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A Biometrics-embedded System Based on Haptics for User Authentication in Virtual Environments

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A Biometrics System based on Haptics for User Authentication in Virtual Environments

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Thesis submitted to the
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Abstract

Haptics is the discipline that deals with the study of the complex sense of touch as an interface between human beings and machines. Consequently, haptic technology facilitates the exploration of and the interaction with the virtual world through touch. This can be done by utilizing special electro-mechanical interface devices equipped with specialized sensors. Haptic technology is being applied in many fields, such as scientific visualization, surgical procedures, education and arts.

This research investigates the issues related to the usage of haptics as a mechanism to extract behavioral features that characterize a biometric identifier system. In order to test this possibility, we designed a haptic-biometric system in which, position, velocity, force, angular orientation of the end-effector and torque data, among other attributes extracted from given haptic interfaces, are continuously measured and stored as users perform a specific task. We first proved the applicability of the haptic technology to analyze the characteristics of human hand movement patterns while users are interacting with a particular haptic device. Then, we analyzed the information content of the haptic data generated directly from the haptic interface in order to select those of the greatest user-classificatory worth. For example, the physical attributes, such as force, angular orientation of the end-effector as well as torque are presumed to provide valuable information content pertaining to a user's unique behavior when he/she interacts with haptics in a Virtual Environment (VE). To analyze the information content, a new

concept called entropic signature has been introduced, which characterizes both the way in which an individual is unique, and the magnitude of that uniqueness when using haptics in VE. Consequently, through a series of experimental works, which were based on the entropic signature approach, it was shown the suitability of haptics for authentication based on behavioral haptic biometrics.

Moreover, we provided evidence that our proposed haptic-based biometric system is best suited in biometrics' verification mode rather than in biometric identification. In addition, we conducted further testing in order to discover individual's abilities and to evaluate their psychomotor patterns through selected tasks under different conditions such as stress, repeatability and concentration. Finally, an important and novel advantage of this research versus current authentication modes (biometrics and non- biometrics) is the fact that the authentication mode can be carried out at any given moment during the multimodal human-computer interaction process.

Acknowledgments

First and foremost I would like to thank my supervisor, Dr.Abdulmotaleb El-Saddik, without whom none of this would have been possible. Not only am I thankful to him for his academic insights and guidance that have helped make my time as a research student extremely enjoyable and productive, but I am also indebted to him for his kindness and belief in my abilities. It has been a privilege to work with him. In addition, I would like to thank my co-supervisor Dr. WonSook-Lee. Dr. N.G. Georganas for allowing me to work in such a nice environment (Discover lab), Dr. S. Shirmohammandi for collaborating in part of my research as well as Dr. A. Adler.

I would like thank my wonderful mother Angelica and father Roberto for giving me theses precious gifts, my life and their love.

Ximena and Valeria, watching you grow up has gifted me with understanding that my life has been brought together for a reason. This thesis is dedicated to you. Maria your love has fostered my spiritual growth; your encouragement and tremendous support have also help to finish this cycle on my life.

I am extremely grateful to Dr. Rosa Iglesias initially for taking an interest in my work, and having the initiative to assume a guidance role, and helping me to submit this thesis. I would like to thank her for being a good friend who has understood and put up with my black sense of humor. I have lost count of the number bad jokes that I owe her. A great friend who one can hang around with and count on, that is, an important ingredient for anyone undertaking a PhD.

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Last, but not least, I would like to thank Yednek Asfaw as well as the COOP's students Alfred Luu, Shaun Pierce and Mathew Graydon at the University of Ottawa for their contributions to this thesis with the writing of good pieces of programming code, research and development contributions.

Contents

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List of Acronyms

Following the definition of acronyms that might have been used in the thesis are described:

AHF: Adaptive Haptic Framework

ANN: Artificial Neural Network

API: Application Programming Interface

CAD/CAM: Computer-Assisted Design/ Computer-Assisted Manufacturing

CDE: Classifier Decision Evaluation

CNS: Central Nervous System

CV: Coefficient of Variance

DAOF: Data Access Object Factory

DFT: Discrete Fourier Transform

DoF: Degrees of freedom

DSV: Dynamic Signature Verification

DTW: Dynamic Time Warping

EER: Equal Error Rate

FAR: False Acceptance Rate

FGS: Feature Generation/Selection

FRR: False Rejection Rate

FFT: Fast Fourier Transform

GP: Graphical Password

GUI: Graphical User Interface

HaBiTs: Haptic-Biometrics auThentication System

HIP: Haptic Interface Point

HDR: Haptic Data Repository

HMM: Hidden Markov Model

HSG: Haptic Scene Graph

HSV: Hand Signature Verification

KL: Kullback-Leibler Algorithm/Divergence Distance

MS: Matching Score

MVC: Model-View-Controller

OFS: Observable Feature Space

PCA: Principal Component Analysis

PHANToM: Personal Haptic Interface Mechanism

PV: Probability of Verification

RD: Relative Dispersion

RMS: Root Mean Square

ROC: Receiver Operating Curve

SPP: Signal Processing Process

SPS: Signal Processing System

UML: Unified Modeling Language

VE: Virtual Environment

VHT: Virtual Hand Toolkit

VR: Virtual Reality

Conventions

Throughout this thesis work the typographic convention selects italic to indicate terms, concepts, phrases or variables. Bold is used in code samples to highlight classes or methods. Text describing classes and methods appears as shown: **HapticApp**. In addition the term *CyberGrasp* unit is used to refer explicitly to the hand-unit (grasped object) which is integrated by three pieces of hardware (the CyberGlove, the CyberGrasp, and the CyberForce) from the Immersion Corporation [ImmTec_A]

Chapter 1

Introduction

Humans have five major senses, which operate to gather information from the world around us; sight, hearing, smell, taste, and touch. They provide sensory input when reacting to stimuli by transmitting an action potential sent to the Central Nervous System (CNS). The sense of touch is found all over the body unlike the others four senses, which are located in specific parts of the body: however, this concept is mainly associated with active tactile senses like our hands. These senses can be categorized in several ways and they form a link to the kinesthetic[1] senses.

Humans are very sensitive to touch, but different parts of our body have different sensitivities. The skin of our fingertips is considered as one of the most touch-sensitive skin of our body. The skin is an interface that centrally discriminates four modalities of sensation, namely touch (including both light touch and pressure), cold, heat and pain. To explain what is happening on the surface of our body during a touch stimulus; it is known that the skin and deeper tissues contain millions of sensory receptors. Without them, a human would not be able to sense and respond to the environment. In general, people interact with the environment by using different devices, such as checking e-mail messages via the computer, driving a car with the steering wheel, pedals and gear, or having a conversation through mobile phones. These devices have become a part of our daily environment. In such a perspective, it is very probable that almost everybody has a

[1]Kinaesthetic adj. Kinaesthesia: awareness of the position and movement of the parts of the body by means of sensory organs (proprioceptors) in the muscles and joints. Concise Oxford Dictionary-Tenth Edition Oxford University Press

unique way of driving a car or typing a message using a keyboard. Such automatically performed activities characterize an individual's behavioral trait. The measurement of such human psychomotor patterns can be used to verify a person's identity by assessing unique-to-the-individual behavioral attributes. In this sense the discipline that explores the possibility of using such measurements for authentication purposed is referred to as Biometrics as Wayman stated: "*The automatic identification or identity verification of an individual is based on physiological and behavioral characteristics*" [Wayman_00]. In this case we recall that the main feature of biometrics authentication is based on an inherent physical or behavioral trait or a characteristic, which is difficult to fabricate.

Seventy percent (70%) of the biometrics market and industry leaders' work are related to fingerprints, face recognition patterns, and hand geometry, leaving the remaining (30%) of work dedicated to voice, iris, signature recognition, and middleware and multi-biometrics fields[IBG_A]. Therefore the biometric technology is playing an important role in developing a system that gathers different parameters such as intrusiveness, cost, distinctiveness and, effort in the same package. At the present time, fingerprint technology can be found in notebook computers to authenticate individuals based on the physical attributes of their fingertips [Germain_04] [STMicro_01].

The computer technology such as faster processors, advanced graphic cards, and multimedia systems are becoming more affordable with the rapid advancement of the technological revolution. Therefore the above-mentioned daily life environments can be simulated as computer-generated imagery. In general, Virtual Environments (VEs) have exploited the visual and hearing senses. Meanwhile, the technology of haptics has been building a theory that relates the human perception and computer technology through software and hardware components. Consequently, the haptic technology is a force/tactile feedback machinery that is growing in the disciplines linked to human-computer interaction. Haptics is applicable across nearly all areas of computing including video games, medical training, scientific visualization, CAD/CAM, computer animation, engineering design and analysis, architectural layout, virtual toys, remote vehicle and robot control, automotive design, art, medical rehabilitation, interfaces for the blind, and authentication among others.

The haptic technology market and development is expanding very fast and reaching almost all customer levels. For example, Novint Technologies, Inc. is developing a haptic device, named Falcon that will be available worldwide soon in 2007, for under $190 USD [Novint_A]. Its features are similar to commercially available devices, which allow users to feel weight, texture, shape, dimension, dynamics, 3D (three-dimensional) motion and force effects. Today, the PHANToM Omni haptic device is the most cost-effective one available with its portable design and ease-of-use features [SenTec_A].

As an interface between human and computer, haptics can be used to capture the human-haptic system movements performed during a particular task-interaction. Those human psychomotor movements can be used to categorize a behavioral path which can be used for authentication purposes. Haptic devices enable the characterization of personalized user-specific physical and biological parameters. These parameters are, similar to those that have been deployed in human interaction with equipment such as signature pads, keyboard buttons, and telephone buttons. When using user-haptic-based interactions, parameters, such as measurements of the force exerted, end-effector device position, and its velocity can be obtained. With the measurements of these parameters, this thesis investigates the possibility of identifying a user with a rigorous level of precision. The quantification and measurement methodology described in this study provides an opportunity for the evaluation of haptics as a suitable and compelling mechanism to be implemented in a biometric system. Applications of such a system are vast, and range from national security applications to access control.

1.1 Motivation

The primary motivation for this work is the development of an architecture that models and tracks human hand psychomotor movements to be used mainly in biometrics, but such a concept could be extended to many other applications, such as rehabilitation and gaming performance. The novel idea can be conceived as mapping or triggering the human-machine interaction into VEs with the addition of haptic stimuli to generate a pattern. In computing, the interaction of humans with haptic devices is implemented through a bidirectional exchange of energy to represent real situations in a simulated world. The interaction spectrum can contain different types of touch sensations that a user can receive and apply force feedback, tactile feedback, and proprioception (or kinesthesia). Based on these interactions, this thesis study develops a fundamental assumption that there are natural differences between the psychomotor patterns exhibited by individuals in virtual domains when using haptic devices. Such an assumption emerges from the analogue principle which assumes that it is very probable that almost everybody has a unique way of writing a note or typing a message. These studies were inspired from literature which addressed key stroke dynamics and dynamic signature verification [Nalwa_97] [Plamondon et al_00] [Qu et al_03] [Vielhauer et al_02]. It is believed that additional disciplines such as haptic perception, haptic illusion and neuroscience could play an important role in the construction of such patterns. In this domain, we can judge how different people interact with a computer by using of a haptic device to carry out tasks that are normally performed via a computer mouse or keyboard to display uniqueness of behavior. Therefore, with the captured data from users' interactions the nature of the uniqueness of behavior can be judged. Finally, we were also concerned about information security systems issues. A haptic-biometric based framework was designed and tested that does not only authenticate an individual but can also verify the authenticity of the user at any moment during a haptic-visual interaction session.

1.2 Research Aims

The general goal for a haptic-biometric based framework is to have the ability to capture, analyze and identify the human hands movement patterns in a stable state that can be used as biometric identifiers. The approach needs to consider the type of haptic interaction as well as the haptic domain, in terms of available hardware and software technologies.

More importantly, it is necessary to take advantage of the haptic interface output of physical measurements in order to capture the dynamic behavior of users while interacting in a VE.

1.2.1 Thesis Statement

A haptic-biometric based framework can be used to verify the authenticity of user working in an environment assisted with haptic devices. The system uses the physical attributes captured for the haptic interface to create a user pattern. Such a pattern can be used for authentication purposes in real-time and at any time. This defined pattern cannot be handled in such a manner by traditional methods such as keyboard, id-cards, finger prints or, digital tables.

1.2.2 Challenges and Requirements

To defend this statement, the thesis will attempt to answer the following research questions:

1. Do haptic devices provide us with a proper mechanism to authenticate individuals?
2. To what extent, are the capabilities of single point-based devices enough for biometric purposes? Or is the use of multi-point haptic based devices needed?
3. Are all physical parameters captured from haptic devices meaningful in order to build a generic pattern to describe human haptic system movements?
4. Which physical attributes captured during haptic-based interactions are important in information content for classification purposes?

In order to answer such questions it is necessary to follow a scientific methodology. This thesis investigates whether the specific quantitative performance associated to a particular haptic device for different classes (e.g. desktop devices, hand exoskeletons devices), say class A, class B, lies significantly in an acceptable range to be considered as a biometric identifier system. To give an answer to the first question this thesis work formulates the problem in the context of statistical hypothesis testing. That is, this work discriminates which of the following hypotheses are correct:

H_1: The quantitative performance of a specific haptic device lies significantly in acceptable range to be considered as a biometric identifier system

H_0: The quantitative performance of a specific haptic device does not lie significantly in an acceptable range to be considered as a biometric identifier system

In this domain H_0 is known as the null hypothesis and H_1 as the alternative hypothesis. The decision is reached based on experimental evidence supporting the rejection or acceptance of H_0.

Therefore, the fundamental goal of this thesis is to provide the proper experimental evidence to validate the research questions. This thesis proposes an approach to generate the reference needed for different situations. In that way, the questions proposed can be answered.

In the sequel, this thesis work gives a number of statistics indices appropriate to make a decision and to consider the haptic technology as a means to build a biometric system.

In practical terms of the problem can be divided into several sub-problems, each of them posing specific challenges and requirements:

- *Feasibility of using haptic devices as a biometric identifier*: This study is appropriated to identify the potential of haptic interfaces as an input device in a biometric system. Haptics desktop devices such as the Phantom haptic device which provides a single point-interaction, is evaluated. Furthermore, more robust devices (Hand exoskeleton devices through which users can grasp and hold virtual objects) need to be studied. The CyberGrasp System is used for this study [ImmTec_A].

- *Designing Haptic-Based Applications*. An important issue is the creation of a set of haptic-based applications, to achieve it, the capabilities and limitations of the haptic technology in terms of haptic interaction have been analyzed. In addition, the application features need to be considered when designing a task in order to capture the human-machine interaction from different conditions, for instance the mental interference when solving a maze or handwriting a signature in a 3D world.

- *Handling the Haptic Data Source.* The haptic data information recorded and generated from the user interaction is very demanding in terms of memory capacity. When designing a haptic based system, the key is to have an efficient storage, pre-processing and updating system to manage the information.
- *Pattern Recognition Algorithms.* In this context this work validates the previous assumptions under different pattern recognition methodologies .Verifying the authenticity of an individual is a classification problem that can be addressed by following the pattern recognition theory. Among a great variety of methods and algorithms, from the classification point of view, we have selected and combined the ones that compensate the overall performance in terms of accuracy.
- *Analyzing the Haptic Information Content.* The precision of any haptic-biometric systems relies on the choice of the biometric identifiers. For accurate identity recognition, identifiers must be chosen so that they are unique to each individual. To measure the uniqueness of the identifiers, we calculate the relative entropy of the biometric feature distributions generated by different users with respect to the population distribution. Such a measure reveals the information content of each user-haptic interaction feature.

1.3 Thesis Overview

This thesis is organized into seven chapters. **Chapter 1** provides the introduction and presents the motivations and background for this work, as well as a list of the major contributions.

Chapter 2 describes a comprehensive study about the haptic technology, background, principles of operation and current commercial and developing interfaces. The potential applications of this novel technology will also be explored for its use in alternately manipulating and exploring virtual objects. In addition, a brief survey is provided to describe the research and commercial products about haptic interfaces focused only on arm, hand exoskeletons or desktop devices.

Chapter 3 discusses the details involved with the acquisition methods that are related to behavioral biometric methods, such as dynamic signature verification and keystroke dynamics. Additionally, the state of the art related to these topics is provided as well as the relationship of current technologies used compared with the haptic technology.

Chapter 4 describes the details of the envisioned idea materialized on a biometric-haptic architecture. All the components and systems that integrate this architecture are designed to create a platform based on an intelligent, extendible and adaptive approach for the interaction between the human being and the digital information technology through the usage of haptic interfaces.

Chapter 5 reports about the analysis and classification methodologies used on two types of force feedback haptic devices. The information captured as output information from a haptic device is processed with either parametric or function-based feature extraction techniques to assess the biometric system evaluation.

Chapter 6 evaluates the use of the relative entropy as a pseudo-metric for extracting unique-to-the-individual parameters and for describing patterns exhibited by users in the virtual domain.

Chapter 7 draws the conclusions reached and offers suggestions for future work.

1.4 Contributions

The major contributions of this thesis are:

- ✓ First ever work in haptic-based biometrics
- ✓ Design and development of a procedure for combining the haptic technology to discriminate human hand psychomotor patterns which can be used for authentication purposes.
- ✓ Analysis and definition of certain features to be used as biometric identifiers in the context of haptic device capabilities and human interaction.
- ✓ Design and development of algorithms for performing feature-based exploration and determining those which provide the richest content and help us to acquire the uniqueness of each individual for further analysis.
- ✓ Design and development of algorithms for providing the guidelines to authenticate an individual. These algorithms allow not only to gain access to the system but also to continuously verify authenticity during the whole session of the haptic interaction.

1.5 Publications

The following papers have been published as a result of this research:

Papers in refereed Journals

- M. Eid, M. Orozco and A. El Saddik, "A Guided Tour in Haptic Audio Visual Environment and Applications", *International Journal of Advanced Media and Communication*, Vol.1 (3), 2007.
- A. El Saddik, M. Orozco, Y. Asfaw, S. Shirmohammadi and A. Adler, "A Novel Biometric System for Identification and Verification of Haptic Users", *IEEE Transactions on Instrumentation and Measurement*, vol.56 (3), pp. 895-906, June 2007.
- M. Orozco, M. Graydon, S. Shirmohammadi, and A. El Saddik, "Experiments in Haptic-Based Authentication of Humans", *Journal of Multimedia Tools and Applications*, Ed. Springer, Published online September 27 2007.

Papers in refereed Conferences

- M. Graydon, M. Orozco, S. Shirmohammadi and A. El Saddik, "Using Haptic Interfaces for User Verification in Virtual Environments", in *Proceedings of the 2006 IEEE International Conference on Virtual Environments, Human-Computer Interfaces, and Measurement Systems*, Spain, July 2006, pp.25-30.
- I. Shakra, M. Orozco, A. El Saddik, S. Shirmohammadi and E. Lemaire, "VR-Based Hand Rehabilitation Using a Haptic-Based Framework", in *Proceedings of the 2006 IEEE Instrumentation and Measurement Technology Conference (IMTC/06)*, Sorrento, Italy, 24 - 27 April 2006.

- I. Shakra, M. Orozco, A. El Saddik, S. Shirmohammadi, E. Lemaire, "Haptic Instrumentation for Physical Rehabilitation of Stroke Patients", in *Proceedings of the 2006 IEEE International Workshop on Medical Measurement and Applications*, Benevento, Italy 20 - 21 April 2006, pp.98-102.
- M. Orozco, Y. Asfaw, S. Shirmohammadi, A. Adler, and A. El Saddik, "Haptic-Based Biometrics: A Feasibility Study", in *Proceedings of the IEEE Virtual Reality (VR) 2006*, March 25-29, Alexandria, Virginia, USA, 2006,pp. 265 - 271.
- Y. Asfaw, M. Orozco, S. Shirmohammadi, A. El Saddik, A.Adler, "Participant Identification in Haptic systems using HMMs", in *Proceedings of the fourth IEEE International Workshop on Haptic Virtual Environments and their Applications (HAVE2005)*, 1-2 Oct.2005, pp. 127 -132.
- M. Orozco and A El Saddik, "Haptic: The New Biometrics-embedded Media to Recognizing and Quantifying Human Patterns", in *Proceedings of 13th Annual ACM International Conference on Multimedia (ACM-MM 2005)*, Singapore, November 06-12, 2005.
- M. Orozco , I. Shakra and A. El Saddik, "Adaptive Haptic Framework", in *Proceedings of the IEEE International Conference on Virtual Environments, Human-Computer Interfaces, and Measurement Systems*, Giardini Naxos, Italy, 18-20 July 2005, 5pp.
- M. Orozco and A. El Saddik, "Signature Identification with Haptic devices", in Proceedings of the IEEE International Conference on Virtual Environments, Human-Computer Interfaces, and Measurement Systems, Giardini Naxos, Italy, 18-20 July 2005.

- M. Orozco, Y. Asfaw, A. Adler, S. Shirmohammadi, and A. El Saddik, "Automatic Identification of Participants in Haptic Systems", in *Proceedings of the IEEE Instrumentation and Measurement Technology Conference (IMTC/05)*, Ottawa, Ontario, Canada, 17-19 May 2005, pp.888-892.

Chapter 2

Haptics

2.1 Introduction

Haptics is related to the study of touch and the cutaneous senses. The word "haptic" derives from the Greek haptesthai, meaning "able to touch". This word was introduced at the beginning of the 20th century by the research work in the field of experimental psychology. However, in the late eighties, the term was redefined to enlarge its scope to include all aspects of machine touch and human-machine touch interaction. The 'touch' of objects could be made by humans, machines, or a combination of both; and the environment can be real, virtual, or a combination of both. Currently, the haptic term has become closely related with many disciplines, including biomechanics, psychology, neurophysiology, engineering, and computer science with the important aim of contributing to the study of human touch and interaction with the external environment. This concept is mainly associated with active tactile senses, like those of our hands. These senses not only involve sensation and perception but also motor and cognitive aspects of active movement. Active movement can be for example self-initiated movement which describes a detailed motor plan that is stored in our memory and it is also compared to the receptor feedback from the muscles, joints and skin [Halle&Stanney_04].

By using special input/output devices such as joysticks or data gloves, etc., users can receive feedback from computer applications in the form of sensations in their hand or other parts of the body [ImmTec_A]. The route of development of haptics has been traced by several research disciplines in terms of theoretical basis and technological applications. Firstly, psychophysical experiments have provided the contextual clues involved in the haptic perception between the human and the machine. Psychophysical studies of touch started with the work of Ernst Heinrich Weber in the eighteenth century. His work is considered the foundation of experimental psychology [Prytherch & McLundie_02].On the other hand, the areas of tele-operation and tele-presence started in the early 1950s, providing the practical flavor of this emerging technology. Currently, computer technology has taken the lead in impulse haptics and has related it to the virtual world by improving an operator's task and by enhancing a user's sense of telepresence [Tan_00]. The haptic research has been focused on designing and evaluating several prototypes with different characteristics and capabilities for the use in VEs. Recently, some of these prototypes have become commercially available to the market. Applications of this technology have been spreading rapidly from devices applied to graphical user interfaces (GUI's), games, multimedia publishing, scientific discovery and visualization, arts and creation, editing sound and images, the vehicle industry, engineering, manufacturing, tele-robotics and tele-operations, education and training, as well as medical simulation and rehabilitation.

2.2 Haptic Systems

As mentioned before, haptic systems increasingly involve multidisciplinary research disciplines that can be categorized into three sub-areas: (1) human haptics, (2) machine haptics and (3) computer haptics[Srinivasan & Basdogan_97], and currently this taxonomy has been extended by Eid et al [Eid et al_07]to include (4) multimedia haptics (see Figure 1). Human haptics refers to the study of human sensing and manipulation through tactile and kinesthetic sensations. It comprises human haptic perception, cognition, and neurophysiology brought together to contribute to the study of human touch and physical interaction with the external environment. Machine haptics involves designing, constructing, and developing mechanical devices that replace or augment human touch. These interfaces are put into physical contact with the human nervous system for the purpose of measuring and displaying touch information.

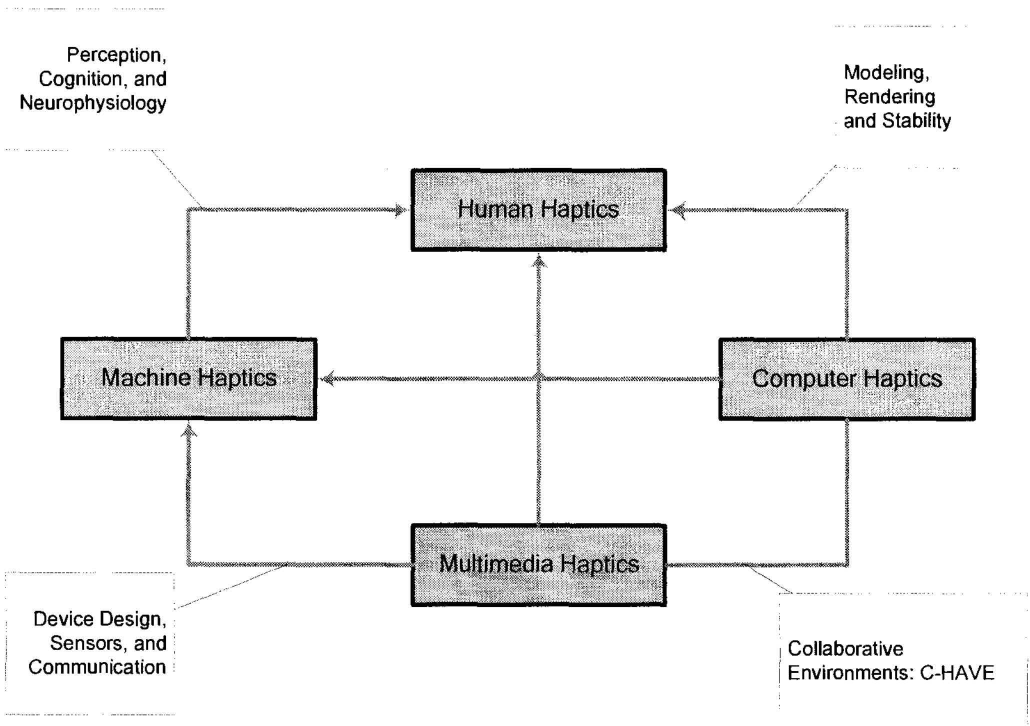


Figure 1: Interdisciplinary haptic research branches

Computer haptics is an emerging area of research that is concerned with developing algorithms and software to generate and render the 'touch' of virtual objects – somehow analogous to computer graphics. Essentially, computer haptics deals with modeling and rendering virtual objects for real-time display. It includes the software architecture for haptic interactions and the synchronization with other display modalities such as audio or visual media. Multimedia haptics involves integrating and coordinating the presentation of haptic interface data and other types of media in multimedia applications to utilize gesture recognition and force feedback [Eid et al_07].

2.3 Haptic applications architecture

Virtual Reality (VR) applications strive to create immersive VEs with which users can interact and perceive their interactions in real time. Typically, the VR application relies on three out of the five human senses: vision, hearing, and recently introduced touch. As stated previously by Srinivasan and Basdogan who have stated that human haptics refers to the mechanical, sensory, motor and cognitive components of the hand-brain system. The mechanism used to interact with VEs is referred to as haptic interface. The function and the taxonomy of haptic interfaces are beyond the scope of this thesis. Firstly the way non-zero flow information between user-haptic-computer interaction and the great variety of mechanisms used to deliver touch stimuli to the user. In addition, haptic interfaces are strongly related with the term computer haptics which refers to the discipline that deals with the generation and rendering of haptic stimuli to the user and all the aspects in haptics applications. The basic process of haptically rendering objects in a VE with the addition of force feedback is shown in Figure 2 .The simulation engine is responsible for computing the VE's behavior over time. The visual and haptic rendering algorithms compute the VE's graphics, sound, and force feedback toward the user. The transducers – audio, video, and haptic interfaces – convert audio, visual, and force signals from the computer into a form perceivable by the human operator.

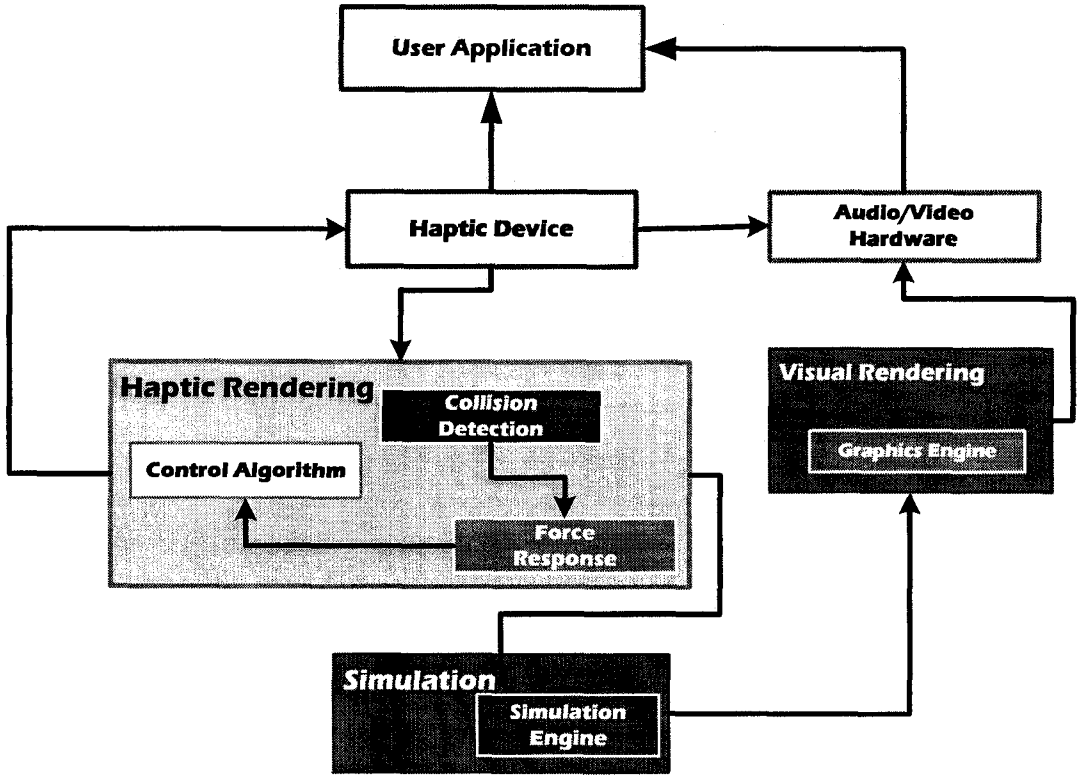


Figure 2: Fundamental high-level architecture for haptic application

Notice that the audio and visual channels feature unidirectional information and energy flow (from the simulation engine to the end user), whereas the haptic modality exchanges information and energy in two directions (from and towards the user).

2.4 Haptic Rendering

The control loop of haptic devices is based on modeling the interactions taking place in the VE. Interactions such a detecting contact between a virtual object and the haptic device avatar, surface deformation, force feedback modeling and physical constraints computation integrate the ingredients of a process called *haptic rendering* (Figure 3). Therefore, haptic rendering is related to the algorithms and techniques needed to perform certain activities that define a haptic-based simulation. In such a scenario, the haptic device is represented as a generic probe –sometimes also called end-effector in the VE and other virtual objects are displayed. Different events or user interactions may occur depending on the type of application. The current and updated position and orientation of the probe is sensed by encoders and displayed accordingly in the VE. Virtual objects can collide with each other or with virtual haptic device representations (i.e. pen or stylus, virtual hand) thus obtaining the information of where, when, and how such collisions, indentations, contact areas and so on have occurred. The collision detection algorithm characterizes such events. Once the collisions between the probe and virtual objects have been detected, the generated tactile and kinesthetic sensations, they need to be represented by computing the interaction forces through the force-response algorithm. The force-response algorithm sends interaction forces to the control algorithms, which send them to the operator through the haptic device while maintaining a stable overall behavior [Salisbury et al_04].

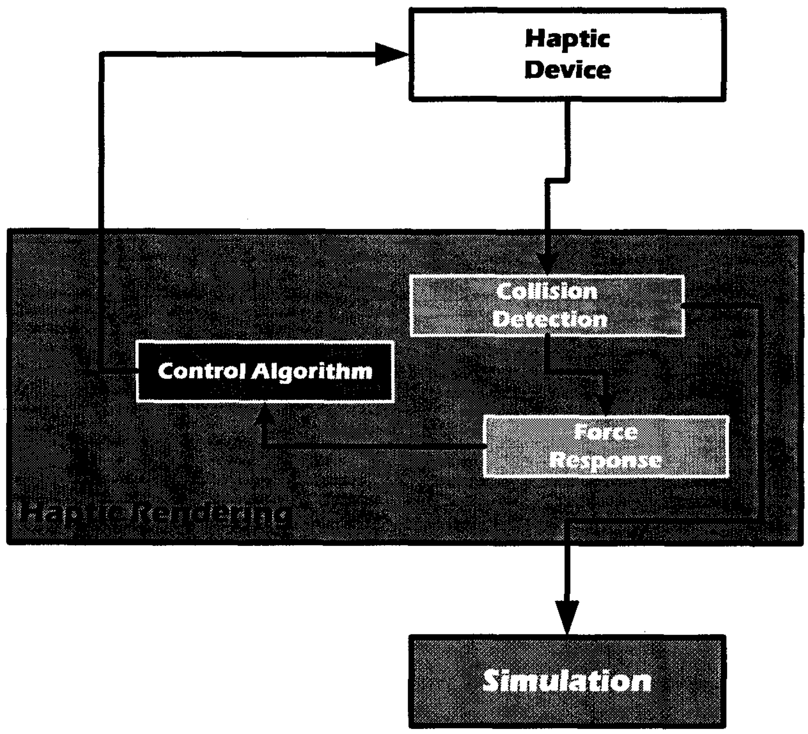


Figure 3: Haptic rendering components

Determining appropriate rendering forces is a complex task and plenty of research has been dedicated to tackle issues related to this domain. The force's exact value cannot be directly applied to the user due to many haptic technology limitations. In order to cope with hardware limitations control algorithms intend to minimize the errors between the ideal and the applicable forces.

A brief description of control architectures used in haptic systems was presented in [Gil & Sánchez_05]. The objectives are to provide the kinesthetic constraint of the VE and improve the transparency of the device by decreasing the inertia felt by the user in unconstrained movement. Essentially, they compute the transfer function that relates the force exerted by the user to the displacement of the haptic interface.

Therefore, haptic rendering can be seen as the core of any haptic-based application. It manages the algorithms to detect and report when and where the geometric contact has occurred. It also computes the correct interaction forces between the haptic device and the virtual objects. In addition, haptic rendering processes coordinates and simulates these actions in the haptic loop with attention to the hardware requirements of the system.

2.5 Machine Haptics

Machine haptics refers to the design, construction, and use of mechanical devices that are put into physical contact with the human body for the purpose of exchanging information with the human nervous system. In general, haptic interfaces have two basic functions. Firstly, they measure the positions and/or contact forces of any part of the human body, and secondly they display contact forces and positions in appropriate spatial and temporal coordination to the user. Currently, most of the force feedback haptic interfaces sense the position of their end-effector and display the forces to the user.

Because haptic devices exchange mechanical energy with users, they can be catalogued as small robots [Salisbury et al_04]. Since the early 1950s tele-robotic systems have played an important role as the main motor to impulse such a technology primary to improve the operator's task in a telepresence sense. This can be observed in the growing interest of safely handling tasks to protect the operators in hazardous environments such as from nuclear substances or radiation. These systems are known as tele-manipulation systems. Consequently, robotic mechanical systems, with a human being in their control loop, are referred to as tele-manipulators [Petriu et al_82]. As a result, some precision-engineered systems were created with the ability of reproducing haptic sensations in order to enhance the interaction between the operator and the remote scenario.

