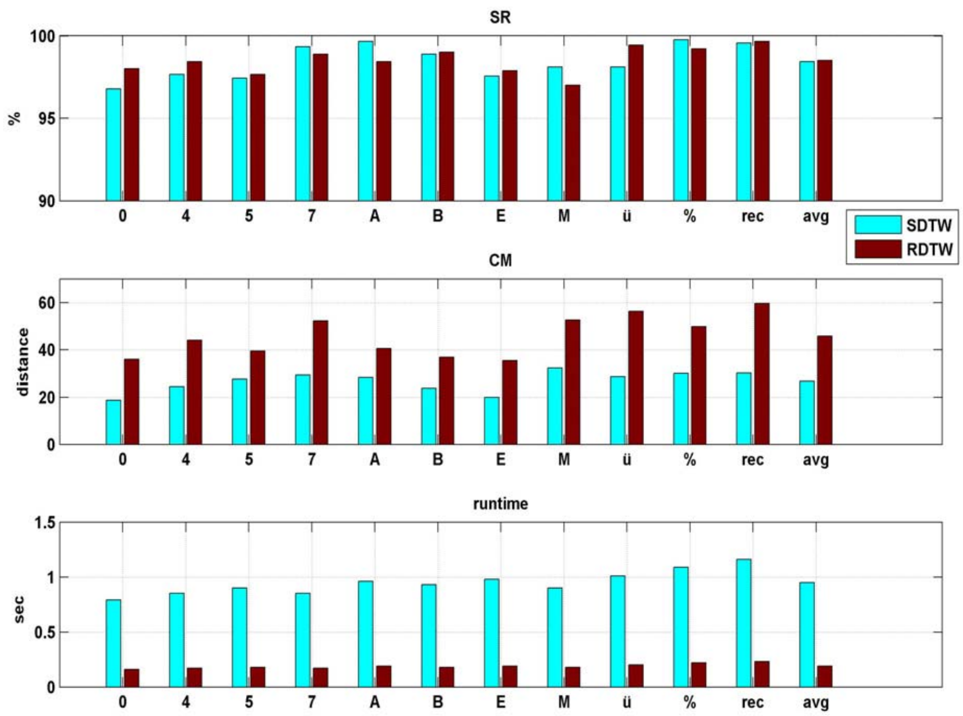


Figure 6.5: Performance parameters for person recognition based on SDTW and RDTW matched single characters shown at M=16.

6.1.2.2 PIN words and Signatures Recognition

An issue of the study work in biometrics is to evaluate the performance of the person authentication by using as well as comparing recognition of handwritten PIN words and (or against) signatures. For this, the procedure of the DTW based authentication is the same as used for single characters.

The DTW distance is an excellent quantitative measure for similarity and dissimilarity of time series. For demonstration, the RDTW matches of two time series of PIN words and signatures written two times by the same person are shown in the Figure 6.6. It indicates that equal items written by the same person are matched very well resulting in lower RDTW-distance (reproducibility). For an example, the PIN word "E37BM%A" repeatedly written by the same person has a lower distance (0.0021) and, in contrast, a higher distance (0.0091) for the same PINs written by two persons or a distance (0.0080) for different PINs "M6B7E3%" and "E37BM%A" written by the same person.

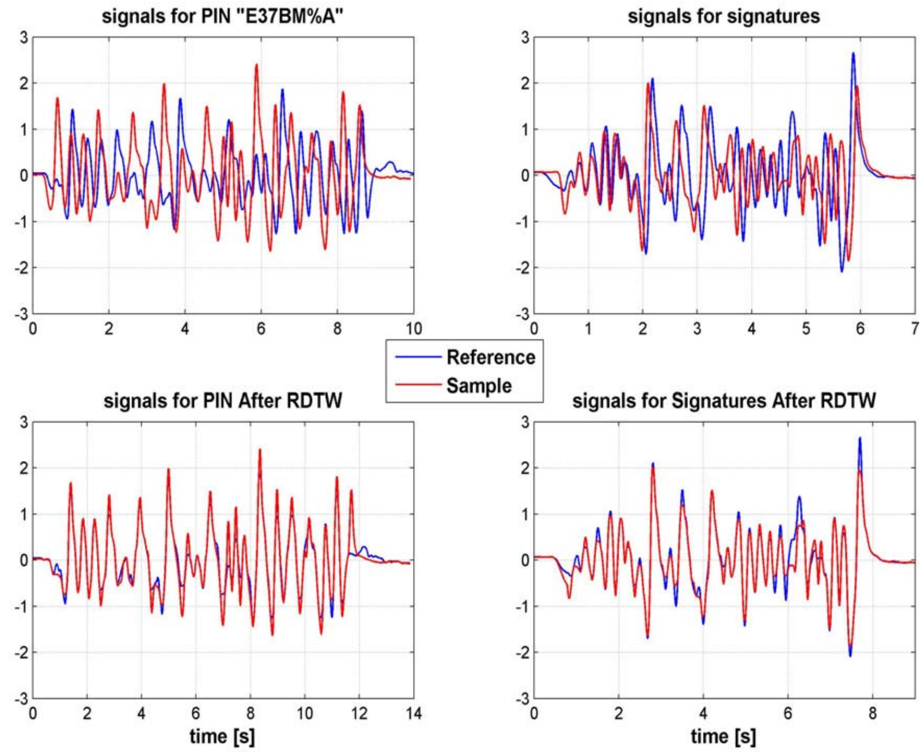


Figure 6.6: Time series of reference and sample signals before and after RDTW match of the two PIN words and two signatures written by one person.

Table 6.2: Performance of person authentication based on PIN word and signature data down-sampled by M=16

Items	SR SDTW/RDTW	CM SDTW/RDTW	Runtime SDTW/RDTW	AUC SDTW/RDTW
PIN	99.97/ 100	49.27/ 78.20	17.86/ 3.57	0.996/ 0.998
Signature	99.57/ 99.90	29.77/ 51.55	7.78/ 1.5	0.992/ 0.998

Table 6.2 shows the values of performance parameters (SR, CM and runtime) average over all writers. Better score rates obtained for private PIN words in comparison to individual signatures suggest that written PIN words may be more suitable for authentication than signatures submitted in a more or less reflex like action.

For a further quantitative validation of performance, the receiver operating characteristic ROC is determined, because it is a common technique for performance judgment. Person authentication based on ROC curves for PIN words and signatures is shown in the Figure 6.7. The area under the ROC curves (AUC) attest the above results obtained with SR and CM, and indicate an excellent grade of performance using SDTW and RDTW (AUC≥ 0.992).

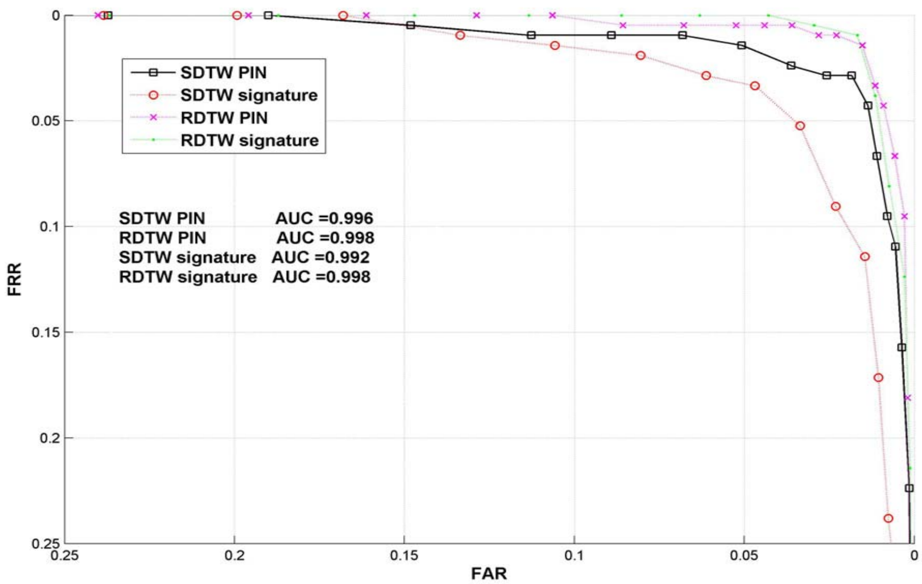


Figure 6.7: ROC curves and Area under the ROC curve (AUC) for person authentication using PIN words and signatures based on SDTW and RDTW distances.

To cope with the computing time problem of classic DTW especially for multivariate time series, RDTW is applied to down-sampled data without a rigorous degradation of score values. For further acceleration, RDTW is applied in a hierarchical classification scheme in terms of a two-step down-sampling procedure. At first stage, RDTW is applied on the heavily down-sampled data to select a small subset of best-matched references very fast. In a second stage, RDTW is used to match the less down-sampled data, now applied on the subset of pre-classified references, selected in the first stage. The procedure can make classification essentially faster at the cost of an assumption that true matches are included in the subset of data selected in the first stage, for details see [41].

6.1.3 Discussion

It is found that the RDTW technique applied to down-sampled BiSP data obtained from handwritten PIN words, signatures or just short isolated single characters is well suited to classify between human individuals or handwritten objects. Reproducibility and distinctiveness have been demonstrated in the reduced univariate time series obtained from multivariate time data. The effect is especially elaborated when applied in the person or handwritten item recognition using a dataset of short time series (single characters) obtained from a small group of writers and is collected repeatedly in a single session. The performance of the proposed method complies very well with the claims of an online recognition system. Handwritten PIN words or signatures can be recognized at high score (≥99%) with a response time of less than one second. A further speed up of computation can be achieved by using RDTW match on a hierarchical classification based on a two-step down-sampling procedure. Higher or equally comparable scores of recognition suggest that handwritten PIN words may be more suitable for person authentication than signatures submitted in a more or less reflex like action. PIN words are also suitable in a situation where personal signatures are too simple or too complex to generate distinctiveness or reproducibility respectively. A further benefit of using PIN words is the security enhancement by involving the two-factor biometric person authentication method, where biometric person and PIN code recognition is combined for more secure person authentication (for details see section 6.6).

6.2 Biometrics using the WACOM Enhanced Pen System

Handwriting dynamics which reflect human fine motor skills of hand and finger movements of the writers are recorded with pen based systems. These measurements are not only used for biometric personal identification or handwriting recognition but also in areas such as medical diagnosis or therapy [53-57]. Generally in biometrics, the dynamic features of handwriting are widely captured by graphic tablet (GT) based pen systems. GT samples the x-y position coordinates, in addition pen tilt, and tip pressures on the surface as well. Very rarely grip forces of fingers holding the pen are used in GT. This section evaluates the performance of an enhanced biometric pen system where the pen device of the widely used graphic tablet of WACOM [46] is additionally equipped with a finger grip pressure and acceleration sensor techniques used in BiSP device. The trace and time series data obtained from handwriting a PIN word is shown in the Figure 6.8. Handwriting dynamics are therefore recorded with the new pen system. The time series of x-y position coordinates are registered by the graphic tablet and of finger grip pressure & inclination-acceleration signals are captured by the pen device exclusively using enhanced pen system. For detailed treatment on enhanced biometric pen, see section 3.4.1. By combining the x-y position data provided by the tablet and the grip pressure data of the pen improved performance in person authentication or handwriting recognition is expected.

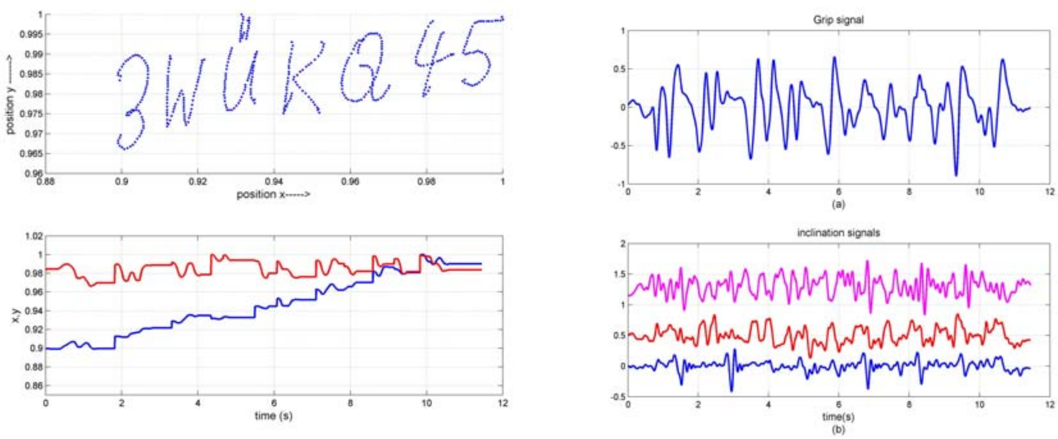


Figure 6.8: Data sampled by enhanced WACOM pen system for handwritten PIN "3WüKQ45": (left) coordinates of x(t) vs. y(t) and against time plot (contribution from GT) and (right) pressure signal grip(t) and three inclination-acceleration signals (contribution from BiSP sensors).

6.2.1 Methods and Data Analysis

The online data is acquired with enhanced biometric pen device. For the evaluation of the new input device, the performance of biometric person identification is studied by DTW. DTW is applied on each single (x/y or grip) and combined (multi-dimensional x & y or x & y & grip) sensor data. The aim of the study work was to estimate quantitatively, the advantage of the finger grip pressure sensor integrated in an existing WACOM graphic tablet. The score of recognition SR (section 4.5.1) is determined for the evaluation of the biometric recognition of handwritten PIN words. The time series of position and finger grip pressure signals obtained from handwritten **(i)** private PIN (unique for each writer) and **(ii)** public PIN (same for each writer) are used.

6.2.1.1 Private PIN word

It is a unique PIN word for each writer consisting of seven different single characters e.g., *3WüKQ45* (a unique PIN is registered for each enrolled person).

6.2.1.2 Public PIN word

It is a public PIN word consisting of seven different single characters equal for each writer (e.g., “A7405B%” is registered for all enrolled persons).

A typical time series of position (x(t) vs. y(t) plot) and grip pressure signal (grip(t)) shown in the Figure 6.9, are obtained from a PIN “A7405B%”, handwritten two times by the same person and once by a different one. It is obvious that personal specific biometric features and object related information are embedded in the finger grip signals essential for person identification.
In order to improve the quality of time series in the signal analysis stage, the time series data is pre-processed. The essential pre-processing steps of smoothing, segmenting, normalizing and down-sampling the data are carried out by using MATLAB tools [12] without discarding valuable information. For details on data pre-processing steps, see section 4.2.
In order to reduce the computational time of DTW based classifier, the data is down-sampled by a factor M equal 10 or 20. For the details on DTW algorithm, see section 5.2.

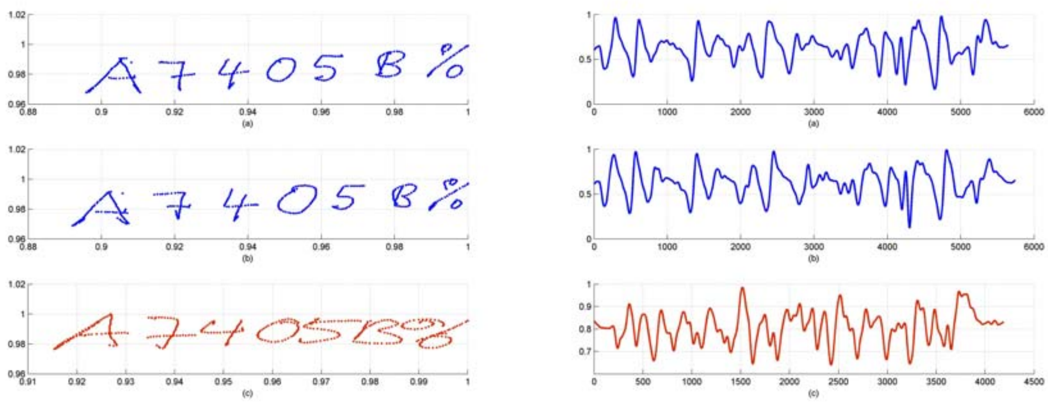


Figure 6.9: Plot of x(t) vs. y(t) coordinates (left) and pressure signals grip(t) (right) of the PIN “A7405B%” handwriting two times by the same person and once by a different one.

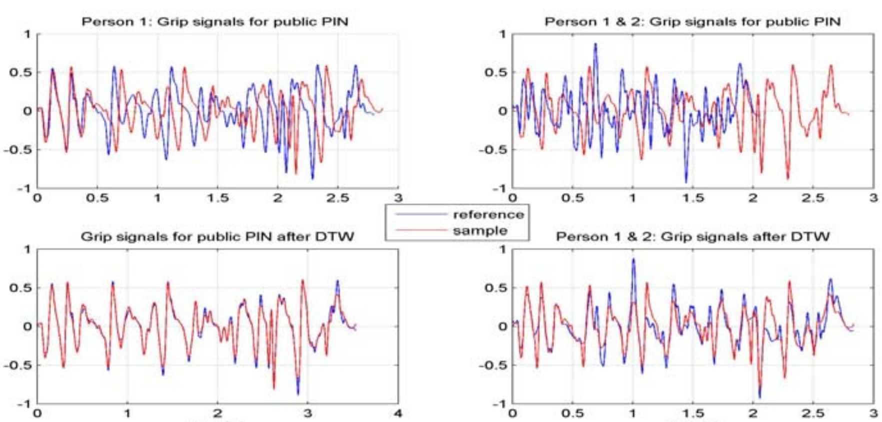


Figure 6.10: Time series of finger grip pressure signals obtained from a public PIN handwritten twice by the same and two different persons and compared before and after DTW match.

A distance obtained by DTW matched sequences determines (dis)similarity of a query and a reference samples quantitatively. For demonstration, time series of the finger grip sensor obtained from a public PIN “A7405%B” written once by two different writers and two times by the same one before and after the DTW match are shown in Figure 6.10. It reveals that the grip signals (time series) generated by the same person match very well and have a considerably lower DTW distance (0.0011) than those obtained by different writers (0.0055). Adequate results are obtained when time series of equal and different PIN words handwritten by the same person are matched.

6.2.2 Experiments and Results

The main issue of the study work presented in this section was to evaluate the improvement of the WACOM handwriting system, when a finger grip pressure sensor technique (used in BiSP) is implemented.
Score rates SR based on data provided by the separate and combined sensor channels: x(t), y(t) and grip(t) are calculated and listed in the Table 6.3 and 6.4, respectively.

Table 6.3: Score of recognition SR values based on single sensor-channel, the values are averaged over all writers and for down-sampling factors M=10; 20.

	x(t) position		y(t) position		grip(t)	
M	**PIN private**	**PIN public**	**PIN private**	**PIN public**	**PIN private**	**PIN public**
10	99.07	96.97	99.54	98.20	99.97	99.72
20	98.97	96.76	99.52	97.91	99.92	99.56

Table 6.4: Score of recognition SR values based on multi-dimensional sensor-channels, the values are averaged over all writers and for down-sampling factors M=10; 20.

	x(t) & y(t) positions		x(t) & y(t) position and grip(t)	
M	**PIN private**	**PIN public**	**PIN private**	**PIN public**
10	99.88	98.95	100	99.77
20	99.88	98.76	100	99.71

The SR values are averaged over all writers enrolled and for data down-sampled with factors of M = 10 and 20.
It follows:

- Slightly better scores of recognition are achieved using private PINs. It suggests that a handwritten private PIN is more suitable for person authentication than a public PIN because it includes both person specific features and object related information for discrimination.
- SR values based on finger grip data are significantly higher than those obtained from separate position coordinates x or y.
- SR values based on single coordinates x and y are increased when the DTW classifier is applied on the combined x & y data.
- SR values based on combined coordinates x & y are significantly improved when grip pressure sensor data are included.

6.2.3 Discussion

In this section, an enhanced biometric pen system is presented where finger grip pressure sensing is also involved for recording and analyzing handwriting movements. In order to judge quantitatively the evaluation of the enhanced system, a DTW based classifier was applied on the time series of single and multi-dimensional sensor channels data including x, y position and grip pressure. The score of performance of handwritten PIN recognition is calculated. The results indicate that the integration of a finger grip sensor in a WACOM graphic tablet system can significantly improve the performance of handwriting and person recognition. This may also apply for graphic design and biomedical investigation because a finger-grip sensor gives excellent information about the fine motor skills of the fingers as a time function of pressure changes during handwriting movements.

6.3 Biometrics using Bio-reference Level Assigned DTW based Classifier

Personal identity verification by means of online signature dynamics is a widely researched aspect of behavioral biometrics. The handwriting environment, mental condition or modification of physical writing system can influence the complex signing process [36], resulting in an intra-class variation of a person's signature. The DTW technique has been successfully used for accessing the similarity of time series of handwritten objects by minimizing non-linear time distortions. However, it needs longer computing time and still suffers from intra-class variation problems having an impact on random forgeries acceptance in identification tasks [34][39]. Generally, in DTW based classifiers, the sequences are normalized in time and amplitude domains. In this section, different length and amplitude normalization procedures are applied on signatures and handwritten PIN word sequences and their influence on accuracy of recognition are examined. A special approach to amplitude normalization based on reference level assigned DTW technique—classic DTW based on an extended functional approach is presented. The proposed method (section 5.9) also includes one parametric feature (namely bio-reference level). The reference level presented here is obtained from the standard deviation values of time series. It reflects a further valuable feature of a writer because it mainly determines the accumulative temporal behavior of a writer. Experimental results show that with the help of proposed length and amplitude normalizations of sequences including the bio-reference levels, the computational time is reduced and false acceptance rates are decreased.

6.3.1 Architecture of the DTW based Classifier

For data analysis, DTW based classifier uses the distance of two DTW matched samples (time series). Generally, the minimum Euclidean distance determined for the optimal aligned time series stays for a measure of similarity. Personal natural variations in the time domain of handwritten genuine signature samples are minimized in terms of non-linear distortions before DTW distance calculation. For details on DTW based classifier see chapter 5.
For clarity the DTW-algorithm is termed as "DTW" when applied to dimensionally reduced univariate time series and "Multivariate DTW" (denoted by MDTW section 5.6), when applied to multivariate sequences of signatures or handwritten PIN words. Further notations are:

(a) DTW1: DTW is applied to two univariate sequences where length is normalized to "$normL_0$" or "$normL_1$" and amplitude base levels are shifted according to person specific bio-reference levels as described in section 6.3.2.

(b) DTW2: it is the DTW1 technique for sequences without the shift of amplitude values.

(c) MDTW: The DTW technique is applied to multichannel (multivariate) sequences in such a way that the length of sequences is normalized only to "$normL_1$"

where $normL_0$ stays for unequal lengths and $normL_1$ for equal lengths normalization of two samples. The amplitude normalizations are of $norm_1$ [-1,1], $norm_2$ [0,1] & $norm_3$ (z-normalization), respectively. For details of length and amplitude normalization procedures see section 6.3.2.