One way to distinguish between haptic devices is by their grounding locations (examples are ground-based and body-based). Another possible classification is according to the number of Degree of Freedom (DoF) that they can handle. A DoF is associated with a direction of movement. Common Degrees of Freedom include a right-left movement (X), an up-down movement (Y), a forwards-backwards movement (Z), a roll (rotation about the Z axis), a pitch (rotation about the X axis), and a yaw (rotation about the Y axis). DoF can refer to both how a device keeps track of a position, and how a device outputs forces.

The desirable characteristics of haptic interface devices include, but are not limited to, the following: (1) symmetric inertia, friction, stiffness, and resonate-frequency properties, (2) balanced range, resolution, and bandwidth of possible sensing and force reflection, and (3) low back-drive inertia and friction [Salisbury et al_04]. Due to the great variety of haptic device characteristics there is not a fixed taxonomy related to such devices. In this sense, the proposal thesis adopts to classify haptic interfaces in two broad classes: tactile interfaces (Section 2.5.1) and kinesthetic interfaces (Section 2.5.2). This will also serve as test-bed for a proof of concept.

2.5.1 Tactile Interfaces

Tactile – cutaneous – interfaces refer to interfaces that interact with the nerve endings in the skin. They can indicate texture, pressure or the sensation of heat .Several kinds of receptors have been found to mediate tactile sensation in the skin or in the subcutaneous tissues. Many proposed mechanisms use mechanical needles that are activated by electromagnetic technologies (i.e. solenoids and voice coils), piezoelectric crystals, shape memory alloys (SMA), pneumatic systems, and heat pump systems. Other technologies are based on electrorheological fluids that change the viscosity, thus changing the rigidity upon the application of the electric field. Medical-specific technologies such as electro-tactile and neuromuscular stimulators are still under development.

A survey of tactile interface devices that have been developed so far can be found in [Benali et al_04]. Currently, few tactile interface devices are commercially available (examples are Touchmaster by EXOS Inc., Tactool system by Xtensory, and Teletact Glove by Intelligent Systems Solutions). On the other hand, the majority of the research groups have focused on the development of tactile interfaces as tools to support the following: investigation into the human tactile sense, hand rehabilitation, and tele-operation. Examples of the research and development of tactile displays are HAPTAC from the Armstrong laboratory, linear and planar graspers developed by the Touch lab at MIT, a temperature display at Hokkaido University, a prototype tactile shape display at Harvard University, a programmable tactile array by the TiNi Alloy Company, and a tactile feedback glove at the University of Salford.

Petriu and his colleagues introduced a tactile sensor with a high sampling resolution (1.58 mm pitch) for active perception of stationary polygonal objects [Petriu & McMath_92 and Yeung et al_94]. The experimental tactile sensor consists of a 16x16 matrix of force-sensing resistor elements, and has an elastic overlay with protruding tabs, which provides the spatial sampling. With a specific application, a model-based method for blind tactile recognition of 3D objects is proposed in [Petriu et al_04]. The geometric symbols representing terms of a pseudorandom array are embossed on object surfaces. The method was tested on two 3D polygonal objects: a cube and a parallelepiped. In 2005, they developed an intelligent multimodal sensor system to enhance the haptic control of robotic manipulations of small 3D objects [Payeur et al_05]. The sensor system is mounted on the end-effector of a manipulator arm – with a relatively high resolution of 1/16 – to refine laser range 3D maps of fine interaction scenarios. Recently, Siegel et al have developed a prototype which can be described as foot tactile measurement system [Siegel et al_06]. This prototype has been designed to investigate the stability in standing, walking and running of humanoid robots using tactile sensing data streams at the foot contact.

In summary, tactile sensing is an important interface in the role of contextually discriminating and manipulating an object. In the processes of haptic exploration, the lack of force feedback makes certain tasks more difficult. Adding different sensing environments through innovative sensors and modeling approaches to represent physical interaction supports the haptic perception and exploration of the current devices. Currently, there are a variety of commercial and development products that provide a diverse range of sensations [Eid et al_07].

2.5.2 Kinesthetic Interfaces

Kinesthetic interfaces – or force feedback interfaces – provide users with a sensation of a force being applied by using the tendons and muscles of our body. Essentially, kinesthetic interfaces have three main functions: (1) measuring the movements and forces exerted by a part of the human body (i.e. hand or fingers), (2) calculating the effects of these forces on objects in the VE and the force response that must act on the user, and (3) applying the appropriate forces to the user. Technologies that are currently in use are electromagnetic motors, hydraulics, pneumatics, and shape memory alloys. Other technologies such as piezoelectric motors and magnetoresistive materials have already been investigated, although they are still the subject of further research and development.

There are a large number of existing kinesthetic interfaces – with quite different types and capabilities – that are now commercially marketed or developed by research groups; a comprehensive survey can be found in [Biggs & Srinivasan_02]. The majority of these devices can be classified as exoskeleton devices, tool-based devices, thimble-based devices, or robotic graphics systems. Exoskeleton devices, such as the Force Exoskeleton ArmMaster, deliver forces to the shoulder, elbow, wrist, and finger joints. Tool-based devices deliver forces to the human hand via a knob, joystick, or a pen-like object carried by a user. Some examples are HapticMaster and Impulse Engine 3000 devices. The most commonly used thimble-based device is the PHANToM device (i.e. Premium, Desktop or Omni), which delivers force to the user's fingertips. Finally, robotic graphics systems use real objects to provide forces to the user's hand. A summary of commercial and research kinesthetic devices is provided in Table 1.

To evaluate the quality of force feedback systems, Rosenberg has proposed a set of minimum performance standards [Rosenberg_96]. The author recommends a force output resolution of 12 bits, position resolution of 0.001 inches, and a passive friction of less than 1% of the maximum force output – the maximum force output and the range of motion is application dependent. Other requirements include a system bandwidth of less than 50 Hz, a minimum sampling rate of 2 KHz, and a maximum latency of 1 millisecond. Currently, only few devices meet all these requirements among which are the PHANToM devices. As a matter of fact, the hardware limitations such as the sensor's accuracy and the actuator's performance, constrain the fidelity with which haptic interactions can be simulated.

Despite the wide spectrum of research prototypes and commercial haptic interfaces, as described in Table 1 the proposed research interest area is concentrated on desktop devices and hand exoskeleton.

Table 1: Commercial and development kinesthetic-haptic interfaces

	Product	Description	Sensation	Application	Vendor
Commercial Interfaces	Force Feedback Master	Desktop	Hand via joystick	3D Interaction	EXOS,Inc.(Microsoft)
	Force Exoskeleton ArmMaster	Exoskeleton	Shoulder and elbow	3D Interaction	EXOS,Inc.(Microsoft)
	CyberGrasp	Force-reflecting exoskeleton: five actuators	Resistive force feedback	Grasping and manipulation	Immersion Corporation
	CyberForce	Mechanical arm	Wrist	Simulate object's weight and inertia	Immersion Corporation
	Omega.x family	Desktop	Hand via tool handle	3D Interaction	Force Dimension
	Virtuose 6D Family	Desktop	Hand via tool handle	VR and Tele-operation	Haption
	Impulse Engine 3000	Desktop	Hand via joystick	Surgical procedure	Immersion Corporation
	Laparoscopic Impulse Engine	Desktop	Hand via tool handle	Surgical procedure	Immersion Corporation
	Interactor	Vest	Torso via vest	Entertainment	Aura Systems, Inc.
	Interactor Cushion	Cushion	Back via cushion	Entertainment	Aura Systems, Inc.
	HapticMaster	Desktop	Hand via knob	3D Interaction	Nissho Electronics Corporation

	Hand Exoskeleton Haptic Display	Exoskeleton	Thumb & index finger joints, palm	Virtual pick-and-place tasks	EXOS,Inc.(Microsoft)
	PER-Force 3DoF	Desktop	Hand via joystick	VR and Tele-operation	Cybernet Systems Corporation
	PER-Force Handcontroller	Desktop	Hand via joystick	Space Station	Cybernet Systems Corporation
	PHANToM	Desktop	Fingertip via thimble	VR and Tele-operation	SensAble Devices, Inc.
	SAFiRE	Exoskeleton	Wrist, thumb & index finger	Dynamic simulation	EXOS, Inc.(Microsoft)
Research & Development	**Robotic Graphics Proof-of-Concept System**	Robotic graphics	Hand via tracker	Aerospace vehicles	Boeing Computer Services
	Force and Tactile Feedback System (FTFS)	Robotic graphics	Throttle and joystick)	Design verification and flight training	Computer Graphics Systems Development Corporation
	Elbow Force Feedback Display	Exoskeleton	Elbow joint	VE simulation	Hokkaido University
	MSR-1 Mechanical Master/Slave	Tool-based	Active limbs	Training	MIT
	7 DoF Stylus	Tool-based	Hand via tool handle	Tele-operation	McGill University
	Force Feedback Manipulator	Desktop	Hand via joystick	VE simulation	Northwestern University
	Second Generation Rutgers Master	Thimble-based	Three fingertips and thumb	Virtual Knee Palpation System	Rutgers University
	SPICE	Robotic graphics	Hand via tool handle	User interfaces for CAD 3D modeling	Suzuki Motor Corporation
	SPIDAR	Thimble-based	Thumb and index finger	3D Interaction	Tokyo Institute of Technology
	Molecular Docking Virtual Interface	Exoskeleton	Shoulder and elbow	Nanomanipulation molecular docking	University of North Carolina
	Pen-Based Force Display	Tool-based	Fingertips or pointed object	Medical microsurgery.	University of Washington

2.6 Applications

Haptic research and development has focused on designing and evaluating several prototypes of different characteristics and capabilities for use in VEs. Recently, some of these prototypes have become commercially available to the market [ImmTec_A] [SenTec_A] [ForceDim_A]. Applications of this technology have been rapidly spreading from systems applied to Graphical User Interfaces (GUI's), games, multimedia publishing, scientific discovery and visualization, arts and creation, editing sound and images, the vehicle industry, engineering, manufacturing, tele-robotics and tele-operation, education and training, medical simulation and rehabilitation.

Traditionally, data visualization uses animation or interactive graphics to analyze or solve a scientific problem. The projects GROPE I, II and III have been a pioneer in the introduction of haptics into the scientific data visualization to develop a molecular system for reproducing the true docking positions for drugs [Brooks et al_90].

Green and Salisbury have produced a convincing soil simulation in which they have varied parameters such as soil properties, plow blade geometry, and the angle of attack [Green & Salisbury_98]. Recently, a research group at the University of Wales has developed a molecular visualization system to provide haptic interaction to the exploration of potential energy surfaces and wavepacket dynamics to support the understanding of complex chemical process [Davies et al_05].

To date there has been a modest amount of work performed on the use of machine haptics for the blind and visually impaired. In [Van Scoy et al_99], the authors proposed a system that provides blind persons with information about the site to be visited (such as the business name, the types and locations of doors, and the types of traffic control devices). A similar work has also been proposed in [Lecuyer et al_03]. Lately, a Haptic & Audio Virtual Environment (HAVE) for allowing visually impaired people to access to the 3D computer generated world by visually impaired people has been developed in [Iglesias et al_04]. The system provides an integrated platform under the name of GRAB system which comprises a haptic interface and haptic geometric modeler. The GRAB interface is able to reproduce two independent force vectors on contact thimbles attached to a user's fingers and the latter simulates the virtual scenes and computes different types of forces to be replicated by the haptic interface. Recently, the MultiVis project conducted by the University of Glasgow allows visually impaired people to construct and browse mathematical graphs effectively [McGookin & Brewster_06].

Plenty of games available in the market take advantage of the haptic effects offered by mainstream haptic interface. For example, you can play a "haptic paddle pong game" with another computer user by using a PHANToM device. Both users can see the moving ball, the position and swing the pong racket (according to the end-effector)and feel the impact of the ball by using the haptic device, position [Morris et al_04]. However, the interaction with the game environment is limited since players can feel only the transient forces generated as the paddle strikes the ball .Recently, a computer implementation of a classic memory card game was adapted to rely on touch [Wang et al_06]. Such tactile sensations are characterized by controlling dynamic distributed lateral strain patterns on a finger pad in contact with a tactile display called STRESS developed at the Haptic Laboratory of University of McGill [Pasquero & Hayward_03].

These days, an approach based on existing and well-developed game engine components—specifically, a scene graph library and physics engine – has been designed adding haptic feedback [Andrews et al_06]. Their actual game is called HapticCast which is an experimental framework for a 3D first-person shooter with wizards and haptically enabled wands.

Simulation environments that utilize force feedback technologies can support medical education and training. The application of a desktop haptic interface in the pre-operative planning of an open surgery procedure has been introduced in [Nikolaos et al_05] for training hip arthroplasty surgeons. Another haptic-based medical training system has been reported in [Abolmaesumi et al_04]. The system allows trainees to visualize a virtual patient's anatomy simultaneously from any desired orientation and location. Medical training for the skill of bone drilling has been investigated in [Esen et al_04]. Langrana et al. used the Rutgers Master II haptic device in a training simulation for the palpation of subsurface liver tumors [Langrana et al_97]. Surgical planning and training tasks have also been developed to support the endovascular surgery to radically change the traditional methods for official certification [Zorcolo et al_00].Many other medical education and training systems have been proposed including a computer-based system for training laparoscopic procedures [Basdogan & Srinivasan_01] and a Munich Knee Joint Simulator [Riener et al_02], among others.

In addition to problems associated with surgical simulation, tele-surgery involves two additional issues: the coherency of the virtual scenes among all participating users and force feedback stability when haptic information is sent over non-dedicated channels, such as the Internet where there is latency and jitter. At the University of Ottawa, El-Far et al. developed a hapto-visual eye cataract surgery training application [El-Far et al_05].

Industry also requires the simulation environments that utilize force feedback technologies for instance, for assembly and maintenance tasks. In this domain a Collaborative Haptic Virtual Environment (CHAVE) for assembly simulation has been developed in [Iglesias et al 06]. Issues such as latency and jitter in a multi-user interaction are tackled by Iglesias et al in a particular fashion. The virtual scene synchronization (consistency) is guaranteed in remote nodes scenario. In addition a force smoothing algorithm was developed to improve the quality of force feedback under adverse network conditions.

The rehabilitation process involves applying certain forces to the injured/disabled organ (i.e. fingers, arm, ankle) to regain its strength and range of motion. Haptic devices have showed benefits in imitating a therapist's exercises with the possibilities of position and force control. A rehabilitation environment has been developed in [Boian et al_03] using the 'Rutgers Ankle' haptic device that is used as a foot joystick. Variations in the exercises can be achieved by changing the impedance and stiffness levels, and vibrations.

By adding force feedback to a system design in conventional 3D designing software platforms such as 3ds max®, maya® and rhino™, free-form virtual modeling has been endowed with some of the benefits that the haptic technology can offer [SenTec_A]. In the art of painting, DAB is an interactive haptic painting interface that uses a novel deformable 3D brush model to give users natural control of complex brush strokes [Baxter et al_01}. Virtual Clay is another example of using haptics to enhance the functionality of deformable models in a natural and intuitive way [McDonnell et al_01}.

Adding audio information makes haptic-based systems closer to the real simulation. Users can interact with more sensory channels and immerse themselves in simulations that are more realistic. Modeling the sound produced when objects collide is the objective of a haptic interface that intends to provide more realism to the feel of a fabric's surface roughness, friction and softness [Huang et al_03].

Little work has been completed in the field of haptic-enabled e-commerce. In this field, a system called vCOM has been developed by Shen et al [Shen et al_02]. It is a VRML and Java3D-based prototype which permits users to navigate around virtual e-commerce worlds and perform collaborative shopping and intelligent searches with the assistance of software agents, in order to find the products and services of interest to them. In another attempt, Shen et al proposes a scenario for the online experience of buying a car[Shen et al_03]. A virtual car showroom is created along with avatars for both the customer and the salesperson that can communicate in real-time where participants may have different kinds of haptic devices, such as the PHANToM device [SenTec_A] the MPB Freedom6S Hand Controller [MPBTec_A], or the Immersion CyberGrasp [ImmTec_A].

Surprisingly after an intensive research review in the area of security systems to the best of this current thesis work, no other work has examined haptics from a Biometric aspect. It can be seen that the application's spectrum is quite vast and its potential for expansion is promising to increase. However, haptics interfaces confront computational challenges that become considerably more demanding, such as the realistic experience that has to result from the collaboration of two processes: one is coordinating the visual system and the other is tracking the position and updating the forces on the haptic device that can be delivered or simulated.

2.7 Conclusions

First of all, it is worth mentioning that even with the significant progress in haptic technology and research, the incorporation of this technology into VEs can be considered in its early years. A wide range of human activities, including communication, education, art, entertainment, commerce, and science, would forever change if we learn how to capture, manipulate, and create haptic sensory stimuli that are nearly indistinguishable from reality. Beyond today's state of the art, many commercial and technological barriers are to be surmounted. First, business models/frameworks are needed to make haptic devices practical, inexpensive, and widely accessible with the ultimate goal of making haptic devices as easily pluggable as the mouse in a computer. Moreover, multipoint, multi-hand, and multi-person interaction scenarios need further investigations to reach enticingly rich interactivity. Finally, we should not forget that touch and physical interaction are among the fundamental questions in haptic systems development. By rendering how objects feel through haptic technology, we communicate information that might reflect a desire to speak a physically-based language that has never been explored before.

From an application perspective, this work envisions an interesting application field where the haptic technology has significant potential. For instance, biometric systems identify users based on their behavior or physiological characteristics [Wayman_00]. The potential of this technology is to continuously authenticate and control access to high security applications/systems for many reasons. Firstly, conventional security systems, which may be based on a password, token, or even a physical biometric, can only assure the presence of the correct person at the beginning of the session; it cannot detect if a hacker takes over the control. Secondly, traditional authentication means such as a login ID and passwords can easily be compromised. In this sense haptic-based biometric systems are significantly more difficult to compromise according with [Orozco et al_06b], [El Saddik et al_07] and [Orozco et al_07].

Chapter 3

Behavioral Biometrics: State-of-the-Art

3.1 Introduction

The problem formulation presented in this thesis is unique when compared to prior work in related areas. An introduction to this domain and its prior and more recent work are discussed in this chapter.

Biometrics is related to the process of identifying an individual based on his or her human traits. Therefore, such traits can be divided into two classes behavioral or physiological. One possible way to measure a behavioral trait is by observing and recording a dedicated activity as whole process [Vielhauer_06]. Physiological traits can be acquired by different acquisition devices (e.g. optical fingerprint scan, video cameras, thermal sensors or ultrasound sensors) directly from our body. Until now, computers process the information in discrete domain. Therefore the sequences generated from observation in the case of behavioral traits measurement need to be reconstructed from temporal to discrete sequences. The process for generating such as digital representation from an analog observation is called signal sampling, which in combination with pattern recognition methodologies are required by the task of biometric user authentication.

The haptic technology has the capability to provide an interface to feel the sense of touch into a VE. During human-machine interactions on a dedicated activity can characterize particular psychomotor human patterns, specially those ones that involve hand dexterity tasks. Such patterns can be mapped and recorded by using the haptic technology. For example, a human handwriting skill consists of making graphic marks on a surface. These graphic marks goal is to communicate something based on a standard that represents the content not only in terms of language, but also by personalizing the characters that represent the information content [Colmas_80]. Such human behavioral characteristics can be captured in real time and, later on be analyzed by pattern recognition methodologies.

In combination with a visual display, the haptic technology can be used to emulate real world tasks. These tasks can range from dialing telephone codes through touchable virtual keys, emulating the task of painting by allowing the user to control a virtual brush, sculpting with the capability of interactively applying textures onto 3D surfaces directly by brush strokes [Baxter et al_01] revolutionizing many surgical procedures, until performing handwriting tasks, among others. The tasks mentioned above can traditionally be handled by different conventional computer-based input devices in a passive way by means of keyboard, mouse, digital tablets and pen-based computers.

In this thesis different haptic-based tasks were developed with the objective in mind to involve hand dexterity behavioral features, which can be used for authentication purposes like in biometrics. The state of the art of behavioral biometrics is organized according to the types of systems and their data acquisition devices. Issues related to authentication and the advent of new technologies like haptics leave this field open to new ideas and further research.

3.2 Fundamentals of Biometrics

Linguistically speaking the synonym "Biometrics" is an integrated term from two ancient Greek words "bios" meaning life and "metron" meaning measure. Consequently, in extended interpretation is referred as the discipline in charge of "the statistical analysis of biological observations and phenomena" [BSi_01]. Hence, different domains have adopted the term Biometrics, firstly under the biology discipline "for the analysis of data from human clinical trials evaluating the relative effectiveness of competing therapies for disease, or for the analysis of data from environmental studies on the effects of air or water pollution on the appearance of human disease in a region or country" [IBS_01]. On the other hand computer science has adopted the definition based on automated method of using numeric measurements based on specific individual physical or behavioral characteristics to be applied for user authentication [Wayman_00].

This thesis adopts the latter definition, more precisely, focus on behavioral identifiers. These identifiers refer to the paradigm that expresses "something you usually do". Behavioral biometrics are learned or acquired over time and are dependent on a user's state of mind or are even subject to deliberate alteration [Bolle et al_04][Wayman_00].

Based on such biometric identifiers most of the biometrics authentication methods are contained in taxonomy depicted in Figure 4. The development of such methods is strongly related with the technology. However, due to the scope of this thesis a current status in the most common methods is mentioned.

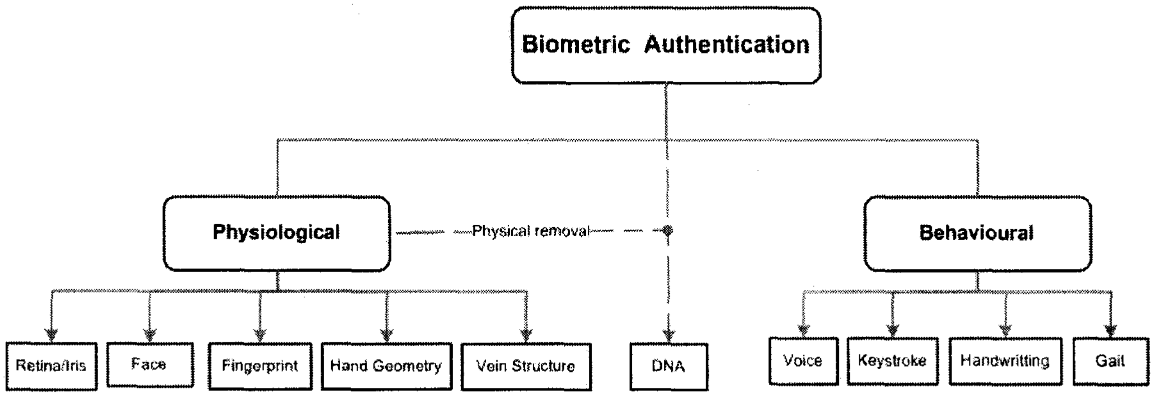


Figure 4: Classification of biometric authentication methods

3.2.1 Biometric Authentication Methods: Reality and Challenges

3.2.1.1 Face recognition

This face modality is probably one of the most popular, user-friendly and non intrusive biometric method. Standard digital cameras can be used for acquiring graphical representation of faces. Research literature in detail of this topic can be found in [Zhao et al_03] [Wechsler et al_02].

Law enforcement agencies have considered using the face technology to enhance security measures in public areas. Some face recognition products found good business opportunities, for instance to scan faces of fans attending the Super Bowl XXXVI in Tampa, Florida in 2002[McCullagh _02]. The Cognitec's FaceVACS system has been applied in a passport check point for the crew members of the Quantas Air Company [Cognitec_01]. Currently the face recognition technology has faced enormous challenges to prove the feasibility as large-scale deployment in practical scenarios. A test performed at the Palm Beach International Airport in Florida by the Identix's face recognition system failed to correctly to identify 503 out of 958 volunteer employees [ACLU_A]. In addition Viisage and Identix technologies obtained similar results from another trial carried out at the Boston's Logan International Airport. The results showed that the system has failed to identify positive matches 38% of the time [Willing_01]. Other companies such as Cognitec had obtained much improved results. In general it is really early to claim reliable performance for any face recognition product especially under different conditions (e.g. lighting, person's posture). Important research on pose invariance and illumination effect is crucial criteria in the overall performance of the face recognition problem.

3.2.1.2 Voice Biometrics

Identifying individuals based on their voice has brought the attention of potential applications such as security online transactions, medical records control, reset passwords, language training and voice indexing. Recent results show the advances in the current technology. For instance a study carried out by Przybocki and Martin has reported a 5% of False Acceptance Rate (FAR) and 10% False Rejection Rate on a two-minute cellular phone conversation [Przybocki & Martin_02]. Such performance also can be affected if a different handset device is used. In contrast much better performance can be achieved from 0.7% to 0.22% Equal Error Rate (EER) if an approach based on fusing low and high level frequencies of the voice signals is adopted [Campbell et al_03]. Issues such as speaker variability of the voice, coder distortion, alteration of speaker's voice can affect the overall performance of a voice recognition system.

3.2.1.3 Gait Recognition

Gait biometrics refers to discipline which identifies particular features on psycho motor movements of individuals captured from video information. In other words such a discipline attempts to identify an individual by the manner in which they walk. Standard video techniques have been used at different levels of resolution (~720x576 pixels) and frame rate (from 25 fps) to provide biometric information [Vielhauer_06]. The recognition accuracy results have been found around 8.6 to 7.3% EER in a verification mode [Bazin & Nixon_05]. Some studies recognize that the accuracy level is affected by the camera viewpoint set and the kinds of shoes that the subject wears [Nixon & Carter_04]. Currently, the interest in gait-based biometrics has led to a stream of results that are lower level than what is required for use in biometrics [Boyd & Little_05].

Regarding the two classes of biometric traits, this research is focused on the methodology related with behavioral identifiers or also referred as active biometric identifiers [Vielhauer_05], mainly dedicated on dynamic signature verification and keystroke dynamics.

3.2.2 Authentication Protocols

Biometric recognition systems have designed around physiological and behavioral identifiers for recognizing individuals in order to produce automated systems. There are important properties that such identifiers need to possess in order to qualify as biometric: universality, distinctiveness, permanence, collectability, and acceptability [Bolle et al_04] [Wayman_00]. In addition, there are attributes that are also necessary to make a biometric system practical: performance and circumvention [Jain et al_04]. The scientific discipline of pattern recognition plays an important role in the implementation of these systems. Generally, after the biometric data is captured, the pattern recognition theory provides the required tools to build a biometric feature set, and compares it versus a pre-stored template pattern. In essence of the application context, the biometric system can represent two modes of operation: enrollment and authentication.

Enrollment process refers to the process of creating reference features (or templates) for each individual which are stored in a system and are associated with the identity of the individual. Authentication describes a process of identity verification or determination by an authentication system. Under the authentication mode two functions can be represented: identification or verification.

In the identification function, an attempt is made to establish the identity of an unknown individual. In short, the, identification systems respond to the query "who am I?". In general terms, subject X provides real world with the biometric B, and the biometric sensor device acquires a sample $f\ (B)$ of that biometric. In this case, the biometric template B_i is extracted by the feature extractor. Subsequently, the biometric matcher determines the similarity $s_i = s\ (B,\ B_i)$ between pattern B (Subject x) and pattern B_i (Template) corresponding to the database entry. Finally, the authentication protocol then declares $X = X_i$ if $s_i >$ a given threshold T or $X \neq X_i$ if $s_i \leq T$ (Figure 5).

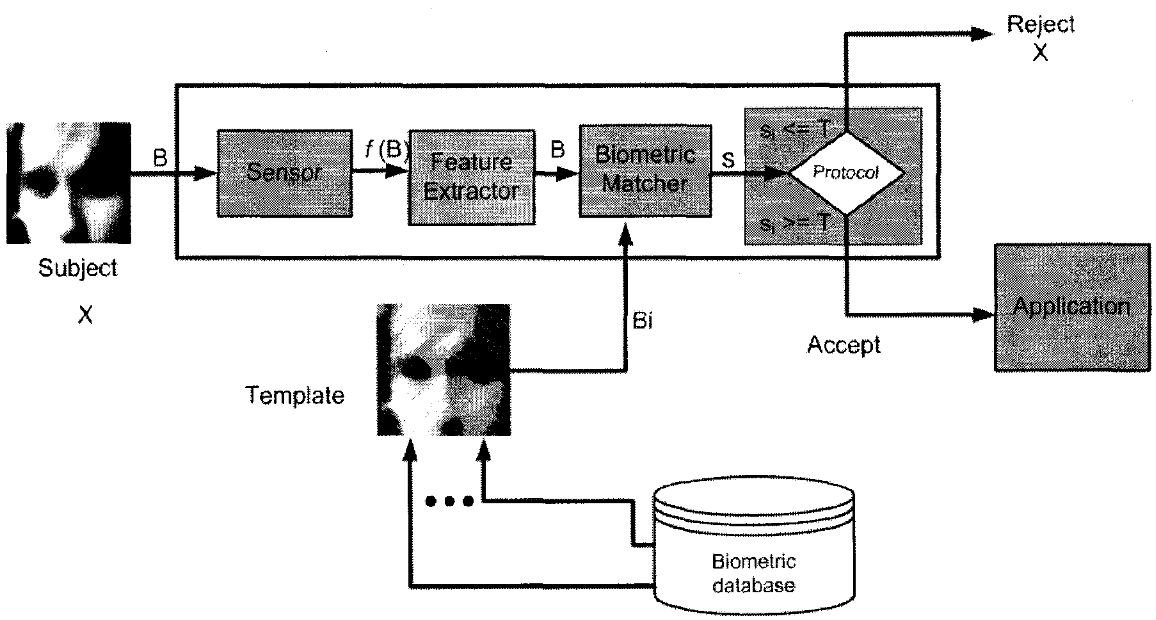


Figure 5: The Identification Mode Protocol

In the verification function, an attempt is made to verify the claimed identity of an individual. In other words, verification systems respond to the query "*am I who I say I am?*". For a verification system, the credentials are the presentation of a biometric identifier, which includes the presentation of possessions and/or knowledge (see Figure 6). Such additional credentials uniquely characterize an enrolled identity in the biometric database and thus an associated biometric machine representation (pattern) B_i. Therefore, subject X claims an ID number in addition to the presentation of biometric B for the sample acquisition of $f(B)$. The feature extractor computes biometric patterns B and B_i, which are associated with i and are retrieved from the biometric database. The biometric matcher computes a match score $s = s(B, B_i)$. The decision is based on if the score of similarity is high enough $s > T$, where T is the threshold, to decide that $X = X_i$ otherwise, it is implied that $X \neq X_i$ and the subject is rejected.

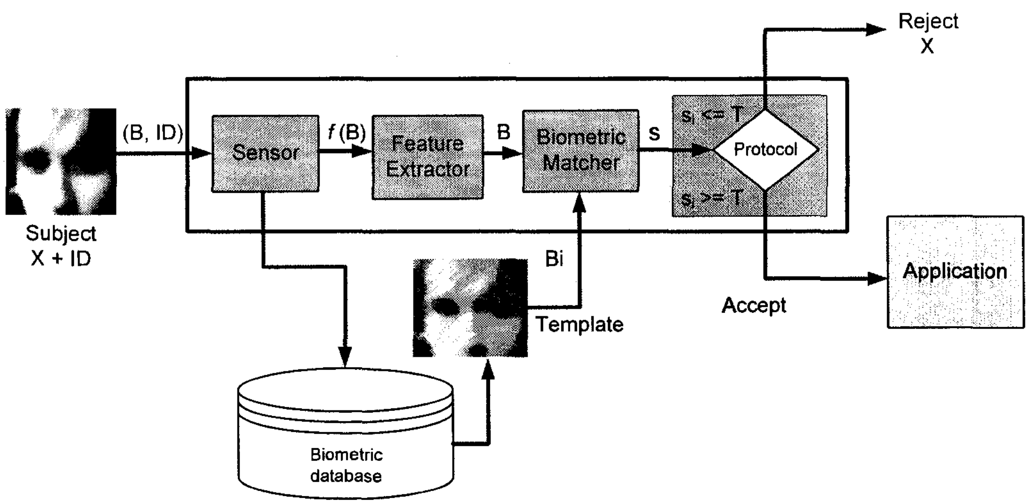


Figure 6: The Verification Mode Protocol

The precision of such systems is reliant on the choice of biometric identifiers and on the operational mode of the application. For accurate identity recognition, identifiers must be chosen so that they are unique for each individual. Today's trend is an extensive spectrum of highly secure identification, automated authentication and personal solutions that are building the basis of the biometric technologies. This phenomenon, mainly influenced by the increase of the level of security bank breaches and transaction frauds, has caused an apparent need for extremely secure identification and personal verification technologies.

Currently, biometric-based solutions are provided to confidential financial transactions and personal data privacy. The application of biometrics can be found in federal, state and local governments, in the military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies. Most of these applications are based on the principle of human-machine interaction for capturing the behavioral features. In parallel, the technology called haptics that introduces the complex sense of touch into the human-computer domain is becoming more reliable and available. This technology enables users to touch and manipulate virtual objects in a bidirectional exchange of energy, which provides a true interface between human and machine.

Prior and current research work carried out in the behavioral biometrics domain has been reached remarkable results. Before going further, there are important accuracy and performance measures that need to be introduced. These metrics serve as mean to characterize the robustness of a biometric system.

3.2.3 Distance Distributions

The most fundamental technical measures which we can use to determine the distinctiveness and repeatability of the biometric patterns are the distance measures difference between sample and template [Wayman_00]. Distance distributions can be conceived as the functions that characterize a dissimilarity measure between points (data) or sets. Wayman in his report stated that there are three main application-dependent distributions based on metric "scores" obtained from the signal processing space. The first distribution is called the "genuine" distribution created from the distance measures resulting from comparison of samples to like templates. The second distribution is the "inter-template" distribution which is created from the distance measures resulting from comparison of templates from different enrolled individuals. The third is the "impostor" distribution which is created from the distance between samples to non-like templates. These measures are referred as non dimensional and serve as evaluation criteria of a biometric system performance.

3.2.4 Non dimensional measures of comparison

Biometric systems sometimes make erroneous decisions: false-accepts and false-rejects which expresses the accuracy of application [Bolle et al_04]. There is a lot of terminology about the definition of these rates of errors' occurrences but five have recognized under a general consensus [Wayman_99]. The False Match Rate (FMR) has been adopted and it refers to the ratio between members truly non-matching samples tested by the system. This ratio also can be found in literature as, False Accept Rate (FAR), or False Positive Rate (FPR). On the other hand False Non-Match Rate (FNMR) refers to the ratio between members truly matching samples, which are not matched by the system and total numbers of tests. In this sense False Rejection Rate (FRR) can be associated with the latter. This thesis adopts the conditions that FAR means FMR and FRR means FNMR In general, a positive verification and a positive identification system can make two kinds of errors, a FAR or a FRR, these error rates are co-dependent - as reducing one increases the other which can be denote as equal error rate (EER). Another way to express graphically the error characteristic is through the form of a Receiver Operating Characteristics (ROC). In general the performance of behavioral biometrics in terms of corrections, rejections, and false acceptance can be affected by circumstances such as health, stress, and other factors [Wayman_00].

A guided tour about literature in the handwritten signature verification and the keystroke dynamics domain is provided. Therefore, issues related to these particular disciplines are discussed. For instance the impact created by the inclusion of the new technology to capture the human-computer behavior to be used for authentication is considered.