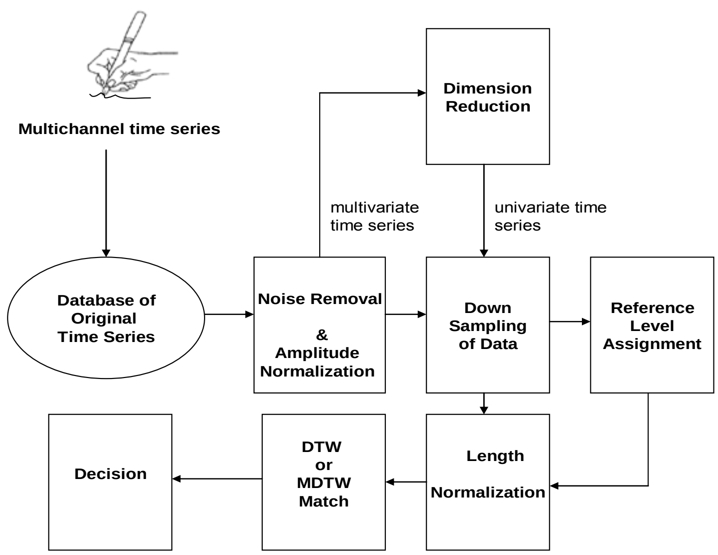


Figure 6.11: Flow chart of the DTW based classifier for multivariate and univariate time series for person identification.

Figure 6.11 illustrates flow chart of the DTW based classifier for multivariate and univariate time series for person identification. It shows data acquisition, pre-processing: normalization, noise removal and dimension conversion, data down-sampling, reference level assignment, length normalization and classification of sample data based on (1) DTW of univariate time series, (2) proposed bio-reference level assigned DTW technique of univariate time series and (3) multidimensional DTW (MDTW) of multivariate time series.

The proposed method comprises several pre-processing steps: noise removal, amplitude normalization of multivariate time series to [-1, 1], [0, 1] or (z-normalization), dimension reduction by sum of all five signal channels, data-down sampling to lower sampling rate, reference level assignment and length normalization. There are three different schemes for classification of data as follows: In the first scheme, multichannel time series are converted to univariate time series by direct sum [40] in such a way that the five channel data is amplitude normalized before conversion. Furthermore, DTW is applied to two length normalized (“normL$_0$” or “normL$_1$”) univariate sequences. On the other hand, in the second scheme besides—amplitude normalization, dimension reduction and time normalization of data, the amplitude values of univariate time series are shifted to their bio-reference levels. Finally, in the third scheme, multivariate dynamic time warping (MDTW) technique is applied to multivariate time series. In addition, two multivariate time series are length normalized to shorter sequence (i.e., only normL$_1$).

6.3.2 Diverse Pre-processing of Time Series

The time series signals sampled by the BiSP device are pre-processed in order to: eliminate sensor noise, detrend, smooth, and normalize and down-sample data without discarding valuable information. For further details on pre-processing steps, see section 4.2.

As an example, Figure 6.12 shows in (a) the original refill pressure signal obtained from a handwritten signature and below in (b) the detrended and smoothed one. The un-normalized time series shown in (b) has amplitude values in the range of about [-2.2, 1.5] values given in arbitrary units.

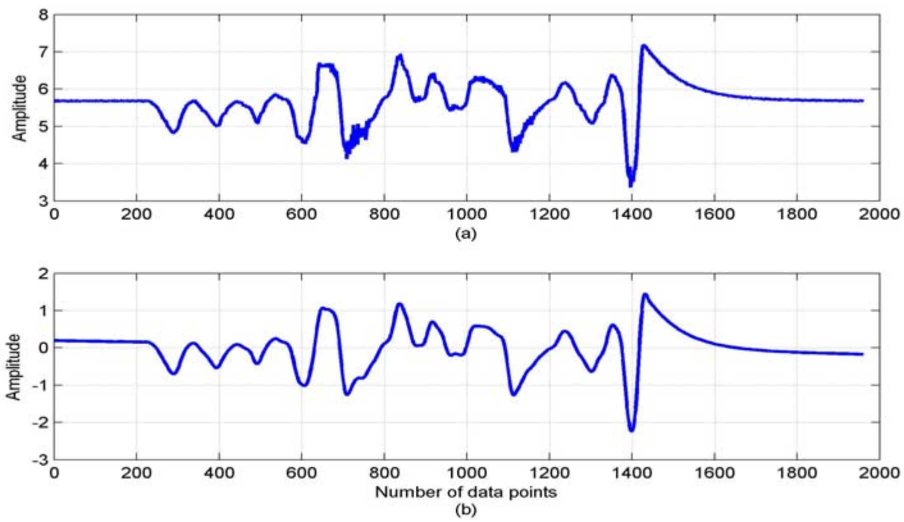


Figure 6.12: (a) Refill pressure signals obtained from a handwritten signature before (a) and after (b) detrending and smoothing.

Sum of Multivariate Time Series: In order to reduce the complexity of the DTW based classifier, five dimensional times series data is converted to one dimensional (univariate) time series by direct sum. To make all dimensions (channels) comparable, the amplitude of the five channel data is normalized to norm_1, norm_2 or norm_3 before sum.
Down-sampling: In order to compensate the complexity of DTW, the low pass filtered time series are down-sampled to reduce the sampling rate or, the size of the database (section 4.2.5).
Normalization: Generally, in DTW based classifiers, the sequences are normalized in time and/or amplitude domains [52],[58-59],[71-74]. Different length and amplitude normalization procedures on time series obtained from handwritten PIN words and signatures sequences are described in the sections below.

6.3.2.1 Amplitude Normalization of Time Series

In order to partially compensate large personal variations of time series in the amplitude domain, normalization of the time series is done in such a way that data is normalized to norm_1 [-1, 1], norm_2 [0, 1] or norm_3 z-score due to the equations (6.1, 2 & 3.).

$$\text{norm}_1: \ R'(t) = \frac{R(t)}{Max(|R(t)|)} \tag{6.1}$$

$$\text{norm}_2: R'(t) = \frac{R(t) - R_{\min}}{R_{\max} - R_{\min}} \tag{6.2}$$

$$\text{norm}_3: \ R'(t) = \frac{R(t) - mean(R(t))}{STD(R(t))} \tag{6.3}$$

Results of norm_1, norm_2 and norm_3 of a smoothed time series related to refill pressure signal of a handwritten signature are shown in Figure 6.13 (a), (b) and (c), respectively. Generally, in the literature on signature verification, $norm_2$ is dominantly used for amplitude normalization [37], [73-74]. In this section, three normalizations of $norm_1$, $norm_2$ and $norm_3$ are investigated.

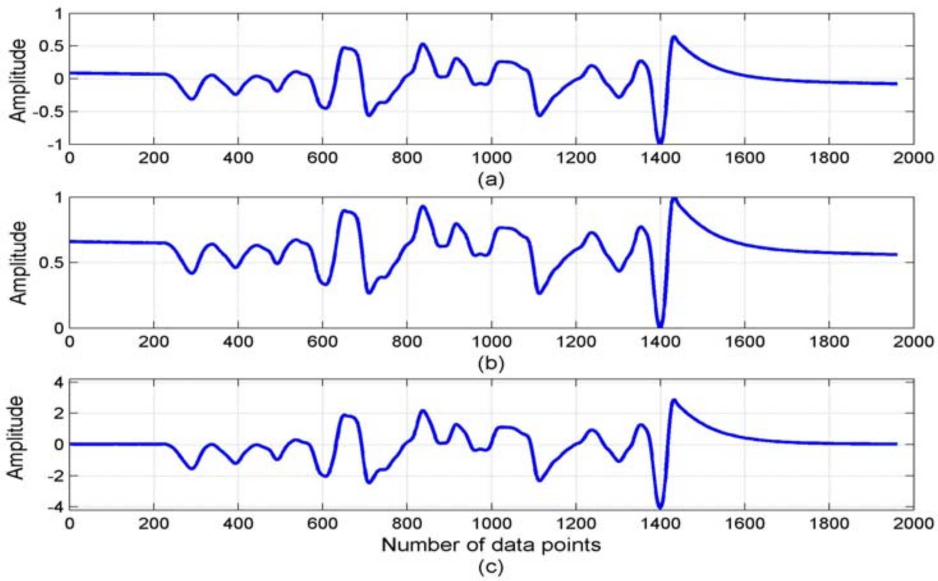


Figure 6.13: Refill pressure signal of a handwritten signature with amplitudes normalized due to (a) $norm_1$: [-1, 1], (b) $norm_2$: [0, 1] and (c) $norm_3$: (z-normalization).

6.3.2.2 Amplitude Shift with Bio-Reference Level

The objective of this study work is to involve a so-called bio-reference level (BRL) in the pre-processing of time series prior to the DTW match. Standard deviation (STD) values are calculated for each signal channel of an original multivariate time series sample data. Different combinations out of these five STD values when added to corresponding acquired univariate time series, have been investigated for the best performance of recognition. A best reference level value attributed to a time series that provides highest accuracy in person identification is termed as the bio-reference level (BRL). The BRL value found in the study work is defined as a function of refill pressure and inclination of the pen as given in the equation 6.4.

$$BRL = \text{mean}\{ STD(x(t), STD(\beta(t))\} \tag{6.4}$$

where time series: $x(t)$ is refill pressure and $\beta(t)$ is vertical angle of the pen during handwriting. For an example, a multivariate time series of a signature sample normalized to [-1, 1] and converted to univariate time series is shown in Figure 6.14 (bottom signal). The median value of the time series is "-0.072" while the same time series with a shift in amplitude by the addition of BRL =0.338 has a median value of "0.266" as shown in Figure 6.14 (top signal). Figure 6.14 illustrates the procedure of amplitude shift by the addition of a person specific reference level for a univariate time series.

Person specific bio-reference level (BRL) values as shown in the Fig. 6.15 and obtained from multivariate time series of PIN words and signatures handwritten by 42 writers are displayed as box plot. Both the quartiles spacing and median value of a box indicate significantly the person specific character of the BRL values. That's why amplitude shifting of attained univariate time series is proposed by means of BRL values added to time series leading to new base levels as illustrated exemplarily in Figure 6.14.

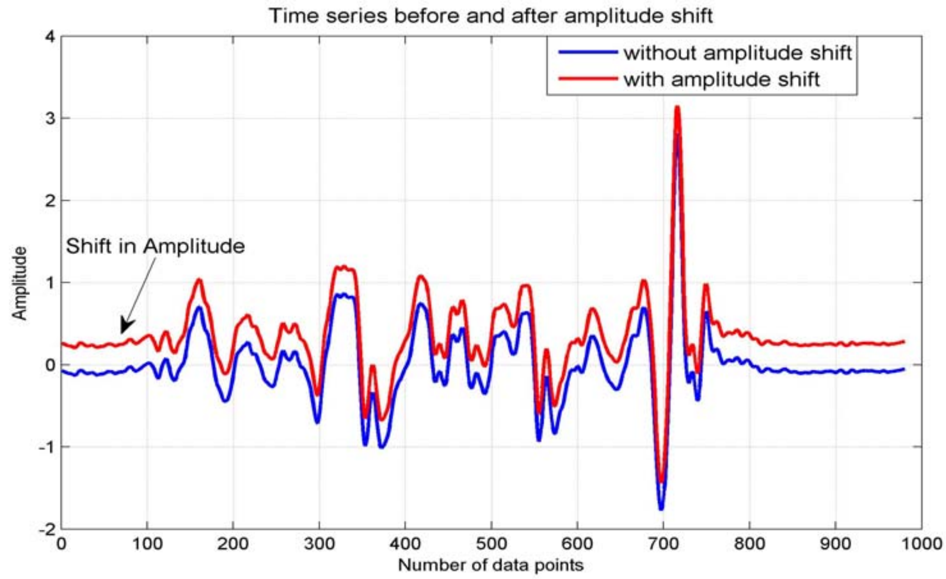


Figure 6.14: Amplitude shift illustrated for a univariate time series obtained from a signature sample. The upper and lower curves represent the time series with and without the amplitude shift.

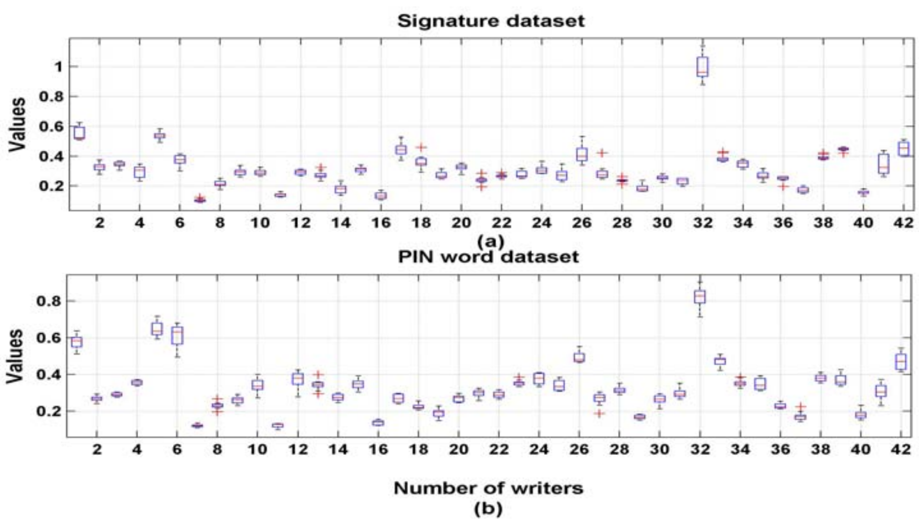


Figure 6.15: Person specific reference level values BRL obtained from all samples for (a) signatures and (b) handwritten PIN words of 42 writers are shown in terms of box plot.

6.3.2.3 Length Normalization of Time Series

The length normalization "normL$_1$" converts a time series of longer length down to the length of the shorter one by data re-sampling. Figure 6.16 shows (a) genuine time series of unequal lengths and (b) time series normalized to equal length.

All pre-processing steps mentioned above and the DTW classification applied to the pre-processed time series were executed on a Pentium 4 processor (2.4 GHz, 3 GB RAM) by using MATLAB tools [12].

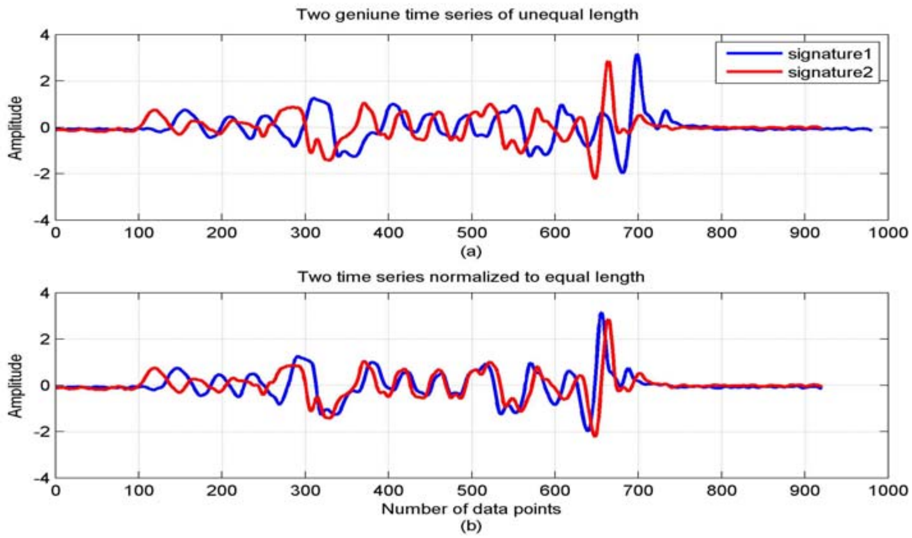


Figure 6.16: Time series obtained from a handwritten signature: (a) genuine signals without length normalization (normL$_0$) and (b) signals normalized by normL$_1$ to equal length.

6.3.3 Experiments and Results

The main objective of the experiments was to investigate the effects of different length and amplitude normalization procedures with and without amplitude shifts on univariate time series for correct classification of handwritten PIN words or signatures. Additionally, the classification performance of sequences in the formats of multivariate and univariate is also investigated. In order to judge the classification performance of time series quantitatively, the accuracy in terms of score of recognition SR, Error Rates (ER), certainty of best match CM and the receiver operating characteristic ROC curved are used (section 4.5.1).

6.3.3.1 Database

The database used in the experiments is collected from 42 different persons each writing a private PIN word (Personal Identification Number) and a signature ten times in a single session. The corresponding database covers 420 samples of the PINs and of the signatures. Although the same group of people contributed to both handwriting tasks, however each database is used for the person authentication independently. The online-data is captured by a BiSP pen. Each captured sample data is represented by multivariate time series of five sensor channels such as: horizontal x(t) and vertical z(t) refill pressure, finger grip pressure y(t), longitudinal α(t) and vertical β(t) angles (for details on BiSP device see section 3.3).

6.3.3.2 Results

This section deals with person identification by applying DTW on diverse pre-processed time series data including the so called Bio-Reference Level Assigned Dynamic Time Warping - a technique that provides fast and accurate classification of univariate time series [42-43]. The work presented here can be summarized as the following:

- Different length normalizations of univariate time series are examined, by comparing the DTW match of equal/unequal length time series.
- Three amplitude normalizations of [0, 1], [-1, 1] and z-normalization are investigated.
- Different amplitude and length normalization procedures are combinations and tested.
- Datasets from both BiSP database (handwritten PIN words and signatures) and a common benchmark signature database (SVC2004 [75]) are analyzed.

- The performance rates based on both multivariate and univariate time series are evaluated and compared.

Table 6.5: Performance values of signature authentication averaged over 42 writers. Error Rates and CM values are shown. M stays for the down-sampling factor. MDTW procedure is applied on *multivariate time* series with the length normalization of $normL_1$ and amplitude normalization of $norm_1$, $norm_2$ and $norm_3$ are used in the pre-processing.

M	MDTW on signatures					
	Error Rate (ER)			Certainty of best Match (CM)		
	$norm_1$	$norm_2$	$norm_3$	$norm_1$	$norm_2$	$norm_3$
6	0.0058	0.3078	0.0	89.49	68.55	90.27
10	0.0058	0.3310	0.0	77.95	62.83	78.29
20	0.0116	0.4704	0.0	52.83	46.47	55.89
30	0.0639	0.7840	0.0116	37.59	34.39	43.73
40	0.5110	1.4053	0.0407	28.54	27.50	33.96

Table 6.5 shows the effect of different amplitude normalization techniques on the performance of classification in terms of ER and CM. The values in the table are calculated for the classification of handwritten signatures where the normalization of length ($normL_1$) was applied to the multivariate time series. It is shown that Multivariate DTW (MDTW) procedure with $norm_3$ (z-normalization) is the best performer.

Table 6.6 Performance values of signature authentication averaged over 42 writers. ER and CM values are calculated from diverse pre-processed *univariate time* series. M stays for the down-sampling factor. DTW1 proposed method with shifted amplitude values, DTW2 without amplitude shift in values are shown. The length normalization ($normL_0$ & $normL_1$) and amplitude normalization ($norm_1$, $norm_2$ & $norm_3$) are used in pre-processing.

Method	M	Signatures					
		$norm_1$		$norm_2$		$norm_3$	
		$NormL_0$	$NormL_1$	$NormL_0$	$NormL_1$	$NormL_0$	$NormL_1$
		ER/CM	ER/CM	ER/CM	ER/CM	ER/CM	ER/CM
DTW1	6	0.0174/ 82.88	**0.0058/ 97.31**	0.5285/71.83	**0.3252/84.18**	0.0058/67.33	**0.0058/81.90**
	10	0.0407/ 63.27	0.0116/ 78.19	0.6214/56.79	0.3252/69.15	0.0348/49.29	0.0058/64.33
	20	0.3600/33.85	0.0290/46.20	1.2718/31.12	0.4181/43.28	0.7143/27.75	0.0871/37.87
	30	0.9756/ 23.77	0.1161/ 32.29	2.2416/22.33	0.9117/31.55	1.2950/20.85	0.3078/27.23
DTW2	6	0.0465/ 76.61	0.0174/ 89.33	0.4878/68.24	0.3194/82.01	0.0058/66.03	0.0058/80.87
	10	0.0755/ 56.93	0.0232/ 70.51	0.6620/53.23	0.2962/66.83	0.0639/48.31	0.0058/63.29
	20	0.5052/28.45	0.0581/40.59	1.3415/28.89	0.4007/41.33	0.7840/26.84	0.0871/37.05
	30	1.5447/ 19.50	0.2265/ 27.47	2.2880/20.95	0.8014/29.85	1.4286/20.86	0.3717/26.48

The effect of different length and amplitude normalization techniques with and without amplitude shifts on the performance of classification are shown in Table 6.6. The ER and CM values in the tables are calculated for handwritten signatures where the normalization of length ($normL_0$ & $normL_1$) and amplitude with (DTW1) and without (DTW2) amplitude shift was applied to the reduced dimensional univariate time series. All values listed in the tables are averaged over 42 enrolled persons and represent the performance at different down-sampling factors M.

It follows that best results are obtained by applying the proposed DTW1 method which includes the amplitude shift. At down-sampling M = 6, the ER of DTW1 is about 3 times lower than that of DTW2 (Table 6.6). In addition, a higher certainty of best match CM value (about 8) indicating a more distinctly separated true match and closest non-match is obtained

by the proposed DTW1 method where the amplitude shift is involved. These issues also apply for increasing down-sampling rates M.
Best results are obtained by using the procedure of MDTW with down-sampling rates M ≤ 30. But this technique needs more computing time, which might become a substantial drawback for online person authentication. Obviously DTW computation can be accelerated by down-sampling the data points due to the computational complexity O (m x n) /M^2, where M is the down-sampling factor and m, n are the lengths of sequences. Note the average number of data points for a signature sequence used in this study work was about m = 3000.
Table 6.6 indicates that a speed up can be achieved by an increased value of M, without a serious degradation of performance. As for a faster DTW1 at M = 20 the ER has a low value of 0.0290 and a high value of CM = 46.20 which might still comply well with the demands of online signature authentication.
The classification error rates shown in Table 6.6 indicate that the best classification of time series are obtained by using the proposed bio-reference level assigned DTW1 under equal length normalization ($normL_1$) when amplitude normalization of $norm_1$ (i.e. [-1, 1]) or $norm_3$ (i.e. z-normalization) are used in the pre-processing.
The results of ER related to time series with length equalization are inconsistent with the findings of [72] where it was suggested, that converting the time series to same length does have a detrimental effect on recognition accuracy (when length was used as a feature). On the other hand, the results are in agreement with the findings of [37],[58],[71].