3.3 Keystroke Biometrics Review

The main practical advantage of a keystroke analysis is the requirement that only a conventional computer keyboard is needed to perform the biometric analysis without the need of special tools, in comparison with other biometric identifiers. As described later, research on keystroke analysis has been ongoing since more than three decades. In addition, some granted patents such as [Garcia_86][Young & Hammon_89][Brown & Rogers_96] and commercial on-line products [Biopass_A] have contributed to this discipline. A comprehensive study has analyzed current research in key stroke dynamics that can be found in [Peacock et al_04].The early work was of Gaines et al is considered as the first step in this domain[Gaines et al_80]. In 1980, they studied the keystroke latency between adjacent letters. Their results were computed from an experimental study using seven professional secretaries. They found the variation spectrum to be from 75 milli-seconds to several seconds. These latencies, also called digraphs, were used as the main metric information in the authentication process. Their approach found that there were 0% invalid user attempts accepted. The limitations of this study refer to the small number of individuals that took part in the experimental tests as well as the limited number of diagraphs. On the other hand, in practical terms, such an approach might not be practical since the system asked the users to type long given paragraphs.

In 1985, a study similar to the previous experiment was presented by Umphress and Williams [Umphress & Williams_85] and involved some programmers typing two samples. Their approach used the mean value of the keystroke latencies of the user, mainly the user's typing speed. They also incorporated the standard deviation of the reference profile latencies as another metric. Their preliminary results were not encouraging with a 30% false alarm and 17 % successful impostor rate. However, they dramatically improved their approach dramatically by further considering lower-case letters, blank spaces and a maximum latency of 500msecs in their digraph features. They obtained a 95% Probability of Verification (PV) and 5% of FAR of impostors gaining access. Again, the major drawback comes from the need to type large character strings to generate a feature set used in the process of authentication analysis.

With the general assumption that the best data for identity verification is derived from an individual typing his/her name, Garcia developed an approach that was granted with a U.S. patent in 1986[Garcia_86]. The latencies generated from that particular method are stable and unique. The metric used by Garcia is the Mahalanobis-distance[2] to compare

[2] Mahalanobis distance is a distance measure introduced by P. C. Mahalanobis in 1936. It is based on correlations between variables by which different patterns can be identified and analyzed. It is a useful way of determining similarity of an unknown sample set to a known one

two feature vectors generated from the suggested attributes. The results reached a (FAR) of 0.01% percent and a (FRR) of 50 %.

Following Garcia's method in 1990, Joyce and Gupta presented a study based on the keystroke information obtained from a login process by asking users to type a login name and password as well as two additional strings that are familiar to the user Joyce & Gupta_90]. Their approach obtained a (FRR) of about 13.3% and an (FAR) of 0.17 %(1 out of 600).

In principle, a biometric system should be stable and able to reach high accuracy levels. In order to fulfill these requirements Bergadano argued that the intrinsic variability of typing dynamics and the possibility of typing errors can lead to low system performance [Bergadano et al_02]. In 2002 to overcome such issues they developed a new keystroke analysis technique. This new technique is based on a metric called "degree of disorder". Given a vector *V* of n-elements representing the typing features with respect to its counterpart *V'* the degree of disorder can be characterized as the sum of the distances between the position of each element in *V* and the position of the same element in *V'*. In addition, they considered the elapsed time between the depression of the first and of the third key of a trigraph (three characters typed one after the other). With this method, a false alarm rate (FRR) of about 4% and an impostor pass rate (FAR) of less than 0.01% (less than one successful attack out of 10,000 attempts) were reached.

To the best of our knowledge, no other commercial product offers the ability to enhance authentications with keystroke dynamics as BioPassword [Biopass_A]. BioPassword can run on Windows OS and also its SDK is offered in order to integrate such a technology on a windows application.

The research in the keystroke dynamics has been dedicated to analyzing the rhythm of a user when typing on the keyboard where attributes such the time pressing and the latencies between each key pressed are captured. Keystroke biometrics has been studied for more than a quarter of decade. Currently biometric systems based on such a behavioral biometric modality face different issues and they are considered still in development. Peacock et al have added that the lack of sharing set of standards for data collection, the size of population considered in key published research and the need of a process to secure biometric data are the main concerns that need to be tackled to enhance the performance and acceptation of such a technology [Peacock et al_04].

3.4 Dynamic Signature Verification Review

Handwriting is a particular skill that belongs to each individual. Several types of analysis, recognition, and interpretation can be associated with handwriting [Plamondon_00] [Earnest_62] [Eden_62].According to Plamondon "*Handwriting identification is the task of determining the author of a sample of handwriting from a set of writers, assuming that each person's handwriting is individualistic*". In particular, handwriting based biometric verification and identification use one specific semantic class; handwritten signatures. They are well-know recognized as proof of authenticity in different type of social transactions. In particular, signature verification refers to the task of recognizing individual characteristics that describe whether or not a signature belongs to a given person or not. Research in signature verification is not a fresh topic and has been studied since the mid-sixties. In the beginning, this research was initially focused on static variables that were not directly associated with a function of time due mainly to the technology available at that time. However, as the advent of digital computer technology became a reality, time-based comparison was more viable, which derived to the concept called Dynamic Signature Verification (DSV). DSV systems are capable of comparing different features such as the shape, speed, stroke, pen pressure, and timing information of a test signature against the reference signature, during the act of signing. That requires the extraction of writer-specific information from the signature signal, regardless of its handwritten content [Plamondon & Srihari_00]. A vast spectrum of approaches have been proposed to provide favorable conditions for the deployment of dynamic signature verification (DSV) systems, which have been exhaustively surveyed in [Leclerc & Plamondon_94] [Plamondon _94], [Plamondon et al_99] and [Tappert, et al_90].

According to previous surveys, it is evident a great amount of work has been dedicated to this domain. Almost all these research works has been based on independent studies. In other words, they have produced their own samples from unique sets of individuals. In addition the data acquisition has been carried out through different mechanisms (e.g digital tablets, pen-based computers, etc), different amount of inputs to train the system and with different levels of data resolution (see Table 2). Therefore if one thinks about making a comparison between different studies, it must be extremely challenging task due to such variability in the comparison policy. Recently, a signature verification competition has been carried out in [Yeung et al_04]. This contest was designed under equal conditions by using two different data sets: data 1 contains only spatial information(*x,y* coordinates), data 2 add further information such as pen orientation and pressure.. In general their results vary between these two data sets in the sense that the additional information does not make any impact in the performance of the algorithms involved. They attributed such a variability was influenced by the method used to collect the signature databases. Therefore it is important to note that in order to design a testing protocol additional issues need to be considered as stated in [Elliott_02]. Elliot's works remarks that a test signature with one or a few references considers the forgery data policy plays an important role in the overall performance of the verification system. In addition, the input mechanism to acquire the data and the data source size validates the system's accuracy. From his work, one can conclude the variables to be considered in the design of a conventional testing protocol and hence make current or further approaches comparable. Firstly, the different data acquisition methods available such as pen based computers and digital tablets can influence the performance of the verification system. It can be reflected in the granularity of data acquired from the device., In addition, Elliot highlighted the context of signing, habituation to the devices, as well as anonymity among all are important issues.. As summary in the context divergence of methods used, the size of data handled and results obtained from DSV studies is provided in Table 2. It has been based on a combination of recent and those ones from the survey's works of [Plamondon & Srihari_00] [Gupta_97].

Table 2: Summary about different techniques and its results applied into the Dynamic Signature Verification discipline

	Reference	Methodology	Feature Set	No-Dimensional Metrics			Database samples (specimens)
				Type I (FAR)	Type II (FRR)	ERR	
Hybrid	Dolfing et al_98	HMM	Feature Value(Hybrid) 13 spatial,13 dynamics and 6 contextual			1 %	Genuine =1530 Forgeries=3240
	Kashi et al_97	HMM	Feature Value(Hybrid) 23 Global and Local			2.5%	Genuine =542 Forgeries= 325
	Wam et al_05	HMM & GMM	Hybrid(Global and Local)	6.7 %	10.3%		Genuine = 375 Forgeries = 15
	Pippin	Euclidean Distance &DTW	Hybrid: Local & Global : average velocity, strokes are segmented using the minima of the velocity			4%	DNP
	Vergara & Santana De Freitas_02	wavelet transforms and DTW	Hybrid	0%	30%		Genuine= 120 Forgeries=30

	Russell et al_05	DTW & GMM	Hybrid(Functional & Parametric)			2.25%	Genuine =480 Forgeries = 260
Parametric	Fuentes et al_02	HMM and NN	Feature value 8 Dynamic and 9 static	4.62%	8.25%		Genuine =1530 Forgeries = 4730
	Yi et al_05	DP Matching	Parametric: Dynamic features			2 %	Genuine =1500 Forgeries = 500
	Richiardi et al_03	GMM(Gaussian Mixture Models	Parametric: x, y, pressure			1.7%	Genuine = 250 Forgeries = 250
	Komiya et al_99	Pen-Based Features (Pressure, Position Inclination)	Pen-position, ,pressure, inclination			1.9%	Genuine =293 Forgeries =540
	Pacut and Czajka _01	NN: Layer Sigmoidal Perceptron and Restricted Coulomb Energy (RCE)	Several : Horizontal and vertical pen tip position, pressure, pen azimuth and altitude angles	0%	11.11%		Genuine =299 Forgeries = 60
	Lejtman and George	Wavelets and Back-propagation NN	Several : pen tip pressure, velocity, angle of pen movement	0.1%	0.0%		Genuine = 922
	Wirtz, B	Probabilistic (Parameter Reduction)	Paramétrique: [PenUp/PcnDown, x(t), y(t), p(t), t]			1 %	Genuine =644 Forgeries = 669
	Yang et al _95	Hidden Markov Models: Baum-Welch(Training and Classification)	Normalized directional angle function of the distance along the signature trajectory	1.75%	4.44%%		Genuine =496
	Igarza et al	Hidden Markov Models	Different topologies(Digital Tablet) similar to Yang et al_95	0.295%	48.21%		Genuine = 3750 Forgeries= 3750
	Wijesoma et al_01	GA	Feature Values: Parametric			4.45%	DNP
Function-Based	Mohakrishnan, et al_98	AR(Autoregressive	Functional: x,y coordinate sequence	2.5%	2.5%		Genuine =150
	Feng et al_03	DTW	Functional : x,y sequences			25.4 %	Genuine = 750 Forgeries = 250
	Nalwa_97	Pen dynamics: Local shape based model	Local shape based model			2%	Various data set: (904,982,790 325,401,424)
	Tanabe et al_01	Dynamic Programming (DP) matching and Discrete Fourier(DFT) methods	1 : Pressure			6%	Genuine = 760 Forgeries = 600
	Di Lecce et al _99	Parametric: Wholistic matching Regional matching	Signature sequence(x,y)	3.2%	0.55%		Genuine = 50 Forgeries = 50

NOTE 1: DNP (Data No Provided), NOTE 2: Only significant No dimensional metrics are showed

In general, it is well-known that signature verification is a widely accepted mechanism in the document authentication and transaction authorization, which had a long history and has even been used before the invention of computers.

To our knowledge, the first work in this domain was reported by the first automated signature system that was developed at Norte American Aviation by A.J Mauceri in 1965 [Mauceri_65]. Mauceri's work has reported a FFR of 37% and it has been referenced along the evolving path of this discipline in different works [Herbst & Liu_77][Lorette_84][Plamondon_00]. Later on, the study of Frag and Chen in 1972 has reported the use of chain-encoded tablet data to achieve a FRR of 27% [Frag & Chen_72]. In 1975, the Sternberg's work proposed to handle the pressure feature as an analog to z-information. His approach obtained a FRR of 0.7% and a FAR of about 2% using random forgeries [Sternberg_75]. In an attempt to distinguish prior and current related work in terms of methodology used the taxonomy presented by Gupta is followed [Gupta_97] which has also been identified in [Plamondon_00] and [Dimauro_93]. The state of the art in dynamic signature verification identifies three different categories. The first category characterizes the signature in terms of a time-function such as position, velocity or acceleration in a point-to-point quantitative comparison. In the second category the construction of the signature for comparison is characterized by measurements that are known as features which used to form the feature vector. A third category is based on the characterization of the shape of the signature rather than time function features, which is contrary to most of the previous temporal-based approaches. In addition, this chapter emphasizes some recent literature which most falls in a fourth category where hybrid approaches are considered. Thus the mouse-based dynamic signature approaches fall in the latter category.

3.5 Time-Function Based Comparison

Function-based approaches consider the comparison of test signature against a reference signature based on the different parts of the signature separately. The best example of an early work is presented in 1977 by Herbst and Liu who proposed a technique based on acceleration measurements and used regional correlations for automatic comparison [Herbst &Liu_77]. The hardware used is defined by two orthogonal accelerometers mounted on an experimental pen to sample a signature at the rate of 200 times per second. They reported a FRR of more than 20% with a FAR of around 1%. Consequently, in 1977 Yasuhara and Oka also carried a set of experiments on students who were asked to write the word "key" instead of their signatures [Yasuhara & Oka_77]. They used a nonlinear time alignment technique on the correlation policy from the previous work to prove better results. Their research reported error rates of less than 5%. Later on, in 1979, Lui and his colleagues improved the former technique by adding pressure to the two acceleration measurements [Lui et al_79]. The improvement is reflected by a FRR of 16% and 1% FAR. In 1984, Brault and Plamondon [Brault & Plamondon_93] provided additional enhancements to the correlation technique by including a four-step procedure based on pre-selection tests to build a set of n histograms for each signature, one for each feature. The acquisition data was through an accelerometric pen, which provides x and y accelerations for the top and bottom of the pen. They reported a FRR of 1.2% and a FAR of 1.0%.

In 1985, Zimmermann and Varady [Zimmermann & Varady_85] presented a method based on only the pen-up and pen-down timing information for verification procedures. They considered that the overall signature execution time can be treated as highly repeatable feature. Therefore, a one-bit quantized pressure pattern is used to obtain from a 4.6% to a high of 12% FARs and from a low of 30% to a high of 50% for the FRR. In 1988, Plamondon and Parizeau [Plamondon and Parizeau_88] combined three types of data, that is position, velocity and acceleration to build a feature set, which was evaluated by using three different techniques; the regional correlation, the time warping and the tree matching. In this experiment they reported a FAR with random forgeries varied from an average of 1.9% to 8.1%. In 1990, Bechet presented a US patent, which described a method that divides the velocity signals into x and y directions from the signature [Bechet_90]. Then, the method compares the corresponding segments of reference signatures with the test signature. Wu et al presented a technique to extract the principal components of the logarithmic spectrum of each signature to compute the similarity against a reference template [Wu et al_98]. They used an OmniPen_OP-1000 digitizer device to capture the signature information and, then to apply such data to the logarithmic spectrum. In that way, it was possible to model the changing rate of the coordinates within the signature. Their study has reported a 1.4%FAR and 2.8% FRR. A trend in the 90's started to look at other features for example: Yoshimura et al based their work on the use the direction of pen movement [Yoshimura et al_91]. In addition Sato et al used the pen's position and pressure to develop a signature verification system [Sato et al_93]. In a later research, the same authors have presented an approach based on the comparison of pen's position, pressure but also inclination trajectories to obtain a 3.0% FRR and FAR rates [Sakamoto et al_01].

3.6 Parameter-based Comparison

In the feature-based approach the signature is characterized as a vector of numerical measurements. Physical measurements signals such as horizontal pen position x(t), pen tip pressure signal p(t), pen azimuth θ(t) among are provided directly from industrial tablets .They can be integrated in the feature set with or without additional features derived in a post-processing task such a mean value of pen pressure.

Early work in parametric comparison starts with a strain-gauge instrumented pen which was made to sample three forces on the writing tip (downward force and x, and y direction forces components) [Crane & Ostrem_83]. Their studies built a feature set that was composed of 44 features including: scaled means, standard deviations, minimum and maximum values, average absolute and so on. The reported FAR and FRR varied from 0.5% to about 3%. Despite the results the experimental work was less robust in the sense that users were allowed three tries for the experiment in the verification process. They also discussed the possibility of using personalized features rather than a predefined set, which would improve the performance.

In 1984, Lorette used a set of 7 geometric and dynamic features [Lorette_84]. Such a set presented characteristics of being invariant under rotation and magnification of the signature. Furthermore, an iterative process enhanced the approach to realize a 93.6% of correct classification. In 1985, De Bruyne and Forre [DeBruyne & Forre_85] proposed a set of 18 global features including 6 dynamic features. In 1991, an approach based on a five-step method was addressed to build a signature reference by capturing the x and y coordinates as well as the pressure [Hastie et al_91]. Chang et al have used the spectral analysis to transform normalized signatures characterized by the values of x and y coordinates as well as the z coordinate (pen up and down) into the frequency domain [Chang et al_93]. Their approach selected as much as 15 harmonics denoted by the largest magnitudes which were used in a stepwise discriminant analysis. They have reported a 2.5% error rate when different users were considered as authentic. Nelson and Kishon described how they computed velocities and acceleration in the x and y directions using spine-smoothing functions and further computations of path velocities, path acceleration, path tangent angles, tangential accelerations, centripetal accelerations, jerks and curvatures [Nelson & Kishon_91]. An interesting finding from this study shows that the shape and dynamics of a signature might play complementary roles in a Hand Signature Verification domain(HSV) since if a forger is trying to get the shape in the right way; he is unlikely to get the dynamics in the right way and the other way round. Hastie and Kishoh added that indeed repeated signatures from the same author are similar but not identical. These variations are shown in the speed of writing and also in affine transformations such as size, rotation and shear [Hastie et al_92]. In 1996, Lee proposed a 42 features set with the possibility of finding a smaller set that performs better than the whole set investigated [Lee et al_96]. On the way to finding a small subset, the authors also studied improvements on the performance when forgery data were used. In addition, they tested the possibility of using the same common subset for all users. A 3.8% of EER was reported. In 1993, a technique based on Bayesian Neural Networks to be applied to dynamic HSV of Chinese signatures was developed by Chang et al [Chang et al_93]. They built a set of 16 features. Their results proved that about 2% of FRR was obtained, 2.5% skilled forgeries FAR occurred, and 0.1% zero-effort FAR.

In 1994, Darwish and Auda presented a comparative study to find the best feature vector for the HSV of Arabic signatures [Darwish & Auda_94]. A fast backpropagation unsupervised learning algorithm was used to reach a FRR of 1.4%. Also in 1994 Fairhurst and Brittan discussed the issues related to the selection of the best features [Fairhurst & Brittan_94]. To achieve it, they generated combinations of likely features and a metric through which it was possible to asses the relative merits of the features and thus select the best. Furthermore, they tried another technique called Sequential Forward Selection with the idea of adding one feature at a time to achieve the best performance. They promoted the use of individual sets of features and individual thresholds for each person. In addition, Nelson et al used a set of 25 features, which was applied to three different methods for computing the distance between the reference signature and the test signature [Nelson et al_94]. They used the Euclidean distance, the Mahalanobis distance and the Quadratic discriminate methods. Overall, the Quadratic algorithm performed the best but it required genuine and forgery data. In the case of the Euclidean distance, they found the best 10 of 25 features and they were used to obtain a 0.5% of FRR and a 14% of FAR. Plamondon described a multilevel HSV system that uses global features including a point-to-point comparison using personalized thresholds [Plamondon _94]. His findings reached a FAR of 0.5% and a FRR of 0.0%, which cannot be considered reliable because the test and reference signatures were used in deciding individual thresholds that minimized errors. Gupta and Joyce [Gupta & Joyce_97a] proposed a set of HSV algorithms with the aim of using a set of features that were simple and easy to compute, and invariant under most two-dimensional transformations. They found that the dynamics involved in execution of the handwritten signatures make more impact in the performance of the system rather than the shape features. They claimed that a FRR of 0%, or very close was reached by using the given features and using ten sample signatures to compute the reference signature.

Bajaj & Chaudhary have developed a signature verification system based on three global features such as the horizontal and vertical projections moments, upper and lower envelope of the signature components [Bajaj & Chaudhary_97]. They referred to the signature envelop as the curve constructed with the points lying on the upper and lower side of the principal axis respectively. Their best performance was reached with a classifier with weight learning value to report a FAR of 3% and 1.0% of FFR. Lejtman and his colleagues have presented a novel approach to characterize a signature based on five features: pen pressure, velocity in x and y directions, angle of pen movement and angular velocity Lejtman et al_01. The proposed methodology was designed to compress the signal by using wavelets and make the comparison analysis by implementing a back-propagation neural network. In their approach an impressive results were obtained a 0.0% of FRR and a FAR of less than 0.1%.

3.7 Shape reconstruction comparison

Shape reconstruction class, which is more related to the static HSV, deals with the capture of a signature shape, or some aspects of it. In 1997, Gupta and Joyce [Gupta & Joyce_97b] proposed a technique that used dynamics involved to characterize the signature shape. In the simplest form, the technique describes the shape by defining particular events such as a peak or a valley of the x or y profiles. The performance evaluation of this simplistic technique showed that this method was able to achieve a small FRR but a highly skilled FAR. Contrary to most of the previous temporal-based approaches, Nalwa based his concept of signature verification perception based on the shape rather than the time function features [Nalwa_97]. He emphasized that temporal features could not be the primary determinants on an automatic signature verification process. He was convinced that the trace of the signature along with its length played an important role in discrimination. He characterized the state of the system by using signature trace attributes such as jitter, aspect normalization, parameterization over the length, center mass, moments of inertia, and torque. The methodology used by Nalwa consisted of three stages: normalization, description and comparison. He have obtained an ERR that ranged from 2%, 3% and 5% tested on three different databases.

3.8 Hybrid Approaches and Recent Literature Review

In this class DSV approaches that are based on the two previous classes are considered as well as recent works. Yang et al characterized a user signature based on the absolute angular direction of a signature as a function of the distance s along the signature trajectory denoted as $\theta(s)$ [Yang et al_95]. They found that including pen-up symbols in the feature set improved the overall performance of their approach (4.44% FAR and 1.75%FRR). They added that the need for additional dynamic information of the signature (i.e. pressure, velocity and/or acceleration) might improve the verification system. Kashi et al argued that the inclusion of global features over a feature set integrated by local features enhanced the overall performance of a DSV system [Kashi et al_97]. They have included 23 global features including the total signature time t among others to reduce the ERR from 4.5% to 2.5%. Later on, in 1998 a model that compares the discriminative value of a 32 feature set (13 spatial, 13 dynamics and 6 contextual features) is proposed in [Dolfing et al_05]. They implied that pen's inclination plays an important role in the classification problem. In addition they have allowed a forger to look over the shoulder of the signer to capture graphically and dynamically the signature information. Based on such an experimental set, they reported a ERR Ranged from 1.0% to 1.9%.

Tanabe et al remarked that there was considerable variance in the signatures among the tester community in terms of writing pressure [Tanabe et al_01]. They also noted that the results could be improved with the elimination of the training effect from the device employed. In addition to this, they pointed out that the variation of the time duration of a signature is a significant measure of a subject's writing stability. It is also worth to mention that they used only one feature (pressure in only one direction). The construction of a more complete feature set, such as speed, acceleration, mass center, inertia axis, linear and circular segment length, and curvature radii, could improve the ERR rate of the system and that was the main concern in the approach of [Igarza et al_03]. The previous approaches coincide with the idea of handling extra attributes to improve the system's performance.

Tong and El-Saddik have developed a DSV system based on the stroke analysis [Qu et al_03]. The feature selection process extracted measurements of physical attributes such as pressure, velocity, position and acceleration as well as a large set of other features extracted from signals such as pen-up time, number of strokes, etc. by using a digital tablet. The performance of such systems has reached a 1.67% FAR and a 6.67% FRR.

In 2005 Alonso- Fernandez et al have implemented a signature verification system for Tablet PC's, which is based on the Hidden Markov Model (HMM) recognition algorithm [Alonso-Fernandez et al_05]. They built a biometric signature, which was parameterized by a vector set of 7 discrete-time functions including 2D coordinate trajectories, pressure signal, path tangent angle, path velocity magnitude in the form of $\{x_n, y_n, p_n, \theta_n, v_n, \beta_n, \delta_n\}$, $n = 1, \ldots, Ns$ (n is the number of, in addition to its order derivatives of all of them. Then they estimated the HHM by using the Baum-Welch iterative algorithm. Their verification performance for skilled and random forgeries with and without considering pressure information resulted in a range of EER values from 5.28% to 12.35%. Wan and Wam have presented an approached composed for two methods: Gaussian Mixture Model (GMM) model intended to handle global signature features and Hidden Markov Model (HMM) model for local signature features. They used spatial and dynamics global features including the total length of signatures strokes and the average and maximum speed among others .The local features are segments at point of high curvature of the signature representing variables such as segment length and direction and average pressure among others. Their model is able to obtain 93.3% of PV when pressure information is included. Otherwise, their composed model performance decreases in accuracy by obtaining only 89.7% of PV. In similar way to the previous work Rusell et al introduced an approach based on discriminative training framework [Rusell et al_05]. They used two different GMM models to characterize the authentic and the forger samples respectively. They also introduced a concept based on the signers' norm that characterizes the most likely variations of their handwritten signature performance. Their system reported an ERR of 2.25%.

Practical commercial systems such as Graffiti for Palm OS, Jot for Pocket PC, and the handwriting recognition built into the Microsoft Windows Tablet PCs have already been implemented. A successful commercial product called SignDoc has already been implemented based on digital tablet technology by the SOFTPRO Group [SoftPro_01].The system allows us to signing electronic documents using the biometric characteristics of a user's signature such as time completion, pressure and speed.

Overall, the dynamic signature methodologies can emulate the dynamics involved in the performance of handwritten signature with very high levels of accuracy and verification. In addition, the technology of pen-base computers, and more precisely, digital tablets are superior to the haptic when referring to mapping the exact and normal behavior of an individual signing.

3.9 Mouse-based Dynamic Signature Verification

Internet signature verification systems have lately increased in development with technology based on pen stylus computers such as digital tablets. Therefore, the requirement of special hardware makes the system less portable. Although the mouse and keyboard are reliable input devices yet less research has been dedicated to propose biometric systems based on non-specialized devices.

In 2003 the pioneer work in this domain was introduced by Everitt and McGowan, when they developed a hybrid system for authentication purposes on on-line applications by using a keyboard and a mouse as input devices [Everitt & McOwan_03] This work has also been patented. They combined a typing style and a mouse-based signature test to ensure authenticity. Their system was based on a combination of genetic methodologies for finding the feature extraction through a ranking process. The metrics used to build a feature set were based on the Euclidean distance and angles from different locations along the signature trace. They achieved a fraudulent access rate of 4.4 % FAR. This system requires entering a large amount of signatures in the enrolment process. Moreover, their method only used spatial features to build the identifier.

Recently, Lei et al presented another mouse based signature verification approach to be used for on-line transactions [Lei et al_05]. Unlike Everitt and McGowan's work, they reduced the number of trails required for the enrolment process to 2 instead of 5 proposed for the previous research. They selected a score matching technique based on linear regression over the points that describe the signature trace. However, this approach is based only on the spatial domain to build the templates used for verification; the temporal features are not considered.

There are several limitations in the incorporation of the computer mouse device as a mechanism for verifying the authenticity of an individual. There are constraints to extract only spatial information. A further limitation is the lack of natural ergonomic mechanisms to allow users to provide their handwritten signature.

3.10 Virtual Environments and Haptics in Authentication

In 1999, A.S. Tolba presented the first attempt to use a virtual reality glove as an input device to capture behavioral data from users performing their hand signature [Tolba_99]. The acquisition data from the glove was based on the optical-fiber sensor situated at each finger, which captured 256 positions. In addition, the input control allowed 60° pitch and roll angle positions. The frequency sample for all the physical parameters was around 200 times per second. Tolba used a self-organizing map and a combination of Principal Component Analysis (PCA) approaches to reduce the dimension of the state of the verification system. The feature set was based on seven 80 dimensional state vectors for the first approach and a reduction to 10 components in the second approach. Results from

Tolba showed a 0% error rate with 100% confidence by combining 21 correlated features with a 6 x10 matrix.

3.11 Conclusions

DSV is a very active area of research and a large number of research papers have been published lately. Unlike DSV, the research on key stroke dynamics is less intensive. The guided tour of the related work on these disciplines presents a picture on recent developments, specially using VEs. As mentioned before DSV and key stroke dynamics studies are based on different variables to characterize their testing protocol. Among others elements considered are: the diverse feature sets, the different fixed and non-fixed thresholds, the different number of signature trials needed to build a reference template, the use of forgeries samples, different databases size. In general, all these variables makes difficult to compare the presented methodologies in order to draw concrete conclusions. However something that we can learn from this review is that there is a trend in parametric-based approaches. The overall approaches are unlikely to achieve an ERR minor than 5%. On the other hand functional-based approaches in general obtain much better performance than parametric ones. Particularly, hybrid approaches combine local and global attributes to obtain mostly very good results.

In this sense, haptic-biometric based applications seem to have the potential of an alternative mechanism to capture a wide range of physical attributes during a user-haptic-computer interaction. This can be translated into a more careful selection of features either to tackle parametric or function-based approaches. Therefore, the advantage is that it is possible to identify among them the features which provide richer information content and can improve a biometric identifier system.

At first glance, digital tablets use software technology that is compatible with standard API's like Wintab, which is the industry standard for acquiring data from a graphics tablet on Intel machines and has been the standard for a number of years. In a sense, this is an advantage in terms of developing applications based on that technology. However, it makes the verification system more vulnerable regarding accessibility to a public software programming interface library.

In terms of the hardware digital tablets are achieving good performance in terms of data resolution as input device. Their related software technology have become compatible with standards API such as Wintab which is the industry standard for acquiring data from a graphics tablet on Intel machines. In some sense this an advantage in terms of developing applications based on that technology. However it makes the verification system very sensitive to attacks since the accessibility to standards API for tablets is a public domain. In this scenario haptics technology make the programmable interface less obvious since rely on more sophisticated calculations to provide the force feedback feeling to capture the behavioral traits of individuals interacting with such devices.

Chapter 4

Design and Development of a Haptic-Biometrics AuThentication System (HaBiTs)

4.1 Introduction

The architecture presented in chapter 4 was implemented as component-based middleware framework. This framework, called *HaBiTs* for Haptic-Biometrics auThentication system which provides the flexibility to construct a protocol for dynamically quantifying human hand psychomotor pattern movements during a user-haptic based interaction [Orozco et al_05c]. The main requirements and design objectives that characterize the proposed Haptic-Biometric based architecture include:

(1) Automatic identification of human psychomotor movements. The Haptic-Biometric system applies the relative entropy approach to discover and load the physical parameters that provide the most valuable information to build the users' reference templates.

(2) Automatic authentication of individuals at any time during the session. Even though a user can be authenticated to gain access to a system, the *HaBiTs* can be activated at any time to carry out any further evaluation to recognize an individual based on the psychomotor movements performed on the current haptic interaction.

(3) Reconfiguration of pattern recognition methodologies for classification. Haptic-Biometrics can use different methods from a limited set of pattern recognition

methodologies. Such methodologies have been implemented as object-oriented components making the architecture extensible and adaptive to new algorithms.

(4) Haptic Data Repository Management. Behavioral haptic data generated as output from the haptic interface during any human-machine interaction is captured and stored on a haptic database subsystem. The idea is to generate a highly adaptive haptic-data repository, which enables data filtering, and database connectivity for efficient storage and retrieval.

(5) Clean separation of the Haptic and Graphic Rendering processes. The proposed framework was designed according to the Model-View-Controller (MVC) design pattern to make the separation of the haptic rendering process from the graphic rendering event.

UML case diagram representation is used to explain the overall implementation of the proposed architecture (Figure 7).

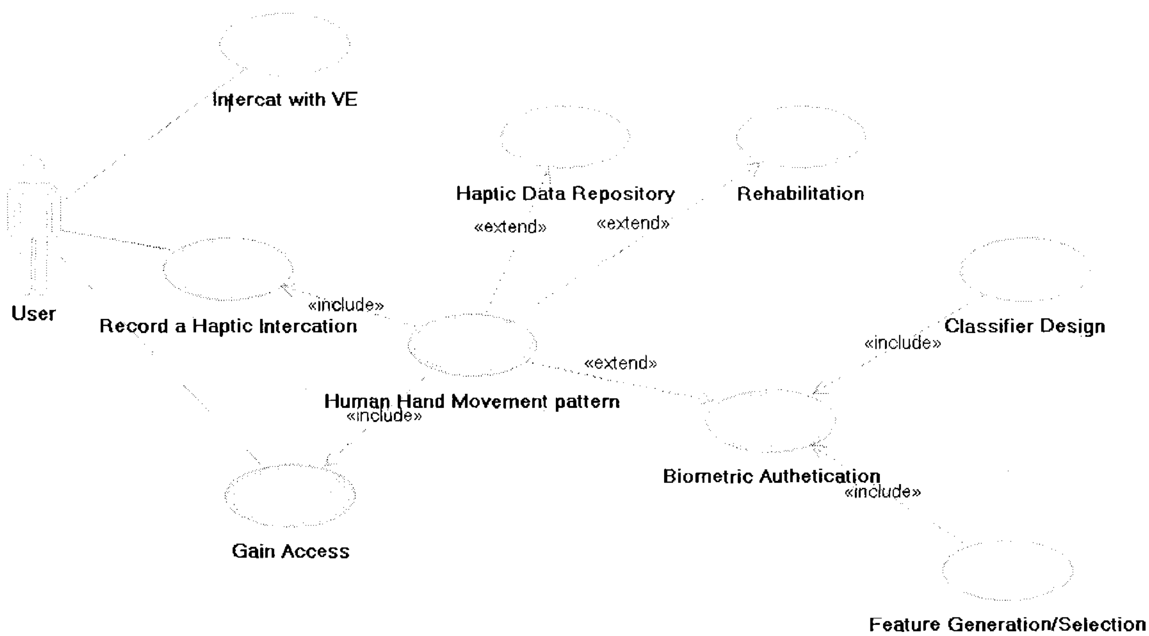


Figure 7: The *HaBiTs* system use case diagram

Figure 7 characterizes a scheme of the *HaBiTs* system at a very high-level architecture. A user is able to work into a VE with haptic feedback meanwhile the system is recording the behavioral performance of such user. The haptic data generated is used to feed an authentication subsystem in order to recognize the human movement patterns described by the original user. The details of the scheme are explained in the remainder of this chapter as well as in the Appendix A.

4.2 HaBiTs Architecture

On this haptic-biometric-based architecture, all the services are developed as components of respective subsystems. Four core subsystems can be identified: Adaptive Haptic Framework (AHF), Haptic Data Repository (HDR), Feature Generation/Selection (FGS), and Classifier Design/Decision (CDD). From Figure 8, the two subsystems: (1) the (AHF), and (2) (HDR) can characterize a biometric enrolment process. In the former, tasks are defined for capturing a person's behavioral characteristics where haptics plays an appropriate human-sensor role. In the latter, a recording process is carried out for instance, resulting in raw biometric data in an unprocessed format. In addition, the HDR has the capabilities of filtering and establishing an interface for storage and retrieval of such haptic information.