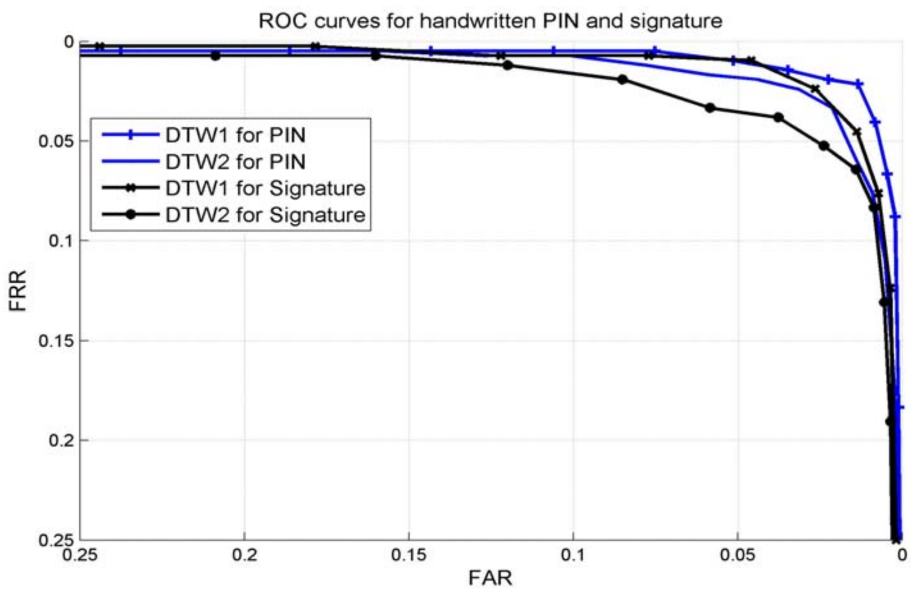


Figure 6.17: ROC curves of DTW1 and DTW2 are shown for PIN words and signatures datasets down-sampled by M=20. The figure is zoomed to lower scale in order to increase readability

Further, for the evaluation of diverse pre-processing techniques, the ROC curves for DTW1 and DTW2 applied to handwritten PIN word and signature datasets are shown in Figure 6.17. The higher values of area under the ROC curve (AUC) confirm DTW1 to be the best classifier for both PIN words and signature data. It also means fewer false acceptances (lower random forgeries acceptance) in personal identification with DTW1.
Due to results shown, it is concluded that a suitable length and amplitude normalization procedure can improve DTW or MDTW based classification of sequences in terms of accuracy and computational time.
Finally, the effect of diverse length and amplitude normalization procedures including bio-reference levels on the performance of recognition was also tested on signature dataset obtained from publicly available database SVC 2004 [75] for details see [43].

6.3.4 Discussion

The goal of the study work was to find out a pre-processing procedure leading to highest accuracy of DTW based classification. Experimental results show that best results are obtained by using DTW1 method which includes the time series of equal lengths, amplitude normalization of [-1, 1] or z-normalization and amplitudes shifted by BRL values. Due to the high accuracy values obtained by using the proposed methods, computational time can significantly be reduced by data down-sampling without rigorous loss in accuracy. As for future work, in biometric person authentication, the proposed method needs to test classification accuracy on a database that includes skilled forgery data.

6.4 Biometrics using Area Bound DTW based Classifier

Although classic DTW provides robust distance measures essential for accurate classification of sequences but it is computationally expensive. To speed up computations, Area Bound Dynamic Time Warping (AB_DTW) technique is proposed that approximates time series by dividing it into several areas bounded by segments of consecutive zero crossing including local peaks and valleys. Two kinds of area bound higher-level data reduction forms—in 1 dimension and in 2 dimensions are proposed. The proposed method warps areas bounded by the local regions instead of all points of the signal as conventional DTW does. Experimental results show that because of a higher-level data abstraction prior to DTW match, the proposed AB_DTW approach is several times faster without rigorous loss in accuracy of authentication performance when applied on handwritten PIN words and signatures sampled by the BiSP device.

6.4.1 Data Pre-processing

BiSP device used for data acquisition records handwriting movements in terms of five sensor channels. The signals obtained from across (t) sensor during handwriting are used for evaluation in this section. The details on BiSP device can be found in section 3.3.

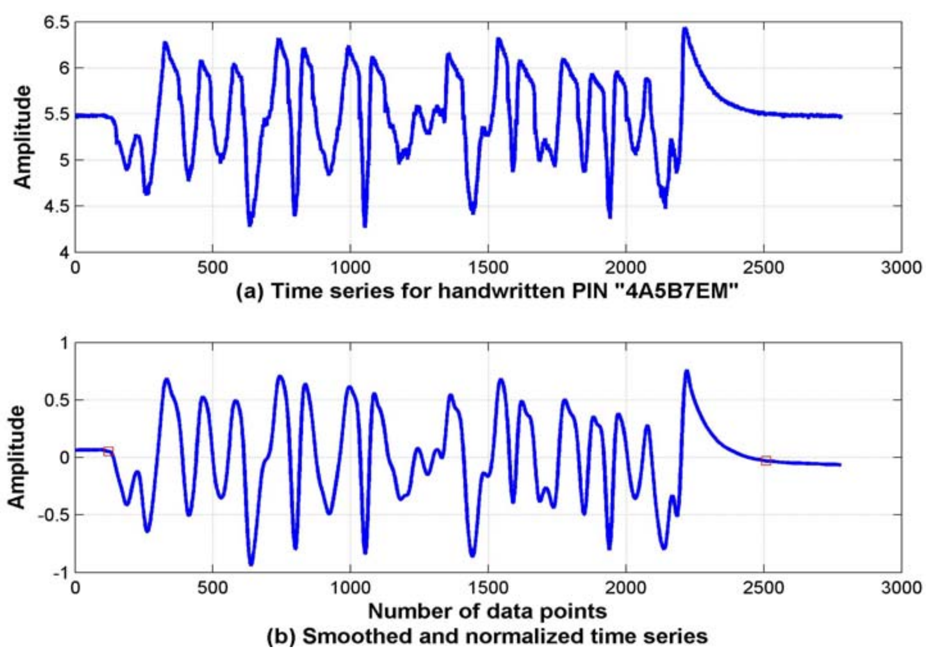


Figure 6.18: (a) An example of signal obtained from handwritten PIN “4A5B7EM” and (b) smoothed and normalized signal is shown. The segmentation points are marked with ‘□’

In order to eliminate the potential sensor noise, the data is pre-processed after acquisition. To compensate large variations in amplitude values, the time series data is normalized to [-1,1]. Further, data is down-sampled in order to reduce complexity of classic DTW based classifier when applied to original length of sequences. An example of a typical across (t) pressure signal recorded for a handwritten PIN word on paper pad is shown in Figure 6.18 (a) and it's smoothed and normalized time series is shown in Figure 6.18 (b). As isolated signature or PIN data were sampled separately with the assistance of the computer beeps during the acquisition of a sample, therefore no separate segmentation was done in the previous sections. In order to select more accurately the signal parts that belong to handwriting or alternatively to detect first and last zero crossing points required in the method proposed, an additional segmentation is done here. For this, a segmented curve between two segmentation points is selected as shown in Figure 6.18. It is done with the help of proposed "peaks and zero-crossings based segmentation algorithm" (see section 5.5.3).

6.4.2 Area Bound Warping Method

The proposed Area Bound DTW (AB_DTW) method (see section 5.5) warps areas bounded by the local regions (areas) of sequences. The speed up of computations is achieved because time series are represented by a higher level reduced form, as vector of several areas bounded by the local segments of consecutive zero crossings including peaks i.e., from zero crossing through positive peaks(s) to zero crossing or like wise via negative peaks(s).

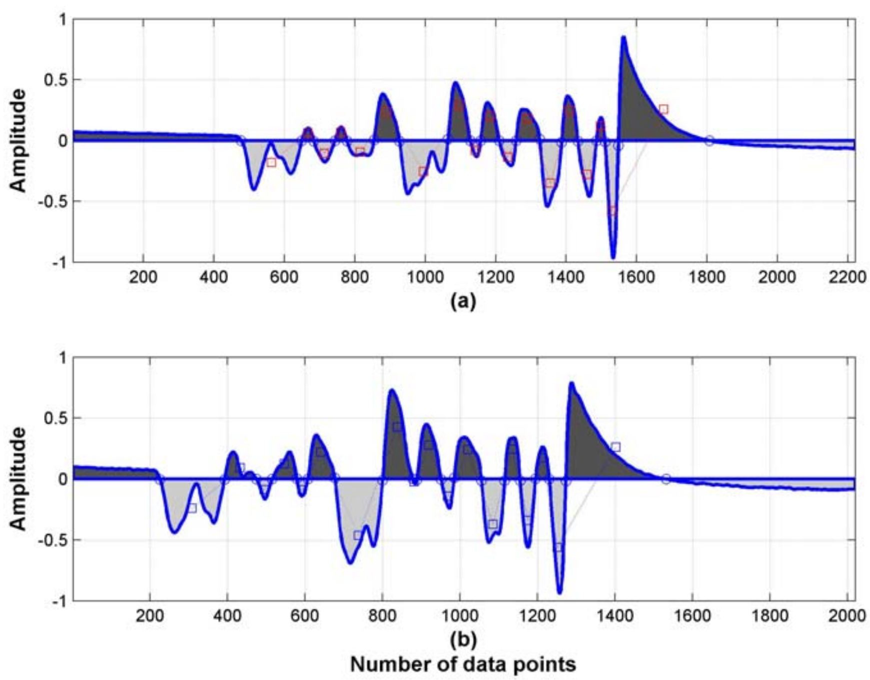


Figure 6.19: Two time series of genuine signatures are shown. The area± are shown in different shades above and below zero-crossing line. The representation of time series in bounded area reduced form is shown with marker '□'and zero crossings are shown with marker 'o'.

For illustration, two time series of the genuine signatures are shown in Figure 6.19 and the area± are shown in different shades above and below zero crossing line. The corresponding vectors of normalized areas calculated between two consecutive ZC are shown as area sequences marked with '□' and dotted lines. The ZC points are marked with 'o'. A time series of about 2200 data points (Figure 6.19 (a)) is approximated to a reduce vector of 18 area bound data-points i.e., ZC=19. Note: area of curve bounded by all data points from first (last) data point to first (last) ZC point is omitted. In this study, the mean of a time series is treated as zero crossing line.

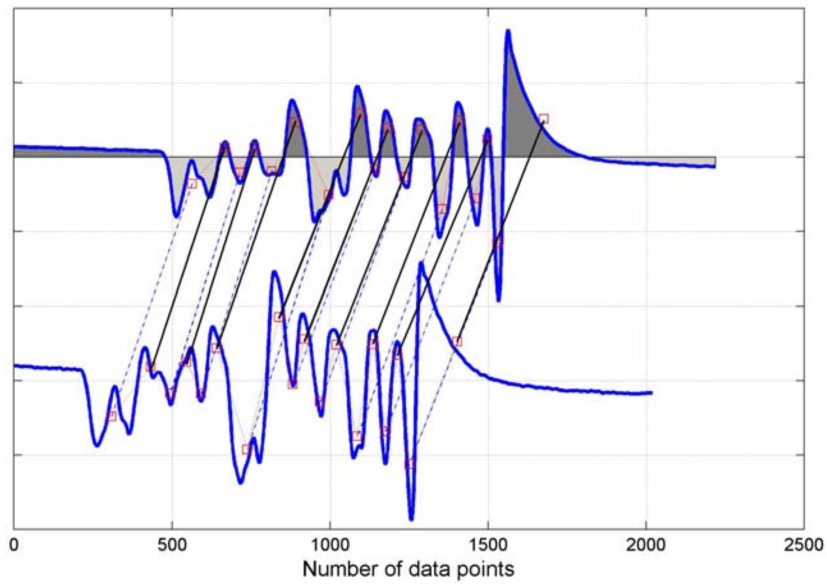


Figure 6.20: An example of optimal signals and area bound representations carrying equal number of area± for two genuine signatures. One-to-one area comparison for match of "area-" (doted lines) and "area+" (sold lines) are shown.

Figure 6.20 shows an example of two genuine signature sequences. Because of equal numbers of zero crossings, there are equal numbers of bounded areas calculated in both sequences. Therefore, one-to-one area-match or simple Euclidean distance calculation is optimal for comparison. The corresponding match of area+ to area+ is shown with solid lines and similarly area- to area- match is shown with dotted lines. The second signal (bottom) is shifted to a different baseline just to increase visibility.

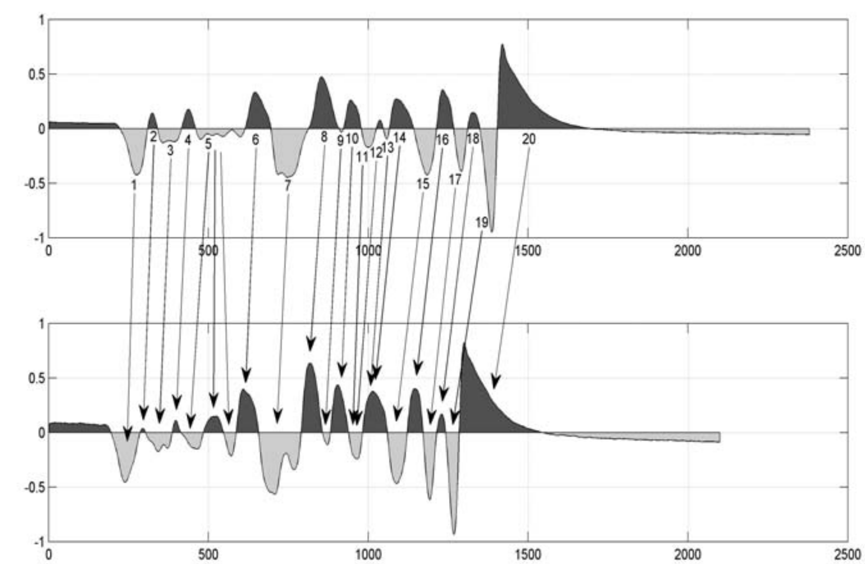


Figure 6.21: An example of two genuine signature signals carrying different number of areas and area bound representations are shown. Possible proposed AB_DTW match for sequence comparison is shown.

Generally, there are natural variations even in two genuine signatures. Therefore, one-to-one area-match is not always an optimal choice because of missing or extra areas may come from extra or missing peaks or, ZC points or because of sensor noises (see results). Therefore, for time series converted into area bound format in terms of vectors of areas bounded by the local waveform, DTW algorithm is used to carry out the optimal similarity match of two sequences. Figure 6.21 shows an example of AB_DTW match for two sequences obtained from two genuine signatures. There are different numbers of bounded areas calculated for two sequences because of unequal numbers of zero crossings and extra or missing peaks. The optimal area bound warping (AB_DTW) of the two sequences is shown. The fifth calculated area of the top time series essentially contains missing peaks and can be warped to three areas of second time series (bottom) for matching. Similarly, the 12^{th} and 13^{th} areas of first time series may come from extra peaks and zero crossings which do not occur in the second time series. The possible DTW match of areas for comparison is shown in Figure 6.21.

6.4.3 Experiments and Results

The main objective of the experiments was classification of handwriting signals obtained from two datasets of handwritten sequences essential for person authentication. The two databases consist of 500 signatures and 500 PIN words samples donated by 50 writers. Each writer donated 10 genuine samples of each item in a single session. Leave-one-out mechanism is used for classification of data for each dataset independently. The focus is to investigate the effect of data abstraction and to compare accuracy as well as runtime of classic DTW and proposed AB_DTW methods. In order to reduce the complexity of classic DTW based classifier, proposed AB_DTW method is applied which operates on reduced area bound representation of time series in 1D and 2D forms. The minimum distance of DTW determines the accuracy of match while the number of data points of the two sequences to be compared indirectly determines the computational complexity.

Different experiments are performed in order to evaluate the performance of the proposed method.

(1) Experiment 1: classic DTW method is applied to classify two signatures or PIN sequences in such a way that longer sequence is normalized to shorter sequence in time domain. This method is denote by "DTW"

(2) Experiment 2: the proposed AB_DTW method is applied to classify PIN or signature time series datasets separately. This method is denoted by "AB_DTW".

(3) Experiment 3: In order to see the effect of DTW algorithm on the area bound representation of time series for accuracy, simple Euclidean distance is also measured for testing accuracy of classification. Therefore, the proposed area bound representation of time series data is classified using direct point-to-point comparisons, denoted by AB_Euclidean.

(4) Experiment 4: the proposed AB_DTW method is applied, on 2D area bound representation (see section 5.5.1) of the time series, denoted by "AB_DTW2D".

(5) Experiment 5: the proposed AB_DTW method is applied, on 2D area bound representation of the time series in such a way that the time index values are normalized to [0, 1]. This method is denoted by "AB_DTW2DN".

Note: normalized area values are very small while time index values can be very large (see Figure 6.19). Further, there are variations in time index values of two similar sequences from the same writer. Therefore in order to avoid large difference of time index values in calculated areas, time values in 2D case are normalized to [0 1].

In order to judge the performance of classification of PIN and signature sequences quantitatively, the accuracy in terms of score of recognition (SR), the runtime and the area under the curve of receiver operating characteristic AUC ROC (see section 4.5) are used. As no skilled forgeries are used therefore False Acceptance Rate (FAR) represents the random PIN word or signature acceptance. The performance parameters for person authentication using handwritten PIN words and signatures based on the experiments are shown in Table 6.7 and Table 6.8

Table 6.7: Performance parameters for person authentication using handwritten PIN. The values of SR, AUC-ROC and runtime are averaged over all writers

Experiment	Score SR	AUC-ROC	Mean time (sec)
DTW_p	99.995	0.9996	12.52
AB_DTW_p	99.971	0.9979	0.31
$AB\_Euclidean_p$	91.126	0.8634	0.02
AB_DTW2D_p	90.971	0.8456	0.37
AB_DTW2DN_p	99.975	0.9983	0.35

Table 6.8: Performance parameters for person authentication using handwritten signature. The values of SR, AUC-ROC and runtime are average over all writers

Experiment	Score SR	AUC-ROC	Mean time (sec)
DTW_s	99.800	0.9961	6.18
AB_DTW_s	99.122	0.9861	0.27
$AB\_Euclidean_s$	86.440	0.8425	0.02
AB_DTW2D_s	96.738	0.9155	0.33
AB_DTW2DN_s	99.383	0.9810	0.30

The SR values of classic DTW and proposed AB_DTW have a difference of about 0.02 (see Table 6.7). Similarly the AUC ROC in case of classic DTW and proposed method are approximately same (difference is ≈ 0.002 see Table 6.7) especially for person identification based on handwritten PIN i.e. AB_DTW_p. The SR and AUC ROC values of DTW and AB_DTW show essentially same high accuracy but proposed AB_DTW_p is faster by a factor of ≈ 42 for handwritten PIN dataset and AB_DTW_s is faster by a factor of ≈ 23 for signature dataset as shown in Table 6.7-8. The performance parameters for proposed AB_DTW in two different forms of 2D cases are also shown in table 6.7-8. Because of very large variations in time index values of even two genuine sequences for same writer, the score SR and AUC ROC values are relatively low in experiment 4 (AB_DTW2D). In AB_DTW2DN_p the increase in accuracy is ≈9% and ≈2.6% in AB_DTW2DN_s method. The accuracy of proposed methods, AB_DTW and AB_DTW2DN cases are similar (difference is very small see table 6.7-8) for both datasets. Although AB_Euclidean can quickly classify sequences but its performance is relatively small in comparison to propose AB_DTW. It essentially shows the advantage of DTW algorithm based distance measures applied on proposed area bound representation of time series.

The time complexity of classic DTW is O(mn) with m≠n, where m and n are length of two sequences [70]. Similarly, the time complexity of proposed AB_DTW is O(MN) with M≠N, where M and N are length of two sequences in proposed area bound reduced representation (see Figure 6.19). The runtime values shown in Table 6.7-8 also depends on running environment, therefore to show the advantage of computation reduction in terms of reduction of the number data point the proposed AB_DTW method is applied.

Table 6.9: The number of data points, mean, maximum and minimum number of data points used in different experiments for handwritten PIN

Number of data points	Mean	Maximum	Minimum
Original	4212.50	6550	2510
Segment	3646.80	6086	2152
DTW_p	364.00	608	215
AB_DTW_p	34.35	42	26

Table 6.10: The number of data points, Mean, Maximum and Minimum number of data points used in different experiments for handwritten signatures

Number of data points	Mean	Maximum	Minimum
Original	2831.20	4299.60	1679.4
Segment	2234.30	3857.00	1047.0
DTW_s	223.43	385.70	104.7
AB_DTW_s	28.50	55.00	12.5

Mean, maximum and minimum numbers of data points (averaged over 50 writers) used in different experiments are shown in Table 6.9-10 In order to reduce the time complexity of classic DTW applied on original sequences, segmentation based on peak and zero-crossings detection (see Figure 6.18) as well as data down-sampling by a factor of 10 are used. Therefore mean number of data points of original data is reduced from 4212.5 to 364 in DTW (8.6% of original data). Similarly, the mean number of data points, in proposed method AB_DTW, is 34.35 (0.82% of original data). Similarly, the effect of data point reduction for handwritten PIN dataset is also shown in Table 6.10.

As shown in Table 6.10, mean number of data points of original data is reduced from 2831.2 to 223.4 in DTW (8.0% of original data). The mean number of data points, in the proposed area bound warping method AB_DTW, is 28.50 (1.0% of original data). Similar effects of data point reduction for handwritten signature dataset are shown in table 6.10. The averaged minimum number of data points in signature dataset is less than that of PIN dataset. It also indicates that some writers have very short handwritten signatures (while handwritten PIN words are restricted to seven single characters). As shown in the Table 6.9-10 the proposed area bound representation of time series can be used for fast classification by heavy data reduction (up to 0.82% of original data in PIN dataset or up to 1% of original data in signature dataset) without rigorous degrading accuracy (see Table 6.7-8).

6.4.4 Discussion

In this section, AB_DTW technique is proposed for fast and accurate person identification using two datasets of handwritten PIN and signature sampled by digit pen. The proposed method warps only the areas bounded by the local regions of sequences. Different experiments are performed in order to evaluate the performance of DTW and proposed AB_DTW methods in terms of accuracy and computational complexity. It is found that the DTW and AB_DTW techniques applied to classify human individuals using a handwritten PIN word have similar high score values (better SR >99.97% and AUC ROC >0.997%). However, with AB_DTW the computational time is reduced by a factor of 40 over DTW (for handwritten PIN words) and by a factor of 23 over DTW for signature dataset. The most important contribution of the AB_DTW method is the benefit of very heavy data reduction for a time series converted into a vector of areas (indirectly determines computation complexity). Therefore, AB_DTW method allows a fast classification by heavy data reduction without a rigorous degradation in accuracy values. The focus of present work was comparison of DTW and AB_DTW for classification of handwritten PIN and signature samples essential for person authentication. Further speed up of computations can be achieved by involving the state of the art fast DTW methods. Future study work would be AB_DTW method for area bound approximation of multivariate time data.

6.5 Biometrics using a Novel Tactile Pressure Sensitive Pad

Tactile screen or touchpad is a new and promising dimension in the field of human computer interactions HCI. With the increasing use of tactile screen or touchpad in HCI, mobile phones, PDA's and other related touchpad or tactile areas, the demand for tactile pads and their biometrics based security has essentially increased.