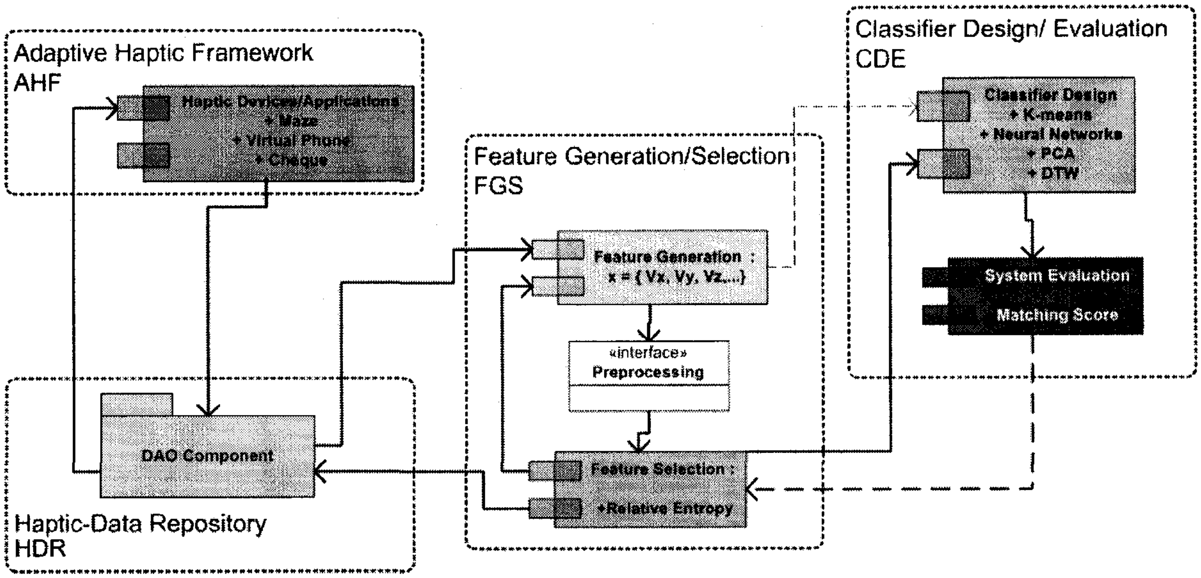


Figure 8: The HaBiTs High Level Framework Architecture

After acquisition, the data is sent to the FGS. Here, a quantitative characterization of the state of the haptic system is formed. The system's state properties are described by an array of vectors, each corresponding to different features to be analyzed. In addition, within the FGS a pre-processing task may be required before the data can be ready to be processed in the feature selection processes. Outliner removal, data normalization, and missing data detection tasks are accomplished via this pre-processing interface. The next procedure, called feature selection, receives a given number of features and selects those of the greatest user-classificatory worth. By using the relative entropy, the reduction of the feature state vector dimensionality is reduced, and chi-squared test features are extracted. For authentication, a set of biometric algorithms are used in the CDD.

4.2.1 Adaptive Haptic Framework (AHF)

The AHF is an integral component of the *HaBiTs* System/framework. The AHF follows a Model-View-Controller (MVC) design pattern. Such a MVC-based modular approach allows the clean separation of the graphical and haptic rendering processes from the rest of the application functionality, permitting us to replace them with different implementations using different APIs. For example, we can replace the **BioHapticsGUI** object (see Figure 9 below) object to use Microsoft's DirectX instead of its current graphics API, OpenGL. Furthermore, we can switch out the haptic module depending on which API we want to use, without needing to modify the rest of the code. To go further the concept of a generic framework, it does not use a specific model format for objects. Instead, it uses an internal abstract class to represent objects. The reason for this is that each model format needs to be inherited from this class. In that way, different file formats can be added when the need arises, without needing to change any code in the subsystem. Figure 9 shows the implemented classes for the AHF subsystem.

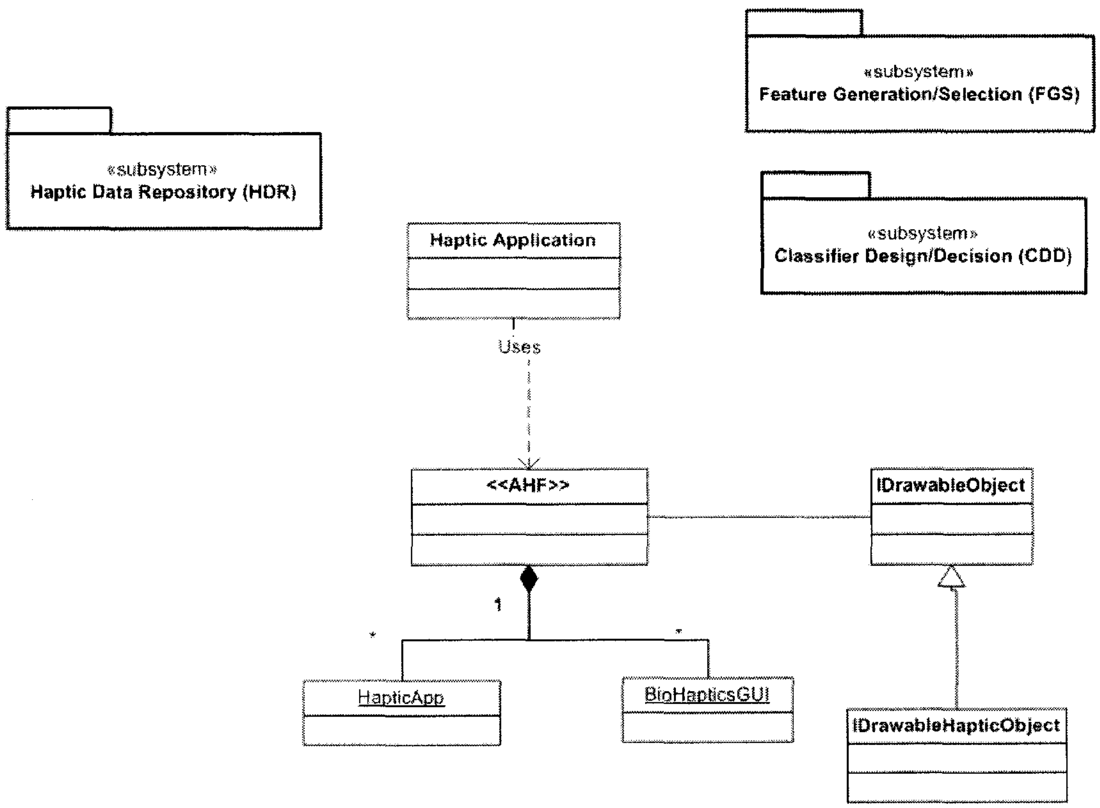


Figure 9 : Class-Diagram representing the Adaptive Haptic Framework (AHF) and its relationships with others subsystems

A haptic based application is implemented via the AHF interface. The AHF's interface provides services such as simulating the haptic interaction, loading virtual objects and setting the scene graph to render all the graphical events through three classes; **HapticApp**, **BioHapticsGUI** and **IDrawableObject** which are below described briefly.

4.2.1.1 Haptic Rendering Module

The class that manages the haptic rendering processes is called **HapticApp**. It is responsible for implementing the haptic commands for handling the complex calculations to simulate the haptic feedback, provided by specific haptic APIs [Reachin_A] [Imm_A] [SenTec_B]. The AHF's interface has access to functions such as **setStiffness**, **translateObject** and so on (see Appendix A, Table 6). It is the role of this **HapticApp** class to implement those functions, as well as to handle any collision detection and haptic rendering event. The functions provided to the framework by this class need to be general functions, such as object translation, setting or retrieving haptic properties and so forth. Therefore, several issues appear in this module. The reason for this is that not every API has the same functionality. The haptic device highly limits a lot of the functionality that the API provides. For example, the CyberGrasp unit is designed to allow the user to grasp and manipulate the objects with their hands: whereas the PHANToM's OMNI device or any other desktop devices are designed to allow users to feel objects with pen-like end effector. Having specific haptic functionalities make difficult to use multiple haptic devices in the same VE.

Nevertheless, this framework managed to incorporate the Reachin and OpenHaptics API's for the PHANToM Desktop and for the OMNI devices. In addition the framework is able to allow plugging the multi-point interaction through the concept defined on

VHT's API for the CyberGrasp unit [ImmTec_A]. Therefore, the framework is able to map the functions that provide some similarities in their Haptic Scene Graph (HSG) representation. Thus, a haptic class was implemented for each of the three APIs, making sure to implement the same haptic commands and providing haptic functionality without modifying the VE. Due to the architecture design, an appropriate module can be inserted for the haptic device used, without either changing the framework code or modifying the VE.

4.2.1.2 Graphic Rendering Module

This module defines an OpenGL GUI; class **BioHapticsGUI**, with an extendible capability, which enables users to replace the Graphical User Interface (GUI) with their own GUI, thus making the framework customizable. An important assumption in this research is that the VE and the haptic device must be decoupled to allow multiple application programming interfaces. In addition, for the framework to remain extensible, developers are allowed to add different file formats for rendering to the graphical scene. In short, this framework avoids dealing with a particular format. It instructs the objects to do specific tasks (e.g. rendering itself), and enables the object to handle the specifics properties (i.e. rendering, these would be graphical properties).

4.2.2 Haptic Data Repository (HDR)

The use of the data that has been recorded with a set of haptic applications finds potential relevance in discovering human hand movements that can be classified as pre-defined user patterns [Orozco & Saddik_05b]. In addition, some type of applications, such as rehabilitation might require the existence of a historical data profile to help stroke patients to recover [Shakra_06a][Shakra_06b]. In this sense the HDR is capable of recording haptic data (Section 4.2.2.1) and accessing recorded haptic data (Section 4.2.2.2).

4.2.2.1 Recording Data

The raw data generated during the haptic-visual interactions is to be recorded and stored via the HDR. For example in order to record data, a call to the **CreateDataFile** method is needed. It takes a *char** as a parameter (the filename without an extension). This function creates the file in txt format. Then**, setRecordFlag,** which takes a Boolean type as a parameter, must be called, giving "true" as a parameter to start writing and "false" to stop. It should be noted that if **setRecordFlag** is called before **CreateDataFile** to check that no data file has been opened, then the **setRecordFlag** is open with the default name "data.txt". The user is informed about it. A wide array of the physical parameters from the haptic device according to a related API can be recorded through the set of applications (i.e. Maze, Virtual Phone and Cheque). For details, the readers and developers are referred to the API shown in the Appendix A-Table 7.

4.2.2.2 Accessing haptic data

In our case, the data is formed by a set of arrays containing the output attributes obtained from the haptic events. As mentioned before, data source is generated and recorded as flat files and thus, it modified to be represented in an object-oriented database. The data files recorded from the implemented applications register a variety of physical attributes, such as the 3D world coordinates of the stylus's position (x,y,z) (from the OMNI and PHANToM Desktop or the CyberGrasp unit), force exerted, and the torque applied from the haptic-based application in the case of a single-point interaction. In the case of a multi-point interaction, other parameters can be captured such as the angle of each finger position during grasping or holding of the CyberGrasp unit [ImmTec_A].

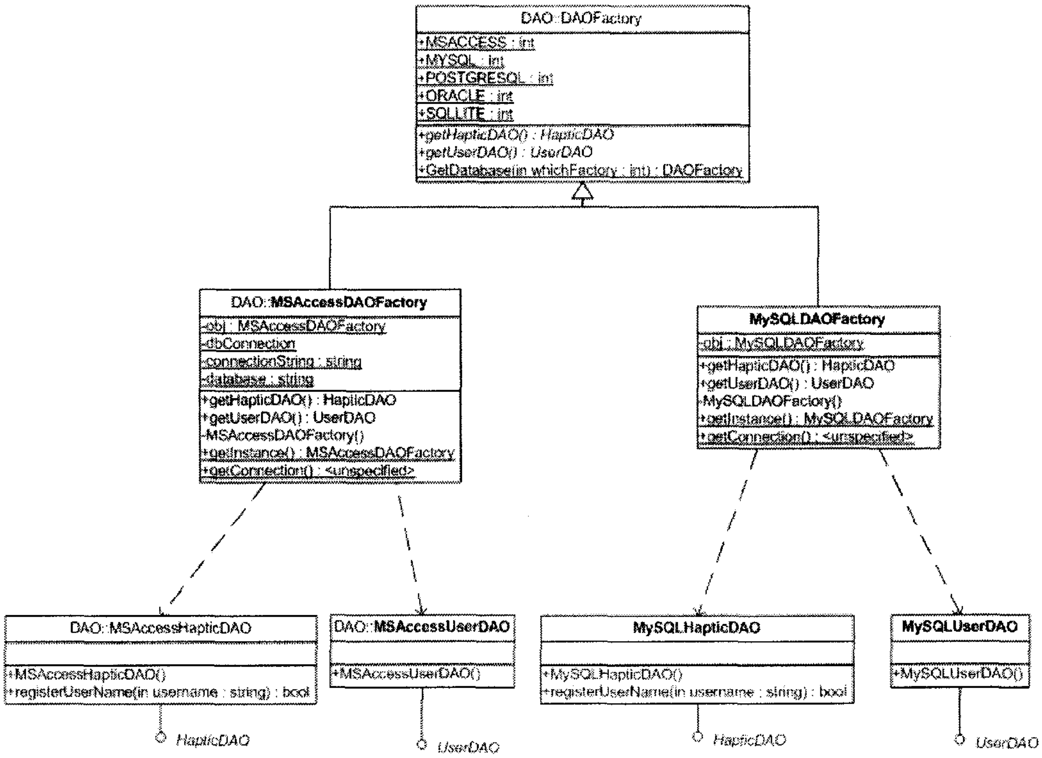


Figure 10: Class-Diagram representing Data Access Object Factory (DAOF) which is the basic infrastructure of the HDR subsystem

The HDR subsystem uses a Data Access Object Factory (DAOF) interface to abstract and encapsulate all access to the data source (see Figure 10). The DAOF manages the connection with the data source to obtain and store data. The DAOF implements the access mechanism required to work with the data source via either MySQL or MS ACCESS. Details and an in-depth demonstration of the design and implementation of this subsystem can be found in Appendix A-Table 7).

4.2.3 Feature Generation/Selection (FGS)

The GFS subsystem is responsible for building the feature set that characterizes the user's haptic-based task (e.g. signature, path navigated in the maze and so on) reference template. Figure 11 is an UML sequence diagram that explains how *HaBiTs* automatically characterizes the psychomotor movements of an individual working on virtual domains.

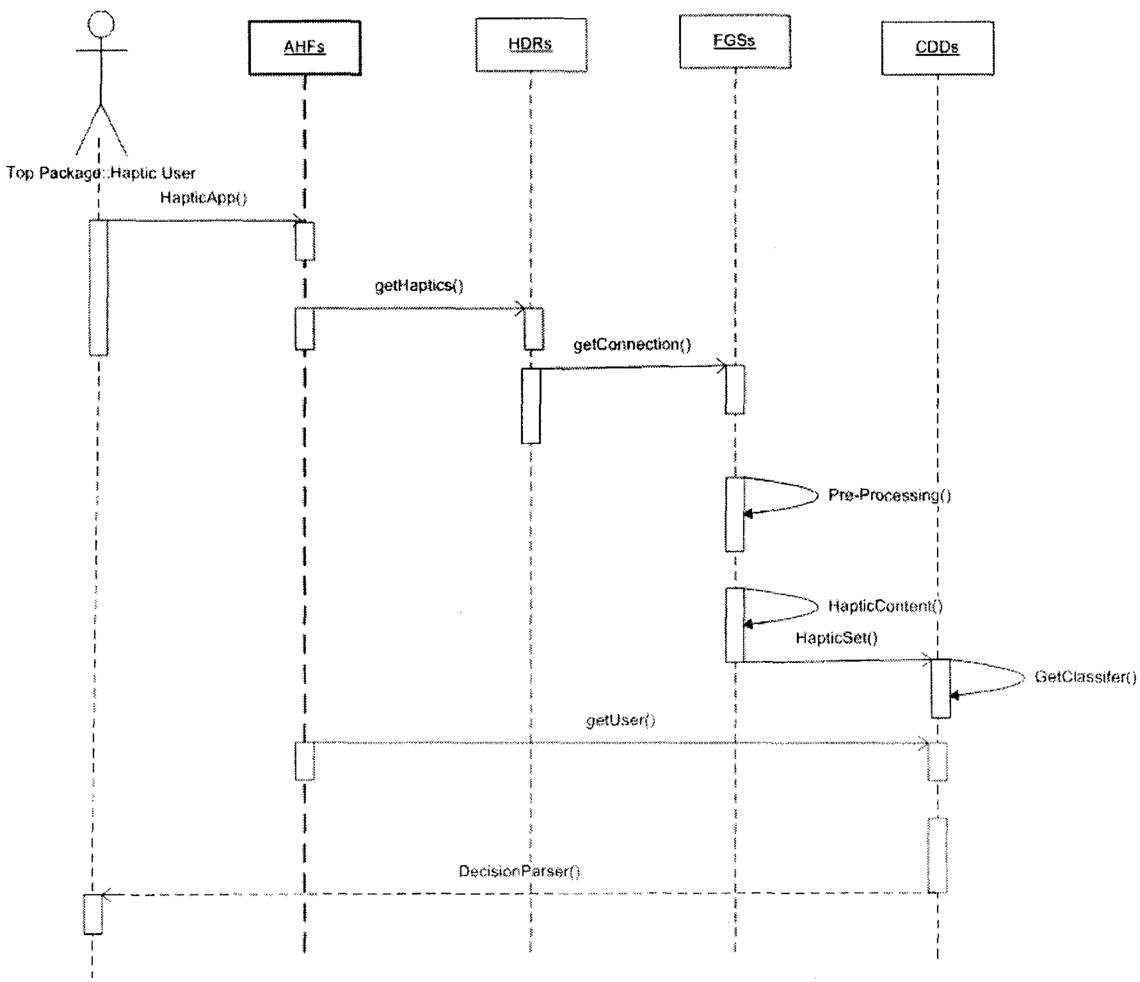


Figure 11: Sequence diagram of FGS subsystem which represents the automatic recognition of Haptic-psychomotor human hand movements from *HaBiTs*

In this subsystem, all the dynamics involved in the haptic session task are retrieved from the HDR via the **getConnection** function. If further computation of the current array of attributes is needed, then the **PreProcessing** method is called up. Once the array of attributes is set, the **HapticContent** implements a model based on the relative entropy algorithm or also called Kullback and Leibler divergence [Lexa_04]. This model assess the uniqueness of each biometric attributes in order to define the final features set, which contains the attributes with the most relevant information in a particular haptic-based interaction(see Section 6.2 for further details). The way that the final feature set is built is by averaging the relative entropy value of each feature and then comparing and ranking them in order to remove the ones that are less informative. The **HapticContent** object also has the option of adding an extra feature to the final set if it is required. It can be either a global, local or pre-computed attribute.

4.2.4 Classifier Design/Decision (CDD)

As mentioned before, some haptic interfaces are good source of richer information to evaluate the user-classificatory worth. In this domain, it has been experimentally proven that different classifiers exhibit several degrees of success under numerous of the classification problems tackled, [Ranawana & Palade_05]. Indeed Ranawana & Palade_05 also pointed out that there is no classifier had been proven to be perfect in the classification tasks of the pattern recognition domain. Hence, several classification schemes for implementation have been taken into account in the CDD subsystem. The idea has been materialized as set of pattern recognition algorithms implemented in an object-oriented fashion. This approach offers the flexibility to enable different methodologies to be applied on the final task. An interface called **ClassifierOptimizer** defines the guidelines in terms of data and behavior needed to implement an individual classifier model (see details in Appendix A). In a situation where a number of classifiers are available, the simplest approach would be to select the best performing classifier and use it for the classification task.

From figure 11 the authentication task is carried by a **GetClassifier** method, which receives the feature set from the FGS subsystem. Then, the **DecisionParser** method computes and evaluates a score between a user's signature reference template and a test signature template generated during the session. Thus, the **DecisionParser** evaluates such scores according to a given threshold in order to make any decision.

4.3 Development of the System

Through the evident need to merge the current haptic technology in a single pipeline and create flexibility in order to be adaptive to the user's needs, we envision a system conceptually visualized in Fig 8. This implies integrating fields such as software engineering models and pattern recognition methodology. This thesis presents variety of applications that have developed and employ the use of three different haptic devices: The PHANToM Desktop™, CyberGrasp unit and the PHANToM-Omni- this haptic-based applications including: Lifting a cylindrical can, Virtual Maze, Virtual Cheque , and Virtual Phone.

4.4 Observational Results

In addition to the wide spectrum of methodologies considered, the computer technology is evolving rapidly by incorporating biometric recognition technologies to devices such as PDAs, laptops and cellular phones. Such devices are becoming the new generation in an interconnected world with the addition of more features. The haptic technology is growing and causing large impact i.e. by providing a high degree of realism in an artifact's surface properties held in museums [Brewster_01]. The main feature of haptics is the exchange of energy between user and machine in a bidirectional way through force feedback stimuli in other words: "Force display technology works by using mechanical actuators to apply forces to the user. By simulating the physics of the user's virtual world, we can compute these forces in real-time, and then send them to actuators so that the user feels them" [Minsky et al_90]. Taking advantage of this feature, the present work incorporates the use of haptic devices associated with DSV analysis. However, the incorporation of haptic devices needs to be considered as additional input for user authentication from the current input devices used as biometric interfaces (digital tablets, pen-based computers and Cyber data gloves). Such an issue exists due to the presence of the motion and/or the force information to simulate a realistic environment with the real world. This idea has been envisioned by the design of a set of applications involving different tasks, and varies from solving a maze, dialing telephone codes, and logging into a system by using a virtual-graphical password or performing a hand signature in a virtual environment with force feedback. There are a variety of physical parameters (i.e. 3 dimensional force, velocity, torque and end-effector orientation), as data source, that characterize the user's hand and kinesthetic movements when using haptic devices that can be recorded and have not yet been exploited exhaustively [Guerraz et al_03]. Guerraz et al had presented a framework for active haptic evaluation using parameters coming directly from the haptic device. In this research we are using and evaluating physical attributes in order to build a biometric identifier to authenticate the identity of a user in a haptic system environment, while helping us to understand human behavior when interacting with machines.

In order to introduce this concept properly, it is important to consider the current available haptic technology that can be used as an input information mechanism. These are haptic interfaces for force feedback and tactile feedback. As the state of art about haptic interfaces is quite vast [Biggs & Srinivasan_02][Eid et al_07][Basdogan &

Srinivasan_01][Hayward et al_04][Salsedo et al_05]. However the present work considers only for kinesthetic force-feedback interfaces such as desktop and hand exoskeleton devices.

4.5 Calibration and basic data resolutions of haptic devices

Two kinesthetic force feedback devices are of interest for the present work: a multiple contact points interaction with a hand exoskeleton the CyberGraps system from [ImmTec_A] and a single contact point interaction desktop device the PHANToM device [Massie et al_94] which has been commercialized by SensAble Technologies Inc.[SenTec_A].

Most of the available literature represents the position of the haptic device as a point or ray-based in the VE, However little work had been conducted in multi-point interaction. In point-based haptic interaction only a single point of the haptic device, known as the end effecter point or Haptic Interface Point (HIP), interacts with virtual objects. Examples of very realistic, convincing, and commercially available single point of interaction devices can be found on [SenTec_A][MFCS_A][ForceDim_A]. However, multiple-point exploration and manipulation of computer generated objects, such as the simple task of grasping objects, is still difficult to achieve, with limitations in hardware and software clearly visible.

The family of a single-point interaction haptic devices, such as the PHANTOM Desktop™ provides a positional resolution ranging from 450 dpi to up to more than 1000 dpi (around 0.02mm)[SenTec_A]. It also offers a range of motion for hand movements that pivots at the wrist. The PHANTOM™ Haptic Devices provide 6 DoF positional sensing through digital encoders but some devices are able to deliver 3 DoF positional sensing and 3 DoF force feedback capabilities, such as, The Premium models 1.0, 1.5, and 3.0.

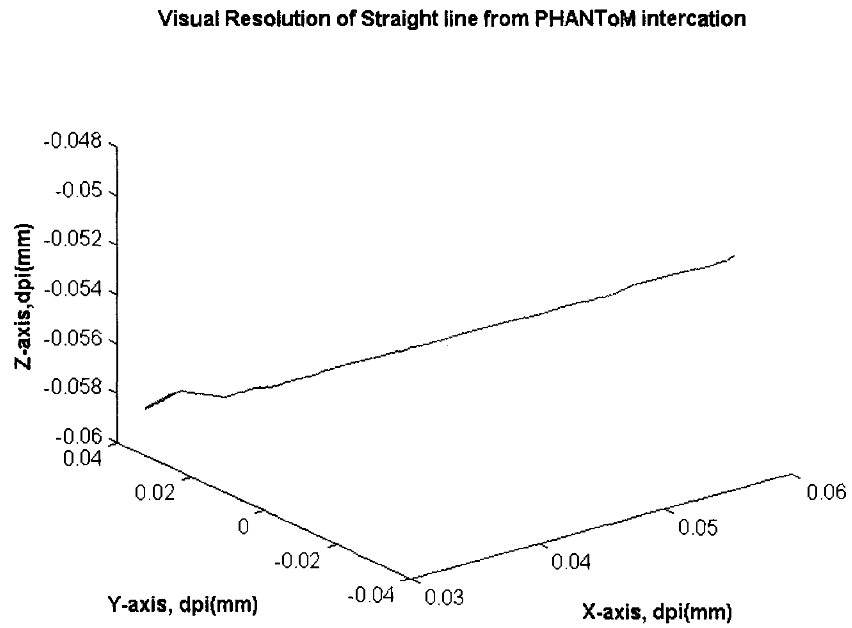


Figure 12: Positional resolution of the PHANToM at the X-axis in the 3D world representation,

The PHANToM force reflecting haptic interface presents high-precision positional characteristics among others [Sens_01] [Çavusoglu et al_02]. From figure 12, a straight line in x-direction drawn by the PHANToM device on the 3D plane, which is visually acceptable. However, at the sensor level, the implementation of complex control algorithms can compute accurate measurements of positional resolution and velocity, among others. Such features satisfy the requirements of applications that require high-performance tasks such as in the areas of medical robotics and virtual environment-based surgical training simulators. At the sensor level, preliminary measurements show that the exact trajectory on the units that traveled in the x-direction against a reference line had a standard deviation of 0.051dpi. This figure does not make any impact in the quality of the measurements and it is enough for the requirements of the hapto-based applications implemented (i.e. Virtual Maze, Virtual Check). The algorithms contained in the CDD subsystem need to represent the consistency of this measurement behavior. The relative dispersion (RD) of a statistical distribution is a good measure of its variance. The relative dispersion is often called the '"Coefficient of Variance"' (CV), which measures the precision of a person during a set of individual tests (replicates) performed for one specific task. With statistical features, we calculate the percentage of relative dispersion in order to compute the percentage error needed to be considered in order to compensate for further analysis in some tasks.

The PHANToM's Omni haptic device can touch and manipulate virtual objects at reliable and precise point-contact interactions for desktop applications. It provides six-degrees of freedom positional sensing with a nominal position resolution of about 0.023mm. It is able to provide a maximum applied force at a nominal (orthogonal arms) position of 1.8lbf (7.9N).

The CyberGrasp unit can provide the feeling of the impenetrable resistance of a simulated wall and sense weight and inertia while picking up a "heavy" virtual object. The CyberGrasp unit consists of three pieces of hardware. The three pieces are CyberGlove, CyberGrasp and the CyberForce armature. The CyberGlove collects data that is related to the hand, such as the bending of the joints of the finger. The data collected is used to display a realistic representation of the hand on screen. The device provides up to 22 high-accuracy joint-angle measurements. The CyberGrasp is an exoskeleton capable of generating force feedback on the fingers. The device can generate forces that are roughly perpendicular to the fingertips and can be specified individually. The maximum continuous force is 12N per finger. The CyberForce armature has 2 functions, one of which is tracking the movement of the hand. The CyberForce armature allows for six-degrees-of-freedom and is capable of measuring hand rotations and translations.

The CyberGrasp unit integrates the Polhemus FASTRAK® sensor technology [FASTRAK_A]. The Polhemus FASTRAK is used to track the position and orientation of users' hands. The most accurate electromagnetic motion tracking solution is reflected with an accuracy of 0.03 inches RMS (Root Mean Square), a latency of 4ms, and a resolution of 0.0002 inches per second (~0.000381mm). In addition, Immersion uses the InterSense IS-900 Tracking Systems. The IS-900 provides accurate position and orientation (6 DoF) data for the CyberGlove®, CyberTouch™ and CyberGrasp® by using a hybrid tracking technology of inertial and ultrasonic components. This solution provides smooth, precise tracking that is free from interference caused by metallic environments or ultrasonic noise.

Figure 13 shows an example of a users' profile – using the CyberGrasp® - when grasping an object is presented. The grasping information is captured from the angular orientations of the fingers' proximal phalanges in a set of thirteen trials.

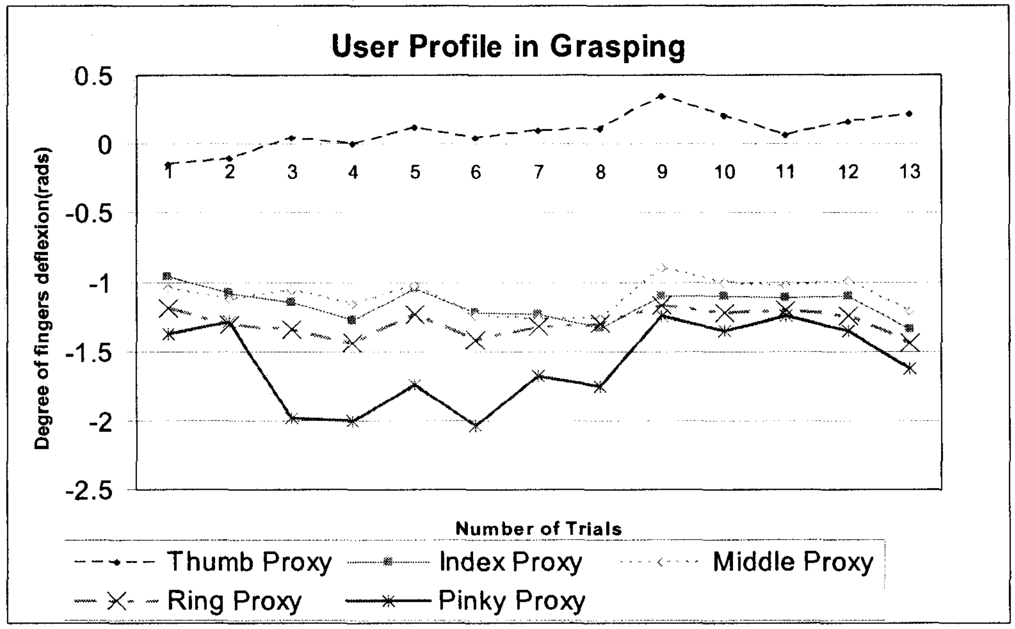


Figure 13: Participant's profile of bending the joints of each finger angle measurements captured during the cup grabbing application

Based on the angular orientations of one's proximal phalanges of the five fingers' measurements obtained from the sensors of the haptic device, we can validate the size of error and obtain other statistical measurements. The mean value, standard deviation, relative dispersion, maximum, minimum and maximal difference of the $d\theta/dt$ distributions for each angular orientation of one's proximal phalange "θ" can be computed, and concrete conclusions can be drawn from comparisons between different trials for the same subject in order to create a user profile.

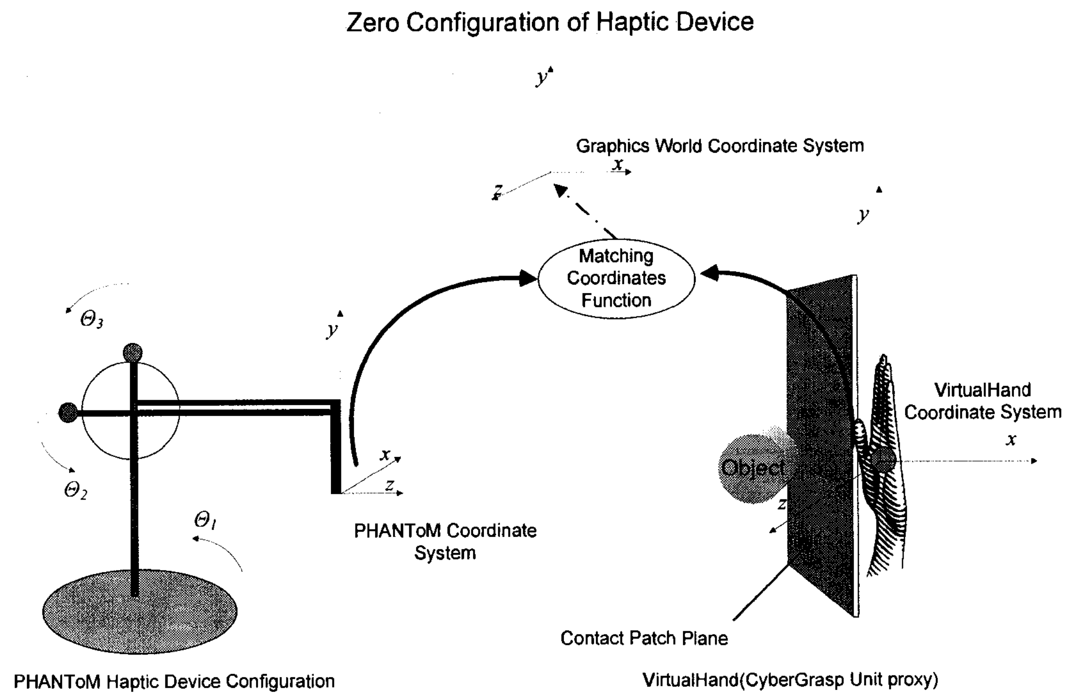


Figure 14: Shows the interpretation of the (AHF) subsystem to handle the world coordinates related with a haptic device

One of the major problems in designing and developing haptic environments is the problem of mismatch between the graphical coordinate system and the haptic device coordinate system. The approach developed in this work to overcome this problem is by implementing a function that detects the device coordinate system orientation and adjusts it according to the graphic coordinate system, as depicted in Figure 14. In this figure, a matching coordinate function contained in the AHF subsystem is able to apply singular transformations, such as rotations of 90 in the z-axis and -90 along the x-axis, which resulted in a match of the two coordinates systems (graphic and haptic coordinate systems).

4.6 Development of Applications for kinesthetic haptic interfaces

4.6.1 Virtual Phone

The primary benefits of a virtual phone application stem from the mapping of keystroke rhythms of users when dialing phone codes, they build a user reference biometric template based on human-device interaction (Figure 15). Analogue to the key stroke dynamics described when a user interacts with a keyboard; we argue that similar patterns also characterize a user when dialing a haptic-based phone.