This section presents a simple, low cost, novel tactile and pressure sensitive writing pad for the input of handwritten characters or signatures used for the biometric recognition. System feasibility and performance test experiments are carried out to measure the accuracy of the recognition and to see reproducibility of the captured signals during real-time handwriting of signatures. The system is expected to be used as an input device for handwriting recognition.

6.5.1 Method and Sensing Techniques

In the development phase of PEF sensors, the terminal connections to PEF and the coating of thin silicon layers on double sides of the PEF was an important task. After terminal connections to PEF, silicon layers were coated on one side after the other one was dried as shown in the Figure 3.22. It was done while coating a silicon layer on PEF that was wedged on a plastic pad. After a silicon layer was dried, the PEF was perfectly stickered to the plastic pad (in the frame). The quality of the signals and terminal connections were studied next at that stage. It was realized that plastic pad with PEF perfectly fixed onto it, was highly tactile and pressure sensitive. The PEF sensor mounted underneath the writing pad behaves as a tactile and pressure sensing element, revealed the realization of a novel tactile and pressure sensitive writing pad. The detailed description on the acquisition device can be found in the section 3.4.2. For the online input of handwritten characters or signatures, the new device can be used in combination of any commonly used ballpoint pen and paper. The ability to measure miscellaneous pressures, lift off & retouch of pen-tip on writing surface with respect to time axis are the key biometric features and are the main potential of the input device. Commonly used pen & paper, and sensitive pad based system provides sensor signals low pass filtered, amplified and digitized by a 12 bit A/D converter at a sampling frequency of 500Hz. The digital data is transferred to computer by a wired (HID-USB) transmission technology.

6.5.2 Experiments and Results

The main objective of the experiments was the evaluation of new input device for its ability to use it as a signature input device. Therefore, reproducibility and distinctiveness of signals for signatures obtained from different writers are investigated.

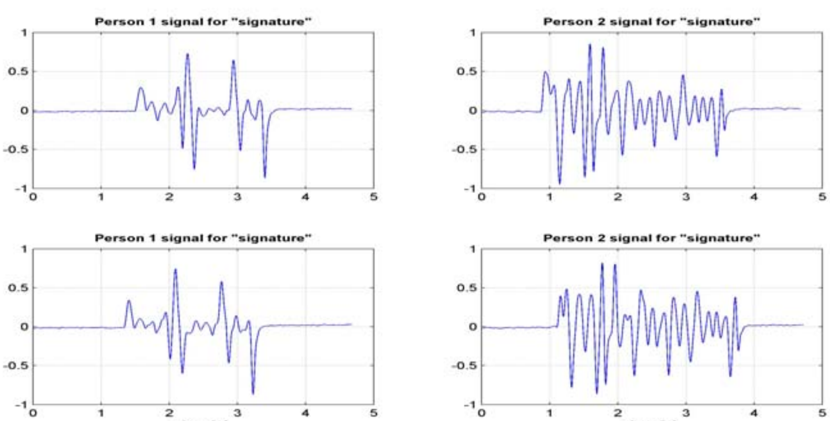


Figure 6.22: Typical output of time series for same (columns) and different writers (rows) recorded with input device for handwriting two signatures.

Typical time series recorded with the input device for handwritten signatures are shown in the Figure 6.22. The characteristics features of the time series are essentially determined by the type of written item and by the fine motor movements of the writer. Examples for similarities between signals obtained from signatures of same writer and distinctiveness of signals of different signatures from different writers are shown in the Figure 6.22.

In a small field test, nine genuine signature samples are collected from ten writers. The writers signed on the writing pad in a sequence in one session. Therefore, the signature database covers 90 samples of signatures and leave-one-out technique is used for classification. For signature comparison, the data pre-processing—smoothing, normalizing and down-sampling is performed first. Next, DTW algorithm is applied for time series analysis. For evaluation, online person authentication using handwritten signatures is determined.

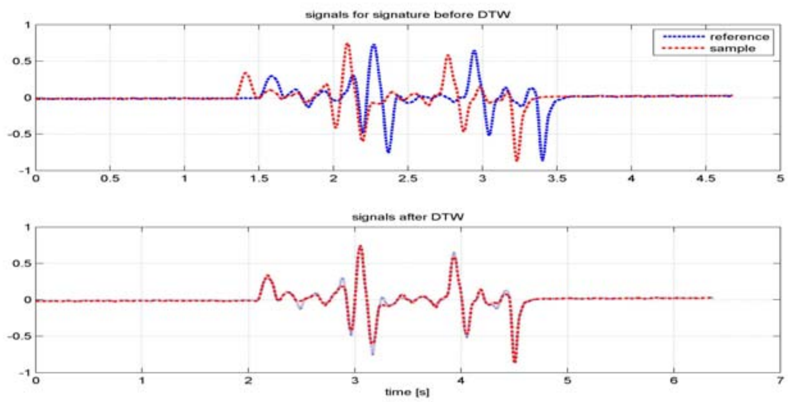


Figure 6.23: Two genuine time series for signatures before and after DTW.

Figure 6.23 shows two time series of genuine signatures before and after DTW match. The non-linear time shifts in the two time series are minimized with the help of DTW technique. The performance of hardware and classifier is evaluated in terms of accuracy of classification of time series data. If DTW is applied on time series down-sampled to 6^{th} part of original data then an accuracy of 99.8% is achieved. The receiver operating characteristic ROC curve which is a commonly used method for the evaluation of biometric person recognition is calculated. The ROC curve is determined for the evaluation of person authentication as shown in Figure 6.24. The area under the ROC curve (AUC≥0.996) indicates an excellent grade of performance. The values are averaged over all writers and down-sampling of data (M=6) are used. This mainly reveals the high quality of the signals obtained from input device used for DTW match.

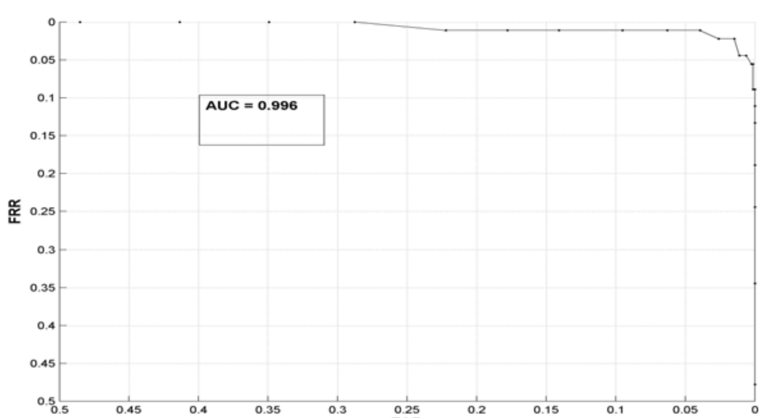


Figure 6.24: ROC curve for person authentication using signatures

6.5.3 Discussion

It is found that simple, low cost, and novel tactile and pressure sensitive writing pad can be employed as input device for the input of signatures. The proposed input device in combination of DTW matcher can be used for person authentication or handwriting recognition for a small group of people or handwritten objects. It is observed that the proposed input device has the ability to measure miscellaneous pressures, lift off & retouch of pen tip and writing surface with respect to time axis that are the key biometric features and are the main potential of the input device. Because of simplicity of design, small size and low cost sensor, the proposed technique can be used in emerging touch screens or writing pads in human computer interactions and person authentication applications. The future work is to extend research work for forgery tests and to do handwriting recognition tasks on a big population of writers and/or handwritten items.

6.6 Enhanced Biometrics using Multi-factor Person Authentication

Reliable biometric user authentication is becoming more and more important to prevent unauthorized human access to the resources during different interactions. Traditional authentications based on the ownership (keys or cards) or knowledge (passwords) do not comply well with the future security requirements [52], hence will be inadequate in future because they can easily be faked, lost or hand over to unauthorized persons. Fortunately, biometrics can provide an accurate and reliable automatic-user-authentication method, hence a rapidly advancing field. But one general problem of the biometric systems is the natural variability of the biometric trait leading to intra-class variability. This is because of the natural biometric variability, changing sensors, different environments, aging and so on [2-3]. It is thus generally agreed that the reliable biometric user authentication needs a higher quality of biometric data (and/or acquisition) and its processing which can be achieved by improved sensing devices and advanced methodologies. A system which includes multimodal biometrics with a combined analysis of human behavioral and physiological characteristics or two-factor authentication requiring both a biometric security method and a PIN or password can be employed to achieve a higher level of security.

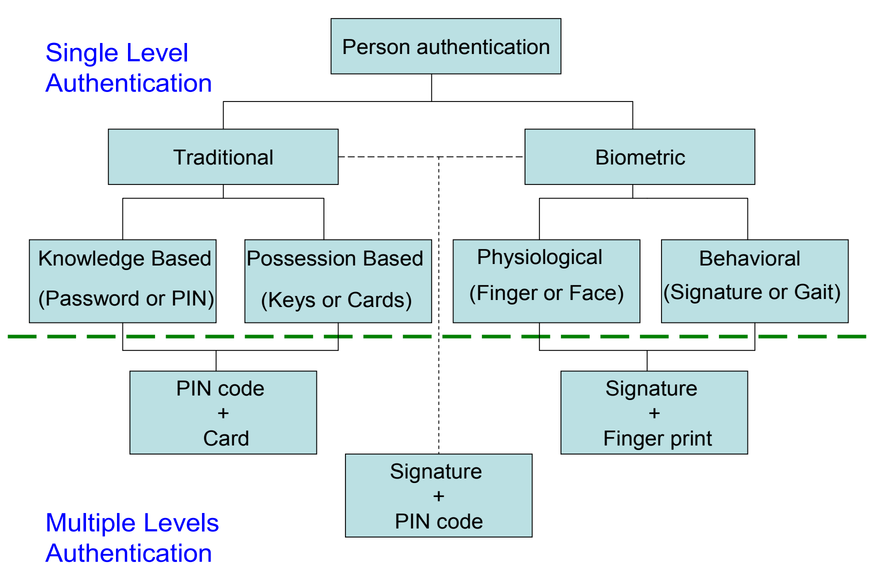


Figure 6.25: Different schemes of personal authentication approaches

Figure 6.25 illustrates traditional and biometric authentication procedures and their combinational approaches (multi-level authentication) for traditional as well as biometrics based methods used for the security improvement.
Though biometric systems provide more security, however in practice, most of the combinational approaches (multilevel authentication) based on biometrics have considerable disadvantages and therefore suffer from low acceptability. Because multimodal biometrics are more or less intrusive, uncomfortable, immobile (sometimes), costly, need a lot of infrastructure and involve complex data acquisition and analysis due to the use of the diverse biometric modalities. If we focus on the concerns of the user's acceptability and the system processing complexity, then the multilevel authentication system using a single biometric modality is expected to be a powerful solution.
The biometric authentication by handwriting signatures or PIN words is promising because of long history of signatures, wide acceptance in public domain and the intimacy of writing with a pen [38][52].
A purpose of this section is to present a new pen based biometric method, which can enhance the reliability and acceptance of current online handwriting based authentication of a person in areas such as access control to machines, network services and security systems.
The proposed method is based on the handwritten PIN (e.g., a single biometric modality) and performs a biometric two factor authentication (TFA) which makes use of both behavioral biometrics and knowledge gained biometrically (simultaneously) from a PIN word handwritten on pad or in air by using a novel BiSP device.

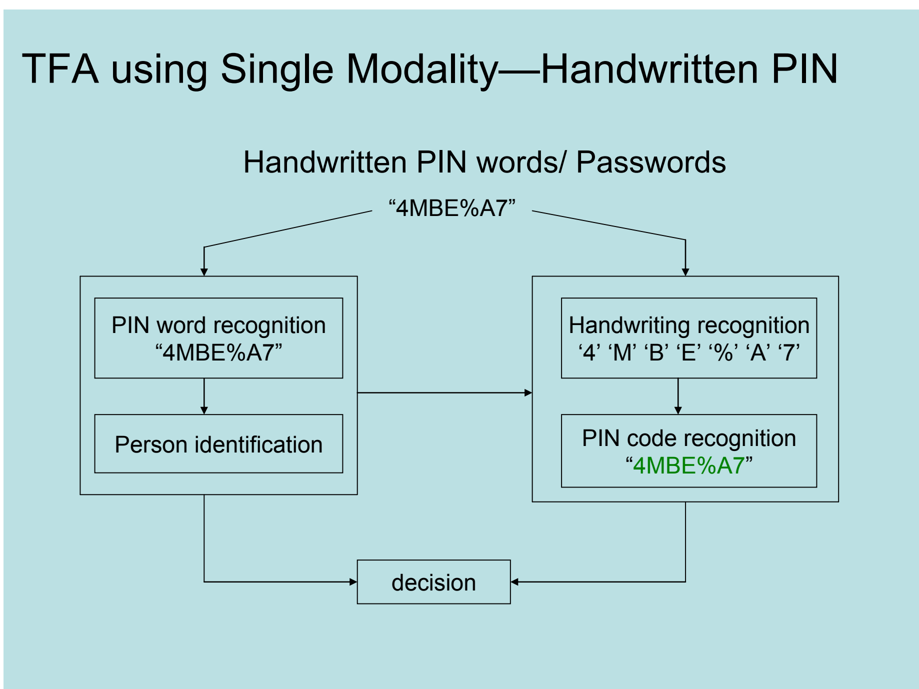


Figure 6.26: Concept of single biometric modality handwritten PIN word used for biometric two-factor person authentication (TFA).

Figure 6.26 illustrates the concept of single biometric modality of handwritten PIN used for biometric two-factor person authentication. The input data represents PIN words (passwords) consisting of letters, numbers and special characters handwritten on paper pad or free in air.

6.6.1 PIN words vs. Signatures Handwritten on Pad

In the literature concerning dynamic signature verification, generally handwritten signature is used, however very rarely handwritten password (passphrase) has also been used for person authentication [28]. In the previous sections, handwritten PIN words and signatures were used for person authentication with equally comparable accuracy of recognition suggests that PIN words may be more suitable for person authentication than signatures especially in a situation where personal signatures are very simple. A further benefit is the involvement of two factor person authentication by using a single biometric modality—Handwritten PIN words.

6.6.2 Two Factor Authentication

Two-factor authentication (TFA) reduces the window of opportunity for fraudsters and can eliminate or mitigate online attacks. Today, there is a myriad of two factor devices and methodologies in the market, which have varying degrees of effectiveness, cost and usability. We propose a strategy where both handwriting biometrics and the gained knowledge are combined as the biometric identifier to enhance the accuracy and reliability of authentication. In TFA method, the biometric writer identification is fused with biometric handwritten PIN (password) recognition. The strategy involves biometrics based knowledge and behavioral biometrics, and includes four important modules: (i) signal data acquisition (ii) feature extraction (iii) matching and (iv) decision. The procedure of TFA is shown in the Figure 6.27.

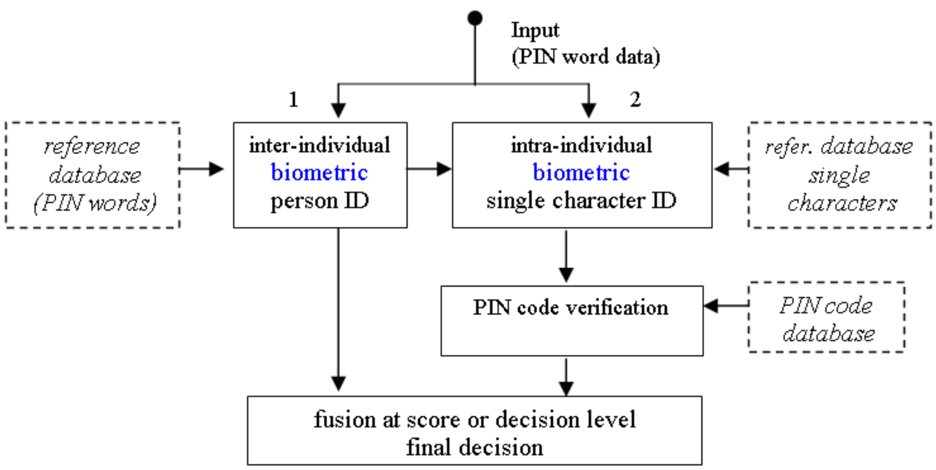


Figure 6.27: Scheme of proposed procedure for two-factor authentication using handwritten PIN.

The authentication is performed by two separate steps. In first step the writer (owner) of a PIN word which figures like a signature, has to be identified among the population of all enrolled persons. The result is a biometric matched score *sc1* (%), denoting the degree of best similarity between a query and references stored as PIN words in the database. This score still can be used to recognize a person in the system. To enhance the level of security, in a subsequent step the PIN characters are recognized as a sequence of isolated single characters using a similarity match, now applied to the owner's specific time series data (or biometric features) stored as references of single characters in the biometric single characters BSC database. The intra-individual recognized PIN word stays now for the personal identification number referred as PIN of the identified user. Now the owner of the PIN is supplementary verified by inspecting a PIN database. This is done by comparing character by character the recognized PIN code with the PIN reference of the enrolled person. The resulting score *sc2* denotes the degree of best similarity match between the PINs and is calculated by separate biometric single character matches of queries q_i and references r_i as defined by the relation:

$$sc2 = \sum_{i=1}^{7} q_i \propto r_i \tag{6.6}$$

where $q_i \propto r_i = \begin{cases} 1 & for\, equal \\ 0 & else \end{cases}$ stands for the similarity match of single characters

The index 'i' indicates the position of the characters within the sequence of the PIN code. The score value <u>*sc2*</u> ranges up to 7 is a measure of the PIN code verification and rates the confirmation of the person identification done before. The score value <u>*sc2*</u>=7 depicts the strongest conformation of the identified person.

Finally, based on these two similarity match-scores calculated for writer identification and PIN code verification, various fusion strategies, as known from multimodal biometrics [6-7][28], can be applied to implement the decision in authorizing a person. At the score level fusion, the final decision <u>*dc*</u> based on the fusion of the equal weighted individual score values <u>*sc*</u> =fused (<u>*sc1*</u> & <u>*sc2*</u>) can be made. Note the fusion has to regard the different nature of score values expressed in (%) and in numbers up to 7 .To face with this problem the values have to be scaled prior to fusion. A simple implementation of the fusion at decision level is applied, i.e., two separate decisions <u>*dc1*</u> and <u>*dc2*</u> are made using the individual score rates of writer identification <u>*sc1*</u> and PIN code verification <u>*sc2*</u>. The dc-value '1' means "**yes**" the person is accepted and '0' means "**no"** and the person is therefore denied. In a final decision process, the equally weighted decisions <u>*dc1*</u> and <u>*dc2*</u> are fused before making a decision .This procedure (fusion at decision level) consists of three decision steps:

Starting with separate decisions

$$dc1 = \begin{cases} 1 & for\ sc1 \geq th1(dc) \\ 0 & else \end{cases} \quad \text{And} \quad dc2 = \begin{cases} 1 & for\ sc2 \geq th2(dc) \\ 0 & else \end{cases}, \tag{6.7}$$

A final decision dc is given by: $dc = (\underline{dc1} \quad \& \quad \underline{dc2}) = \begin{cases} accepted & 1\&1 \\ ambiguous & 1\&0 \\ denied & else \end{cases}$

where th1(dc) and th2(dc) are given thresholds for decision. The interpretation of all cases of fusion (<u>*dc1*</u> & <u>*dc2*</u>) used above is most suitable for the access control or authorization of persons in business–legal and private sectors of territories, devices and services such as banking.

6.6.3 Experiments and Results

The main objective of the study work was to evaluate the proposed biometric two-factor person authentication based on PIN words handwritten on pad and in air. For this purpose, the data of handwriting on paper pad and in air were captured by BiSP device. Evaluation is made by investigating special features of data acquired by handwriting in air and by comparing their performance rate with the results obtained by writing on pad.

6.6.3.1 Database

The database used in the experiments was collected from 40 different persons. Each of them has written ten times on paper pad and in air his private PIN (e.g. *3WüKQ45*) section 4.2. As the PIN word is a sequence of seven single characters and a sequence is written separately (i.e. timely spaced) so, no complex segmentation of the PIN signal is required to achieve the appropriate time series of corresponding single characters (see Figure 6.28 as an example).

Multivariate time series data of PIN words and the involved single characters is stored separately in two databases used for TFA procedure. For the evaluation task, the databases of both writing modalities (on pad, in air) are subdivided in query (test) and reference (prototype) samples using leave-one-out mechanism. The queries are classified by a DTW based similarity match. In TFA method, handwritten PIN word sequence (Figure 6.28) is recognized as a first step, in a second step the individual PIN characters are recognized by matching time series of single characters data obtained by the segmentation of the PIN data. The time series of a PIN word and its segmented characters are shown in the Figure 6.28.

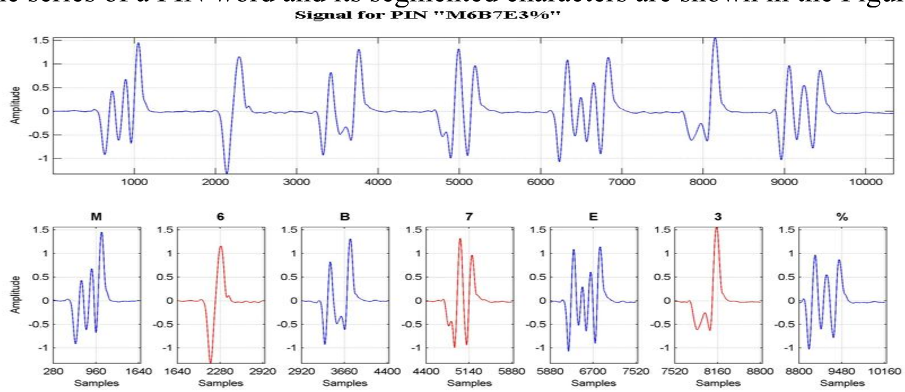


Figure 6.28: Finger grip signal (time series) of handwritten PIN word "M6B7E3%" and of single characters {'M', '6', 'B', '7', 'E', '3', '%'} separated out of it.

6.6.3.2 Data Pre-processing

After data acquisition, data is pre-processed. The data is smoothed and detrended to remove sensor noise and linear detrend. Amplitude normalization of all sensor channels is done to make them comparable and to minimize partially the variation of time series in amplitude domain. As described in previous sections, there are enough specific biometric and objected related information included in the time series obtained from the sum of all channels. The summed signal depicts a high reproducibility and distinctiveness (section 6.1) which is a fundamental prerequisite for PIN word or person recognition. This dimension reduction also reduces computational loads. Therefore, multivariate time series data is converted to univariate time series by sum. Time series are down-sampled to reduce the complexity of DTW further. For classification, DTW similarity match is performed on length normalized time series (i.e. time series is re-sampled to equal lengths). Therefore, data is pre-processed by smoothing, detrending, converting dimension to univariate, down-sampling and normalizing length of data.