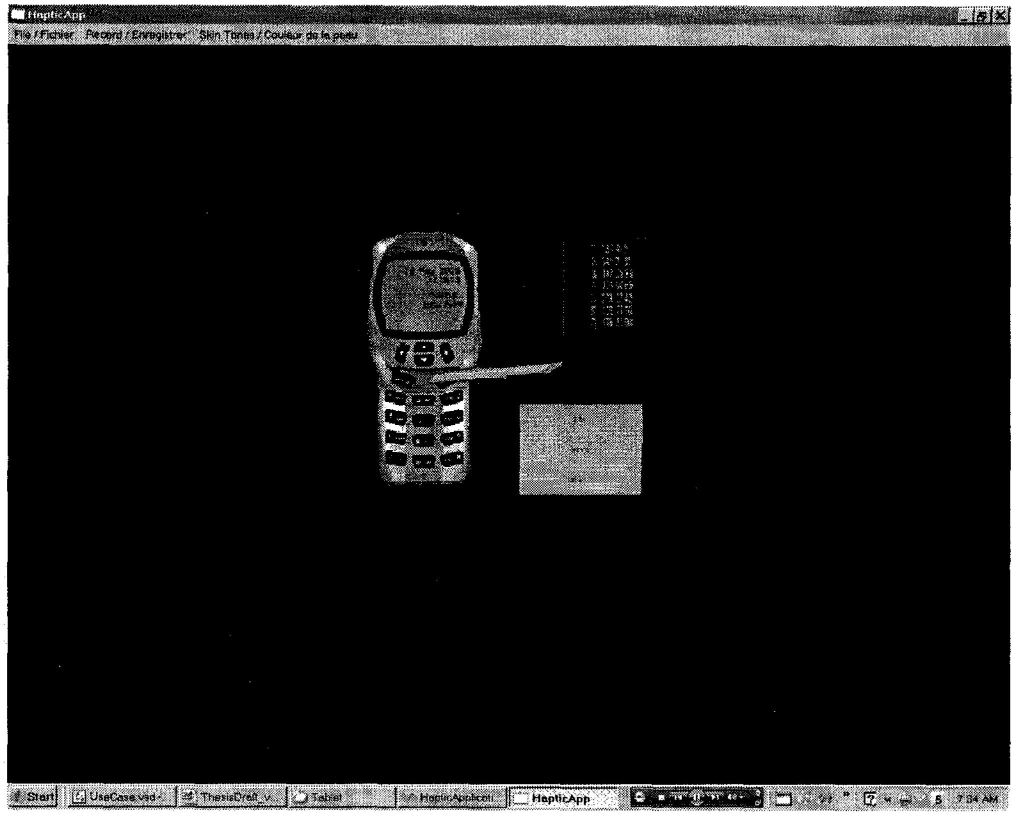


Figure 15: Virtual Phone Haptic Based application where users dial code phones. User is required to dial the 7 numbers that appear on the screen

The application implements a force feedback action between the end-effector of the haptic device, which is displayed by a proxy pen, makes contact with the virtual buttons. By pressing each of the virtual phone's keys, an event is activated haptically and graphically. The haptic stimuli that a user can receive is characterized with an force feedback when a phone's key is pressed, which is obtained from mapping the orientation and velocity of the proxy object based on a spring-mass scheme implemented by the associated haptic API. In addition, the virtual phone application renders graphically any key-button action on the phone-display panel. The virtual phone application delivers complete haptic-visual stimuli.

4.6.2 Virtual Cheque

Another behavioral biometric pattern can be described via the handwritten signature by means of a haptic device. The way a person signs his/ her name is known to be a characteristic of that individual [Plamondon et al_99]. Although, even handwritten signatures are a behavioral metric that changes over time, some particular features of the writer such as the overall signature duration has be found highly repeatable feature [Zimmermann & Varady_85]. These changes are also influenced by conditions such as an individual's physical and emotional state. Nevertheless, handwritten signatures have been widely accepted as a method of verification. Therefore, we implemented a virtual cheque environment with a haptic feedback which emulates a user performing his/her handwritten signature on paper. The design of the cheque was built on an elastic membrane surface with particular mechanical attributes to mimic realistic paper surfaces. The application set methods called **get/setStiffness** and **get/setInertia** through the proper haptic API to emulate the desired force feedback stimulus. The haptic stimuli that a user can receive are translated with the sensation of a frictional surface when the user is performing his/her hand signature. At the same time, the user is signing a colored blue path that is displayed in the graphic scene to represent the precise shape of the hand signature (Figure 16).

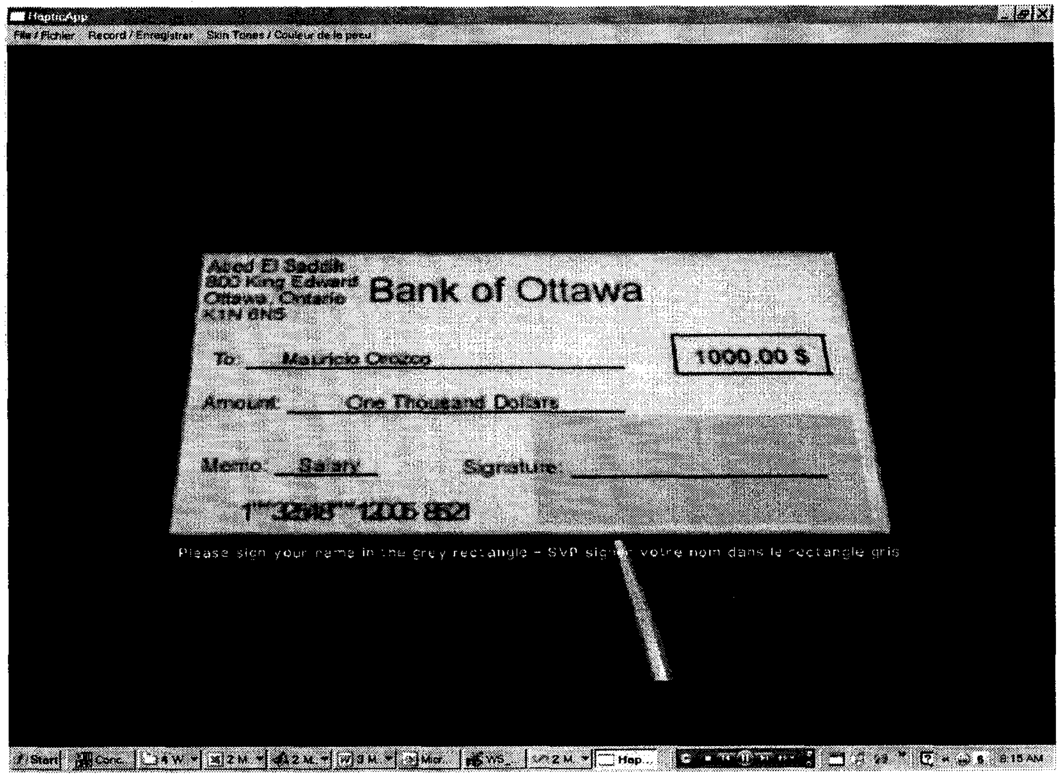


Figure 16: The virtual cheque haptic-based application. User is required to perform his/her hand written signature in the area selected

4.6.3 Maze

In addition to the virtual phone and cheque application, this work considers the development of a virtual maze application. The main purpose is to record the hand movements of different users during different maze solving events. The experiment involved the participant in completing a flat 2D maze, which was placed on one surface of a cube. The haptic stimulus is provided by a function that emulates a given force response in order to prevent a user from passing through the walls of the maze. The sensation is as if the walls were made '"sticky". This application also graphically renders the pen's maze trajectory using a line path (colored in light blue) (Figure 17).

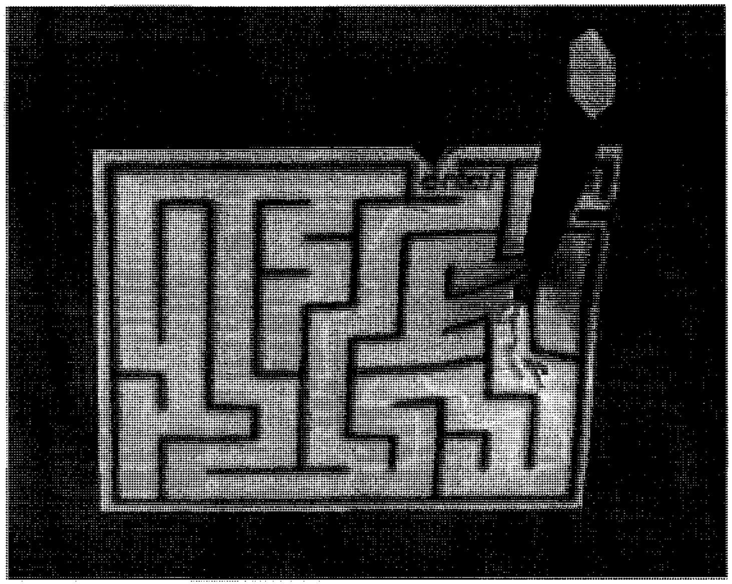


Figure 17: Screenshot of a user navigating the maze. The stylus path is indicated with the blue line

The application also sets the actions to initiate a maze solving process as well as to stop such a process. Therefore, color coding was also added to the maze to inform the user when recording was taking place. Prior to starting the maze, it is colored red. While recording a trial through the maze, it is colored white. When recording completes on the maze, it is colored green. In this manner, the application only records data under such constraints (see the left side of the Figure 17 of the maze recording process). The stylus path is indicated with the blue line.

4.6.4 3D Virtual Maze and Cup

The 3D Maze solving process requires from the user to navigate through a maze with a wand. The collisions between the maze's wall and the wand are counted and provide the user with a realistic feeling of navigating through a maze. The main goal of this application is to acquire a user's behavioral data that can be used for biometric authentication purposes.

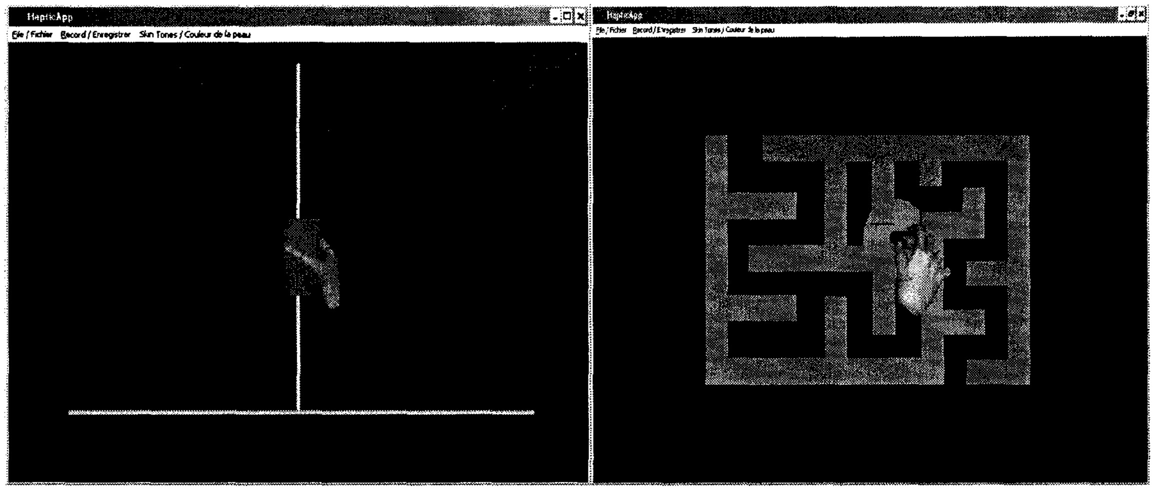


Figure 18: Shows a screenshot of the 3D Maze application on the CyberGrasp unit

In the Cup Grabbing application the user has a 3D view of a cylindrical cup. Users can grab it by moving their hand which appears on the screen (Figure 18). In addition if the user touches the virtual ceiling with the handling cup he/she will receive a force feedback interaction as virtual wall effect.

4.7 Developing the Experimental Environment

The experimental environment was comprised of the below three haptic-virtual applications .Within the VE, graphics depicted a realistic mobile phone model, a virtual cheque, a graphical password, a cup and a maze. The virtual phone's key buttons were dynamically deformable and provided a real pressing sensation. The walls of the maze were made "sticky" to prevent a user from passing through them. The virtual cheque and the graphical password were placed on a 2D rigid surface of a cube that bent as the pressure from the pen was applied to it.

4.7.1 Virtual Phone

In the virtual phone, two types of test took place. In the first testing mode the users were asked the users to dial 7 phone codes that appeared on the right side of the screen.

Moreover, to represent a phone call, the subject had to press the "green-phone" key. Then, after a short interval of time, the subject pressed the "red-phone" key to terminate the call. Consequently, the user was able to carry on with the next telephone number, until the seventh number was dialed. In the second testing mode, the user dialed a familiar number five times in order to eliminate any mental interference in the experiment. The first part of the experiment was designed to find out the user's possible pattern movements. The latter experiment allowed the user to emulate a situation similar to typing an already known password represented by a particular phone code, which is familiar to the user.

4.7.2 Maze

This experiment involved participants to complete a flat 2D maze placed on a surface of a 3D cube (Figure 19).

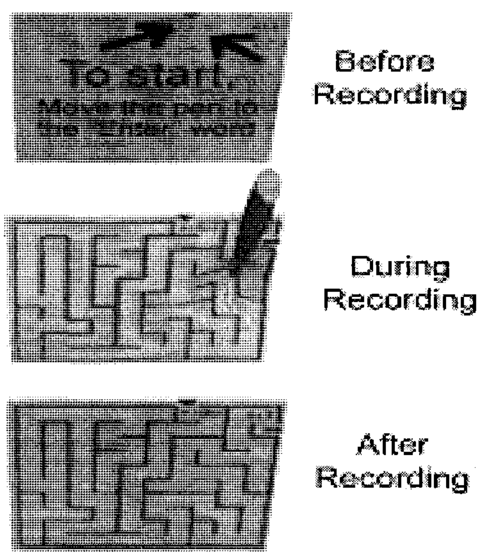


Figure 19: Maze Solving Process and Recoding data

The haptic-based application began recording data when the pen device made contact within a reasonable radius of the starting point of the maze. The end condition of the recording process was done when the pen made contact within a reasonable radius of the exit point of the maze. In order to inform the user when recording was taking place, color coding was also added to the application. Prior to starting the maze, it was colored red. While recording a trial through the maze, it was colored white. When recording completed, it was colored green (see Fig 19). Therefore, the maze was used to capture psychomotor patterns of each individual by solving the same maze.

4.7.3 Virtual Cheque

This experiment is very straightforward and it requires users to perform their handwritten signatures on the signing area of a virtual cheque. The virtual cheque was built on an elastic membrane surface with some mechanical attribute effects, such as friction. This effect makes users feel a slightly rough cheque signing surface when he/she navigates the stylus through it. The stylus or pen position, force exerted, and the velocity, among other parameters, were computed from the haptic-based application to obtain users' patterns. The haptic-based application recorded data only when the pen made contact with the cheque and only in the area designated (Grey rectangle), and stopped when no more contact was detected.

4.8 Participants

The haptic-biometric experimental set consisted of 131 different participants divided into five groups, at different times A, B, C, D and E. They were introduced to basic concepts of haptic interaction as well as, they got familiarize with some types of force feedback from the haptic interfaces. Therefore, the purpose of the experiment and the instructions to perform each of the tasks involved were presented.

Group A was integrated by 22 participants and 20 formed the Group B.

The Group C consisted of 39 participants which were subdivided into two groups. Group C1 was comprised of 22 users where each person performed the exact same haptic-based application 10 times, one trial immediately after the other. The second group C2 of users did the same test, except that this group was subjected under particular conditions by asking the users to perform the maze trial in password-like mode during their last four trials. In other words, users have to provide a particular behavior in solving the last four trials [Orozco et al_06b]. Group D was formed from 18 participant including 14 males and 4 females mostly ranging in ages from 22 to 25. The smallest group was E which was integrated by 10 participants. This group was only dedicated to perform tasks under the exoskeleton haptic interface CyberGrasp unit.

4.9 Assessing the examination

Each person performed the exact same application 10 times, one trial immediately after the other to provide enough room to create the user's reference template. Participants were given the opportunity to practice on the application before the trials were actually recorded, in order to mitigate the training effect. The participants' hand movements were captured for the purpose of analysis. Almost all the experiment's tasks were straightforward because the ability to solve them was not being judged. We also ensured that participants understood the instructions correctly in advance. The system immersed the subjects in each VE by having them wear specialized stereo glasses, and enabling them to see through a semi-transparent mirror for single-point interaction [Reachin_A] and a head mounted display in the case of multi-point interaction. The glasses and the mirror became the interface where graphics and haptics are located, allowing the users to both see and feel objects.

4.10 Conclusions

A haptic-VE framework/architecture has been presented which is based on the available haptic research and technology. It includes a set of haptic-based applications to carry out a series of novel experiments. Such experimental work has allowed us to explore the use of haptics for the authentication of human identity. The architecture also handles the haptic-human computer interaction information capture and store data repository set to be used for validation. Haptic interfaces provide rich data in user-classificatory worth; hence, through a feature correlation analysis, which is been carried out by the FGS subsystem provides the requirements to characterize a behavioral human identifiers are provided. The FGS subsystem measures the uniqueness of identifiers based on the relative entropy theory. Such a measure reveals the information content of each user-haptic interaction feature. Based on such measurements the CDD found in which way an individual is unique, and the magnitude of that uniqueness through pattern recognition methodology implemented in such subsystem. The haptic-biometrics applications implemented such as the virtual maze, the virtual phone, the virtual cheque and graphical password have been inspired on behavioral trait of subjects. In this domain aspects of the user awareness and cooperation are clarified by [Vielhauer & Steinmetz_04] under the umbrella of passive and active biometric schemes. The advantages of the HaBiTs system traditional methods such as digital tablets, pen-based computers are vast, allowing for the continuous automatic authentication of human identity through the analysis of psychomotor patterns exhibited in virtual domains.

Chapter 5

Feasibility of Haptic-Virtual Environments as Biometric Identifier

5.1 Introduction

The human haptic perception can be defined as a complex dexterous manipulation action which involves two distinct components: *cutaneous* information from touch sensors and *kinesthetic* information about the positions and velocities of the kinematic human structure [Lederman et al_92]. Based on such components haptic technology refers to the mechanical interfaces that can deliver two types of interactions: force and tactile feedback. Force feedback can be delivered to a user primarily through musculoskeletal forces, but also through the skin that touches the physical interface of a haptic device. Tactile feedback can also be applied to a user through electrical currents applied directly to the skin or by touching the skin with objects that vary in temperature. Our sense of proprioception can be defined as "the process by which the body can vary muscle contraction in immediate response to incoming information regarding external forces" according with [Sargant_00]. Therefore, the sensation of joint motion and acceleration are characterized by proprioception and kinesthesia. Both are the sensory feedback mechanisms for motor control and posture. In this sense the goal of the haptic technology is to develop an interface able to reproduce as close as possible the complex sense of touch that humans can deliver or receive. As consequence, haptic devices vary in terms of complexity, and in the way that they reproduce the interactions in which the human haptic system is involve with the real world. It is possible to say that, using haptic devices allow users to intuitively explore and interact with the simulated world via the most natural interface possible - the human hand. However, the haptic interaction has been limited to the synthesis of a single point interaction with devices such as the PHANToM's family products [SenTec_A] or the 3-DoF Delta haptic device [ForceDim_A]. On the other hand, few haptic devices provide, the interaction via the modality of multi-fingers force feedback for instance, the CyberGrasp unit [ImmTec_A]. This thesis explores the feasibility of automatically identifying participants in haptic systems based on the current haptic technology and on the fundamental assumption that each person interacts with haptics in a unique way. This type of authentication can be beneficial in scenarios where haptics is used to carry out tele-collaboration and tele-operation tasks, as well as, in desktop systems. In order to pursue this goal, the theory and the analysis for biometric systems were studied.

5.2 Haptic System State

Raw data in the HaBiTs system can be characterized by the output from the device sensors. Haptic devices, such as the PHANToM devices, can record a variety of physical parameters as functions of time for instance 3D position, force, torque and angular orientation of the end effector. These measurements describe a sequence of data points of each associated parameter, which can be sampled at a determined frequency. To allow a person to touch a virtual scene, the haptic rendering process simulates the forces generated when touching or grasping the virtual objects. Haptic interfaces use a force reflecting mechanical device to apply a force to a user. This force gives the illusion of physical contact with a real object [Mendoza_00]. The contact and reactive forces in the haptic devices have to be refreshed at frequencies around 1KHz to give a realistic touch. However, in VE simulations with objects, the graphical display is updated at rates of about 30-50Hz. In our case, we are able, through our haptic device's APIs [Reachin_A] [SenTec_A] [ImmTec_A], to sample data of user interactions of around 70 samples per second. The sequence of observations occurs in the form of time series, which can virtually found in every discipline. Therefore, measurements from the haptic device can be represented as the following notation:

$$X = \{X_1, X_2, X_3, ..\} \tag{5. 1}$$

Equation 5.1 defines a sequence of data points measured at uniform time intervals. A single interaction with the haptic system in the VE generates a number of attributes characterized as features at some moment in time. These features can be integrated in a vector $\boldsymbol{x}$ which provides a quantitative characterization of the state of the system. In a dynamic domain, there exists a set X of all state vectors with a finite, non-zero probability of measurement. To describe the state of a system, one constructs a vector X that provides a quantitative characterization of the system's features at some moment in time. The definition of X assumes the existence of a probability distribution function:

$$f : X \rightarrow [0,1) \tag{5. 2}$$

Via the formulation of $\boldsymbol{f}$, we define the probability of measuring a system to be in some unique state $\boldsymbol{y}$, as:

$$f(x = y) \tag{5. 3}$$

5.2.1 Biometric Profile

The function of the FGS is to form the biometric profile of a user. Such a profile is formed by raw input from the haptic-visual interaction and it depends on the decision-making process carried out from the selected methodology in the FGS subsystem. The biometric profile created, which is created by FGS, follows similar principles as stated on base biometric standards [BSi_A]. The set of haptic-based applications implemented specify the functional environment or its application, for example the biometric profile is created in order to gain access control to a system. In the same way, biometric functions are defined for an application in questions such as the enrolment, the verification and the identification modes. The process of defining a biometric profile starts from n-dimensional state vectors obtained via frequent measurements of the haptic interaction. These state vectors provide quantitative snapshots of the interaction. The rate of sampling is around 0.015 seconds (70 samples/sec). For each dimension of the state space, there is an associated biometric feature, i.e. 'force in the z direction' among others. Thus, the measurements of different features are considered as separate signals. Therefore, our *HaBiTs* system is based essentially on a pattern recognition methodology that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against a template set in the database.

5.2.2 Haptic System's State Vectors

The *HaBiTs* system characterizes the state of a haptic system by measurements of velocity (v), force (f), torque (τ), and the angular orientation of the probe (stylus) (θ) derived directly or indirectly from the haptic interface. In general terms, a haptic state vector $\boldsymbol{x}$ can be defined as,

$$x = [x_1, x_2, x_3, \ldots, x_N]^T \tag{5.4}$$

Where, N is the total number of features considered according to the haptic device selected.

In the particular case of using the single-point interaction PHANToM device, *HaBiTs* can form a state vector $x = (t, v_x, v_y, v_z, f_x, f_y, f_z, \tau_x, \tau_y, \tau_z)$, where the subscripts, x, y, z indicate spatial dimensions and t is time. For example, v_x is the projection of the velocity vector onto the x axis. In the case of the CyberGrasp haptic device, state vectors of 9 dimensions are formed according with: $r = (t, x, y, z, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$, where t is time, xyz are 3D world coordinates, and $\theta_1 - \theta_5$ are angular orientations of one's proximal phalanges. Phalanges are the bones in our fingers and the thumb and the proximal phalanges are the closest to the hand palm.

A great variety of features can be obtained from haptic interfaces as data source to define the state of a system through state vectors. This research work decided to follow a step-by-step path to identify all the features (haptic data) to characterize the hand movement's patterns during a haptic interaction. Such patterns are intended to be used in individuals' authentication while interacting with VEs. This journey started from a point-to-point comparison approach of spatial features to validate the suitability of the haptic devices for authentication purposes. Therefore, a parameter analysis is addressed to evaluate the role that additional local and global features play in the performance of the HaBiTs system. Finally, the mutual information methodology is selected to conduct an additional feature selection process to focus only on the features that provide the greatest classificatory content.

5.3 Functional-based Comparison of Haptic Interactions on Desktop Devices

5.3.1 Introduction

Biometric systems allow individuals' identification based on behavioral or physiological characteristics [Wayman_00]. In order to validate this theory, the scenario of interest was set to gain access control by using haptic systems. Currently, to control access, current sensitive systems have some type of login requirement, which may be based on a password, token, or perhaps a physical biometric (i.e. analyzing fingerprints, face, iris or retina). However, this login authentication, at best, can only offer assurance that the correct person is present at the start of the session; it cannot detect if an intruder subsequently takes over the haptic controls (physically or electronically). In this thesis, it is shown how this research establishes an avenue of research to overcome this problem, by allowing continuous identification of participants in a haptic system.

5.3.2 First-Order Statistics on the Haptic Data Content

Statistics principles on the proposed fundamental assumption appear to constitute a good starting point for such an enterprise. The set of the proposed experiments/applications provide data that describes particular user behavior. In the case of a 3D world, the display of the haptic device's stylus/pen on the VE reflects how consistently the user handles the pen device or grasps a virtual object.

The structure of the data must be as simple as possible in order to obtain answers to the following questions: Do all users perform a particular task at the same speed, for instance, when signing a cheque or solving the maze? How inconsistent is the time spent among different trials to solve the maze or to perform a hand written signature? The statistical analysis is elementary in this case.

Firstly, each subject's comparable positions through the maze were evaluated during different trials, thus allowing the calculation of a user's mean normalized path, and velocity in units traveled per second (i.e. dots per second). Each trial provided data for each subject, and it was shown how dispersed this frequency distribution is. To measure such discrepancies, it is needed to express the variance of the random variable (i.e. $x\ (t)$ or $v\ (t)$) in the same units. It was measured that the standard deviation (square root of the variance) of the 3D world location of the pen frequency distribution presented a high dispersion measure. However, this discriminator concluded that relying only on spatial features make the classificatory problem very difficult. On the other hand, the variability in velocity on the evaluated sets of trials presented a possible path to characterize the uniqueness of each subject. In this sense, preliminary conclusions of various experiments state that the average speed describes a particular "character" to each subject's handling of a haptic task. While the speed is relatively steady for a particular subject, it appears that subjects with higher speed of the stylus showed more variability in speed across different trails than those performing at a lower speed. These results are shown in Figure 20 where mean speed and mean standard deviation in speed across trials were compared among participants. There is a direct correlation between speed and standard deviation with a slope of 0.433. In other words, the quickest subject completed the maze path with the highest unpredictability in speed; on the other hand, the lowest had the steadiest speed to complete the task.

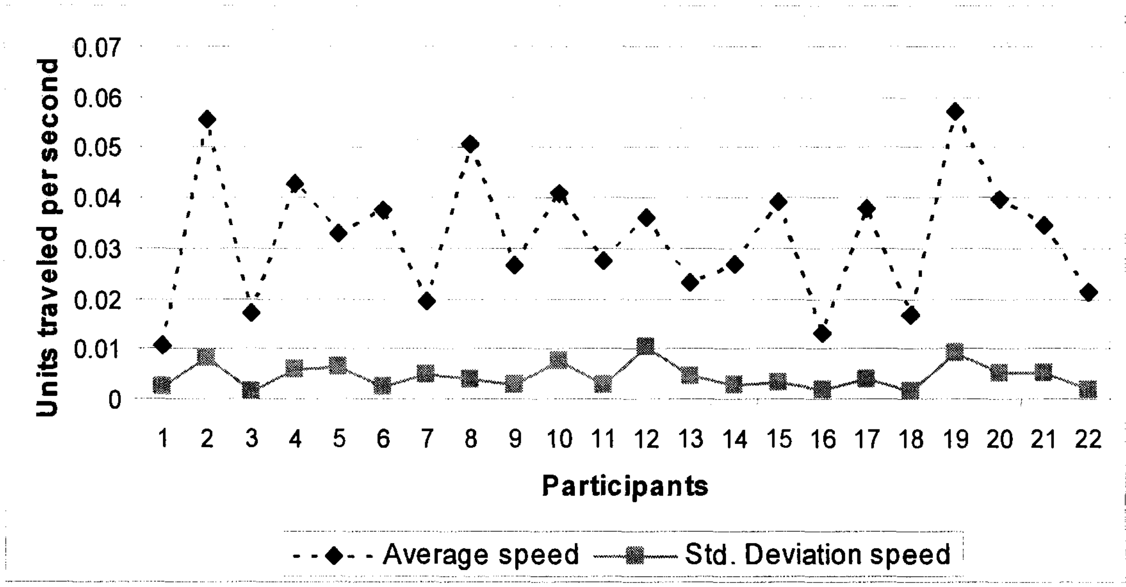


Figure 20: Comparison of an individual's average speed and hers/his standard deviation during the maze exercise

Although the described results are from the maze exercise, similar results have been obtained from the other haptic-based applications. We conclude that the same user usually varies both the speed and the time completion of the task under different conditions, although his/her domain seems to lay in a particular space. In addition, the experimental setting has observed that as soon as the user gets used to the *HaBiTs* system his/her speed and time completion of the task tend to be more stable.

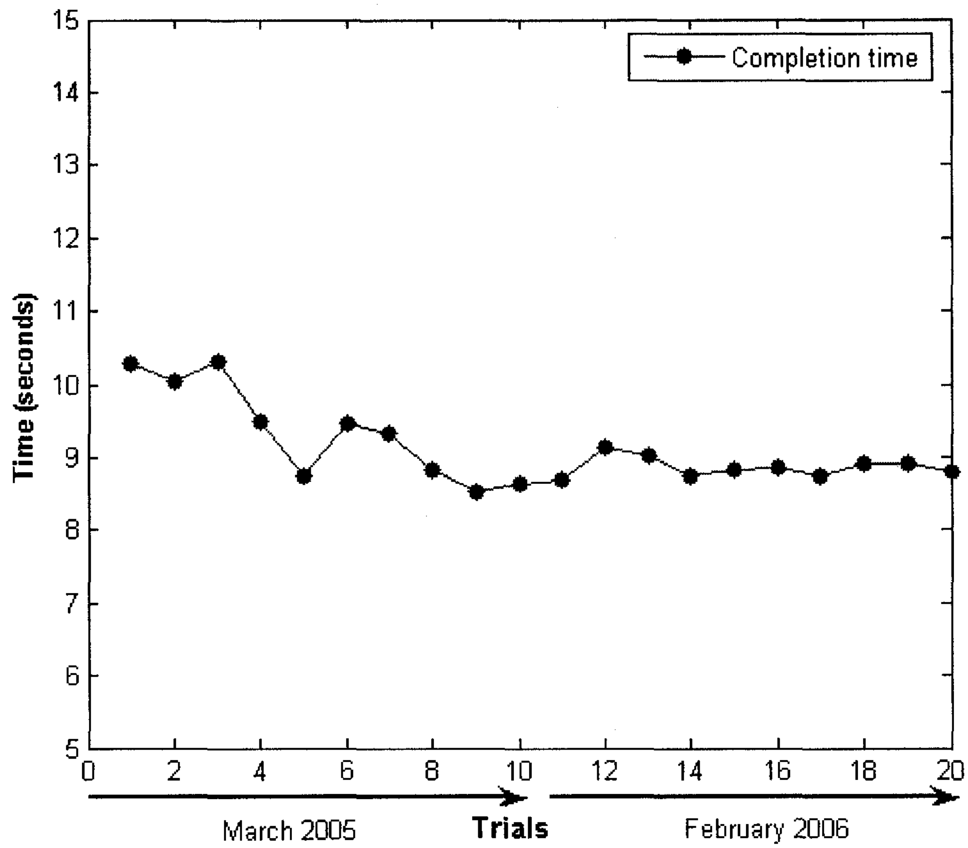


Figure 21 : shows how consistent is the time to complete the same haptic-based task ten times from the same user performing, at different times, over a period of one year

From the Figure 21, the time employed by the user to complete the task is 10.06 seconds. In addition, it can be seen from the figure that undesired data appears at the beginning of each session. This observation confirms that there is training effect which affects the consistency of the behavioral data. After removing data which is superior to 3 standard deviations, the time completion of the task of the subject in question is 9.182942 seconds which agree with the most of the trials. Therefore, there is a relation time performing task- speed employed for an individual interacting with VE.

5.3.3 Comparison of Discriminant Functions

In this approach the mathematical time functions $f(t)$ values of the signals directly to constitute the feature set. The planar position of the haptic end-effector (proxy object) on the virtual world can be characterized by the state vector of the form: $(u_x\ x= [(t),\ u_y\ (t)])$ or in other circumstance by the pressure $p\ (t)$, or velocity $(u_v(t))$. In our case the dynamic system is defined by the state vector of the form of: $x = [x, y, z]$ which gives a representation of any trajectory, in the written signature, or in the used path for solving maze provided by the different positions of the end-effector/stylus on the VE during the session.

Our first assumption was to consider the measurements of the position of the stylus/pen to characterize the user's personalized psychomotor motion patterns. This assumption can be illustrated by the following Figure 22, which graphically denotes the difference in performance for two participants; one user makes more angular turns of the stylus, while the other shows a more rounded path. User 1 and User 2 are two data sets captured from two trials carried out by two different users.

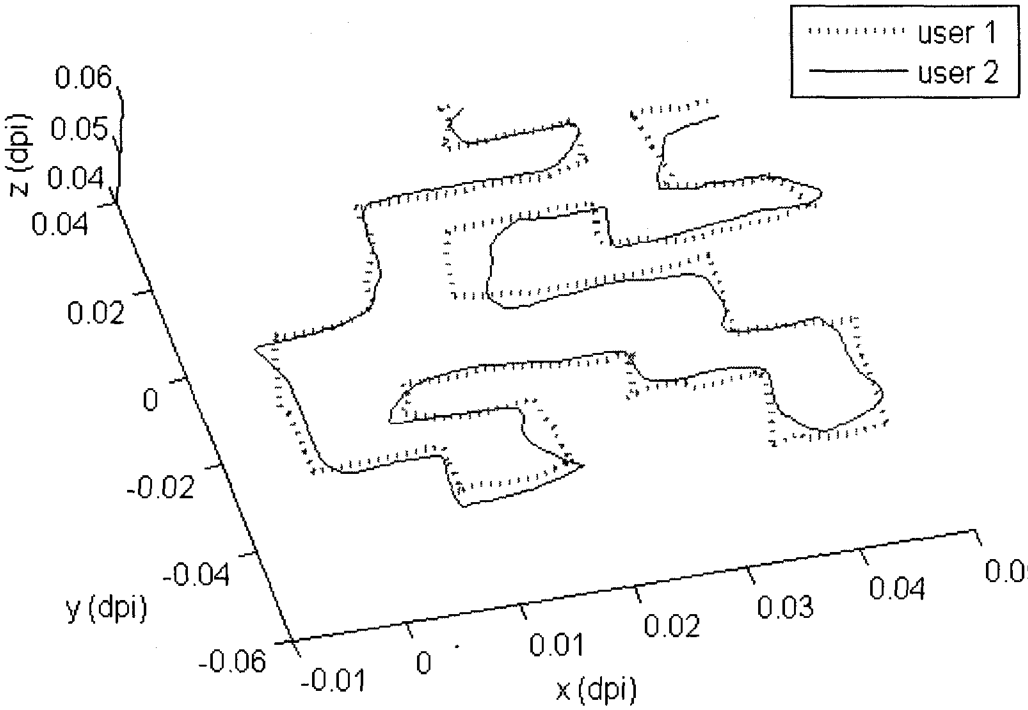


Figure 22: Representative paths taken by navigating the maze application by two different users.

These first observations influenced us to consider a preliminary analysis of the point-to-point comparison of the signal functions from different users, also called the signal correlation or point-to-point analysis. Correlation techniques imply comparing the different parts of the signal (i.e. the measurement of the force exerted by the user in x-direction) separately and combining these comparisons to achieve a general similarity metric. In order to quantify the consistency of the shape exhibited by solving, for example, the maze application, we recurred to compare temporal functions such as $x(t)$,$y(t)$, and $z(t)$.

Since each participant provided a particular level of variation at the starting and end points, this made a direct point-to point analysis very challenging. To produce more accurate comparisons, some kind of alignment needed to be considered by the system.