6.6.3.3 Results

The evaluation of the TFA is carried out by inspecting the performance parameters of person identification and PIN word verification based on data sampled during handwriting in air and on paper pad independently. Results and discussion first are addressed to the peculiar properties of handwriting in air, which are essential for the proposed biometric authentification method. Thereafter the performance rates of single character recognition, PIN word recognition, person identification and TFA are determined. The results obtained attest writing in air is a successful competitive version to writing on pad which allows reliable person authentication at high level of security.

A) Handwriting in air and on paper pad

Typical output signals as shown in Figure 6.29 are recorded during handwriting letter "*Ü*" *on* paper pad and in air.

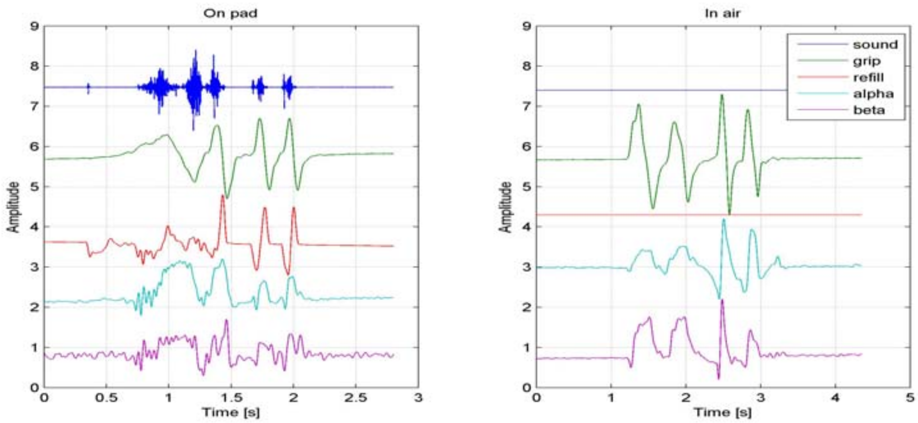


Figure 6.29: Typical output signals recorded during handwriting a letter *Ü* on paper pad and in air.

Writing in air activates only the sensor channels of finger grip pressure and tilt–acceleration, whereas vibration and refill pressure signals are extra generated during writing on paper pad. As a user writes on a paper surface, the pen-tip movements over the paper fibres generates vibrations with excitation frequencies and amplitudes controlled by the roughness, hardness and the velocity. It was found in [30] that vibration data alone can provides high performance rates of handwriting recognition. Low frequency oscillations (about 10 Hz) sometimes observed in tilt-acceleration signals are primarily because of small tremors of the hand holding the pen device.

The properties of signals in Figure 6.29 are mainly determined by human biometric traits, object specific features and the modality of writing—on pad or in air.

Depending on the modalities, the writing movements are more or less controlled by the biomechanics of fingers, wrist, arm and shoulder joints so that the diverse writing modalities lead to quite different movement patterns. For comparison, the typical parameters of writing on pad and in air are listed in Table 6.11.

Table 6.11: Typical values of parameters estimated in comparison for handwriting on paper pad and in air, 'g' terms the gravitational acceleration (9.81 m/s^2).

Typical values	Angular tilt. Δφ	Writing speed	Acceleration	Writing size	Grip forces	Refill force
On pad	±5°	~2cm/s	0.05g	0.5-1cm	<10N	<10N
In air	±10°	~2cm/s	>0.05g	1-2cm	<10N	-------

The values estimated are close to such found in literature [29]. Force levels of finger grip and refill impact of both modalities vary in the range of about 10 Newton. Writing on paper pad occurs in two dimensions and requires more biomechanical constraints providing smaller movement amplitudes and patterns. The common size of cursive writing on paper pad is about 0.5-1 cm.

For handwriting in air, the biomechanical constraints are minimal due to increased degree of freedom and more flexion and extension of joints. This results in bigger writing sizes (typ. 1-2cm) and angular values of tilt (up to 10 degree). Further, acceleration-tilt effects are more pronounced, due to higher degree of freedom when writing in air. The inclination is characterized by the angles measured between the longitudinal axis of the pen and the gravity direction. It can be recorded with a resolution of less than 0.5 degree. The acceleration varies in the range of about 0.05g, where g stands for gravitational acceleration.

If the pen is not supposed to rotate around its axial axis and the pen tip remains in touch with the paper during cursive writing, the wrist joint has only one effective degree of freedom, formed by a fixed combination of palmar flexion and radial abduction/dorsal flexion. Further, the thumb-and-fingers system has two, or maybe more, effective degrees of freedom. Various features and properties differ for wrist and finger movements, and may have an intermediate or cumulative effect for movements of the wrist and fingers combined [29]. Though writing movements in air is dominantly organized in terms of two muscle systems, one corresponding to finger-joint movements and one to wrist-joint movements, the elbow and shoulder joints can take active part. This leads to a higher degree of freedom. Note: when writing size increases, the arm and shoulders get more involved and the fingers less.

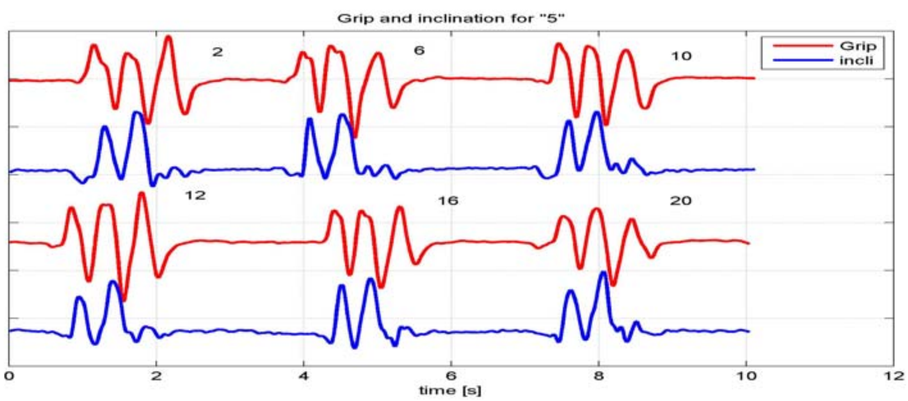


Figure 6.30: Grip pressure and tilt signals obtained from character "5" handwritten in air up to twenty times in a succession.

Even though various features and properties of writing on pad and in air differ considerably, both provide quite similar performance rates of person authentication or character recognition. The movement patterns are the result of an abstract neuro-motor program for controlling the fine motors of fingers, wrist, etc., which can be executed largely independent of visual feedback. As a consequence, a high reproducibility of signal features is obtained even if the item is written in air many times in succession without optical feedback. As shown in Figure 6.30, the grip pressure and tilt signals obtained for character "5" after handwritten in air up to twenty times in a succession are very similar., i.e. reflect a high reproducibility in wave shape. In conclusion, not only writing on pad but also writing in air complies well with the fundamental prerequisite for handwriting and person recognition: high reproducibility irrespective of the type of written items let it be a character, word or the individual PIN, and high distinctiveness in order to discriminate between various human individuals or written items.

B) Person two-factor authentication

The aim is to attest that the two writing modalities yield comparable performance of the proposed TFA method. For this the performance rates of the two modalities are determined and compared for single character recognition SCR, PIN word recognition PWR and person identification PID.

Single character recognition SCR

For SCR of all enrolled persons, an intra-individual DTW similarity match is accomplished to calculate average-accuracy (SR) for each person. The results charted in Figure 6.31 present writer independent SR values reveal comparable results of performance for both writing modalities. Writing on pad yields slightly higher SR values than that of in-air (average difference is less than 0.5%). The time series data obtained from writing on pad and in air and down-sampled by a factor M of 10 is used.

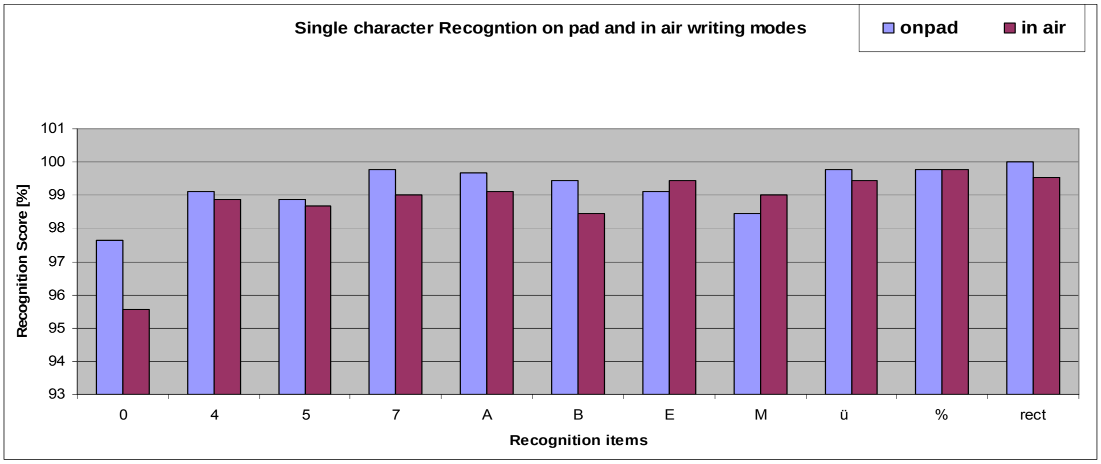


Figure 6.31: Bar chart of performance rates of single character recognition based on writing on pad (blue—left) and in air (red—right). The values are averaged over all enrolled persons.

Person or PIN word identification

Because of PIN words recognition is required as a first step in the proposed TFA, the performance parameters (SR, CM and run time) of person or PIN word identification are presented for both writing modalities in the Table 6.12 that are also comparable. A drawback is the computing time of a few seconds needed to identify a PIN word among its population. It is shown that in-air-data requires higher computing time because of larger size of writing leads to more data points per sample. To cope with the problem of slow computing, the speed up DTW methods as described in [38-39][70][84] can be helpful especially for a bigger population. Alternatively, response time can be reduced by using down sampled data. As indicated in the Table 6.12, it still leads to excellent results of performance (SR=99.83, CM =23.83) with lowered run time to 2 seconds if time series provided by writing in air are down sampled by a factor M=80.

Table 6.12: Averaged performance parameters (SR, CM and runtime) of Person or PIN word identification based on handwriting on pad or in air for 40 enrolled persons.

M	Score SR		Certainty CM		Run time (s)	
	On pad	In air	On pad	In air	On pad	In air
10	100	100	125.27	78.01	31.5	45
20	100	100	84.94	65.89	10.5	14.5
30	100	100	58.02	54.74	5.4	7.3
40	99.98	99.97	41.74	45.16	3.8	4.9
50	99.92	99.84	31.35	36.82	2.7	3.6
60	99.83	99.83	26.15	31.36	2.2	2.8
70	99.46	99.79	21.03	27.38	1.8	2.3
80	99.13	99.83	18.20	23.83	1.6	2.0

It is concluded that the performance based on writing in air complies very well with the claims of an online person authentication system. Handwritten single characters and PIN

words in air can be recognized at an extremely high score (better 99%) with a response time of less than two seconds.
These excellent results lead to a promising application, namely the biometric two-factor person authentication (TFA) method.
Person two factor authentication TFA

The TFA procedure is outlined above. The values listed in the Table 6.13 are the scores sc1, sc2 and runtime averaged over all writers. The decisions dc1 and dc2 are made based on arbitrary chosen score-thresholds (th1=99.2 and th2=5.8).

Table 6.13: Two-factor person authentication results based on handwriting PIN words.

M	PIN word ident. score sc1	PIN verif. score sc2	PIN verif. run time (s)	Decision dc1	Decision dc2	Final decision dc
10	100	6.53	2.6	1	1	accepted
20	100	6.31	1.3	1	1	accepted
30	100	6.12	0.9	1	0	ambiguous
80	99.14	3.97	0.4	0	0	denied

The experimental results show that the designed biometric method complies very well with the claims of an online person authentication system. The score rates of identification are better 99% and the response time is below 2 seconds for a population of 40 enrolled persons. Further, the proposed TFA method applied on the handwritten PIN words is a promising approach to enhance the accuracy and reliability of the biometric person authentication.

6.6.4 Discussion

It is generally agreed that reliable biometric user authentication needs higher accuracy and quality of biometric data acquisition and processing which can be achieved by improved sensing devices and advanced methodologies such as two-factor authentication TFA.
The TFA system is proposed where biometric PIN word or writer identification is combined with the verification of the biometrically recognized PIN code. This method is less complex and has a low infrastructure because it needs only a single acquisition device for generating the two factors of authentication by using a handwriting PIN word. A further advantage arises from writing in air, because it requires no solid pad and leaves no visible image of the PIN word, which can easily be copied or guessed otherwise. Apparently, the proposed method based on the multi-sensor acquisition device BiSP is a promising approach to increase user's acceptance, level of security and enhance reliability of biometric person authentication, which is required in the future for access control of social and commercial interactions. Experimental results have shown that the designed biometric method has an excellent performance of authentication with a high potential for further improvement. In verification mode, the proposed TFA procedure allows user to generate new PIN codes without new enrolments of data. In further respects, the proposed method is superior to the state of the art pen based authentication techniques. Because writing, drawing or gesturing in air is creating a new dimension of freedom in unconstrained data input and access control especially for more and more downsized mobile units like cellular phones, PDA's, mobile flash memories, etc. In addition, it needs neither a keyboard nor a touch screen, and gets closer to a paperless work environment.
A future objective of our ongoing work is to investigate the feasibility of the configured personal authentication system now applied to movements of any hand held body using

gestures as biometric signatures, passwords or PINs. It is to understand whether any handhold mobile system like pen, cell phone, etc., can recognize its owner by how the person performs a particular gesture, acting as a gesture signature, password or PIN in air. The gesture in air can be used for obtaining handwritten items or access to the mobile device, but the hand held device could also act as an intelligent key to provide access to services in an ambient intelligence scenario. For these modalities object movement resulting from well-defined gesturing patterns has to be captured, analysed and classified using the sensor and software techniques developed for the BiSP system.

Gesturing used for handwriting in air also is a prerequisite to design methods allowing human–computer interaction (HCI).The area of gesture based HCI shows a high diversity with respect to the modalities. Approaches exist by either video-based tracking and data gloves or the analysis of hand held object (pen tip, cell phone) movements resulting from well-defined gestures like those used in handwriting. The latter addresses the problem of automated recognition of textual content of handwritten items like letters, digits or words. Thus, an ultimate goal is to build a constraint-free input interface for character recognition by involving our proposed method. Such an interface would enable the user to write freely in the air, without putting much attention on the relative position of the writing hand with respect to the acquisition system.

7 BiSP System for Medical Applications

7.1 Introduction

In fact, there is essentially a great potential in handwriting analysis for medical research, according to Arie Naftali in his book "Graphology and Medicine" [94]:

"*Every disease causes a disturbance in the functions of the systems and distortion of their basic rhythm. This is how such disturbances become apparent in handwriting, not only after the disease has set in but already in the intermediate state prior to its development*"

Therefore, if there exists a dysfunction within a body due to psychological, physical or/and pathological problems, the human brain may transmit it through the handwriting [95].
It is well known that the diseases that cause deficits in motor performance or certain drugs that cause side effects have a distinct impact on human fine motor skills influencing handwriting. As Parkinson's disease PD affects fine motor control of human movements, therefore the movements of hand and fingers may also affect handwriting in particular [108].
Movement investigations and its deficits in human motor performance have been evaluated in psychology and medicine for diagnosis in neurology and psychiatry for a long time. The assessment of disorders in fine motor movements (e.g., hand movements), the methods such as clinical rating scales, electromyography (EMG) or other computer-based methods such as using accelerometers have been employed. Unfortunately, such methods are not much reliable or very expensive, complex or painful sometimes. In a clinical assessment for an example, the classical method of tremor analysis is based on the recording of muscle activity in terms of EMG prints with the help of skin surface electrodes (steel needles) pinned into the muscle through the skin [55],[98]. In contrast, other promising methods are based on the digital analysis of handwriting features where a pen based system is used to register handwriting biometric features of hand-movements in an efficient and non-invasive way [55-57][67][98-108].

7.1.1 Parkinson's Disease, Symptoms, Diagnosis and Treatment

Parkinson disease (PD) is a degenerative disorder of the central nerves system of the human brain. The major symptoms are slowness, impairment and disorder of movements, tremor, rigidity, stiffness and instability of posture or balance. One of the reasons believed for PD is the depletion of dopamine. For an example, to move a muscle in a movement task such as to lift an arm, the brain initiates an impulse that passes through a collection of nerves known as basal ganglia (BG). The BG helps smooth out the muscle movements. A nerve cell in BG releases a chemical (dopamine) which serves as neurotransmitter which triggers the next cell in the pathway to send an impulse. In PD, the nerve cells in BG (called substantia nigra) degenerate resulting in:

(i) Reduced production of dopamine and
(ii) Depleted or lost number of connections between nerve cells in the BG

Therefore, BG cannot smooth out movements in PD which results in PD symptoms. The clinical diagnosis of PD has shown the following symptoms:
Movement abnormalities: These movement dysfunctions are caused by a delayed signal transmission from the brain to the muscles resulting in:

(i) the reduction of movement amplitude and speed called hypokinesia,
(ii) the reduction of spontaneous movements initiation known as akinesia and

(iii) a slowness in voluntary movements such as walking etc especially when initiating a movement known as bradykinesia.

Tremors: It may cause the shaking of the feet, legs, arms, hands or fingers.

Rigidity or stiffness of muscles: PD may cause pain in muscles during movement because of the muscle's stiffness resulting in impairment of movements.

Loss of balance and control: for a PD patient it may become difficult to maintain a posture or a balance sometimes leading to a fall. It happens because of loss of reflexes and slowness of movements.

There is no single defining symptom in a patient or a definitive diagnostic test. However, a patient can live for many years with undiagnosed and then the symptoms severity reveals PD which might be at a potentially damping and dis-ease stage.

The major medical treatment is with the L-dopa drug which works well for controlling the symptoms but has caused some side effects in patients. This drug is converted into dopamine by the dopaminergic neurons in the brain in order to overcome the depleted striatal dopamine. Therefore, neurons release more dopamine and the PD patient is provided with the relief of the symptom. Doctors may examine the structural disorders and brain abnormalities by using complex techniques such as computed tomography CT [96-99][111] or nuclear medicine diagnostics (e.g., DatScan) [110].

A noninvasive, simple and less complex systematic neurological examination of the PD patient will be in addition testing reflexes, muscle strength, coordination, control and balance of the body movements and other gross and fine motor movements of fingers or hand etc.

7.1.2 Parkinson's Disease and Handwriting

For the assessment of human movement disorders, the computerized methods that involve handwriting analysis and use of graphic tablets (or digital pen systems) have already been widely accepted due to their benefits. Handwriting or drawing can be used to measure and study human motor performance in normal controls (NCs) and in patients with movement disorders such as PD, essential tremor (ET) etc. Such diseases or some drugs like neuroleptics have effects on human motor skill. The neuro-motor dysfunction in handwriting movements of a patient in relation to a normal person (NC) still have been analyzed in [53-54][105].The writing of Parkinsonian patients is often found distorted and smaller because of tremors, reduced movement amplitudes, slowness and rigidity [99]. The disturbances associated with handwriting movements of patients with PD are due to problems in the processing of:
—motor planning —motor programming —motor sequencing —movement initiation and —movement execution [106]. Micro graphing is another problem with their handwriting. It is due to hypo metric movements. The handwriting is going on diminution and the letter or the stroke size becomes smaller and smaller with the continuous handwriting. It is because of the fact that the movement amplitudes become smaller in patients with PD. Handwriting movement sequences are rapid, sequential and ballistic. Therefore, for healthy writers, these movements are automated and do not require resources such as extra attention. However, in PD, the automation in the execution of a task sequence is lost and the sufferer shows problems in the movement initiation and exhibits delay in a subsequent movement performance. Consequently, handwriting of PD patients is characterized as the one that is produced with movement disorders. Therefore not only the distortion in shape (or becoming tiny with time) but also the kinematic and dynamic aspects of movements—speed, acceleration, force, and amplitude and stroke duration are also affected. On the other hand, handwriting in healthy subjects is expected to be automatic. Hence it is characterized by more consistent, efficient and more fluent in general and less variable in temporal (time), spatial (length, height & width) and pressure (finger's pressure) measures.

In other words, for an automatic handwriting process, there should be fewer pauses, less variations in stroke or letter size, more spatial accuracy, precise pen pressures and better control of the hand and finger's movements [104-107]. One possibility to assess these degradation effects is to register and analyze the complex and highly practiced task of handwriting. It is reported by several researchers that the computerized analysis of writing with the digital pen in terms of wrist, hand and fingers movement provides the objective measures to study motor performance of the handwriting process. The observed distortion (dis-automation) in the handwriting process will result in more variability in the above-mentioned parameters.

In [103] for an example, the ability of PD patients to discrete and dynamic scaling of the size of continuous movements involved in the drawing of circles (emphasis on size) and in the spirals (emphasis on accuracy) was investigated. The movement size and output variability were assessed in comparison to NCs. It was reported that PD patients show more variability and smaller movements than NC's in different handwriting tasks.

In the thesis, the kinematics and dynamics of hand and fingers movements are recorded with the BiSP system, which allows extracting not only biometric but also neuro-motor features.

In the medical field, while using pen-based systems, the neuro-motoric features obtained from handwriting or drawing movements of relatively simple objects (or figures) such as the letter 'ℓ', slashes, backslashes, circles, spirals, meanders or pyramids [35][53-57][98-108] are recorded and analyzed. The registration and the analysis of such neuro-motoric features obtained from online handwriting-data is also a topic of this chapter.

In the previous studies, a prior version of the BiSP pen was used to record handwriting features during handwriting backslashes or meanders. It was reported that by using such features, the low temperature, physical strain, alcohol, side effects by using a drug or writing with the non preferred hand (mostly left) or a disease (e.g. PD) have bearing on the human hand movements [53-55][108]. The [54] was a first attempt to show that the handwriting dynamics can be used to distinguish a healthy person automatically from that of a person using drugs (schizophrenics) and therefore, appropriately medicated person. It was shown that the differences could be detected by using hand movements data recorded by the pen during drawing "meander".

The objective of the thesis in medical data analysis is to develop an early diagnosis system that is capable of recording and analyzing dysfunctions of the dynamics and kinematics of handwriting movements for:

—diagnosis of Parkinson's disease

—to distinguish a Parkinson's disease patient from a healthy person automatically

Note: For the clinical assessment of handwriting movements, the samples are often recorded with graphic tablet based systems where the pen's x, y position or/and pressure and angles are registered for the analysis. However, in [55], it was reported that for the tremor assessment in PD for instance, the absolute positioning are not important rather the grip forces are of interest. In order to address the issue of involving the handwriting pressures, in the previous study [55], a pen that has the ability to record x, y, and z pressures of pen-tip was used to analyze PD data. This thesis deals with the analysis of data obtained from handwriting, drawing or gesture movements on pad or free in air by using a novel pen (BiSP). It also involves changing pressures of a pen-refill in three directions and of the finger grip sensing.

7.2 PD Neuro-motor Dysfunction Characterization by BiSP System

7.2.1 Probands

In our study work, two field tests were performed. All participants were informed about the task and, the neurologist and the patients signed an information protection document approved by the ethics commission. All patients are moderately or seriously affected with PD and are under medication. However, only a few patients are in their best-controlled health conditions due to medication. For recording the motion tasks, the task was started after a computer beep and was monitored by the observer for the completeness. Each participant was instructed about the tasks and a trial session was provided for practice and familiarity of the system.

7.2.1.1 Field Test 1

In the first field test, 58 volunteers: twenty healthy probands aged in the range 32-65 (including 8 females) and thirty-eight patients with the clinical diagnosis of PD aged in the range 50-82 (including 9 females) participated in the first test. The data of patients was recorded in the department of neurology health care center and clinic Regensburg and, the normal control subjects (NC) were recorded at both: the clinic and the BiSP research center.

7.2.1.2 Field Test 2

In a second field test 94 volunteers were involved: forty-seven healthy students aged between 20 and 32 (including 7 females) and forty-seven patients aged in the range 43-82 (including 14 females). For this field test, the movement data of participants is collected at the university hospital Erlangen in the department of molecular neurology and at the BiSP laboratory Regensburg.

7.2.2 Apparatus and Movement Tasks

BiSP pen was used for the registration of handwriting, drawing and gesture movement tasks using a datasheet shown in the Figure 7.1. The dynamics of movements of hand and fingers were recorded in terms of time series data during handwriting—circles, spirals and meanders, and gesturing—circles, finger-tapping and Diadochokinese (hand-wrist) movements. The BiSP is used in two modes: **(1)** on pad mode **(2)** off pad mode (in air) as shown in Figure 7.1.

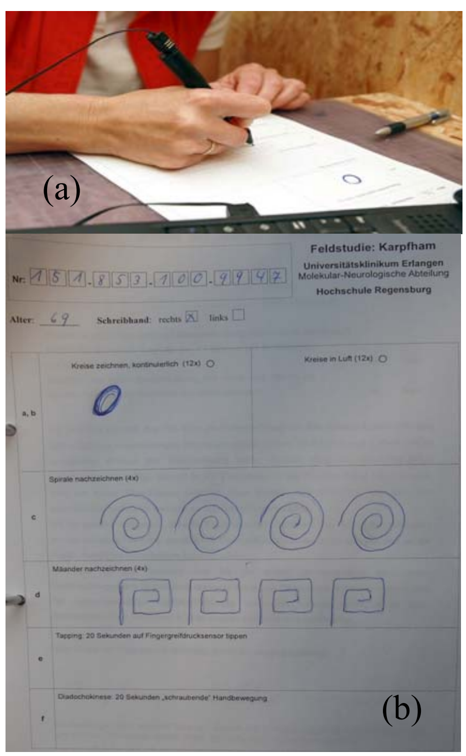


Figure 7.1: The BiSP acquisition device in action for handwriting and the data sheet used for the hand movement-tasks.

The following movement tasks have been registered.

7.2.2.1 Circles on Pad

The participant's habitual writing sized circles are recorded with BiSP pen drawn on the paper pad. Each participant draws concentric superimposed (roughly) circles for up to 12 repetitions without lifting off the pen-tip and in a fluent way in one session. Note: there were no lines or traces of circles drawn on the paper-sheet to follow.

7.2.2.2 Circles in Air

The gesture movements of hand and fingers during the drawing of circles in air (in free space) are also recorded with the pen (BiSP) for each participant for up to 12 repetitions in a single session. The mechanism of: elbow placed on the table with arm perpendicular to the tablet and with fingers holding the pen parallel to the table is used for data registration (Figure 1.3).

7.2.2.3 Spirals and Meanders

Each participant was asked to write four times as much as normal traces of spirals and meanders, starting from inward to outward. The analysis of movement data provided by drawings of circles, spirals and meanders is for quantifying normal motor activity in a NC as well dysfunction of patients with movement disorders (e.g., PD).
Abnormal movements (due to tremor for instance) during drawing tasks such as severity, deviation from the expected path, pausing, etc are also evaluated. The participants with movement disorder do not execute drawing tasks in a controlled and consistent manner. Therefore, poor execution of movements generates artifacts in a drawing path as shown in the Figure 7.4-5.

7.2.2.4 Finger tapping

Finger taps investigation is a clinical test that is one of the Unified Parkinson's Disease Rating Scale (UPDRS) tests for motor performance of the upper limbs (fingers).The finger-taps are recorded with BiSP device using the finger grip sensor signals. For the finger taps motion, the participants (NCs & PDs) strike on the pen at the tactile finger grip area. It is done by the striking and lifting of his/her index finger continuously and repeatedly, as quickly and widely as possible for about 20 seconds. The experiment was executed only for the preferred (often-right) hand. In a separate session, the neurologist evaluated the score of UPDRS finger taps.

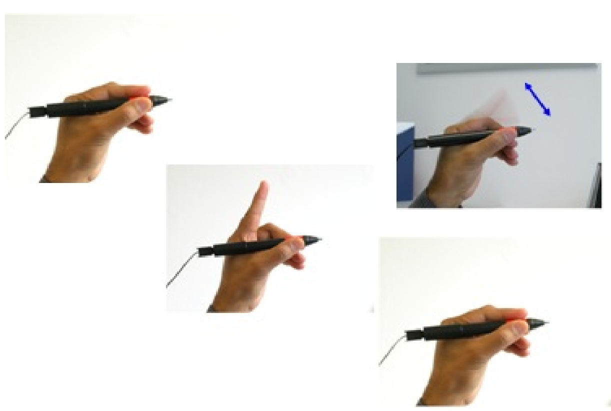


Figure 7.2: The pen (BiSP) used for finger taps measure experiments

Figure 7.2 shows the finger taps measurement procedure with the help of BiSP. In PD, the rhythms, amplitude, speed, finger tap intervals, contact force etc are affected and such information are found to be important for the diagnosis of PD. For quantitative evaluation of the finger taps, several other techniques such as the keyboard and the mouse of PC, 3D position measurement by using high-speed camera etc have been employed. In [109], a finger taps measurement system was developed using a 3-axis accelerometer and a touch sensor. For the taps measurement, the sensors were worn on the fingers and the accelerations and the contact forces were determined (for details see [109]). Therefore, the BiSP is efficient, simple and easy to use for recording finger taps, as there is no need to wear exclusive sensors on fingers as shown in Figure 7.2.

7.2.2.5 Diadochokinese (hand-wrist movement)

In this assessment test of DIADOCHOKINESE (DDK), the subjects hold the pen in the preferred hand. The pen was moved by rotation of the hand-wrist by an angle of $\pm 90^0$ to horizontal in both clock wise and counter-clock wise direction whilst holding the pen as shown in the Figure 7.3. The 3-axial inclination sensor installed inside the pen records the hand movements in this experiment.

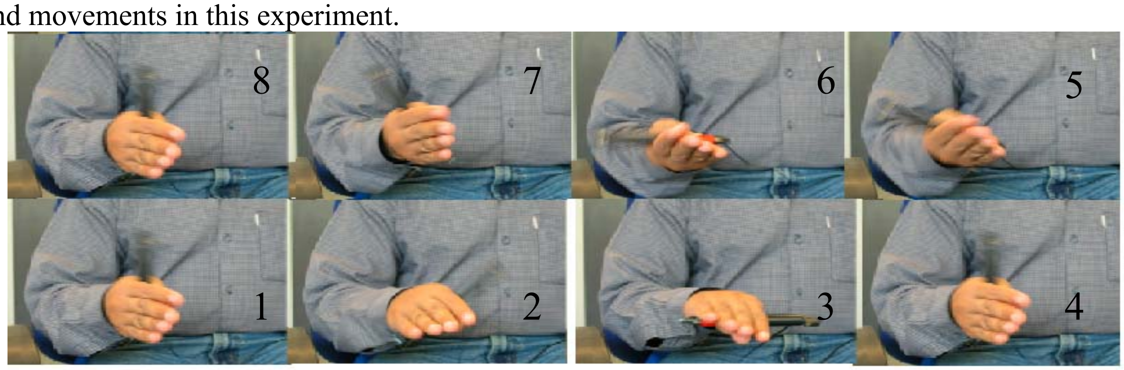


Figure 7.3: The pen (BiSP) used for hand gestures (Diadochokinese) measurement experiment. Figure panels of sequence numbers 1-8 illustrate the hand movement procedure.

Note: All participants received instructions on procedures and protocols for the movement tasks. A practice session is provided if required.
The experiments described above for movements assessment tasks can be considered as handwriting, drawing and gesturing tasks in two modes: on pad and off pad (free in space).

7.2.3 Features and Parameters Selection Methods

7.2.3.1 Local Features

For the quantitative analysis of movements, the pre-processing procedures performed on time series are segmentation, detrend, normalization, and re-sampling for details see section 4.2. The time series data that includes the essential features is used for classification (section 7.3.2). Further, in a subsequent step, different reduced representations of data have been obtained. For this, multivariate time series data is subjected to different numbers of frames and the data in each frame is reduced by using different feature transformation methods. The following different procedures are used for data modeling.

- Subject a multivariate time series data into different numbers of frames.
- Calculate the area under the curve (AUC) in a frame for all channels and a reduced feature vector is formed by appending all area values.

- Singular value decomposition (SVD) of multivariate time series sample data (matrix) is computed for a frame. The reduced feature vector is formed by appending: (i) all right singular vectors or alternatively (ii) all singular values.
- Similarity, Nonnegative matrix factorization (NNMF) of multivariate time series data in a frame is computed. The non-negative factors are formulated to generate a reduced feature vector.

In the next step for each data model, the net feature vector for a given transformation technique is formulated by combining feature vectors of all frames by appending them in a sequence. Hence, based on AUC, SVD and NNMF, three different reduced representations (feature vectors) from multivariate time series (matrix) are extracted.

7.2.3.2 Global Features

From the time series of movement data, the following parameters are calculated.

- **Reaction Time (RT)**: Reaction time is a measure of movement initiation [56]. RT is defined as the time interval between a computer beep (a start call) or the beginning of a task and the actual onset of handwriting or movement onset for a particular task.
- **Writing Time (WT)**: Writing time is the time interval between movement onset and offset for a particular task. It is also denoted as the actual action time for a task. Figure 7.4 illustrates WT that is actually a time associated with the handwriting or movement task.
- **Movement Time (MT)**: MT is the total time for a handwriting or movement task. It is defined as the total length of the time series signal.
- **Number of Peaks (PK)**: It is the count for number of peaks (local extremes) in a time series (signal).
- **PK in derivative of a signal (PKD)**: It is the count for the number of peaks (local extremes) after the first derivative of a time series (signal).
- **Number of Zero Crossing (ZC)**: It is the count of the number of zero line crossing for a time series.
- **ZC in derivative of a signal (ZCD)**: It is the count of number of zero line crossing for a time series after its first derivative.
- **Peak Pressure (PkPr)**: It is the absolute averaged pressure value at the extreme peaks of a pressure signal.
- **Cumulative Peak Pressure (CPk)**: It is the sum of absolute pressure values calculated for a pressure signal at all peaks.
- **Estimation of Automation 1 (Est1)**: It is the measure of smoothness of a movement task. It is calculated as the difference between the number of peaks in PKD and PK divided by PK.
- **Estimation of Automation 2 (Est2)**: It is another measure of smoothness of a movement task. It is calculated as the difference between the number of zero crossings in ZCD and ZC divided by ZC.
- **Area under the Curve (Area)**: It is the absolute area under the curve value determined for a time series.

Figure 7.4 illustrates RT, WT and MT values of time series signals obtained from NC and PD subjects handwriting spirals on pad.

The number of peaks, number of zero crossings, estimates est1 and est2 determine the number of changes in the direction of a signal indirectly. Such parameters determine the smoothness, consistency and degree of automation of the movement tasks.

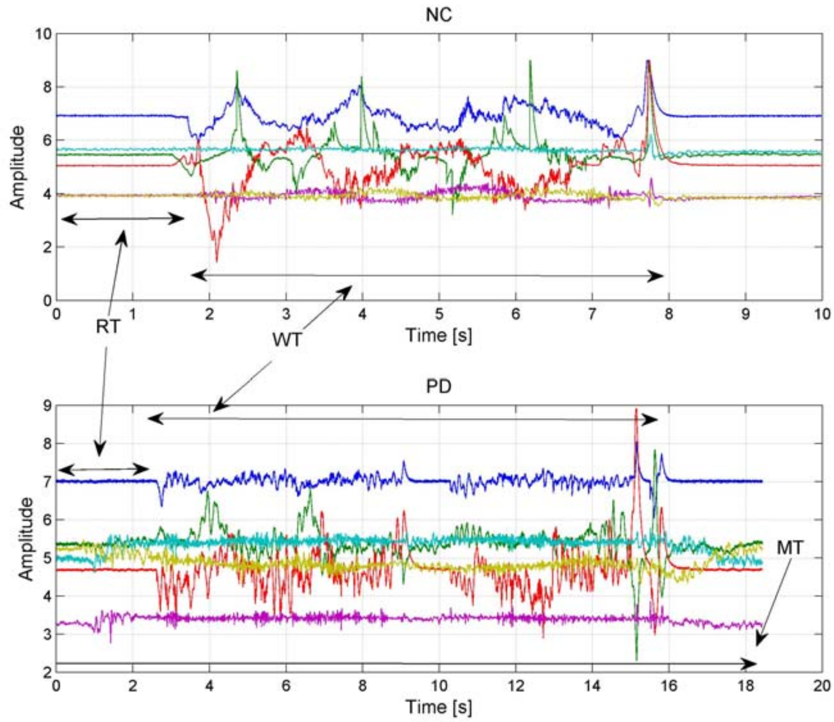


Figure 7.4: An illustration of reaction time RT, writing time WT and movement time MT for handwriting time series recorded with BiSP from NC and PD test subjects drawing spirals.

7.3 Experiments and Results

Different experiments are performed where a number of features extraction and data analysis methods have been employed to classify participants due to their health condition (i.e., NC and PD). Handwriting, drawing or gesture motions are recorded for six tasks as presented in section 7.2.2. This section first gives a comparison of features of PD and NC subjects then presents their classification.

7.3.1 Comparison between Features of Patients with PD and NC Subjects

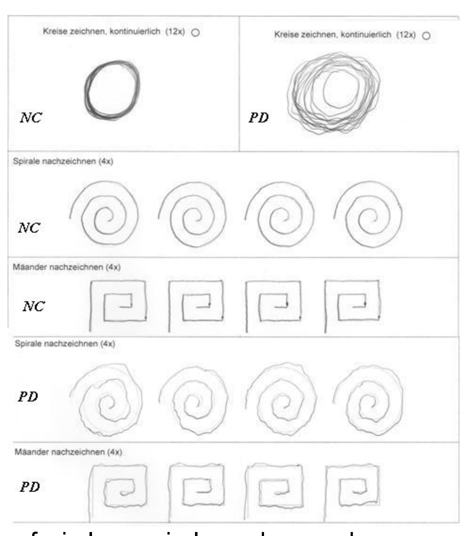


Figure 7.5: Handwriting lines of circles, spirals and meanders are shown while drawn by Normal Control NC and Parkinson's disease PD test subjects.

The tracing or drawing lines of circles, spirals and meanders recorded from NC and PD test subjects are shown in the Figure 7.5. The two writers chosen for the figure show easily distinguishable writing behavior. The lines of PD patient's handwriting are more distorted from the expected figures and are less smooth in comparison to the drawings obtained from NC. The effect is essentially visible also from the time series of spirals recorded by the BiSP device as shown exemplary in the Figure 7.4.

The concept of automations or alternatively distortions in the signals of handwriting meander obtained from NC or PD subjects in terms of peaks and zero crossings is shown in the Figure 7.6. It indicates high distortions in the handwriting signals (Figure 7.4, Figure 7.6) or in the traced lines (Figure 7.5) are characterized by more numbers of peaks and zero crossings which may come from movement disturbances—more pauses, hesitations, tremors etc., especially in PD test subjects.

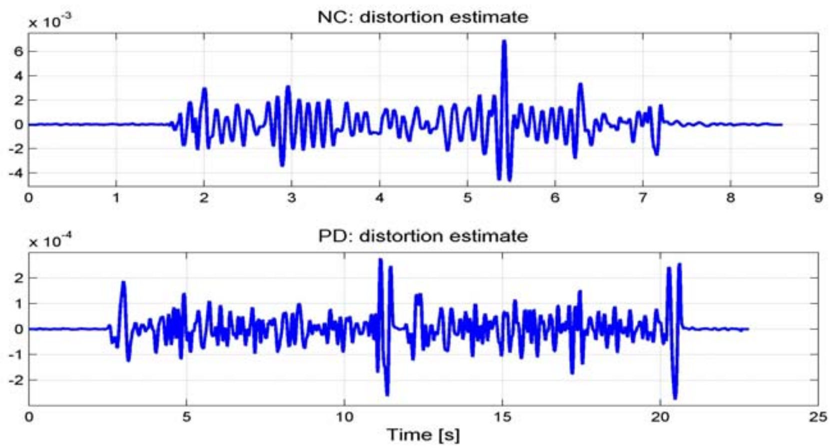


Figure 7.6: The refill pressure signals of drawing a meander obtained from NC and PD subjects. The time series as shown in the second derivative illustrates disturbances of drawing movement (PK=93, ZC=88) in NC, compared with the PD patient with a higher degree of distortion (PK=175, ZC=140).

Circles in air: Finger grip pressure and two inclination signals obtained during handwriting circles in air from NC and PD subjects are shown in the Figure 7.7. The signals illustrate more disturbances of drawing movements with a greater degree of variability in PD patients compared to NC subjects.

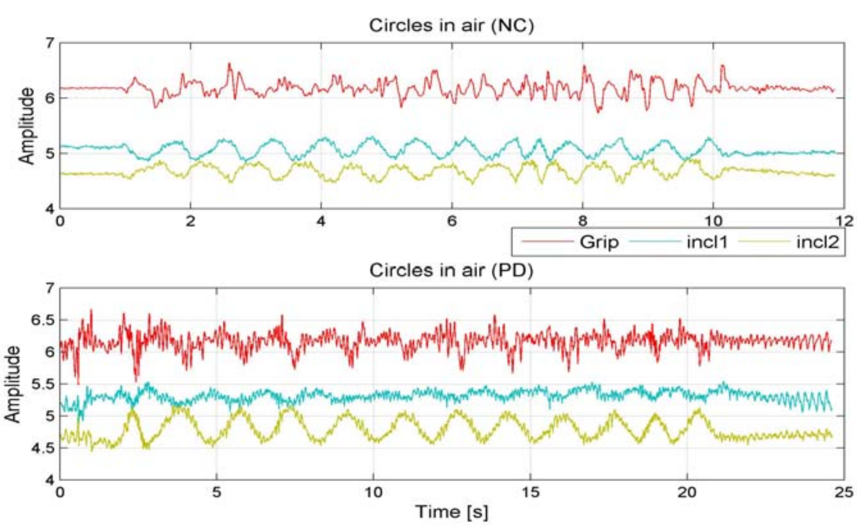


Figure 7.7: The finger grip pressure and two inclination signals of gesturing circles in air obtained from NC and PD subjects. The time series of PD patient show more distortions.

Finger tapping: Finger-taps pressure signals recorded with the BiSP pen for NC and PD subjects are shown in the Figure 7.8. The signals illustrate more disturbances of taps movements in PD compared to NC subjects. The number of finger-taps pressed on the pen grip during a limited time is lower in a PD patient compared to that of a NC subject. Similarly, finger-tap force is also lower in a PD patient as also illustrated below in the expanded Figure 7.8 (b) for the signal shown for 0-5 sec.

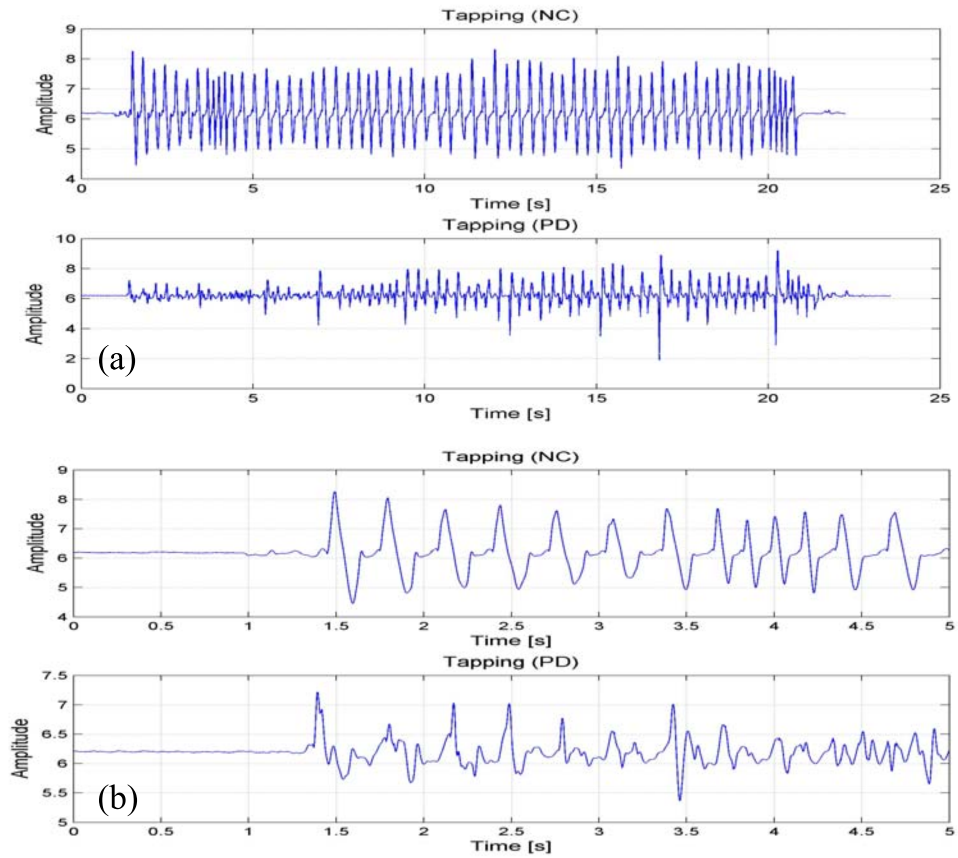


Figure 7.8: The pressure signals recorded during finger-taps movement obtained from NC and PD subjects, for (a) about 22 sec (b) the expanded signals for 0-5sec.

Diadochokinese: The inclination signals for hand-wrist movements recorded with BiSP for NC and PD subjects are shown in the Figure 7.9.