Therefore, the *HaBiTs* system followed a technique based on stroke regional correlations. For instance, the approach matches test signatures by first segmenting them at places where high gradients of positions occur (strokes). In the case of the maze application each participant's particular strokes are identified by sudden directional changes in the spatial domain. Once the strokes are defined, it is sought the optimal affine transformation between each segment and its stored prototype. Furthermore, to avoid committing more errors or undesired effects, if M different strokes were detected, then the first four and the last four were discarded. That is, not considering data at the starting point or when lifting the pen at the end of the maze (Figure 22). Based on the state of the *HaBiTs* system, it is possible to apply a Dynamic Time Warping (DTW) and spectral analysis techniques to create a match score between two sets of data and, measure the similarity between different strokes.

5.4 Methodology

5.4.1 Dynamic Time Warping Approach (DTW)

Time series data capture from different trials of the same task can be compared with one trial sequence and another one. In some domains, a simple distance measure, such as the Euclidean distance can be adequate. However, a disadvantage can be highlighted. It is often the case that two sequences have approximately the same overall component shapes, but these shapes do not line up on y-axis. In order to find the similarity between such sequences or as a pre-processing step before averaging them, we must "warp" the time axis of one or both sequences to achieve a better alignment. The concept of Dynamic Time Warping (DTW) or alignment has been applied to solve the problems related to data mining, gesture recognition, speech processing, manufacturing, and medicine [Keogh & Pazzani_00].

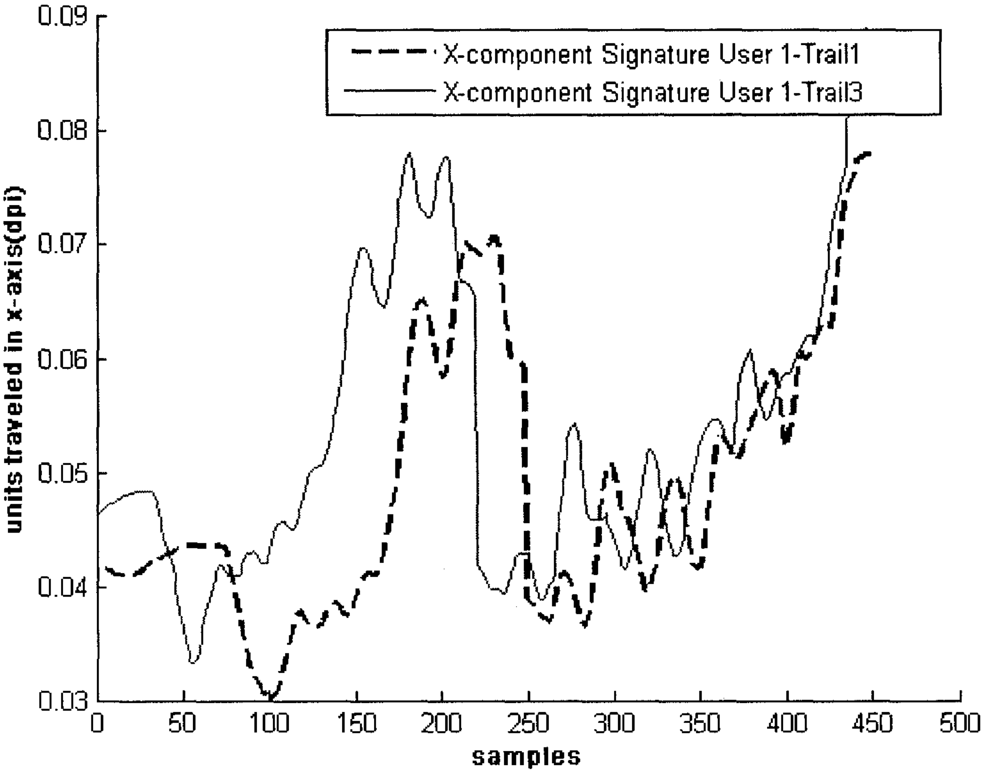


Figure 23: An example of two sample sequences that represent the X axis position of an individual's handwritten signature where the DTW technique can find the best alignment between the two sequences.

Figure 23 represents two sample sequences of the x-axis position of an individual's hand while signing the word "pen". This methodology is subsequently used for signature verification. The sequences were recorded on two separate days. Note that while the sequences have an overall similar shape, they are not aligned in the time axis. A distance measure that assumes the i^{th} point on one sequence is aligned with the i^{th} point on the other would produce a pessimistic dissimilarity. DTW can efficiently find an alignment between the two sequences that allows a more sophisticated distance measure to be calculated [Keogh & Pazzani_01].

The classic DTW algorithm states: given two time series A and B, of length n and m respectively, where:

$$A = a_1, a_2, a_3, ..., a_i, ..., a_n \tag{5. 3}$$

$$B = b_1, b_2, b_3, ..., b_i, ..., b_m \tag{5. 4}$$

In order to align these two sequences using DTW it is necessary to construct an n-by-m matrix where the (i^{th}, j^{th}) element of the matrix contains the Euclidean distance $d\ (a_i, bj)$ between the two points a_i and b_j. Each matrix element (i, j) corresponds to the alignment between the points a_i and b_j. This is illustrated in Figure 24. A warping path W, is a contiguous (in the sense stated below) set of matrix elements that define the mapping between A and B. The k^{th} element of W is defined as $w_k = (i, j)_k$ so we have:

$$W = w_1, w_2, ...w_k, ..., w_K \qquad \max(m, n) \leq K < m + n - 1 \tag{5. 7}$$

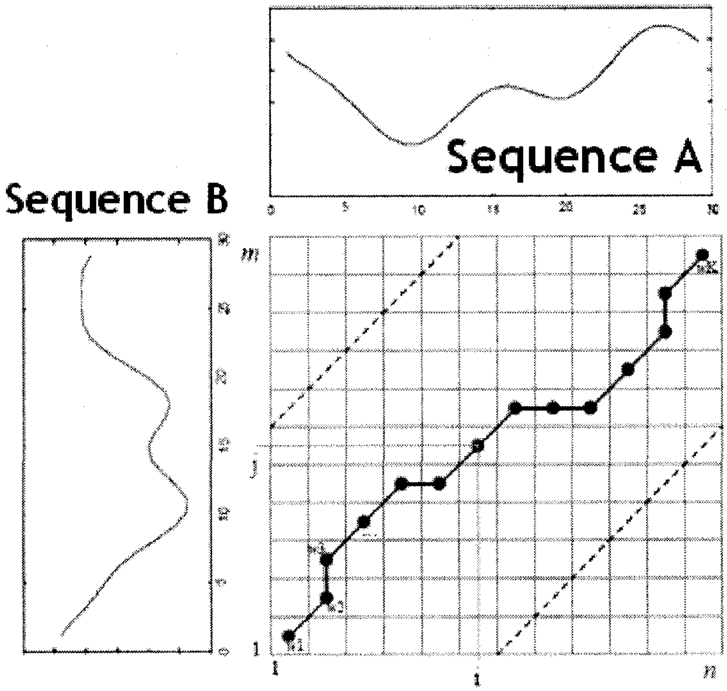


Figure 24: An example of a warping path extracted from [Keogh &Pazzani_01]

In our context the DTW analysis creates a match score (MS) of two data sets, for example let us define d_1 and d_2, by comparing their respective strokes: sudden changes in direction on the xy plane of the virtual application (e.g. Virtual Maze, Virtual Cheque, etc.). Initially, the approach matched the time scale of d_1 to d_2 through interpolation so that the data points represent similar xyz locations. The data of l_2 is the interpolated version of d_1 matched to d_2 based on linear interpolation.

$$MS = \sum_{c=1}^{3}\sum_{i=1}^{N}(d_{1c,i} - l_{2c,i}(t^{p}))^2 \qquad (5.8)$$

The best interpolation match is selected according to the Nelder-Mead non-linear minimization [Gill et al_81] which is used to determine the appropriate p value. The initial p value is set to be 1 and the non-linear minimization determines a local p that provides the lowest mean square error.

After that, the MS is determined by using the equation 5.8 and taking the velocity approximated by the first derivative of d_1 and l_2. The reasoning is that the actual *xyz* position is more sensitive to changes between different data sets of the same user, whereas the stylus velocity would be more constant.

5.4.2 Results and Discussion

In the signature verification domain, research has demonstrated that there are temporal and spatial variations in the production of similar handwritten signatures performed by the same individual. Based on the standard biometric verification analysis, The HaBiTs system uses two templates (e.g. two samples of signatures) that characterize a particular haptic-based application which were represented by the set of data d_1 and $d_2$to produce a MS. Such scores were compared with a decision threshold p to calculate the biometric Receiver Operating Curve (ROC) statistics [Asfaw et al, 05]. In addition, it is possible to define the Probability of Verification (PV) as 1-FRR.

This analysis is based on two modes; firstly, the analysis considers the whole set of data trials for each individual. In the second mode, the assumption considers the last five haptic-based interactions for the analysis. The first five haptic-based task's solutions were discarded to avoid variability due to training effects. As per figure of merit the PV at FAR=25% is calculated with both spectral analysis and DTW algorithms.

With the spectral analysis, the results showed that a PV of 78.8% at 25% FAR was reached when the first 5 data sets were removed for each individual participant. The EER stood at 22.3 % with a MS threshold of 0.195. When all the data sets were considered, the PV showed lower performance 67.6% at 25% FAR r by using spectral analysis. On the other hand, when using the DTW algorithm the results provided a 60.1% of PV at 25%

FAR with the first 5 data sets discarded for each individual participant. In the case that all data sets were considered, the PV also decreased a standing of 49%.

Table 3 shows the PV results for both algorithms at 25% FAR. The difference in the PV value can be attributed to the training effect. Therefore, the spectral analysis algorithm provides an increase in the PV of approximately 18% compared to the DTW with or without the training effect. The spectral analysis algorithm shows better results than the DTW algorithm, however the removal of the training data improves the PV regardless of the algorithm [Asfaw et al_05a][Orozco et al_06a].

Table 3: Summary of the PV results at 25% FAR

PV	Training Effect	
	With	Without
Time Warping	49.0%	60.1%
Spectral Analysis	67.6%	78.8%

5.4.3 Conclusions

Overall, the results obtained with the point-to-point analysis (the signal correlation approach) are far from being accepted if compared with current implementation of biometric technology such as fingerprint. However, important issues have been identified which have impact in the performance of the *HaBiTs* system. These issues were found from the preliminary stage based on a simple functional comparison approach. Firstly, the results showed that there was a training effect which is mainly based on the user adaptability to the haptic systems that was reflected directly on the performance of the classification system. Perhaps, combining globally specific characteristics of signing action (i.e. the total time taken, the average speed, acceleration, force, pressure or the initial orientation) could lead to better performance. Furthermore, a deliberate action such as solving the maze, presents overall shape characteristics that are similar to the ballistic or reflex action, such as hand written signature, which is related to the task objective as pointed out by Nalwa[Nalwa_97]. As consequence the mental interference plays an important role in solving the task. Such observations are supported by results obtained from trials performed on the signature cheque application. In other words, the DTW approach can be improved significantly to be more accurate for this problem just by constraining the warping window, see [Ratanamahatana & Keogh_04] or [Xi et al _06]. Finding the right warping constraint does improve the accuracy. In this case unconstrained warping gets a 10% error, but constrained warping gets only 6.25 %(see Figure 25).

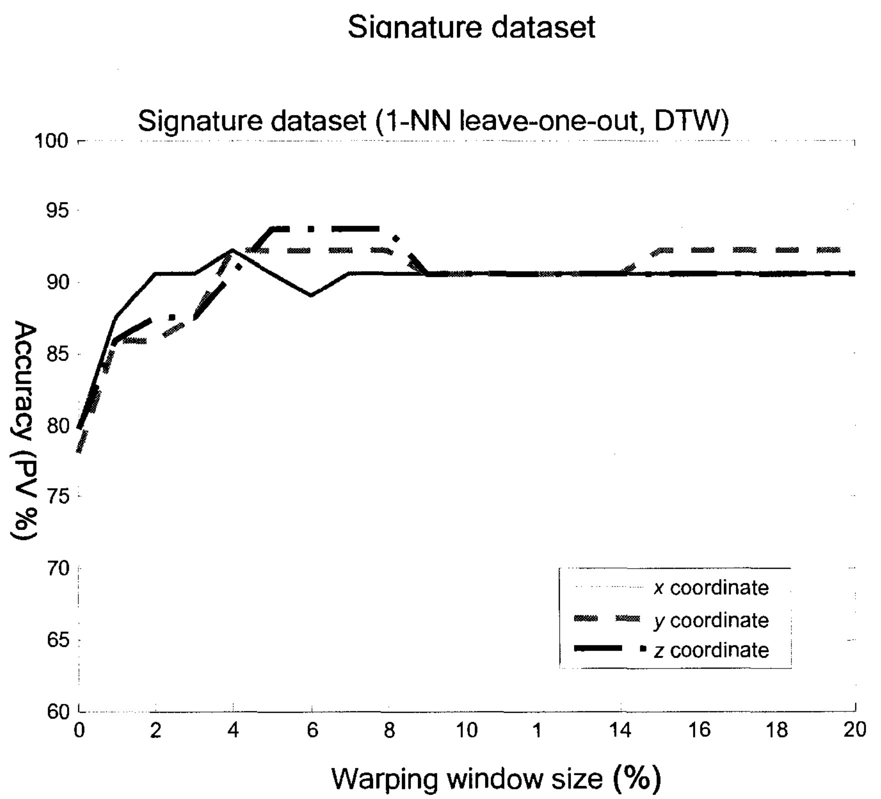


Figure 25: constraining the warping window of sample test

The sample test consisted from 16 different signatures , which length varies from 152 to 1759 data points, which were normalize to 160 (also tried 320, the same accuracy).

Therefore, the warping window was changed from 0 (Euclidean) to 20% to obtain the highest accuracy of 93.75% using z-coordinate at warping window 5%

Thus, with the results obtained in combination with the reduction of the issues previously mentioned we can conclude and answer the first research question that indeed, using haptics as mechanism to authenticate individuals is feasible. Implicitly, the suggestion is that further analysis on feature selection stage is needed in order to improve the former results.

5.5 Parametric-based Comparison of Haptic-based interactions on Desktop Devices

5.5.1 Introduction

The pattern recognition theory recognizes that the feature generation is a difficult task when it involves a number of features. These features are required to characterize a reference pattern which can be used for comparison with another test specimen. There is a vast array of possible features that can be extracted from the raw human-haptic interaction information [Reachin_A] [SenTec_B]. An important objective of the feature extraction or generation is to collect a set of attributes/features directly from the input samples which are more meaningful for authentication. In addition, the feature generation allows the system to apply linear transformations, or other transformation techniques, on the raw information so as to create a new set of features. These data transformations allow exploiting and removing information redundancies. One of the many advantages of using this approach is the freedom of choice to build different modes of feature sets from the attributes captured from the haptic sensors. Raw signals can characterize a particular attribute, such as the trajectory of the device's end-effector along the x axis or the phalange fingers' angles in a multi-finger grasping action. Haptic-based user's performances vary among repetitions; therefore, the system's verification can misjudge a user as a result of false rejection. When a maze path is solved, a dialing telephone code is mapped, or a signature is digitalized a wide range of dissimilarities can be observed among different trials.

5.5.2 Haptic-based Dynamic Signature Analysis

The type of interaction of the haptic-based applications proposed in this thesis falls on the traditional dynamic signature verification analysis. In this thesis, it is shown how user's haptics movements during the interactions can characterize the uniqueness of an individual. Such uniqueness should be based on a particular feature or a combination of features.

A feature vector integrated by 35 personalized characteristics was created to investigate the human haptic dynamics involved during the haptic-based interactions proposed (See Appendix B). Some features were inspired by existing approaches in the dynamic signature verification and keystroke dynamics literature [Lee et al_96] [Monrose&Rubin_97][Qu et al_04] The goal of the feature selection process is to select the number of variables that contain important information in order to enhance the classification task. After that, the K-means algorithm was used [MacQueen_67] to identify the features that appeared with high relative frequency in the list of each subject.

5.5.3 Methodology: K-Means

If there was a sufficient grade of distinction between the psychomotor patterns of different haptic users when using haptics, the *HaBiTs* system could compute the similarity between a given pattern and pre-stored reference patterns. Poor performance of pattern recognition systems must receive careful consideration. Specifically, in our

HaBiTs system weakness might not be due to the core classification algorithm. Poor performance could result from a strong similarity amongst the set of reference patterns. In this case, subsequent to given modifications of the core algorithm, the resulting performance improvements could be bound by a relatively low upper bound. Put otherwise, the system could never achieve perfection due to strong similarities in the reference pattern collection. Taking this into consideration, the development of support for the existence of natural differences between the psychomotor patterns exhibited by individuals in VE is a fundamental assumption.

Unsupervised machine learning is related to the concept of clustering a set of patterns on the basis of similarity [Nabney_02] [Theodoridis & Koutroumbas_03]. Moreover, unsupervised learning takes the approach of disregarding the class in the clustering of patterns. Unsupervised clustering techniques provide us with a way to measure haptic user psychomotor pattern similarity, without labeling each pattern with its associated identity. Such an approach allows us to assess the fundamental assumption of our study without having to assess the suitability of a certain pattern recognition scheme, for the haptic authentication task.

The k-means algorithm is the unsupervised clustering procedure that we utilized [MacQueen_67]. The algorithm clusters a set of patterns into k disjoint subsets. Geometrically, the k-means algorithm can be thought of as the careful relocation of cluster centroids in n-space, whereby n we denote the dimension of the vectors used in pattern representation.

The mean vector μ_i for each cluster is calculated as follows:

$$\mu_i = \frac{1}{N_i} \sum_{n \in S_i} x^n \tag{5. 9}$$

More specifically, the k-means algorithm begins by placing k centroid (points) in n-space and assigning each pattern (vector) to the closest of these k points. Next, the locations of the centroid are adjusted so that they coincide with the barycenters of their associated cluster [MacQueen_67]. Following this relocation, patterns are, again, reassigned to the closest cluster. The process continues until the minimization of J (see Eq.5.10).

$$J = \sum_{j=1}^{k} \sum_{n \in S_j} \left\| x_n - \mu_j \right\|^2 \tag{5. 10}$$

In Equation 5.10, x_n is the nth pattern vector, and μ_j is the geometric centriod of the vectors in cluster S_j. Pairwise dissimilarities were calculated using the Normalized Euclidean distance sample. This comparison process provides an intuitive representation of the feature set data embedded in a high dimensional space. This clustering technique can serve to identify the features with greater frequency of appearance. Thus, it also provided an intuitive estimation of the more meaningful features. This process can be seen as an evolutionary stage providing feedback to the *HaBiTs* system. Then the system was able to recognize particular human hand patterns through a haptic device. Subsequently, the classification stage followed the so-called majority classifier [Lee et al_96] [Lam & Suen_97]. The majority rule described in the CDD subsystem declares the authenticity of a personalized action. A performed feature T is considered genuine when the number of the feature values, which pass a pre-determined test, is larger than half the total number of tested features.

Therefore, on the parameter comparison domain, the CDD subsystem was able to identify the features that provided meaningful information and those ones that delivered less worthwhile information. It has been demonstrated that combining the results obtained from several classifiers can lead to better recognition results [Lam & Suen_97]; however, majority rule or voting is the simplest policy to design and apply [Roli et al_96]. In addition, the majority voting or majority rule algorithm does not require prior knowledge and it can always be used as a type of classifier output with very effective recognition outputs[Lee et al_96].

The majority rule is implemented in the CDD subsystem, which is used to declare the authenticity of a personalized action [Lam & Suen_97]. A performed feature T is considered genuine when the number of the feature values, which pass a pre-determined test based on delta function explained below, is larger than half the total number of tested features [Lee et al_96].[Orozco & ElSaddik_05b].

$$\sum_{i=1}^{n} \delta(\varepsilon_i) = \begin{cases} \geq n/2 & \Rightarrow T \quad is\,a \quad genuine \\ < n/2 & \Rightarrow T \quad is\,a \quad forgery \end{cases} \tag{5. 11}$$

In other words let m_i and σ_i represent the sample average and sample standard deviation of feature i, respectively. Let n be the total number of features used for the decision. Consider the following event for the value ε_i of feature i:

$$\varepsilon_i = \left\{ \frac{|r_i - m_i|}{\sigma_i} \right\} \leq \alpha \tag{5. 12}$$

Where α is the decision threshold used in the majority classifier. Thus, each individual pair (m_i, σ_i) with the event value ε_i is evaluated according to the delta function given as:

$$\delta(\varepsilon_i) = \begin{cases} 1 \, if \; event \quad \varepsilon_i \, holds \\ 0 \qquad otherwise \end{cases} \tag{5. 13}$$

for $\boldsymbol{i}$ = 1,2,3,…n features evaluated and the human patterns are recognized through a process described by the overall majority decision rule described above.

5.6 Haptic-based Key Stroke Analysis

In addition, the 'theme' of the virtual phone experiment is somewhat related to the keystroke dynamics. In this case, the ability of haptics interfaces to capture discrete actions, such as when signing, typing rhythm or dialing, are also possible. In this approach, we were motivated by the idea of using the haptic devices as a mechanism for analyzing individual's biological and physical attributes such as hand-finger positions, velocity, and force exerted during the haptic sessions. Behavioral characteristics such as signing, typing or dialing, and voice fall into the behavioral biometrics. Typing rhythm is associated with the keystroke dynamics research which has been studied in terms of latency timings [Joyce & Gupta_90] [Monrose & Rubin_97].These studies describe a particular pattern defined by a simple approach that the keystroke durations provide. It can be said that the study presented here is a child from such previous works, but it extends the concept by using the haptic devices that provide physical parameter so as to obtain a biometric template for each user. Therefore, this study investigated the potential of capturing and analyzing particular features, such as the force applied to the keys in a keypad of the virtual phone application. In addition, another feature that can be extracted is the angular orientation of the stylus or pen mechanism held during the dialing operation. Extracting these features and defining the subsequent individual pattern is part of the objectives of this thesis.

The exercise of dialing telephone codes characterize a similar pattern form the one described when a user types on a keyboard or autographs a handwritten signature. Therefore, the design of the feature set borrows requirements related with dynamic signature verification expressed in [Qu et al_04b], and the authentication presented in [Monrose & Rubin_97]. Moreover, this proposed approach takes crucially advantages from the physical outputs recorded by the PHANToM Desktop [SenTec_A].

The state vectors are formed by building a set of mean values based on memorized phone codes. These phone's codes represent an analogy to the work of Joyce and Gupta where the users' signature of the username, password, first name, and last name were analyzed based on latency timings [Joyce & Gupta_90]. In addition, the state vector is complemented by extracting the keystroke characteristics of the gradients of pressure, velocity, and pen's angular orientation.

In the general case, four variables represented by state vectors of the keystroke information generated during the dialing code session were used to characterize the state of the haptic system. These are the duration when you press the key (t), the speed of dialing (v), force exerted (F) by pressing each key and the pen's orientation of the haptic device (θ) during the dialing phone code process.

$$s_i = [t, v, F, \theta] \tag{5. 14}$$

The mean values of each variable were calculated and an outliner removal process was applied to remove the values if they were far away from the mean. The removal threshold was set to evaluate data values that were than 3 times of the standard deviation in order to reduce errors. Thus, for example, the sub state vector of the feature of dialing duration (t) is defined as follow:

$$t = [\overline{t_1},\ldots,\overline{t_m},\sigma_1,\ldots,\sigma_m]^T \tag{5. 15}$$

For $m = 1, 2, 3$

A set of 4 vectors for the mentioned variables, based on the mean and standard deviation of each keystroke of the particular code number dialed, were built. Therefore, the final feature set (S) was integrated by 24 parameters according to the following:

$$S = [s_1, s_2, \ldots, s_N] \tag{5. 16}$$

For i= 1, 2,…, N

In order to identify common attributes between users, according to the way they handle the pen or the dialing code speed or by the force applied and the rank of such features, we decided to organize the user's templates into more sensible groups or domains. We incorporate the K-means method to observe the mentioned user attributes in terms of differences and similarities among patterns [MacQueen_67]. Following the clustering task, the use of a proximity measure was suggested. The well-known Euclidean distance, D is selected as a proximity measure but other metrics could also be considered such as the Mahalanobis distance which takes into account the correlations of the data set and is scale-invariant [Theodoridis & Koutroumbas_03]. Thus the dissimilarity measure between two one-dimensional vectors X and Y, based on D is defined as:

$$D(X,Y) = \sqrt{\sum_{i=1}^{l}(Xi - Yi)^2} \tag{5. 17}$$

Heuristically, we believe that in this experiment, the way that a user's stylus is handled in terms of position is considered as a good measure for the sensibility of classification of the information.

5.7 Results and Discussion

5.7.1 Dynamic Signature Verification applications

Haptic-based user's performances vary among repetitions; therefore, the *HaBiTs* authentication system can misjudge a user as a result of false rejection. For each feature value of the test involved, the CDD subsystem through this binary classifier divides the features space into regions that correspond to either authentic class or forgery class. When the maze path was solved, the dialing telephone code was mapped, or the virtual signature was digitalized and a wide range of dissimilarities were observed. The performance curves (ROC) were obtained by evaluating the corresponding database. Three different sets of information (for the virtual cheque, maze and virtual phone applications) with 10 genuine executions per user were evaluated. Figure 26 shows the performance of the majority classifier described in section 5.5.3 for the 35-parameter feature set for the mentioned applications [Orozco & El-Saddik_05b]. From Figure 26, it is possible to observe that this classifier distinguished between a genuine and a forgery group satisfactorily by achieving an ERR of 6% with a threshold α of 1.6, particularly for the case of the virtual cheque-signature verification application. In the other applications, such as the virtual phone and elastic maze, the performance varies from an ERR around 15% and 22%. The ROC curves reveal that the majority classifier has significant much better performance over tasks, for example, the virtual cheque verification application where no mental interference is involved. On the other hand, the tasks that required some kind of mental concentration, such as dialing a set of unknown phone codes or navigating through a maze reveals that more effort is needed to reach high classificatory performance and in some cases inconsistency from the users' behavior was also noted.

One possible answer to such an obtained performance is that there are particular behaviors that are difficult to classify and quantify in the same domain. It is also important to note that the performance of some volunteers in the last trials in the dialing code and maze navigation tasks was quite differently from their previous attempts. This variability can be classified as intrapersonal and interpersonal variability [Lee et al_96]. The influence of this variability plays a significant role in terms of differentiation between features and subjects for successful authentication.

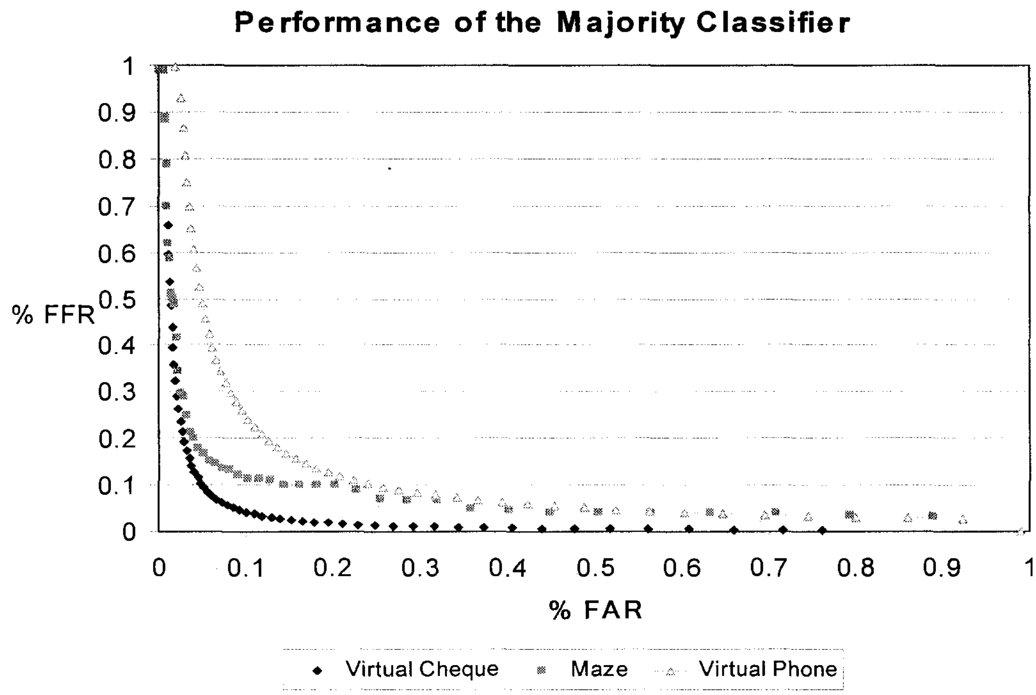


Figure 26: Performance of the majority classifier over the three different applications (maze, cheque and phone)

At this point, as a general conclusion, we can state that using the haptic technology is a feasible mechanism in a biometric interface: the overall results have been. In this sense, a concrete answer to the first research question can be given (Section 1.2.1) and also partially to the second one. Indeed, haptic devices like PHANToM device can be used as mechanism for authentication purposes. However, it is evident that further analysis is needed in the FGS subsystem, considering other type of haptic devices to support such observations (multiple-point haptic devices). In addition, it possible to deduct that a larger than necessary number of features candidates can be generated and then the "best" of them need to be identified.

Even tough the feature extraction and selection have been considered further; there is still no distinguishable sign of which one of all the parameters captured for the haptic interface provide the greatest rich content that can lead to a better performance. In addition, the results also proved that haptics is a flexible and extendible tool that can be applicable to more than just dynamic signature verification applications. The haptic technology can be used to verify the authenticity of an individual in other applications such as dialing a code or solving a task, which can be embedded in virtual scenario as part of a whole environment to remove the mental interference.

5.7.2 Key Stroke Dynamics application

In another attempt to discover the correlations among parameters needed to characterize human psychomotor movements on VEs, a keystroke analysis was carried out. The users pressed the buttons to receive visual and force feedback when dialing a phone code on a virtual phone. Providing an acceptable level of accuracy by using keystroke analysis presents an enormous challenge, which is characterized mainly by intrinsic variability of the typing dynamics, versus other very stable biometric characteristics, such as face or fingerprint patterns [Bergadano et al_02]. Nevertheless, the *HaBiTs* system takes advantage of exploiting the wide range of physical attributes captured from haptic devices to incorporate additional features to the keystroke analysis [Orozco & El Saddik_05a]. A dynamic model of a virtual phone with touchable keys is used for classifying the data of each user while dialing a set of phone codes. The force feedback provided to the user through these touchable keys ultimately provides an index of reliability in this VE. Therefore, it is assumed that force measurement among other features such as velocity and angular orientation of haptic end effector can add a piece of uniqueness needed for keystroke analysis.

From the four attributes considered in the final feature vector, three classification tasks were performed: 1) including the whole set, 2) considering only time and force, and 3) considering only time (*t*) and force (*f*).The best performance of the classifier and the statistical analysis obtained a Probability of Verification (PV) of about 80% in the task 1 (Figure 27). Therefore, the experimental results revealed that the best feature candidates were those related to the pen's position. Such features provided the weighted value for recognizing individuals. The variables such as velocity (*v*) and keystroke duration (*t*) provided inconsistent behavioral values in the definition of the patterns from the same user. The force measurement (*F*) did not provide the remarkable dissimilarity weight expected. In addition, the force applied for most of the users fell into a very compact interval of values where the EER was high. However, this phenomenon is assumed to be present by the training effect that the volunteers introduced during the haptic-based interactions. By minimizing this effect it is assumed that the performance of the *HaBiTs* system will be improved.

In particular, the speed profile for each user varied considerably in the first two trials then it exhibited a more stable performance. According with that, it is possible to conclude that dialing speed is an important parameter to be considered further in the analysis to define a user's pattern when using haptic systems.

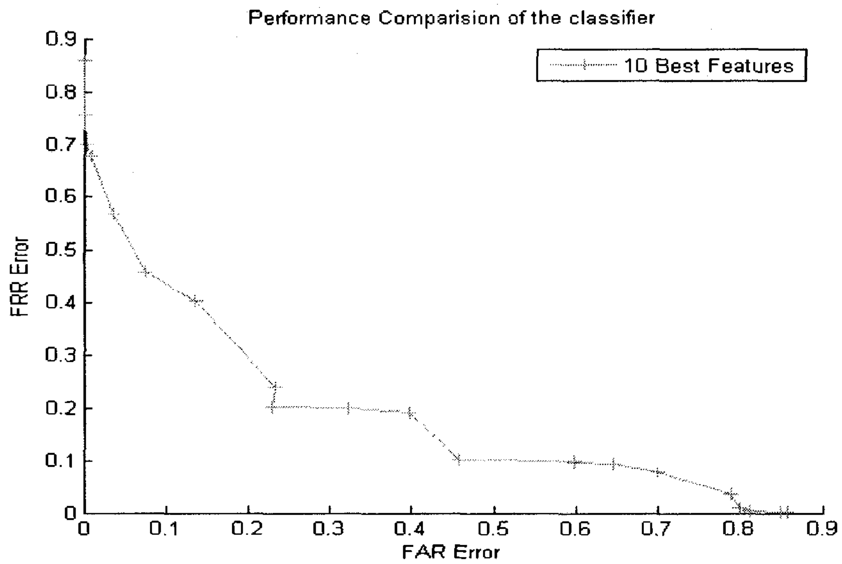


Figure 27: The output of the clustering analysis identifies two classes of errors FAR and FRR. The performance of the classifier proposed in this study (Virtual Phone application) with 10 of the best features has obtained at 25% of FAR a PV about 80%.

The experimental results reveal that the best performance was when the features related to the pen's position were included. However, in overall, the parameters captured to generate the participant's templates showed high variability in the keystroke information from the same user. Such variability is strongly related with time that the user got familiar with the haptic system [Orozco & El-Saddik_05a]. Thus, it assumed that more stable data or repetitions could bring forth a much better performance. On the other hand, the assumption that some features presented a level of dependency is also considered. Building a feature set with correlated features could not improve the performance since their contribution is very little. Therefore, such a conclusion leads us to apply further analysis in the extraction of the features that are more important in terms of behavioral content, which demonstrates the need to assess the uniqueness of the biometric identifiers selected (Chapter 6).

5.8 Evaluating Exoskeleton Haptic Interface

5.8.1 Introduction

Extensive work, both from research and development, has been conducted for single-point interaction in VE scenario, where the most widely used haptic interface are the PHANToM devices [Nikolakis et al_04]. Nonetheless, lately the demands for complex interactions for many applications have been escalating. For instance haptic devices need to be able to simulate multiple-point contact interaction to support tasks such as grasping or holding. Several prototypes have been proposed [Barbagli et al_03] [Burdea & Zhuang_91]. The industry's response to the need of multiple-point interaction haptic device led to the introduction of haptic interfaces such as the CyberGrasp unit, system integrated with a CyberGlove data glove and an exoskeleton device with individual pulling ability for each finger [ImmTec_A]. The workstation allows the users to sense weight and inertia while picking up a "heavy" virtual object or feel the impenetrable resistance of a simulated wall. In this sense, the *HaBiTs* system allows users to grasp and manipulate a virtual object with the whole hand and collide it with other objects in the virtual scene to mimic some real human tasks such as grabbing a cup or lifting a dumbbell. In this case, from the biometric point of view it is expected that user could describe a pattern in the way of grasping the virtual stick used to solve the maze (see Figure 18) or in the way to grab a cup an perform a given task.

5.8.2 Quantification of the User Hand Movements for Authentication with the CyberGrasp unit

We characterize the state of a haptic system when the CyberGrasp unit is used by measurements of completion time (t), 3D position of the CyberGrasp unit (x,y,z), and angular orientation of each of the fingers proximal phalanges (θ). Phalanges are the bones in our fingers and thumb. The fingers have three phalanges: proximal (closest to the hand), middle, and distal (farthest from the hand). The thumb has only two phalanges: proximal and distal. Thus, the state vector of the CyberGrasp unit are 9 dimensions and with the form: $r = (t, x, y, z, \theta_1, \theta_2, \theta_3, \theta_4, \theta_5)$. These state vectors are sample at a rate about 20 samples/sec; however, the rate of sampling is not a stable parameter. For instance, during the first second of one trial we recorded 150 samples; whereas, later on in another the trial only 12 samples were recorded in one second. The sampling was done while users were completing the 3D maze application. In addition, a function was designed to analyze the following parameters which characterize a set of sampled state vectors:

- Time to do the exercise
- $d\theta/dt$ for each finger (variation of the angle over time)
- Idle time on each finger (i.e. percent of the data where $d\theta/dt = 0$)
- Accumulated distance for over each axis (x, y or z)
- Speed over each axis

The relative dispersion of a statistical distribution is a good measure of their variance. Defined by (standard deviation / mean), the relative dispersion is often called the '*coefficient of variance*'.

5.8.3 Analysis of the Results

From the smallest group E which was integrated by 10 participants. This group was only dedicated to perform tasks under the exoskeleton haptic interface CyberGrasp unit. The analysis resulted in a 57 dimensional feature vector which contains the following information:

- Mean, standard deviation, relative dispersion, maximum, minimum, and maximal difference of the $d\theta/dt$ distributions for each θ, and also for the dx/dt, dy/dt, and dz/dt distributions.
- Time taken to do the exercise and percent of this time where $d\theta/dt = 0$ for each θ (idle time).
- Accumulated distances for all of x, y, and z.

From a biometric viewpoint, a concrete conclusion cannot be drawn from the comparisons obtained among the ten user's 57D feature vectors. Ideally in a statistical analysis, it would be 30 users required to obtain a reasonable approximation by normal distribution. Although, one of the users completed the maze application 43 different times, which allows us to at least test the consistency of this user's behavior. Some data was missing and so we chose 20 "good" files to calculate the Relative Dispersion (RD) results. The average Relative Dispersion (RD) of all 57 dimensions of the 20 feature vectors was 138.35%. This large percentage led us to immediately dismiss the possibility of using this haptic data for biometric purposes: although some parameters showed low RD statistics, amongst which were the total time mean of 22.538%, and the idle time mean 6.4% (Table 4).

The major problem with using the idle times for identification is that all users had almost exactly the same percentage of idle time: 95% for each finger. This suggests that either the users were very steady with their hands, or that the measurement processes were not very precise according with the collision detection algorithm implemented by the device [ImmTec_A] [Mirtich_98].The fundamental assumption of this conclusion is based on the method by which collision detection calculations are computed. In other words, virtual objects are represented by optimized geometry for faster collision and haptic detection. This approach introduces significant errors in measurements on the grasping angles of the finger, which indirectly affects to the measurement of the idle times. The analogy of how an optimized geometry is represented in the haptic rendering process is to imagine taking a plastic bag and wrapping tightly an object such a star. Therefore, the haptic optimized geometry of the star object will create a pentagon shape which is the same shape that the star.

Table 4: Relative Dispersion of Idle Times of one user sample

Proximal Angle	Relative Dispersion of Idle Times
Thumb	4.52 %
Index	7.00 %
Middle	6.18 %
Ring	7.67 %
Pinky	6.90 %

The RD figures are low (Table 4); however all of the 10 users had similar amounts of idle time. Therefore, this feature cannot be used to identify them.

Table 5 : Example of the relative dispersion of one feature from one user

Feature ($d\theta_1/dt$)	Relative Dispersion
Average	17.88 %
Standard deviation	285.99 %
RD	22.78 %
Max	42.54 %
Min	22.51 %
(Max - Min)	320.21 %

Table 5 shows the RD of features describing the distribution of $d\theta_1/dt$ (the change in the angle of user 1's proximal thumb phalange with time) of a particular user. The figures are high which immediately support the observations mentioned.

5.9 Results and Discussion

By accepting the null hypothesis (H_0) this work draws the conclusion that no all haptic devices are suitable to be used as mechanism for authentication of individuals. Firstly, from a biometric viewpoint the comparisons between the ten user's 57-dimensional space feature vectors are not acceptable as biometric identifiers. Secondly, the CyberGrasp device's capabilities introduces a limitation which is represented by the continuous calibration of the device each time a new user is set and after the device has powered down(each session). The process of calibrating all the components of the CyberGrasp device takes 3-5 minutes; although the time does make any impact, the cumulative calibration errors are the main concern. Another limitation of the CyberGrasp unit is the amount of load/repetition that armature can handle. The steel cables used to generate the force effect cannot handle heavy loads and repetition. The steel cables have been known to snap due to fatigue. Thirdly there some software issues regarding the collision detection implemented by the optimized geometry approach. In overall such issues can be reflected in the non-accurate measurements collected that related to the hand the hand, such as the bending of the joints of each finger. In conclusion from biometric point of view the accuracy of such measurements are very far to be used as behavioral identifiers in a biometric system.

5.10 Conclusions

The studies presented in this chapter provides a proof that there is a possibility of using particular single-point interaction haptic devices such as, a PHANToM device for authentication of users working in a process, which involves haptic systems. The data generated for the purposed experiments plays an important role in the path to find the valuable parameters which define individuals' behavior. In general the results have showed a significant improvement of the *HaBiTs* system. It can be reflected by a reduction of a 30% of the EER in the worst case (i.e. dialing phone codes application). Furthermore, it is important to note that Haptic-based user's performances vary with repetitions; therefore the system's verification can misjudge a user as a result of false rejection. Furthermore, the mental concentration requirements to solve the tasks also affected the performance of the users. Such observations are supported by results from quite different performances from the same user, which were obtained from the last trials. This variability can be classified as intrapersonal and interpersonal. The influence of this variability plays a significant role in terms of differentiation between features and subjects. However not all the results were promising, the experiment carried out with the hand exoskeleton haptic device CyberGrasp suggests that this technology is a bit far to be used on tasks that require a certain level of precision, such as biometrics. This conclusion has been reached on the basis that the haptic data measurements on the finger's phalanxes during a haptic-grasping session were not reliable. Such measurements were affected by continuous calibration of the system at every session. In addition, the software limitations are in terms of non-accurate measurements from the collision detection algorithm implemented by the CyberGrasp unit. As result, the relative dispersion distribution of haptic data generated was very high which immediately dismiss the possibility of using this data for biometric purposes.

Chapter 6

Haptic information content for assessing hand movement patterns performance on VE

6.1 Introduction

In pattern recognition problems, the feature selection's major goal is to choose a subset of original variables (features) by eliminating the redundant, uninformative, and noisy ones. In general, the feature selection problem is regarded as the optimization process due to the so-called curse of dimensionality, which is difficult to handle. We believe that in behavioral biometrics this issue is even more difficult to tackle especially due to human behavior changes over time and under conditions (i.e. mental stress, tiredness) [Orozco et al_06b]. Therefore, in a classification system the number of features available at the level of design is usually very large. Moreover, there are a number of factors involved that need to be considered to optimize the classification problem in the pattern recognition theory. Firstly, the higher the numbers of features that are treated, the higher the computational complexity. On the other hand, there are features that are highly correlated to each other; therefore, a small outcome can be presented if they are combined together in the feature set. Furthermore, the generalization of the properties of the classifier is a requirement. In other words the higher the ratio of the number of training patterns N to the number of free classifier parameters, the better the generalization properties of the resulting classifier [Theodoridis & Koutroumbas_03] .

At the end of the day, the feature selection process involves the techniques designed to select the most valuable features without losing the ratio of discrimination information. Therefore, this thesis envisions and plans a strategy to discover what set of features can contribute with the valuable information to build a consistent biometric identifier model. This analysis has been motivated from the previous results and also from the first order statistical perception. In other words, two users may present the same average velocity performance; therefore they are identical users from the first order perspective. In addition, preliminary findings revealed that indeed there is spatial similitude on the psychomotor movements from the same user. Therefore, such findings suggested that other features such as force, torque and the stylus' orientation captured, should be considered at the same time to find more individualistic identifiers. For the validation of this study, the principal assumption here is that using haptics supports the extraction process of the dynamics involved in many user-computer interactions. Therefore, the mechanism that enables us to personalize the identifiers that characterize an individual's patterns, thus, the selected features are refined in an attempt to achieve the desired level of performance. User interactions with haptic devices are considered features of an unique individual in terms of biological and physical attributes [Asfaw et al_05a] [Orozco et al_05]. Such observations are supported by the signature verification literature, which elucidated the existence of special parameter values, which are inherent to a particular person. These values can be determined when the signature is repeated several times [Qu et al_03]. This consistency is created mainly by natural motion and practice over time, which creates a recognizable pattern, where practically no mental interference is introduced. In this sense, the feature-based analysis of previous studies the dynamic signature verification and the keystroke dynamics identified some correlation among the features. As consequence the role of the features depends on the type of application task. As a result, the evaluation of the haptic information content from the experiments is considered the next step in this journey which is presented in this chapter. Hence, the assessment of the uniqueness of each biometric identifier was carried. To measure the uniqueness of the identifiers, the relative entropy of different users' biometric feature distributions with respect to the population distribution was computed. Such metric reveals the information content of each user's haptic interaction feature.

6.2 Relative Entropy

The purpose of the present analysis is to evaluate the information content of this behavior haptic data (i.e. measurements of position, velocity, force, and torque data as biometric identifiers); hence, we assess the uniqueness of each biometric identifier. To measure the uniqueness of identifiers we look at the information theory to provide the solution. Specifically, the mutual information was used which is a measurement of the amount of information that one random variable contains about another. This is also known as a special case of a more general metric called relative entropy or the Kullback-Leibler divergence [Lexa_04].The relative entropy is a measurement of the distance between two probability distributions. In a discrete space, let assume X to be a discrete random variable with $p(x)$, $x \in X$ and $q(x)$, $x \in X$ to be two mass probability functions, therefore the Kullback-Leibler (KL) distance or the relative entropy, can be defined as the expected value of the likelihood ratio between $p(x)$ relative to $q(x)$:

$$D(p \| q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)} dx \tag{6. 1}$$

where $D\ (p||q)$ denotes as the "distance" of q from p. The term "distance" is not intended to be taken in its most literal sense, since $D\ (p||q)$ is not a true metric [Lexa_04]. Indeed, $D\ (p||q)\ \neq D\ (q||p)$, in the general case. From an information theory viewpoint, The interpretation of $D\ (p||q)$ is as a measure of how much information is contained in the assumption of a distribution p on X, when the distribution is actually q on X [Adler et al_05]. By definition, $D\ (p||q)$: $D\ (p||q) = 0 \leftrightarrow p = q$ [Lexa_04]. This result indicates that no information is gained by correctly assuming that the distribution is p.

The choice of a logarithmic base used in the integration of $p(x)\ log\ (p(x)/q(x))\ dx$ corresponds to the units used to measure information [Shannon_48]. In this work, the selection of log_2 was based on the information measurements were in 'bits.' This choice suits the potential application (i.e. human-haptic interaction) where measurements of a user's features also in bits.

6.2.1 The State Vectors using Relative Entropy

As previously described, the representation of the state of a haptic system is based on measurements of a great number of physical attributes such as velocity (v), force (f), torque (n), and the angular orientation of the stylus (θ). In the more general case, we defined the state vector as $x = (v_x,\ v_y,\ v_z, f_x,\ f_y, f_z, n_x,\ n_y,\ n_z,\ \theta)$, where the subscripts x, y, z indicates spatial dimensions. For example, v_x is the projection of the velocity vector onto the x axis. In order to evaluate the information content of specific features, we consider state vectors of a reduced dimension. For instance, in the analysis of the information content of the velocity data, we consider state vectors of the form $x = (v_x, v_y, v_z)$.

6.2.2 Construction of Biometric Feature Distributions

The Kullback-Leibler distance, or relative entropy provides a truly mechanism to extract the most informative features from the Observable Feature Space (OFS). Given probability distributions p and q of various subspaces of the OFS, calculations of the relative entropy between p and q assess the uniqueness of different observable features. Let define p to model the general, interpersonal biometric feature distribution whereas; allows construct a unique q as intra-personal biometric feature distribution. Indeed, the relative entropy between p and q is then interpreted as the amount of information contained in the assumption of a distribution p on the OFS, when the actual distribution is q [Adler et al_05].

The mean vector, μ, and covariance matrix, cov, are used to characterize a Gaussian probability distribution f on X. For an arbitrary dimension n of all $x \in X$, $\mu = (E[x_1], E[x_2] \dots E[x_n])$ and $cov_{ij} = cov(x_i, x_j) = cov(x_j, x_i)$. If two Gaussian distributions p and q are defined on X then the relative entropy measured in bits is:

$$D(p \| q) = \frac{1}{2}\log_2\left(\frac{(|\mathrm{cov}_p|)(e^{trace((\mathrm{cov}_p + (\mathrm{cov}_p - \mathrm{cov}_q)^t(\mathrm{cov}_p - \mathrm{cov}_q))}\,\mathrm{cov}_q^{-1} - I)}{|\mathrm{cov}_q|}\right) \quad (6.2)$$

In Equation 6.2, subscripts refer to the distributions p and q, and I refer to the identity matrix of rank n [Adler et al_05]. Via the selection of the observable features that maximize Equation.6.2, to form the feature sets used for identity verification.

Subsequently, it is possible to compare the probability of measuring the user's interaction which is characterized by x versus the probability of measuring any user's interaction to be characterized by X This comparison is performed by calculating the relative entropy between the general (interpersonal) biometric feature distribution, p, and the specific (intra-personal) biometric feature distribution, q. $D(p||q)$ measures the information content on the assumption that all individuals will have a feature distribution p, when indeed each individual has their own feature distribution q.

To construct the general p distribution, the process selected is to fit the measurements of all users' identifiers to a Gaussian distribution. For each individual user, a different feature distribution q was constructed. In order to do that the formulation of q was carried out by fitting the measurements of a single user's identifiers to a Gaussian distribution. A set of 21,346 data points was used to construct the interpersonal distribution for each biometric feature. These points were collected from a data set of the group A of users' completion of a haptic-based application during the maze solving process. To construct the intra-personal distributions, we consider data from 5 trials for each user completing the haptic-based application. In the data collection process, each user completed the task 10 times. The *HaBiTs* system through the FGS component has chosen to compile intra-personal distributions based on the last 5 trials completed by the user, to mitigate the warm-up effect [Asfaw et al_05a], [Asfaw et al_05b] and [Orozco et al_06a].

6.2.3 Haptic Information Content

To maximize the precision of identity verification, we utilize features of optimal uniqueness; thus, permitting the characterization of an individual's interaction. Such features contain the most information pertaining to an individual's identity. Therefore, in order to evaluate a given biometric feature, the average the information content (relative entropy) for each individual user was calculated (Figure 28). Certain features provide more worth classificatory information than others. Indeed, the use of the force measurement as an identifier would, on average, reveal the most relevant information about a user (15 bits relative entropy); whereas, using *xy*-torque would reveal the least amount of information (3 bits relative entropy).

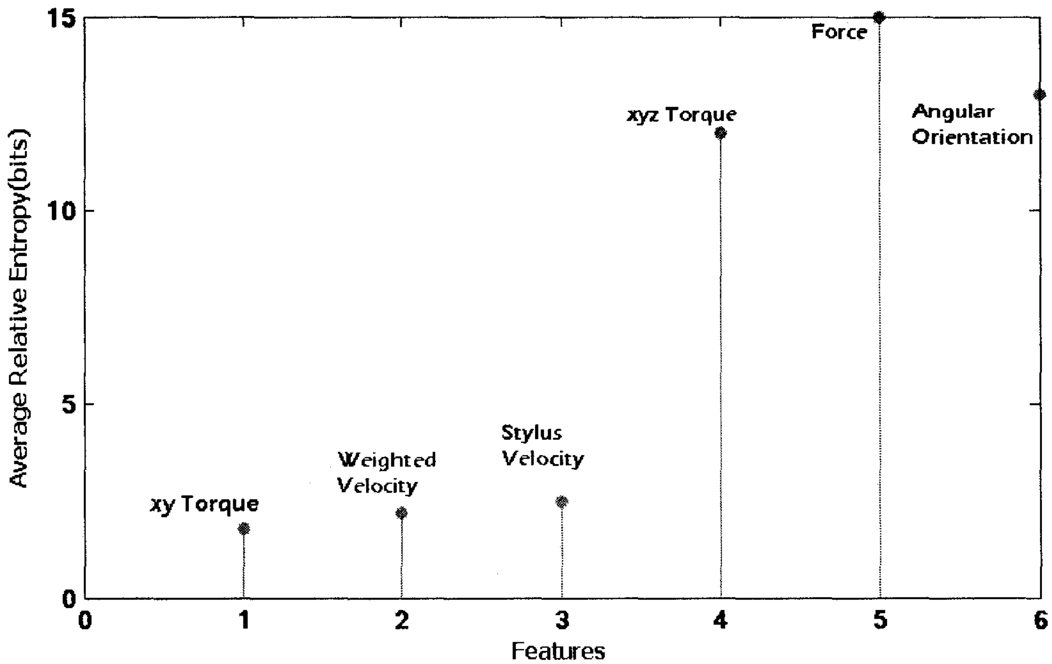


Figure 28: Average Information Content of Biometric Features (Relative Entropy)

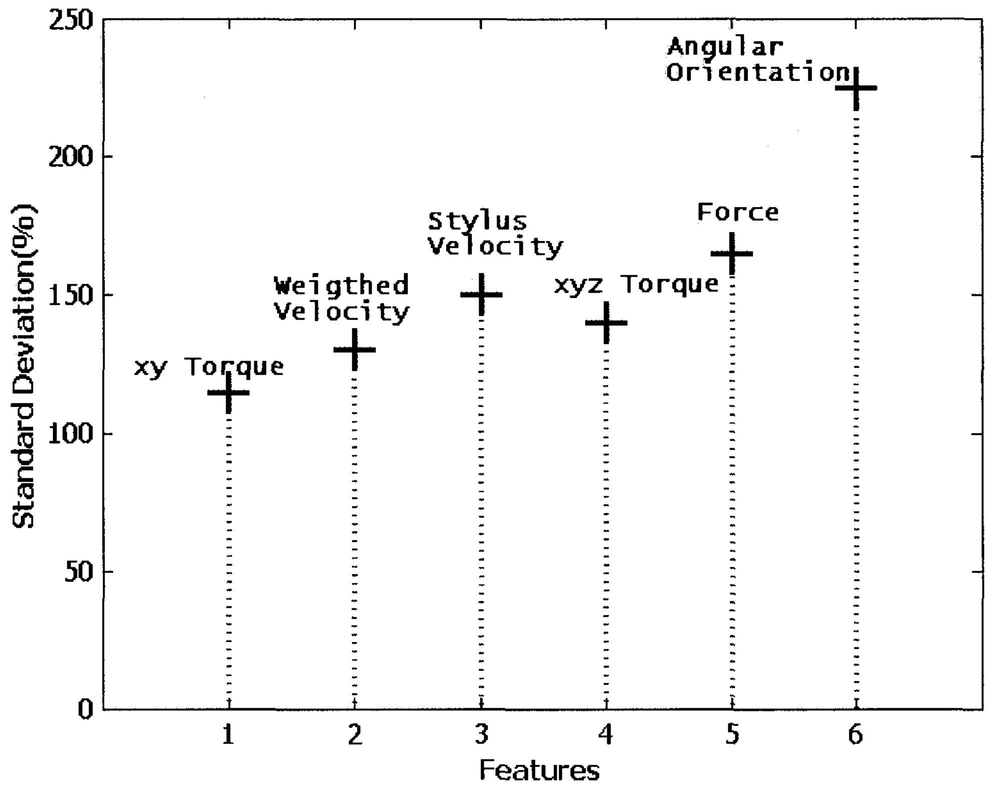


Figure 29: Standard Deviations from Mean Values of Information Content

However, the amount of information of the features varies among the different users (See Figure 29). The most non-variable information found in any feature was in User 9's angular orientation distribution (142 bits). The least amount of information was found in User 14's *xy*- torque distribution (< 1 bit). The standard deviations from mean values of information content suggest that choosing a single identifier would not be the most effective approach in identifying individuals.

6.3 Entropic Signatures

The information content of biometric features differs amongst users of the haptic system (Figure 30). As $D(p||q) = 0 \Leftrightarrow p = q$, and considering that all users had non-zero information content of all features, the previous analysis confirms that the biometric identifiers are at least somewhat unique to an individual. Indeed, the measure of that uniqueness is $D(p||q)$. Therefore, the proposed system can characterize the identity of an individual by how unique their features are. The characterization takes the form of a concept defined as *entropic signature.* An entropic signature is a measure that characterizes both the way in which an individual is unique by the features of his/her signature, and the magnitude of that uniqueness with regard to a collection of signatures. In that way, the uniqueness of an individual's signature is not assumed but evaluated. Moreover, the shape of letters in a handwritten signature is analogous to the distribution of information content in an entropic signature.

From a statistical perspective, an entropic signature is a vector $s = (D(p_1||q_1), D(p_2||q_2) \ldots D(p_n||q_n))$, where the subscripts 1 to n denote the different biometric identifiers. By its definition, this s vector characterizes the uniqueness of various biometric features of each individual. From a geometrical perspective, an entropic signature can be modeled as a curve in the plane. Figure 31 presents a small collection of entropic signatures obtained from 10 users. Indeed, the information content of biometric features differs amongst users of the haptic system (See Figure 31). As $D(p||q) = 0 \Leftrightarrow p = q$, and considering that all users had non-zero information content of all features, our analysis confirms that the biometric identifiers are at least somewhat unique to an individual.

As a result the following analogy is proposed: users interact with the haptic device within the VE in a similar way to how people sign their name. The scale and size of each letter in a handwritten signature is analogous to the magnitude of each $D(p_i||q_i)$ in an entropic signature. The shape of letters in a handwritten signature is similar to the distribution of information content in an entropic signature.

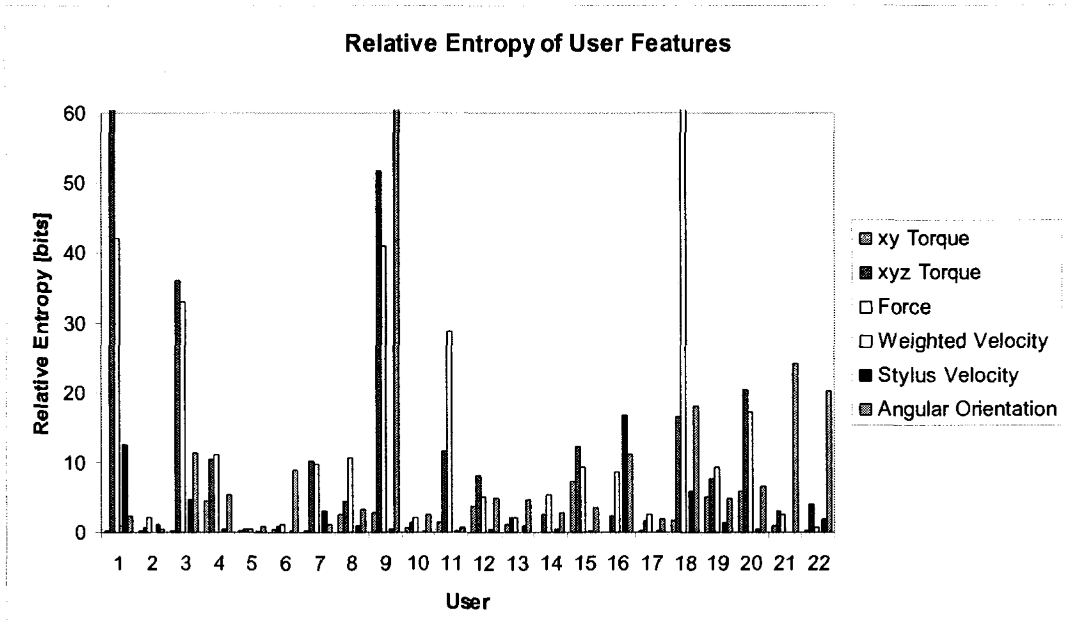


Figure 30: Relative Entropy of User Features

A biometric recognition system, based on handwritten signatures, would operate differently from a system based on *entropic signatures*. The underlying assumption of identity recognition, based on handwritten signatures, is that each signature is unique. From this assumption, traditional system (with no haptic interaction) makes a geometrical analysis of a sample of handwriting for authentication. A biometric authentication like the HaBiTs system based on entropic signatures would operate in a distinctive way. The uniqueness of the signature features are evaluated, not assumed. Therefore, instead of evaluating geometry based on an assumption of uniqueness, the HaBiTs system would evaluate uniqueness based on an assumption of different behavior from each user. The geometrical assumption translates into the statistical assumption that one can indeed construct the s vector for any individual.

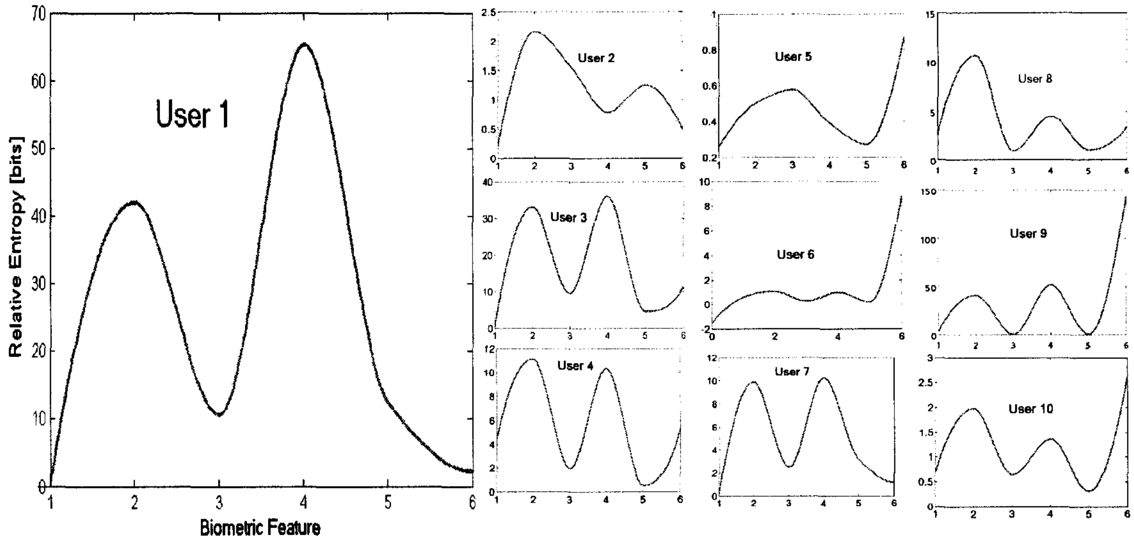


Figure 31: Sample entropic signature of User 1 (left). Sample entropic signatures of different users (right).

6.4 Evaluation Domain

The precision of a biometric system is reliant on the choice of the features used to form biometric profiles. For accurate authentication, the features must be chosen so that they are unique for each individual. The relative entropy metric allows the system to identify such features embedded in raw human-haptic interaction data. Digital representation and the processing methods of these signals allow the HaBiTs through the FGS subsystem extracts these features from the raw data to form biometric profiles of every user. Next, the CDD subsystem employs pattern recognition methods to authenticate the identity of these users. Authentication decisions are made by a variety of metric classifiers, such as measuring the match score between two profiles or applying a majority rule. A predetermined threshold value places an upper bound on acceptable match scores.

6.4.1 Profile Recognition

The Profile Recognition Function (PRF) that belongs to the CDD sub-system differs depending on the type biometric system. If the system is of the identification function variety, then the PRF makes comparisons between the input biometric profile and all sets of profiles from the template storage area. If the system is of the verification function variety, then the input biometric profile is compared with one set of profiles from the template storage area (the set associated with the claimed identity). In both cases, the construction of the templates must be done prior to any login attempts.

A degree of variability exists between profiles of the same user. We assume that this variability is in part due to a user's increased familiarity with the system after repeated trials. Moreover, this variability is rooted in the physiological/ behavioral changes humans experience with the passing of time. Given that this variability exists, we choose to construct the template profiles so that a user's template consists of signals gathered from 3 separate data acquisition trials.

6.4.2 Quantitative Score

The sample versus template comparisons produces a quantitative Match Score (MS). The MS between two biometric profiles d_1 and d_2 is calculated using:

$$MS = \ln[\sum_{i=1}^{N}\sum_{j=1}^{L_w}(\|d_{1,i,j}\| - \|d_{2,i,j}\|)^2] \tag{6. 3}$$

In the above equation, *ln* denotes the natural logarithm and $||d_{1,i,j}||$ denotes the complex norm of the i,j^{th} element of biometric profile *1*. The summation indices run to the number of features N (6 in our case), and the length of the windowed signals L_w (256). By definition, a low MS implies a small difference between two profiles, while a high MS implies a large difference. Essentially, the MS measures the separation between two biometric signals.

6.4.3 Decision Domain

The CDD sub-system designates a Decision Domain Function (DDF) which serves to either accept or reject a user. The authentication DDF accepts a user by establishing their identity, and rejects a user if this establishment cannot be formed. To authenticate a biometric profile, the MS between that profile and one of the template profiles must be less than or equal to some upper bound, τ. The performance of the authentication system varies with the choice of this upper bound. If τ is chosen to be large, many imposters will match with template profiles; whereas, if τ is chosen to be small, many genuine users will fail to match with their template profile, as shown in Figure 32.

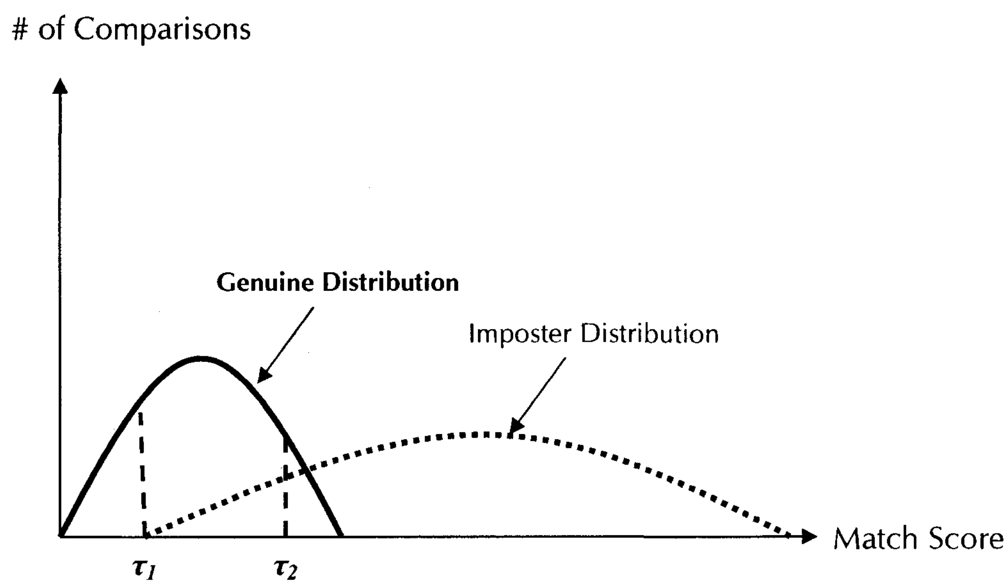


Figure 32: Match scores less than τ2 would allow access to a significant portion of impostors; whereas, Match scores less than τ2 would deny access to a significant portion of genuine users.

By sending many raw signals through the FGS sub-system and the PRF of CDD sub-system, we evaluate system performance. Comparisons between profiles of the same user yield a "genuine" MS distribution. On the other hand, comparisons between dissimilar profiles yield an "imposter distribution". For different values of τ, the evaluation of the FAR is carried by integrating the imposter distribution from zero to τ. In similar way, the calculation of the FRR is carried out by integrating the genuine distribution form τ to infinity. The set of points FRR (τ), FAR (τ) form the ROC (Receiver Operating Curve). The verification function of DDF operates differently. Using the pre-stored template profiles, we determine a different threshold MS for each user. To calculate a specific threshold for a user, we first construct a genuine distribution based only upon comparisons of this user's template profiles. Then, we form an imposter distribution by comparing all dissimilar user profiles to this user's profiles. We construct several sets of threshold values where the FAR rate is constant amongst the users; hence, allowing the construction of the ROC.

6.5 Discussion of Relative Entropy Analysis

The fundamental assumption of this work study is that there exist natural differences between the psychomotor patterns exhibited by individuals in VE. Based on this assumption, we have proposed the use of haptics in the authentication of human identity. The available PHANToM haptic devices provide us with a rich description of the observable physical parameters that define human-machine interaction. In a previous endeavor, we have found the user-classificatory worth of parameters varies amongst the set of all observables [El-Saddik et al_07] [Orozco et al_06] [Orozco et al_07]. Indeed, force and torque measurements contain the most information pertaining to a user's identity. This conclusion is drawn by calculating the relative entropy between intra-personal and inter-personal time-based physical parameter distribution functions. The interpretation of relative entropy is as a pseudo-metric that defines the distance between an individual's features and those of the entire population of users. Therefore, relative entropy provides a metric for the extraction of the most relevant features to employ in user authentication task. For authentication, a set of biometric algorithms are used in the CDD sub-system. From a great variety of pattern recognition methodologies, we have chosen the well-know PCA, DTW, Neural Networks, and K-Means methods to classify haptic user feature vectors extracted characterizing their psychomotor patterns as it is described in the following section.

6.6 Methodology

6.6.1 K-Means

The *HaBiTs* system utilizes this recognition technique into two ways, first we apply k-means as part of the feature selection process (see Section 5.5.3) but in this section k-means is applied to cluster psychomotor patterns with similarities in the reference pattern collection [Orozco & Saddik_05]. In the former case, the development of pattern vectors is discussed in order to identify which features provide a more stable frequency among users in order to be ranked.

In the latter case, the psychomotor pattern state vectors are represented by $r = (\Sigma_{fx}, \mu_{fy}, \Sigma_{tz}, \mu_{tz}, \sigma^2_{tz})$ from the relative entropy analysis. As input to the k-means algorithm, from groups A and C, 45 participants navigating the virtual maze application, where each user contributed three patterns to the total collection. These 135-five-dimensional vectors were clustered into k = 45 disjoint subsets using the k-means algorithm towards user authentication based on the keystroke dynamics of virtual phone dialing.

Testing was experimented with a variety of different pattern vectors. We found the subsequent user-classificatory results to be varied with the features chosen to form the pattern vectors, which were expected, once given our relative entropy analysis of similar data generated from the haptic device. Contrary to the data generated directly from the virtual maze application, rarely are user-specific patterns found in the force data of the virtual phone users. According to this approach, position data contains the most information pertaining to a user's identity.

6.6.2 Spectral Analysis: The Discrete Fourier Transform (DFT)

The method of analysis was developed by Fourier in 1807 and is called Fourier analysis. Generally, the spectrum analysis identifies the correlation of sine and cosine functions of different frequencies with the observed data. If a large correlation (sine or cosine coefficient) is identified, one can conclude that there is a strong periodicity of the respective frequency (or period) in the data.

One-dimensional DFT can be characterized by given N input samples $x(0), x(1), \ldots x(N-1)$, and their DFT is defined as

$$y(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n) \exp(-j\frac{2\pi}{N}kn), k = 0,1,\ldots, N-1 \tag{6. 4}$$

and the inverse DFT as

$$x(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} y(n) \exp(-j\frac{2\pi}{N}kn), k = 0,1,\ldots, N-1 \tag{6. 5}$$

where $j = \sqrt{-1}$. The processing cost of both equations requires $O(N^2)$ computations however one can take advantage of the use of the windowed discrete time Fast Fourier Transform algorithm by reducing the operations to $O(N \log_2 N)$ computations.