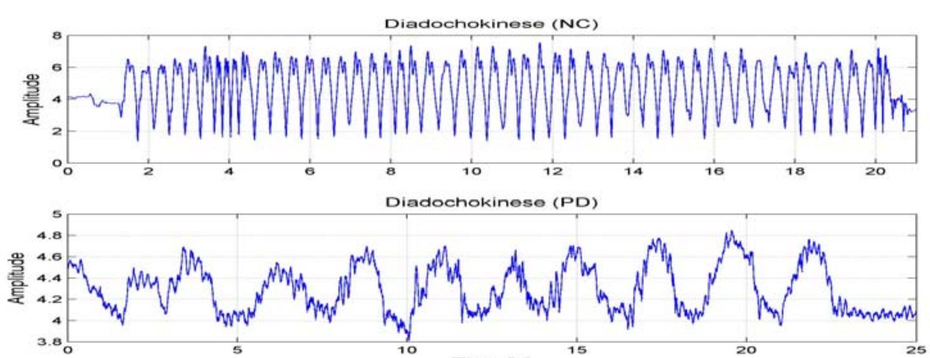


Figure 7.9: The inclination signals of hand-wrist movements (Diadochokinese) recorded for NC and PD subjects.

The signals illustrate more disturbances that may come from more tremors of hand-wrist movements in PD compared to NC subjects. The number of repetitions of the task is much

lower in PD patients compared to those of NC subjects in a limited time. Similarly, the superimposed high frequency signal (more peaks) essentially shows more tremor effects in the PD patient compared to a NC subject as illustrated in the Figure 7.9.
The averaged values for RT, WT and MT for both types of writers are shown as bar graphs in the Figure 7.10. PD patients show a little more reaction time than NC subjects. They also show obvious longer writing and movement time values than NC subjects do.

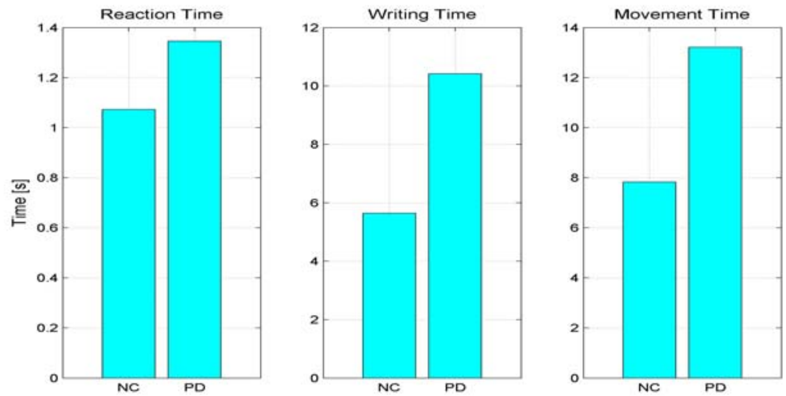


Figure 7.10: Shows bar graphs of features: reaction time, writing time and movement time averaged values for Normal controls NC and Parkinson's disease PD writers.

A comparison of PD and NC subjects based on parameters obtained from different movement tasks—circles in air, circles, meanders & spirals on pad, hand-wrist movements and finger-taps is given in the Table 7.1. PD patients have shown longer MT, more PK & ZC and higher peak pressure values in general. NC subjects have better automation of hand movements than PD ones. The latter showed less smoothness of movements characterized by the parameters of higher number of peaks & zero line crossings, less degree of automation and higher values of total peak pressures in the signals of their hand movement tasks. The effect is also shown by the parameters est1 and est2 which determine the degree of movement automation. For finger-taps & hand-wrist tasks, the number of repetitions of a task (e.g., number of taps) is lower in PD subjects than that of NC subjects due to the slowness of their motions. The last two tasks are performed for a fixed time interval (denoted as task-independent), while all other movement tasks depend on the task itself (denoted as time-independent).

Table 7.1: Means of movement time (MT), numbers of peaks (PK) & zero-crossings (ZC), automation estimates Est1 & Est2, and cumulative peaks pressure (CPk) in different motion patterns for the normal control NC and Parkinson disease PD subjects.

Motion Pattern	MT	PK	ZC	Est1	Est2	CPk
NC Subjects						
1) Circles on pad	11.65	184.25	169.87	1.49	2.26	42.13
2) Circles in air	11.22	172.14	169.63	1.02	2.07	46.97
3) Meander	7.83	147.86	147.72	1.19	4.93	41.80
4) Spiral	8.63	165.40	165.31	1.41	6.01	46.36
5) Diadochokinese	--	97.51	75.87	1.02	1.58	--
6) Tapping	--	144.66	147.33	0.36	0.22	4.76
PD Subjects						
1) Circles on pad	20.88	232.34	217.36	0.93	1.65	62.83
2) Circles in air	14.89	192.04	192.19	0.69	1.76	61.70
3) Meander	13.26	184.29	188.36	0.59	2.83	69.28
4) Spiral	14.43	196.19	196.56	0.61	3.98	68.15
5) Diadochokinese	--	110.57	91.76	0.85	1.28	--
6) Tapping	--	151.0	139.0	0.26	0.03	3.57

7.3.2 Classification of PD and NC Subjects using HC of Time Series Data

The local features or the complete signals in terms of time series data obtained from PD and NC subjects for handwriting movements (e.g., meander) are used for classification of the two types of writers. After pre-processing, the time series data is analyzed by the hierarchical clustering (HC) method in combination with an extended Dynamic Time Warping (DTW) technique. So, a modified HC method (section 4.4.3) is employed where an inter component (inter-person) distance is calculated by a DTW-match of the two samples. The modifications suggested to the pre-processing and post-processing stages of DTW and to the HC method used are described below.

Pre-processing: Multivariate time series data is pre-processed and a cumulative multivariate (cum) time series is determined by taking cumulative sum of the elements (numerical integration) of each channel of a multivariate time series. Now two cum multivariate time series, Q & C of lengths m and n, (to be compared) are length normalized by re-sampling to equal lengths.

Matching: Multivariate DTW (section 5.6) is used to calculate a distance between two cum series.

Post-processing: A plenty term (gn) that depends on the original lengths (m & n) of the two samples is then added to the calculated DTW distance given by the following equation.

$$gn = |m-n| / (100 \times (m+n))$$

Clustering: Further, a distance vector is determined where each element contains the DTW distance between a pair of writers (NC and/or PD). This distance information is used to group the objects (writers) into the hierarchical cluster tree (sec section 4.4.3).

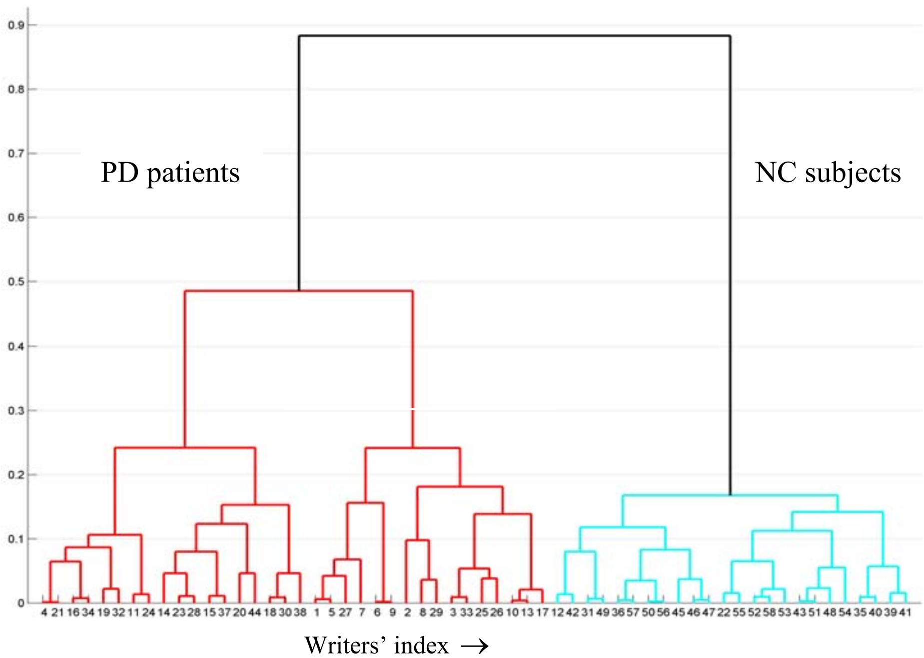


Figure 7.11: A dendrogram plot of hierarchical binary cluster tree for PD (1-38) and NC (39-58) subjects. The x-axis shows writers and the height indicates the distance between them.

A hierarchical cluster tree shown in Figure 7.11 illustrates the partition of the subjects (field test1) into two broad groups (i.e., either PD patients or NC subjects). A single NC subject (44) is miss-classified into PD patient group. The patients—12, 22, 31, 35, & 36 who are in their most stable health conditions due to the medication are miss-classified into NC group. The overall accuracy of classification for the data obtained from the field test1is about 90%.

7.3.3 Classification of PD and NC Subjects using SVM on Global and Local Features

For every participant, the numbers of features such as reaction time, movement time, the number of peaks or zero crossings etc (section 7.2.3.2) are calculated. The main trends in the features of both groups (NC and PD subjects) are given in Table 7.1. Here, the classification of data into two groups is presented. The features calculated from the time series of handwriting movements obtained from NC and PD test subjects are used as inputs for an SVM classifier. SVM uses a hyper-plane to separate two classes. For separation of data, an optimal separating hyper-plane is searched by mapping data nonlinearly into a high-dimensional feature space. For example, the above features are provided to SVM for classification of NC as well as PD writers and the best features of a sample (motion data) are chosen by "trial and error estimates". Therefore, different numbers of features are involved in the classification using cross-validation and the features set that provides best accuracy are later selected for training and testing of data. SVM is known for its good performance even if trained by a small training dataset. The database (field test 2) is divided into two subsets (denoted as dataset1 and dataset2) in such a way that one subset is used for training (or for testing), while the other subset is used for testing (or for training) respectively. Two important parameters to search in the training phase are C (penalty parameter of error) and γ (kernel parameter), for details see [11]. A grid-search on C and γ using cross-validation is applied to pick up the best values that give the best cross-validation accuracy. The best values are used in the testing stage for the classification of data. Therefore, only a subset of handwriting samples data taken from both PD and NC subjects is used for training at a time.

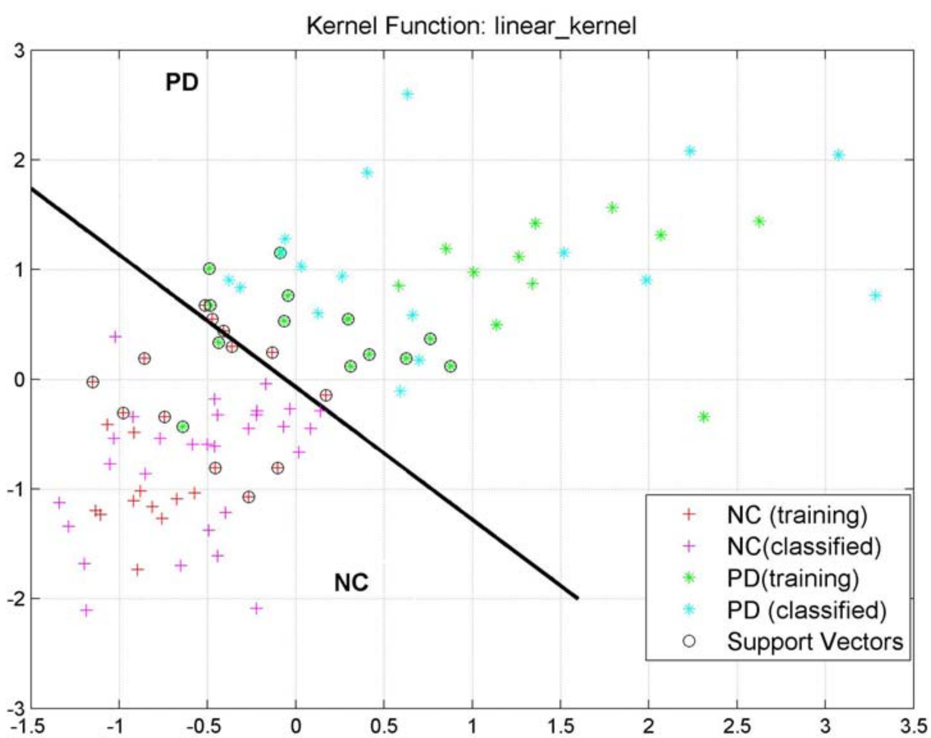


Figure 7.12: Classification of NC and PD subjects using support vector machine (SVM).

For classification of the remaining subset (treated as unknown), the trained SVM is used to recognize a sample data that belongs to either PD or NC subject's class. The result of this two-class classification problem by using SVM including the training and testing of datasets is illustrated in the Figure 7.12.

Table 7.2: Classification of patients with PD and NC subjects using support vector machine (SVM) based on (1) global features and the local features derived from data by applying: (2) Singular value decomposition (SVD), (3) Area under the curve (AUC) and (4) Nonnegative matrix factorization (NNMF) on data.

Parameters	Accuracy dataset1 (%)	Accuracy dataset2 (%)	Accuracy overall (%)
1. Global features	100	86.66	93.33
2. SVD	91.17	90	90.58
3. AUC	91.17	86.66	88.92
4. NNMF	76.47	75	75.74

In another step, for each data model obtained by using AUC, SVD and NNMF, the SVM classifier is employed for the classification of each model's feature vectors separately and independently. Classification results based on SVM applied on global features as well as formulated local features are shown in the Table 7.2. The SVM classifier is found to be the best performer when applied on global features obtained from handwriting data.

7.4 Discussion

The BiSP system that can measure two refill pressures, a finger grip pressure and three inclination signals is used for the quantitative diagnosis of Parkinson's disease (PD). By using BiSP, diverse handwriting (circles meander & spiral) and gesture movements (circles in air, finger-tapping & hand-wrist) have been recorded and analyzed. The handwriting circles, meanders or spirals are known due to their use in computer based motor assessments methods in connection with pen based system. However, the movement tests like finger-taps or Diadochokinese are of importance because such clinical tests are employed in a clinical rating scale such as UPDRS. Therefore, contrary to the state of the art complex and diverse acquisition devices used to record handwriting and gesture movements, a single input device (BiSP) has been used for recording not only the handwriting and gesturing movements but also finger-hand movement tasks involving diverse movement patterns. Due to experimental results, PD patients have shown longer reaction and movement times in general. NC subjects have better automation of hand movements involved in different handwriting and gesturing tasks (time independent tasks—circles, meanders, spirals) than PD ones. The latter showed less smoothness of movements characterized by the parameters of higher number of peaks & zero line crossings, less degree of automation and higher values of total peak pressures in their hand movement signals. The parameters est1 and est2 are used for the determination of movement automation or consistency. The lower values of these parameters in PD patients show less automation or control in movements' execution. The features indicate strong effects of PD on hand movement tasks. Similarly, for time dependent motion tasks (i.e., finger-taps & hand-wrist), the number of repetition of a task (e.g., number of taps) is lower in PD subjects than that of NC subjects due to the slowness of their motions. For consideration of kinematic handwriting parameters, hierarchical clustering of time series data in combination with DTW based inter-component distance is used to cluster data into two classes (either PD or NC). A number of global features are determined and several local features are calculated by many feature transformation methods where diverse feature normalization procedures are tested in the preprocessing stage. Finally, the selected global and local features are provided separately and independently to support vector machine for automatic classification of PD and NC subjects. The SVM classifier is the best performer when applied on global features obtained from handwriting data. It is genuine to say that pen based techniques are not substitute for a clinical diagnosis or for the assessment of PD motor features, but they may aid the diagnosis and assessments techniques. As two types of movement tasks are presented here: task-dependent—circles, meanders and spirals, or time-dependent—finger-tapping and Diadochokinese. To improve repeatability of the feature extractions and classification methods applicable to all movement patterns registered in this study or in general, otherwise, all movement tasks should be enrolled due to a task-dependence scheme. To improve the reliability of the assessment or to distinguish the stage of PD or ideally for an early diagnosis of the PD, the test subjects need to be personalized. The comparison of NC and PD subjects should be performed according to their age-matched comparisons in the two main groups. Further, the patients under medication and especially those with no active symptoms should be characterized separately for comparisons in future studies.

8 Conclusion and Future Work

8.1 Conclusion

The major aim of this thesis was to design and apply a novel multisensoric smart device (chapter 3) to record and analyze human fine motor features for biometrics (chapter 6) and medical applications (chapter 7). A novel Biometric Smart Pen BiSP has been developed which is a ballpoint pen like device for the online input of the handwriting movements. Different to common tablet-based input devices, BiSP data is sampled exclusively by the pen. BiSP device is equipped with a diversity of sensors and the data is acquired in terms of two refill pressure, finger grip pressure signals as well as signals of inclination-acceleration in three dimensions. The specific sensors implemented in the novel BiSP, especially those of finger grip and inclination sensors, allow it to record hand, fingers, and wrist movement in two modes of operations: (1) on paper pad (on pad) (2) in air (off pad). Due to the sensors involved and the modes of operations proposed, it is possible to monitor the kinematics and dynamics of hand, fingers and wrist not only for the handwriting or drawing movements but also for the movements of the hand gesture tasks. In combination of newly developed data analysis methods, the BiSP system inspires us to multiple applications in—human computer interaction (HCI), biometrics and biomedical diagnostics. To create such a biometric input system, various issues were studied from sensing to signal analysis, from feature extraction to classification and so on.

It is generally agreed that reliable biometric user authentication needs a higher accuracy and quality of biometric data (and/or acquisition) and processing which can be achieved by improved sensing devices and advanced methodologies such as two factor authentication (TFA). In this thesis, a TFA method is designed and evaluated where biometric identifier and knowledge, e.g., biometric handwritten PIN word (or owner) identification is combined with the verification of the biometrically recognized PIN code. This method proved to be less complex and has a low infrastructure because it needs only a single acquisition device for generating the two factors of authentication by using a single biometric modality—handwriting a PIN word. A "further advantage" arises from writing in air, because it requires no solid pad and leaves no visible image of the handwritten PIN word, which can be copied or guessed otherwise. Handwriting in air is called here a "further advantage" because it is not a mandatory condition. The TFA method has shown that a higher level of security is achieved by implementing a multi-factor authentication procedure based on the combination of writer identification and verification of biometrically recognized PIN word code. Experimental results have shown that the designed biometric method has an excellent performance of authentication with a high potential for a further improvement. The score rates of person identification are better 99.9% and the response time can be less than 2 seconds. Hence, the multi-sensor acquisition device BiSP is a promising approach to increase the user's acceptance, level of security and enhance the reliability of biometric person authentication, which is required in the future for access control of social and commercial interactions. In further respects, the proposed method is superior to the state of the art pen based authentication techniques. Because the handwriting, drawing or gesturing in air has almost equal rates of performances like those obtained by writing on pad. This is creating a new dimension of freedom in unconstrained data input and access control especially for more and more downsized mobile units like cellular phones, PDA's, mobile-flash memories, etc. In addition, it needs neither a keyboard nor a touch screen, and gets closer to a paperless work environment.

For the data analysis, dynamic time warping (DTW) technique is applied to multivariate time series data. But classic DTW is slow in computations. To speed up computations and for the efficient processing of the BiSP data, several reduced representations of the time series data have been proposed. A number of efficient data modelling procedures treated as pre-processing of time series data have been suggested. It is found that the proposed RDTW technique applied to down-sampled BiSP data obtained from handwritten PIN words, signatures or just short isolated single characters is well suited to classify between human individuals or handwritten objects. Reproducibility and distinctiveness have been demonstrated for the proposed reduced-univariate time series obtained from multivariate time series data of PIN words, signatures and single characters. Higher or equally comparable scores of recognition obtained for PIN words suggest that handwritten PIN words may be more suitable for person authentication than signatures submitted in a more or less reflex like action. Handwritten PIN words are also suitable in a situation where personal signatures are too simple or too complex to generate distinctiveness or reproducibility respectively. A further benefit found by using PIN words is the security enhancement by involving the two-factor biometric person authentication (TFA) method just described above.

In the thesis work, a new biometric input device was developed (section 6.2). It is actually an enhanced version of the standard WACOM graphic tablet where its pen is additionally equipped with a grip sensor technique typically used in the BiSP device. The enhanced biometric pen system is used for recording and analyzing the handwriting movements on the graphic tablet. For the quantitative evaluation of the enhanced system, a DTW based classifier is applied to the time series data of single and multi-dimensional sensor channels including x, y position and grip pressure signals. The calculated scores of performance of the handwritten PIN recognition indicate that the integration of a finger grip sensor can significantly improve the performance of the handwriting and person recognition. Further, slightly better scores are achieved when private PIN words instead of public ones are used. It suggests that a handwritten private PIN is more suitable for person authentication than a public PIN because it includes more person specific features and object related information required for the discrimination of the writers.

In data analysis, DTW based classification of diverse pre-processed time series data obtained from handwritten PIN words and signatures is done (section 6.3). The pre-processing includes different normalization procedures of length and amplitude of the time series. A new reference level assigned DTW technique for person authentication was also introduced where amplitudes of the time series are shifted by using the person specific bio-reference levels (BRL). Experimental results show that the best results are obtained by using DTW method which includes the time series of equal lengths, amplitude normalization of [-1, 1] or z-score and amplitudes shifted by BRL values. Hence, an enhanced pre-processing procedure leading to highest accuracy of DTW based classifier is proposed which reduces significantly the computational time by heavy dimension reduction of data without rigorous loss in accuracy.

In section 6.4, Area Bound DTW (AB_DTW) technique is proposed for fast and accurate person authentication. A higher level of the data abstraction is achieved by representing time series into a vector of several areas bounded by local segments of consecutive zero line crossings including peaks and valleys. So, the proposed method warps only the areas bounded by the local regions of the sequences. Different experiments are performed in order to evaluate the performance of the classic DTW and proposed AB_DTW methods. The performance is investigated in terms of accuracy and computational complexity. It is found that DTW and AB_DTW techniques used to classify human individuals using a handwritten PIN word have similar high score values (better SR >99.97% and AUC ROC >0.997%). However, with AB_DTW, the computational time is reduced by a significant factor. The most important contribution of the AB_DTW method is the benefit of a very heavy data reduction of a time series into a vector of areas (indirectly determines computation complexity) without a rigorous degradation in the accuracy values.

Section 6.5 presents a simple, low cost, novel tactile and pressure sensitive writing pad for the input of handwritten signatures for biometric person authentication. The writing pad or tactile screen developed can be used in a combination with any ballpoint pen to detect the handwriting by capturing the tactile effects, contact and lift offs, sliding and the pressures of pen-tip on the sensitive writing pad. System and performance evaluation experiments are carried out to study the feasibility of the system and to measure the accuracy of the recognition of handwritten objects like signatures. Due to the preliminary results, the novel system is expected to be an attractive input device for handwriting recognition.

In medical diagnostic (Chapter 7), while using BiSP system, the neuro-motoric features obtained from handwriting, drawing or gesturing movements of relatively simple tasks are analyzed. The tasks such as, drawing circles, spirals and meanders on pad, the circles in air, as well as finger-taps and hand-wrist movements are recorded. In the thesis, the registration and the analysis of such neuro-motoric features obtained from online acquisition of BiSP-data have been studied for diagnostics of the Parkinson's disease (PD). For this, different new trends in the registration of the movement data such as the finger-taps, the hand-wrist movements as well as drawing circles in air have been introduced. The enhanced BiSP device has been used for the recording not only the handwriting and gesturing movements but also finger-hand movement tasks involving diverse special movement patterns.

Experimental results indicate that the drawing or tracing lines of circles, spirals and meanders recorded from PD test subjects are more distorted from the expected figures and are less smooth in comparison to the drawings obtained from Normal control (NC) probands. The PD patients have shown longer reaction and movement times in general. NC subjects have a better automation of hand movements involved in different handwriting and gesturing tasks (time independent tasks—circles, meanders, spirals) than PD ones. The latter showed less smoothness of movements characterized by the parameters of higher number of peaks & zero line crossings, less degree of automation and higher values of total peak pressures in their movement signals. The movement automation or consistency is determined and the PD patients show less automation or control in movements' execution. The features indicate strong effects of PD on the movement tasks. Similarly, for time dependent motion tasks (finger-taps & hand-wrist), the number of repetition of a task (e.g., number of taps) is lower in PD subjects than NC subjects due to the slowness of their motions.

For the automatic classification of the PD and NC subjects, a hierarchical clustering (HC) of the time series data is carried out. In HC method, the DTW based inter-component (person) distances are used to cluster data into two classes (either PD or NC). Furthermore, a number of global features are determined and several local features are calculated by applying many feature transformation methods on the time series data. Diverse feature normalization procedures are tested in the pre-processing stage. Finally, the selected global and local features, separately and independently, are provided to SVM for automatic classification of PD and NC subjects. The SVM classifier is found to be the best performer when applied to global features obtained from handwriting data. It is genuine to say that pen based techniques are not substitute for the clinical diagnosis or for the assessment of PD motor features, but it may aid the diagnosis and assessment techniques.

8.2 Future Work

Other application seen for the BiSP device is the biometric protection of the mobile USB memory stick. For this, the stick is plugged on the USB port of the pen device. The required biometric data is generated during handwriting on a paper pad or free in space. This pen-based technique is expected as a promising alternative for fingerprint to secure a USB stick. We expect a major market due to the booming USB memory stick, the increasing demand of its data security, the high user acceptance as for writing and the enormous popularity of widely used ballpoints pens.

A further objective of our ongoing work is to investigate the feasibility of the configured personal authentication system now applied to the movements of any handheld object using gestures as: biometric signatures, passwords or PINs. It is to understand whether any handheld mobile system like pen, cell phone, etc., can recognize its owner by how the person performs a particular gesture, acting as a “gesture signature”, “password” or “PIN” in air. The gesture in air can be used for obtaining handwritten items or access to the mobile device, but the hand held device could also act as an intelligent key to provide access to services in an ambient intelligent scenario. For these modalities, the object movement resulting from well-defined gesturing patterns has to be captured, analysed and classified using the sensor and software techniques developed for the BiSP system.

The main objective of the future study work is a more critical validation of BiSP-hardware and software with respect to person authentication or handwriting recognition performed under more realistic conditions, e.g., data sampling from a large population of writers at different sessions and times. To cope with the computing time problem in character or person recognition of large population, DTW will be applied in a hierarchical classification scheme: First DTW (or its variant e.g., RDTW or MDTW etc) is applied on heavy down-sampled data providing a fast pre-classification of data among a big population (characters or signatures). In a subsequent step, it follows a more detailed final classification by applying DTW on a small set of low down-sampled data selected by the pre-classification. This procedure is expected to be an effective approach to reduce the computing time without a pronounced degradation of performance. Further speed up methods in DTW as described in the literature needs to be involved. Excellent performance is achieved if each writer uses handwritten PIN words on pad or in air for person authentication. It indicates that it may not necessary to use the private “signature” for online person authentication especially in a situation where private signatures are too complex or too simpler. So, there is a potential in future study work, if a person uses the short handwritten single characters or the hand gesture or likewise PIN words on pad or free in air or otherwise easy-to-write and frequently used words, e.g., something like “good morning”, or “hello sunshine” etc., handwritten on paper pad for authentications.

In multimodal biometrics, multiple biometric traits are acquired from the user therefore, naturally it is more complex to acquire multiple enrolments of different biometric traits. A TFA method is proposed that only uses the single acquisition device (BiSP) for multi-level authentication. Unlike handwritten signatures where you need a fresh enrolment in the database for your new signature, the proposed method can choose a new handwritten PIN word without a fresh “enrolment” session. Hence, a change in the handwritten PIN does not require a new data acquisition to store in the database. The idea of the proposal is the following: in the testing stage, the separated single characters of a new handwritten PIN can be matched with the segments (characters) of the previously enrolled PIN provided by the same writer. Consequently, the sequence of the characters of his private PIN word is changed only at anytime resulting in user’s new PIN which can be used for verification work. For example, the signals of the enrolled PIN word (EMBA%37), new PIN word (E37BM%A) and its segmented single characters provided by the same writer are shown in the Figure 8.1.

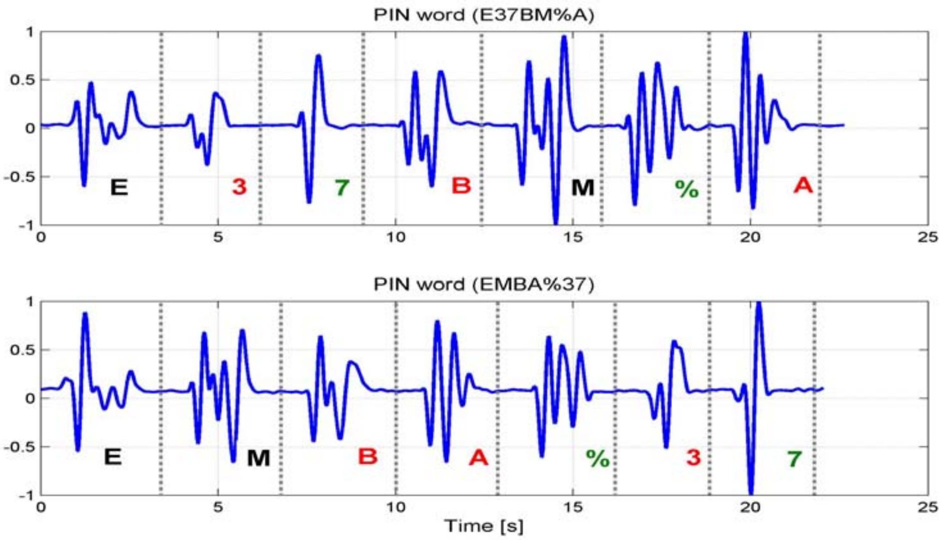


Figure 8.1: An illustration of an enrolled PIN (E37BM%A) and a new PIN (EMBA%37) with their segmented signals obtained from the same writer.

The proposed method is inspiring us to a possible future research which provides the user a freedom of changing his PIN at anytime during the verification stage for person authentication. Instead of x-y position coordinates obtained from handwriting, the BiSP systems developed in this thesis, evaluate the pressure and inclination-acceleration profiles of handwriting for person authentication. Such profiles of handwritten sequence (e.g., PIN word or signature) are expected to be invisible to the forger to copy. An enhanced pen system is already used to compare the performance of the sensor channels including the x, y position and grip pressure signals for handwritten PIN recognition. The results indicate that the integration of a finger grip sensor in a WACOM graphic tablet system can significantly improve the performance of handwriting and person recognition. This may also apply for the graphic design and biomedical investigation because a finger grip pressure sensor gives excellent information about the fine motor skills of the fingers as a time function of pressure changes during handwriting movements.

In addition, for future study the idea of the proposal is to implement position and displacement sensor based on ultrasonic or magnetic techniques in BiSP. Preliminary work has shown well suitability of such position sensing of pen tip movement for handwriting and gesture recognition in air [1].

Future direction of the study work is to analyze handwriting data for evaluation and comparison of the pen-refill pressure and pen-position profiles for person authentication. For this, the same BiSP device, writers and handwritten objects should be used for data collections. Hence, an integration of a location sensor in the future BiSP would open up new possibilities to use or extend state of the art feature extraction and classification methods for BiSP data.

For efficient processing of BiSP data, several reduced representations of the time series data such as piecewise area approximation, reduced univariate approximation, area bound approximation, bio-reference level assigned approximation etc have been proposed. Such time series data approximations can be used in other domains of time series data analysis. Moreover, SAX (Symbolic Aggregate Approximation) of time series is one of the popular symbolic representation techniques. Two extended SAX based techniques are suggested (section 5.10). A great similarity between PAA and proposed PArA is shown and further improvements are suggested. Therefore, it is expecting that the extended SAX techniques can be applied as future work to analyze BiSP data by adopting ideas, definitions, algorithms and data structures commonly used in the bioinformatics domain.

As in medical application, the movement tasks were recorded due to task-dependent or time-dependent schemes. To improve repeatability of the feature extractions and the classification methods, all movement tasks should be enrolled due to a task-dependent procedure. To improve reliability of the assessment or to distinguish the stage of PD, or ideally for an early diagnosis of the disease, the test probands need to be personalized. Therefore, the features of an individual may be analyzed to study the individual disease history and its effects on the features for a long time. The comparison of NC and PD subjects should be performed according to their age-matched comparisons of the two main groups. Further, the patients under medication and especially those with no active symptoms should be evaluated differently for comparisons in the future studies. Using BiSP system, it is required to study neuro-motor dysfunctions in a large group of people. It is required to correlate BiSP results with the medical indicators.

We can see another application to detect or predict the effects of medication. As only a few PD patients are misclassified into the NC's group due to their medications representing them in the most controlled health condition. This may also lead to see a proper drug dosage resulting in the desired effects of medication.

The methods described for automatic classification of PD patients among the NC subjects may be applied to confirm PD. It may detect a writer with a high risk of the disease due to his high scores of features-match with the features of the PD patients. Hence, it may lead to an early diagnosis of the disease or a proper medication.

BiSP system can also be utilized for the classification and quantification of hand-motor dysfunctions and the analysis of fine motor movements of patients under drug treatment or medication.

Currently we are improving the BiSP system to make it more practical for diverse applications not only in biometrics, computer-human interaction but also in health care and robotics just to name a few. Ongoing clinical field tests, which are focused on Parkinson disease, encourage us to develop a non-invasive instrument for objective low cost patient monitoring and medication control preferably applied in the homecare and tele-medicine area.

9 Appendix

9.1 GUI Programs for BiSP Data Analysis

MATLAB based graphical user interface (GUI) programs have been developed for BiSP data analysis. A brief overview of these programs is given here.

- **Single File Viewer (SFV)**

It is a BiSP data viewer program. One can see graphs of all channels of the file selected from the list box.

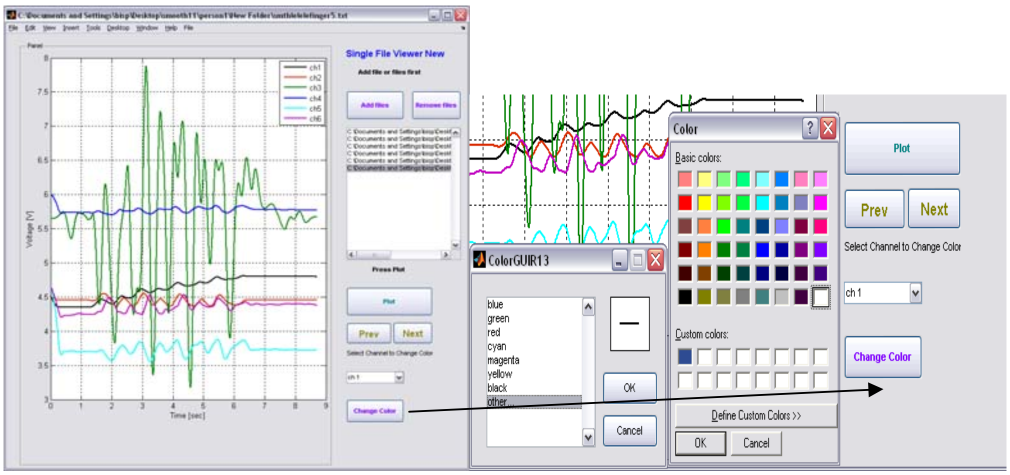


Figure 9.1: A snapshot of Single File Viewer program.

Procedure of SFV:

1. load file(s) into the list box with the help of add files pushbutton
2. More files can also be loaded by repeating step 1.
3. One can remove file(s) from the list box by using "**Remove files**" pushbutton
4. Select one file from the list box.
5. Push "**Plot"** button to see the graphs (signals).
6. Repeat 4 and 5 to see the graphs of a different file
7. Use "**Next**" and "**Prev**" pushbuttons to see the graphs of next or previous file automatically selected from the list box.
8. Select channel 1 through 6 to change the color by pressing "**Change Color**".

- **Single File Viewer with Channel(s) Option**

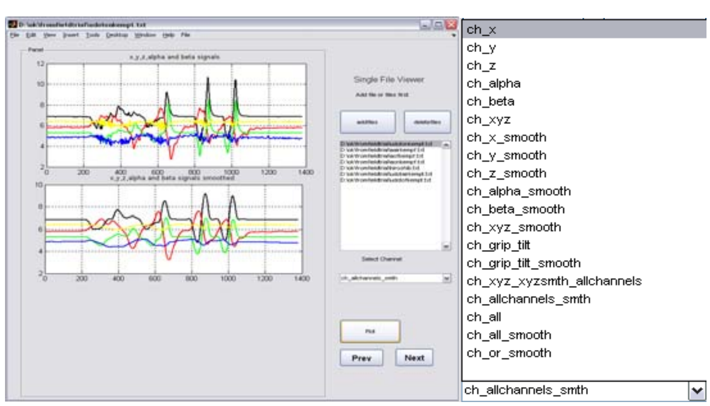


Figure 9.2: Single File Viewer shows all channels for (i) original data (ii) smoothed data.

In this viewer program, one can select any channel(s) of the file selected from the list box to see the graphs of: (i) original data (ii) smoothed data in one screen shot as shown in the Figure 9.2. The procedure of file selection is same as that of SVF program. Additional feature provided in the program is the selection of channel(s) from the popup menu (default is channel x)

- **BiSP M Program to Smooth and/or Delete Channel(s)**

The program M is used to delete and/or smooth the channel (s) of BiSP data as shown in Figure 9.3.

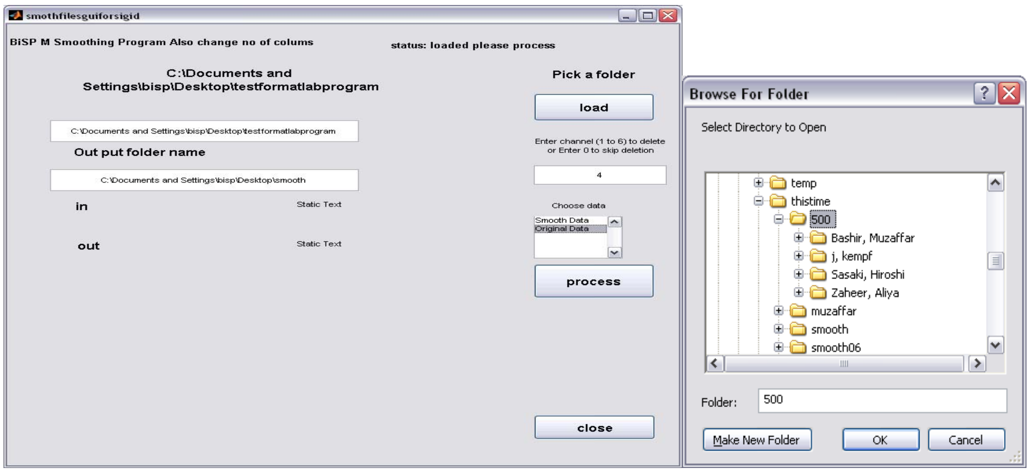


Figure 9.3: The screen short of the program used to smooth and/or delete channel(s)

Here, two edit text boxes are used to show input/output file names.
The program uses three pushbuttons

1. load
2. process
3. close

Press load to pick up the folder containing data, and then select the channel and data format (i.e., smooth data or original data). The “process” button processes the data accordingly. The fields **in** and **out** are used to show the full file names while the smoothing of data or/and deleting of any one of the channels is in progress.
The field “status” shows status “in process” while data is being processed and program is running, otherwise it shows status “process complete”.
The user can select suitable output folder name for the data. The program will automatically create folder name if the provided output folder name does not exist. An edit text box is provided to input channel numbers (1 through 6 only) to delete one or input zero to skip channel deletion process.

- **Biometric Character Recognition (BCR) Tool**

BCR Tool provides a graphical user interface for biometric character recognition as shown in the Figure 9.4. The folder “BCR” is the data folder containing the writers including the handwritten objects. For intra-individual BCR tasks, the recognition of a person specified by a given number can be done by entering person number (e.g. person No.1 is first writer in BCR folder). One can input the number of references (e.g. 1 to 10) in the edit text field. In order to speed up computations of DTW algorithm, data is down sampled by providing a value of “Decimation M” in the edit text field. In order to eliminate potential sensor noise, “Smoother” field is made available for smoothing of data. The default value is 0.022. After parameter setting, "load Refs" pushbutton is used to load the desired reference samples into the BCR Tool. As a next step, a query sample (often from the same reference object) is selected from already populated list box. The procedure for recognition is as follows:

1. Select channel(s)
2. load reference samples
3. load query file(s) into the list box with the help of "**Add files**" pushbutton
4. Perform the match of a query sample with the set of reference samples by using "**recognize**" pushbutton.
5. "**Prev** or **Next**" pushbuttons can be used to see the match results for previous or next query sample automatically selected from the list box

The recognition results are presented in table format as shown in the Figure 9.4, where the first column shows the list of closest matched (recognized) objects with their object IDs. The second column is the serial number. The third column shows distance values provided by DTW-match between an object shown in the first column and a given query sample. The fourth column shows the object ID of reference data. As shown in the Figure 9.4, the object "B" is assigned an ID of 2 denoted by "2 B". Select only one file in list box for recognition tasks. A pushbutton "**extra setting**" is provided to load only the selected objects (characters) for the reference list. A pushbutton "**Complete test**" is provided to investigate the recognition performance of all handwritten single characters (intra-individual) provided by a writer.

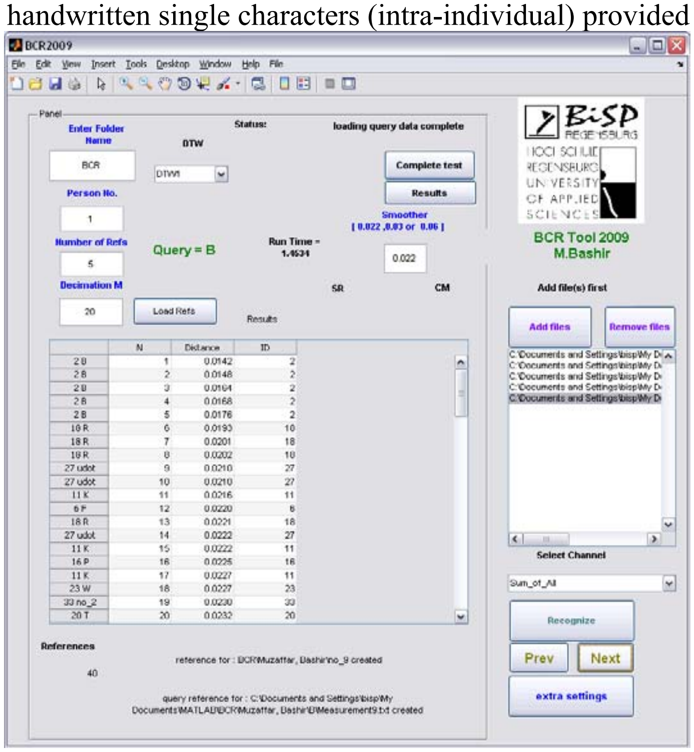


Figure 9.4: The screen shot of (Biometric character recognition) BCR tool

- **Biometric Person Recognition BPR Tool**

BPR Tool is developed that provides a graphical user interface for biometric person recognition. The use of the tool is similar to that of BCR tool with the difference of the fact that the objects—characters in BCR should be replaced by the signatures or PIN words of the owners (e.g., a writer with his private signature) in BPR tool.

A pushbutton "extra setting" provided in BPR is to load only the selected writers into the reference list. A pushbutton "Complete test" is used to investigate the recognition test for all writers (inter-individual) by using handwritten PIN words or signatures.

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9.3 Contribution to Conferences and Journals

Conferences:

- **Muzaffar Bashir** and Jürgen Kempf, "Person authentication with RDTW using handwritten PIN and signature with a novel biometric smart pen device. In SSCI Computational Intelligence in Biometrics, **IEEE**, **Nashville, USA**, **2009**.

- **Muzaffar Bashir** and Jürgen Kempf, "Bio-inspired reference level assigned DTW for person identification using handwritten signatures". In BioID_MultiComm2009 Madrid, Spain, LNCS 5707; pp. 208-214, **Springer-Verlag 2009**.
- **Muzaffar Bashir**, Jürgen Kempf et al, "Online person authentication using dynamic signature on a novel tactile and pressure sensitive pad". In 17th Telecommunication forum, TELFOR Belgrade, **Serbia** (**2009**)
- **Muzaffar Bashir** and Jürgen Kempf, "Reduced dynamic time warping for handwriting recognition based on multi-dimensional time series of a novel pen device". World Academy of Science, Engineering and Technology, 45, **Paris** (**2008**).

Journals:

- **Muzaffar Bashir** and Jürgen Kempf, "DTW based classification of diverse pre-processed time series obtained from handwritten PIN words and signatures". In Journal of Signal Processing Systems, **Springer** (**2010**). DOI 10.1007/s11265-010-0501-x
- **Muzaffar Bashir** and Jürgen Kempf, "Reduced dynamic time warping for handwriting recognition based on multi-dimensional time series of a novel pen device". In Inter. Journal of Intelligent Systems and Technologies, 3.4, Paris (**2008**).
- **Muzaffar Bashir**, Florian Kempf, "Advanced Biometric Pen System for Recording and Analyzing Handwriting" In Journal of Signal Processing Systems, **Springer** (**2011**).
- **Muzaffar Bashir**, Jürgen Kempf, "Area Bound Dynamic Time Warping Based Fast Person Authentication with a Biometric Pen". **Submitted**.
- **Muzaffar Bashir**, Florian Kempf, "Two Factor Person Authentication by Handwriting in Air using the Biometric Smart Pen Device" **Submitted**.
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Erklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit selbständig angefertigt und keine anderen Hilfsmittel außer den angegebenen verwendet habe.

Regenburg, den 10.12.2010___________________________