This study employed the spectral analysis based on the Fast Fourier Transform algorithm for the two approaches; the point-to-point correlation on user's trajectories (Section 5.3) and the feature-based set built according to the relative entropy described in this section.

In the former, first, we calculate a preliminary match on the time scales using linear interpolation and Nelder-Mead non-linear minimization as described in the previous section 5.4.1. Subsequently, the frequency content of the *xyz* position data was analyzed based on windowed discreet time Fourier transforms.

$$w(n) = 0.54 - 0.46(\cos \pi n/128) \qquad (6.\ 6)$$

Due to the low frequency content of the data, a large Hamming[3] Window function size of length 256 with non-overlap data points of 128 is applied. The Fourier Transform of $\boldsymbol{d_1}$ and d_2 is calculated (see Fig. 33) where d_1 and d_2 are the MS of two data sets. The square of the difference is calculated as in equation 5.8. Any waveform can be analyzed as a combination of sine waves of various amplitudes, frequencies and phases.

There is a significant difference in magnitude between data from different users and a near perfect match between data from the same user. The frequency profile of data 1 and data 2 are better matched than data 3. MS decreases when the spectral content of the two data sets are similar.

[3] Hamming Window function is a spectral analysis terminology to refer to particular width in samples of a discrete-time window function

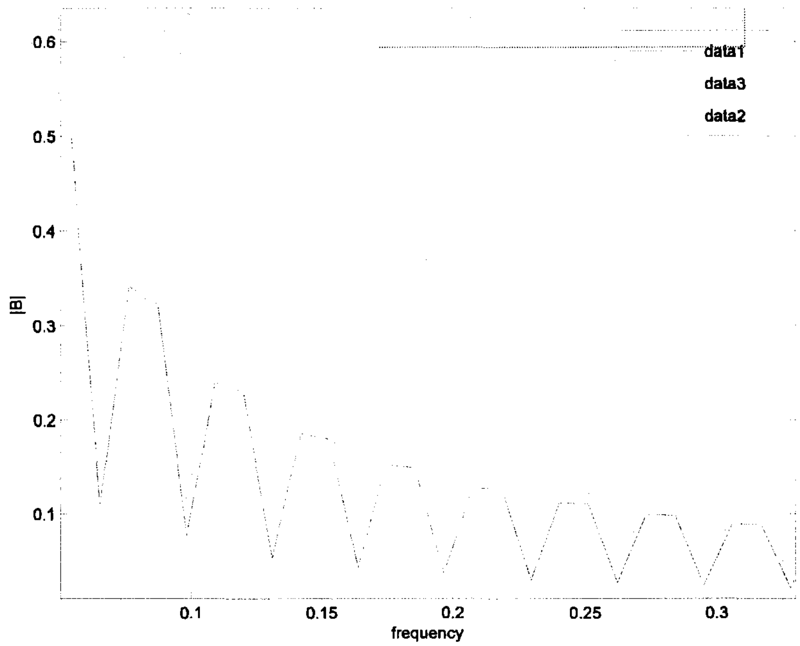


Figure 33: Spectral content of data from three data sets. data1 and data2 are from a single user and data3 from a different user (note that data 1 and data 2 are overlapped).

In the latter case, the function of the FGS sub-system is to form the biometric profile of a given user by using the input of data from the relative entropy analysis. The data is a set of six-dimensional state vectors obtained via frequent measurements during the user haptic interaction. These state vectors provide quantitative snapshots of the interaction. The rate of sampling is ~ 0.015 seconds. For each dimension of the state space, there is the associated biometric feature, i.e. "force in the z-direction". We consider measurements of different features as separate signals. To process these signals, we first apply a Hamming window function of length 256 data points with non overlap data points of 128. Subsequently, we take the fast Fourier transform of each windowed signal. The given coefficients of the window allow us to optimize transition width with respect to maximum attenuation.

After the hamming-window is applied, the (FFT) of each signal is taken. As a result, the state vectors are transformed into a 256x6 matrix, whose 6 columns are associated with distinct biometric features. Hence, the input data to the FGS is transformed into a 256x6 matrix in the frequency domain, whose 6 columns are associated with pairwise distinct biometric features. We refer to this matrix as the biometric profile. The relative entropy feature extraction mechanism and the spectral profile constructor permit the development of a generalized identity verification system. The decision policies of such systems vary with their application context.

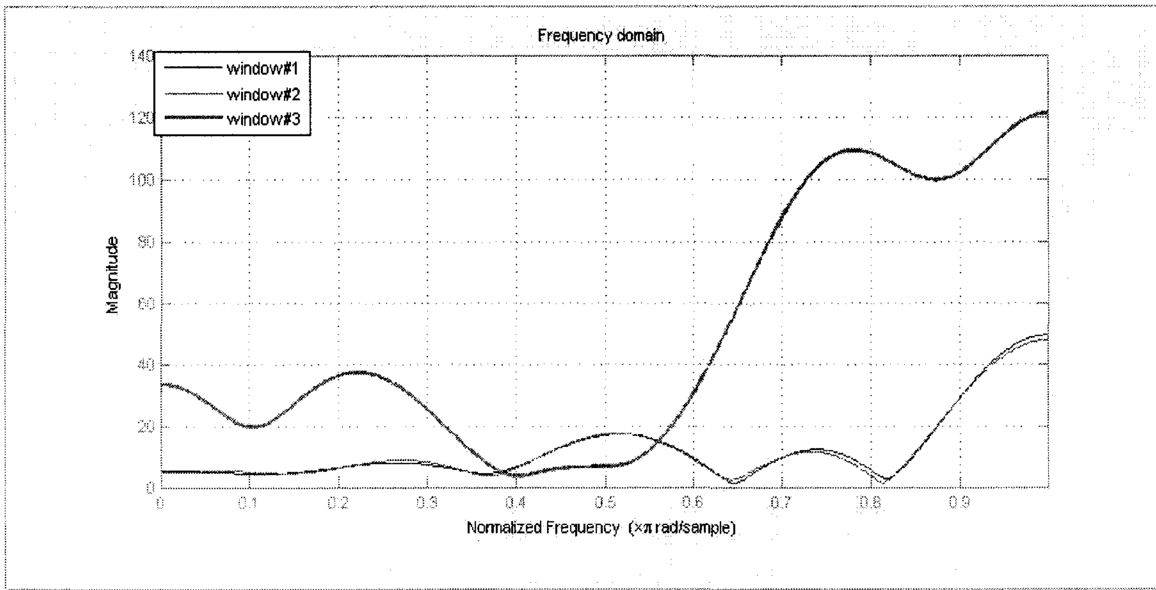


Figure 34: Window #1 and Window #2 are from the same user; whereas Window #3 is from a different user.

Our methodology requires the spectral analysis of biometric signals produced by the FGS. We assume that two signals from the same user will have a closer match when compared with the signal from another user. Our findings support this claim; however, due to the time-variability of an individual's biometric profile, the like-signals are not perfectly matched, as illustrated by Figure 34.

6.6.3 Neural Networks

Inspired on the biological nervous systems, an Artificial Neural Network (ANN) processes the information in a similar fashion. Like people, haptic applications learn by example. Therefore, the *HaBiTs* system through the CDD subsystem decides to configure an artificial neural network for the specific task of recognition of psychomotor patterns. The artificial neural network involved adjustments similar to biological systems to the synaptic connections, therefore with 5 inputs, 13 hidden and 22 output neurons for the user, the identification task was implemented. The network architecture is organized into layers allowing for signals to travel one-way only; from left to right. Each node in each layer is connected to every node in the next layer as it is depicted in Figure 35 shows the implemented network which also was tested by using Weka [Witten & Frank_05].

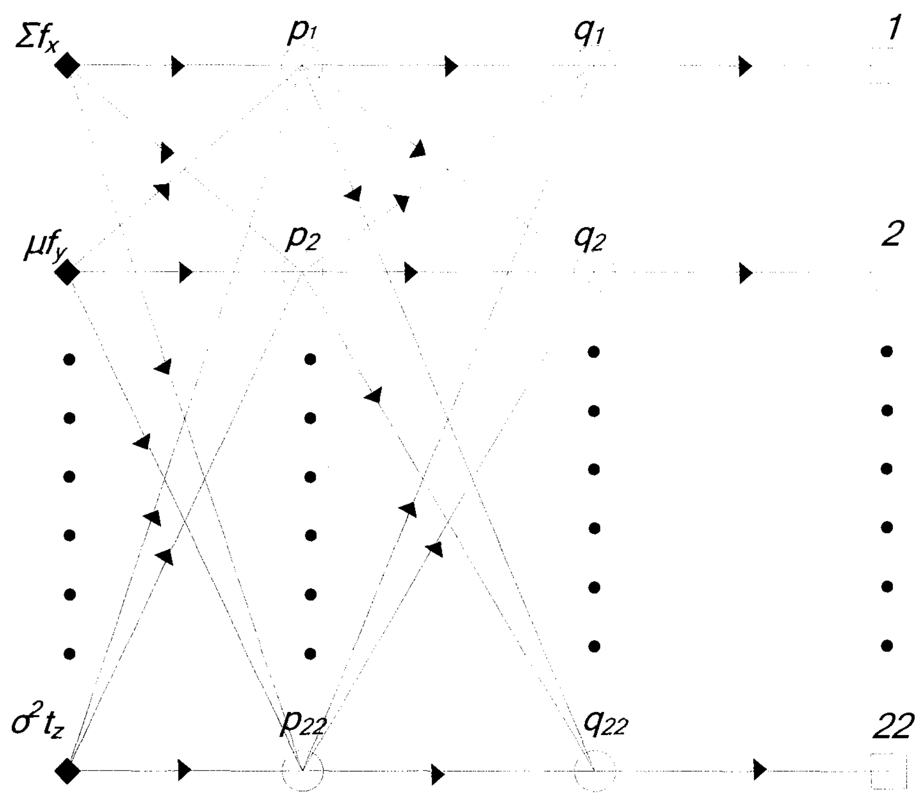


Figure 35: The 3-layer feed-forward architecture chosen for ANN implementation

The input neurons operate with numerical values from different dimensions of the 5-Dimensional pattern vectors. Each "neuron" is a sigmoid function, which receives input p and outputs $\{q\ (0,\ 1)\}$ according to Equation 6.7. Neural connections are essentially characterized by weight, denoted by w. To explain it, consider the passing of output q_j, from neuron 'j', to neuron 'k': then, neuron k operates on input p_k in relation to Equation 6.8. The weights and biases are adjusted using stochastic back-propagation. This process is referred to as "training", and, as we discuss next, makes adjustments beginning from the output layer and working backwards.

$$q = \frac{1}{1+e^{(-p)}} \tag{6. 7}$$

$$p_k = w_{kj} \bullet q_j \tag{6. 8}$$

The training process involves a set of reference pattern vectors, $R = \{\, r : r = (\Sigma f_x,\ \mu f_y,\ \Sigma t_z,\ \mu t_z,\ \sigma^2 t_z,\ I),\ I \quad \{1,2,3,....,22\}\ \}$. The last (sixth) dimension of the pattern vectors is an integer used to store the identity of the user who generated the vector; hence, The ANN is trained to identify twenty-two different haptic users (Group A). Training begins via the random initialization of all weights and biases. Then, until a termination condition is met, we adjust the weights and biases to minimize the error between the ANN's user-classification decision, and the correct decision. More specifically, for each pattern vector, we take the error on output values to be δ_z (see Equation.6.9), where t_k is the correct output, and O_k is the actual output. Next, we calculate the corresponding error on the values passed to the output from the hidden layer, δ_h, according to Equation 6.10;

wherein, O_h is the output of hidden neuron h, and w_{vh} is the weight of the connection between "h" and the output neuron whose error is δ_v. Finally, the weights are updated according to Equation. 6.11, where we introduce new notations: 'learning rate' and 'momentum', denoted by η and τ respectively. Also, in Equation 6.11, Δw_{ji} denotes the value of the change made to w_{ji} during the previous training cycle (epoch). The learning rate is used to control the magnitude of the changes, and the momentum is a value used to prevent unwanted oscillations of the weight values.

$$\delta_z = o_z(1 - o_z)(t_k - o_k) \tag{6.9}$$

$$\delta_h = o_h(1 - o_h)\sum_{v=1}^{22} w_{vh}\delta_v \tag{6.10}$$

$$w_{ji} \rightarrow w_{ji} + \eta\delta_j p_j \tau(\Delta w_{ji}) \tag{6.11}$$

6.6.4 Principal Component Analysis (PCA)

Mutual information analysis as well as the classification methods, such as ANN approaches, demands a high level of computational process costs. On the other hand, the data storage is required for the purpose of post-processing and post-examination of acquired data sets. Furthermore, we faced additional issues related to haptic-data rates (between 600 – 1000 Hz) that can be translated into data accuracy and relevancy, and the availability of formats to capture, filter, and present the data. In order to tackle such all issues and to prove the concept of the proposed recognition method to identify psychomotor patterns exhibited by individuals in virtual domains, while still delivering effective results, the decision made was to implement the Principal Component Analysis approach (PCA).

PCA is a linear transformation technique that has been applied in many disciplines related to face recognition and image compression among others, and is a common technique for finding patterns in data sets of a high dimension. PCA transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so forth. Since patterns in high dimensional data can be hard to find, PCA is a powerful approach for analyzing such data [Abdi_03].

The available haptic device (PHANToM™) allows us to capture time-series measurements of many physical parameters, as discussed in Section 6.2.1 A can be denoted as the matrix where each columns correspond to a unique physical parameter obtained, as discussed in section 6.2.1. Each row of A corresponds to an instantaneous "snapshot" of the state of the haptic system (at a specific time). The dimensionality of A is quite large, making the interpretation (and transmission) of its information content a cumbersome task. Therefore, the implementation the PCA algorithm reduces the dimensionality of A and allows us to retain most of the information content of A. Therefore, this technique is used to compress the feature space such that the important information is not lost.

To describe the PCA algorithm, let A be the matrix with size denoted $m \times n$. The first step of the algorithm is to calculate the mean values of each column of A, which can be denoted by μ_j. where, $\forall i \in 1,\ldots m, \& \forall j \in 1,\ldots n, A_{ij} \rightarrow A_{ij} - \mu_j$; hence, $\mu_j \quad \forall j \in 1,\ldots n$. With the empirical mean of each column non zero, the next step is to find the covariance matrix of A, which is denoted cov. From cov, the calculation its eigenvalues

$\{\lambda_1, \ldots, \lambda_n\}$ and corresponding eigenvectors are carried out. The eigenvectors are placed in the rows of a matrix denoted by F. This is done in such a way that the first row of F contains the eigenvector that corresponds to $max\ \{ \lambda_1, \ldots, \lambda_n \}$. We call this first row of F the '1^{st} principal component' of A. The second last step of this algorithm is where we must choose the number of the principal components to be used in the compression of A. In this analysis, it is considered selecting only the 1st principle component. This choice is made so that it is possible to access the worst-case cost of employing PCA; put otherwise, it is possible to analyze how much information will be lost if the maximally compress the dimensionality of A is carried out. It can be reflected by choosing to use only the 1st principal component, $A \rightarrow FA^T$. Therefore, the objective to use PCA is to reduce the size of A to $1 \times m$.

By quantizing the values of FA^T in such a manner that $FA^T \rightarrow Q$, whereby $Q \subseteq \{0, 0.1, 0.2, \ldots, 1\}$. From Q, we obtain a sequential representation. This sequential representation is of the form $s = (q_1, \ldots, q_n)$; whereby q_j stores the j^{th} discrete value appearing in $\boldsymbol{Q}$. For example, in the case of a flat Q, s would contain only one element. It is these s vectors, which can be taken as the final compressed version of physical parameter matrices characterizing virtual signatures. These s vectors can be taken as the final compressed version of physical parameter matrices characterizing virtual signatures. These s vectors are compared using a DTW, producing a similarity score: MS, where a low MS indicates a strong similarity.

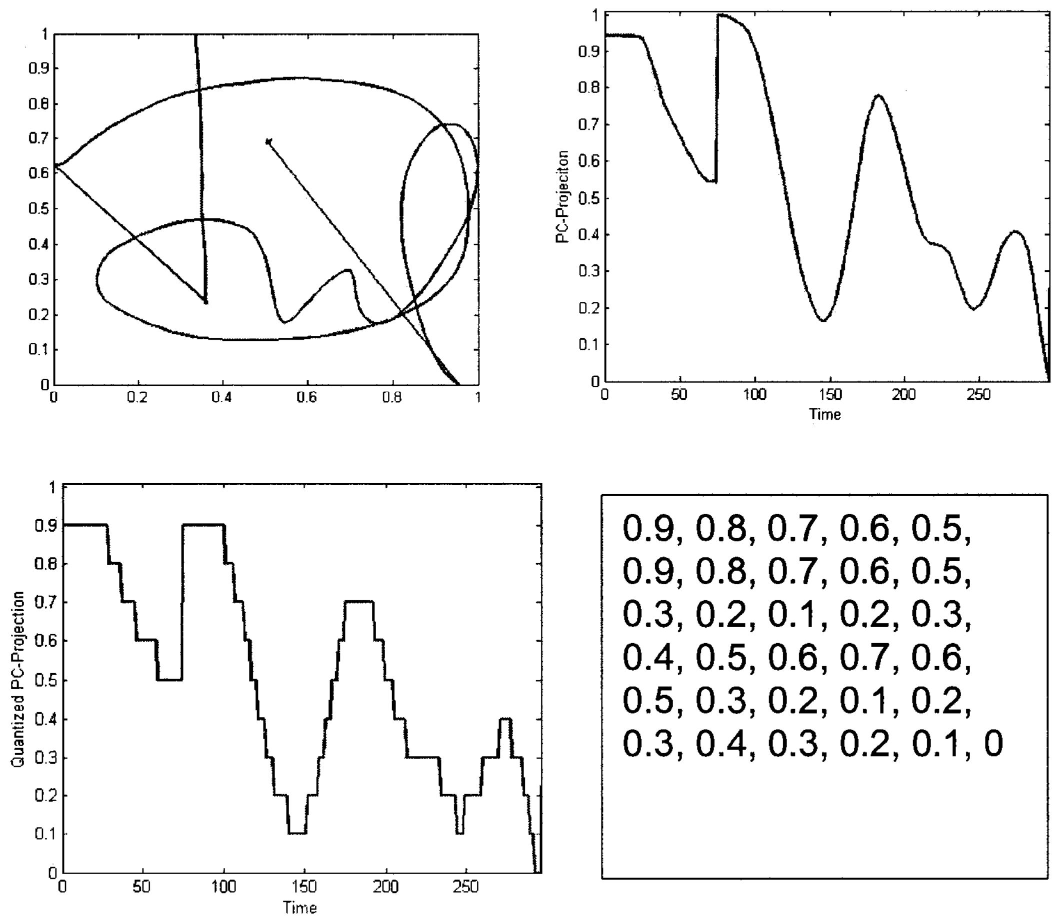


Figure 36: Top Left: Original 2D signature (4.87 kB); Top Right: 1D projection on the 1st principal component axis; Bottom Left: Quantized Version of the PC-Projection (0.238 KB); Bottom Right: Final Sequential Representation (0.2 kB)

As this study choose to project physical parameter matrices only onto their first principal component axis, information loss is inevitable in the general case. Moreover, as these projections undergo quantization and discrete sequence extraction, we expect the information content to degrade further. Such transformations are depicted in Figure 36, where it is evident that the virtual "size" of the signature representation is reduced to 4.1% of its initial value. This data compression suits the goal of such present experiment: to reduce both the dimensionality and the size of a virtual signature.

6.6 Analysis of the Results

In this section the results of this last experimental work are presented, which encouraged the pursuit the different pattern recognition methodology selected. As it has been stated previously that the fundamental assumption of the present thesis is based on that there are natural differences between the psychomotor patterns exhibited by individuals in VEs with haptic feedback. Haptic devices are a good source of producing a variety of attributes from the human-machine interaction that can be converted into numerals. Such a process can be seen as an analogue manufacturing process whereas a manufacturing process leads to a physical object, a measuring process results in a mere number or an ordered set of numbers [Mandel_64]. In order to provide a scientific interpretation of the experiments' findings we need to consider the data as a subject of intrinsic values to test the present work's hypotheses. Thus, the statistics science plays an important role in the interpretation of the behavior of data under different conditions. However further interpretation is required to find the relationship between measurement parameters. Applied statistics can lead to methods of data analysis that are suitable to find the level of correlation between the variables that play a similar role in the system. The relative entropy is a metric that allows for differentiating between how much information two variables share. Thus, reaching the best performance of the *HaBiTs* framework is based on the relation among attributes and their role in the state of the haptic system obtained from the mutual information analysis.

Therefore, we conducted the experiments by using two well-recognized authentication functions. Firstly, the identification function is established in order to find the identity of the users by comparing specific parameters of their haptic-based task performance against all N volunteers enrolled (Section 6.7.1). Secondly, a verification function is selected to establish a claimed identity of volunteer i by a one-to-one comparison (Section 6.7.2).

6.7.1 Identification Mode

The most challenging possible application of the biometric technology is automated as a positive identification of an input subject against some member of the database M of n subjects s_i. The authentication protocol demands only the presentation of the biometric to the authentication system and a subject is identified or not based only on the biometric [Bolle et al_04].

6.7.1.1 Spectral Analysis

Based on the relative entropy or the Kullback-Leibler divergence method to build the feature vectors, we conducted the identification mode by using the FFT as a linear classifier (Section 6.6.2) on the haptic-based applications (e.g. the virtual maze). Our analysis shows that the probability of successful identification (PV) depends on which sections of the windowed signals are used in the calculation of the MS.

Figure 37 shows the variance of the PV with a signal section. At 25% FAR, PV was the highest value for data from the 6th, 7th, and 8th trials completed by the users. The genuine and imposter distributions pertaining to from these data sets are shown in Figure 38. The analysis of these trials through window 8 resulted in the highest PV at 25% FAR (Figure 38). The ROC curve using data from the 7th, 8th, and 9th trials is shown in Figure 39 and the line of identity is used to show the equal error rate of EER around 27%.

The PV also depends on the length of the hamming windows that are applied to the raw data. By doubling the length of the window, the PV improves from 71.2% at 25.5% FAR to 75.5% at 24.7% FAR. Despite the improvement of the PV with an increase in window size, one cannot simply choose an arbitrarily large window size, due to the finite length of a raw signal. In the cases where the length of the window exceeded the length of the raw signal, the signal was padded with zeros.

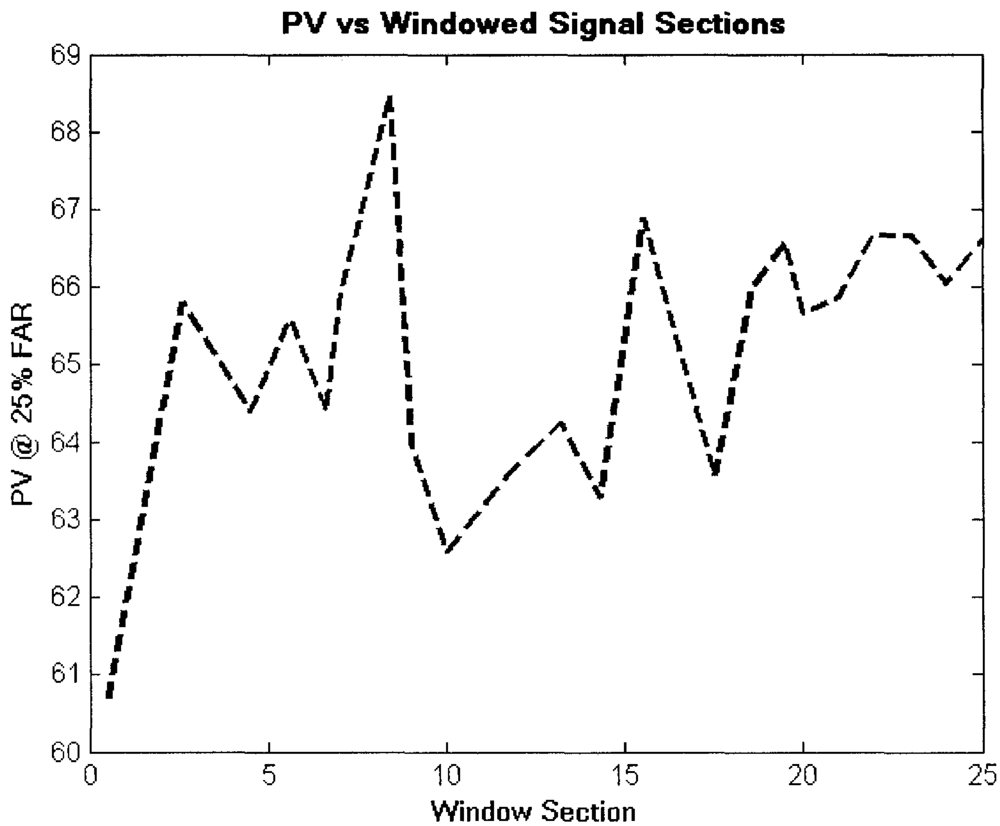


Figure 37: Probability of Verification seen through different windowed signal sections.

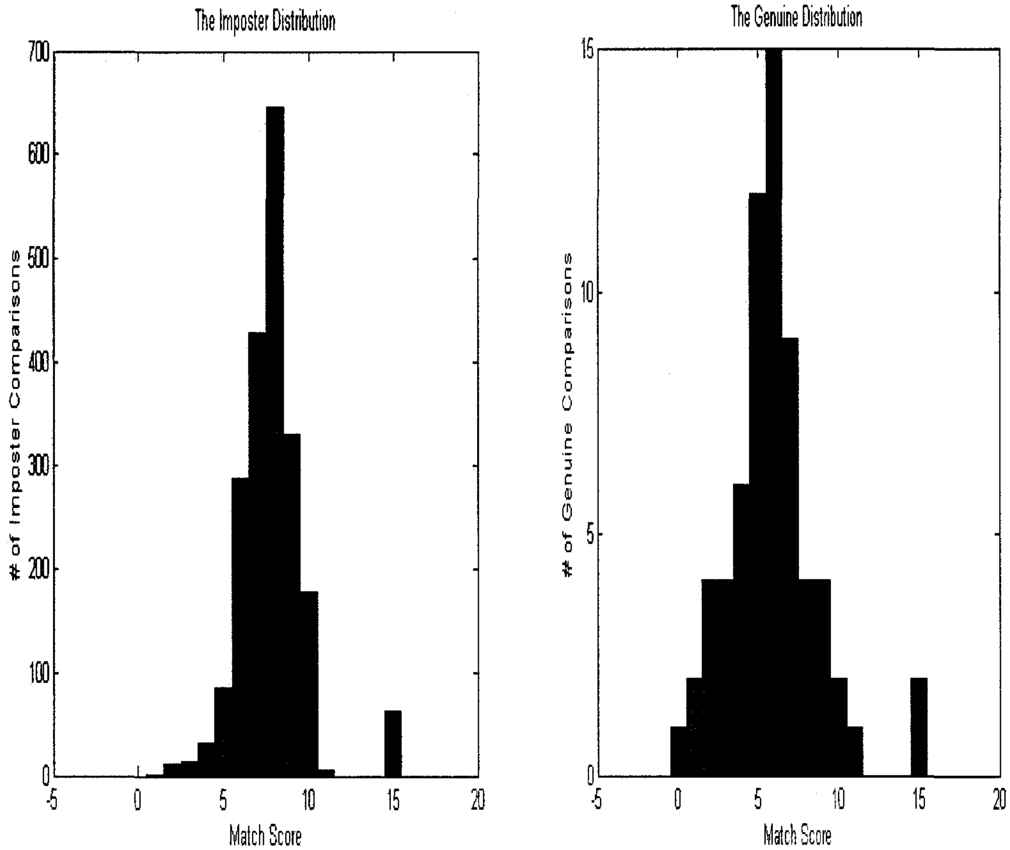


Figure 38: The imposter (left) and genuine (right) match score distributions from profiles constructed from trials 7, 8 and 9 of the maze test.

The genuine distribution is bimodal, which shows the significant inconsistency that certain users have between their different profiles (Figure 38).

Data from the virtual cheque signatures was also analyzed as input to an identification system. Each of the 20 users signed their cheque 9 times (Group B). Using the samples taken from the first 8 trials, the PV was calculated as 50% and at 25% FAR. By removing samples from the first 4 'warm-up' trials, the PV increased. This trend continued as shown in Figure 40.

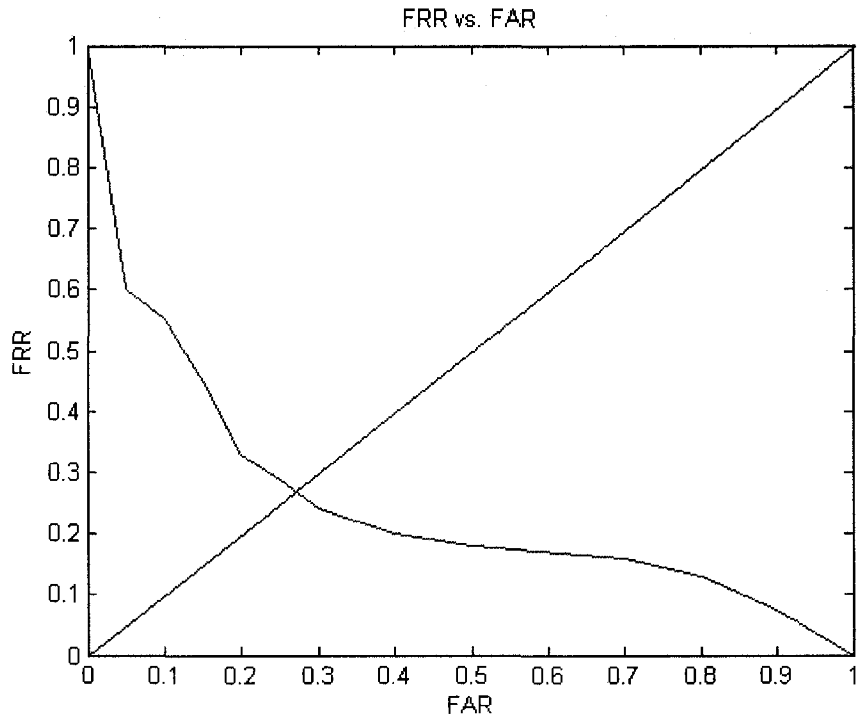


Figure 39: ROC for the identification system based on 3 trials from the maze tests seen through window 8.

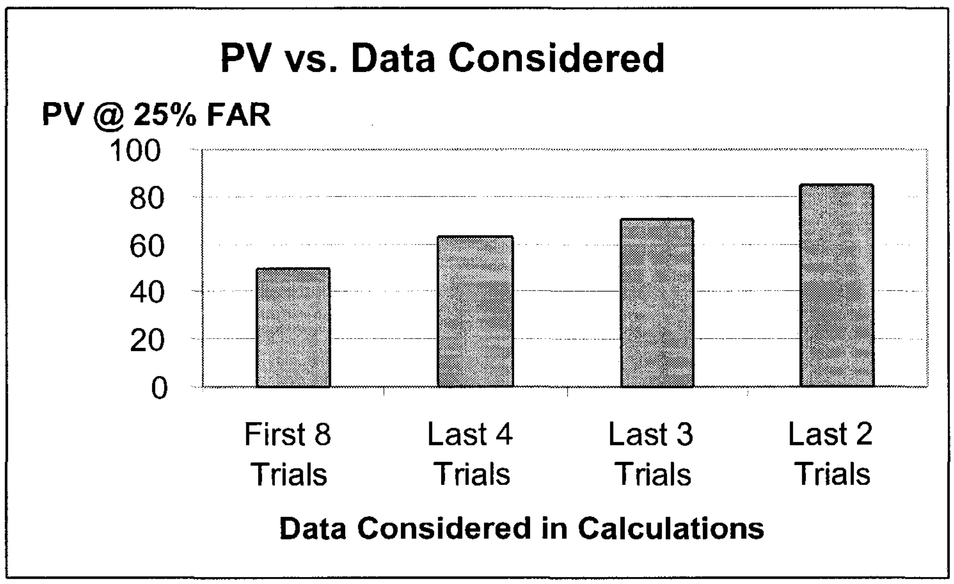


Figure 40: The probability of successful identification as a function of the dataset used for testing (discarding samples from the first training trials).

6.7.1.2 Neural Network

In previous sections, our study has shown that by using feature-based comparison techniques based on spectral analysis, the system can successfully identify haptic users 75.5% of the time. Using the neural network architecture described in Section 6.6.4, after learning to associate the 5D psychomotor pattern vectors with usernames, our artificial neural network correctly identified 90.9% of users for the maze application. The network was trained for 500 epochs, and we set $\eta = 0.4$ and $\tau = 0.2$. The values of these parameters were determined in an ad hoc manner, and we leave a statistical procedure seeking "optimum" parameter selection for future research.

The most significant disadvantage of the Spectral Analysis (SA) approach is that a particular signal may match with many biometric templates. With ANNs, a biometric signal is made to match with only a single identity. This dramatically reduces the experimental FAR. Using PV=91% as a common comparison point, the FAR of the ANN is 0.4%, remarkably better than the FAR which is approximately 3% from the SA system. The computational cost of using ANNs is perhaps their most significant drawback. The time taken to train the ANN increases with its complexity. We hypothesize that the complexity should increase with the number of enrolled users. Essentially, the complexity of the network is characterized by the number of neurons and hence the number of connections. We trained eleven different networks for 500 epochs (cycles). As a result, the time taken to train the networks was found to increase with complexity. While simplistic networks are less expensive to train, we found that their pattern recognition ability was superseded by more complex networks; however, our results suggest that there is an optimal upper bound on network complexity. A network with 13 hidden neurons is best suited for our purposes, yielding the best verification results.

6.7.2 Verification Mode

In the case of biometric verification, the protocol is based on the presentation of possessions (i.e. ID card) and/or knowledge (i.e. PIN number). These additional credentials uniquely characterize an enrolled identity i in the database repository M and therefore an associated biometric machine pattern B_i [Bolle et al_04].

6.7.2.1 Spectral Analysis

With processed data obtained from the analysis of the haptic content machine, we formed three template profiles for each on the maze application. The aforementioned templates are generated using data from the seventh, eighth, and ninth trials completed by each user. We then used the data from trials 6 and 10 to create sample profiles, in order to make comparisons against the templates. The test results from trial 10 were more accurate than the test results when using samples from sixth trial. This agrees with the notion that users behave more consistently as they become more familiar with using the haptic application. In this mode, we integrated additional features into the biometric profiles: the total time taken to solve the maze, and the average angular orientation of the stylus. The system accepts a user claiming to be X, if their biometric profile meets the following criteria:

(1) The MS based on spectral analysis (with template X) is below a predetermined user-dependent threshold,

(2) The total time taken to solve the task (e.g. the maze) is no more than 26.4% different from the average of times recorded in the X template,

(3) The average angular orientation is no more than 20% different from that of the X's template. By using test samples gathered during trial 10, the system performance is evaluated: PV = 95.4% at 4.5% FAR; moreover, the ERR of the system is 4.5%.

When using feature vectors for characterizing users' interactions with the virtual cheque, our verification system performance is variant with the chosen methodology for the match score generation. Template profiles are formed for the first five each user's signatures, and sample profiles are created by using the remaining four signatures. Considering a spectral analysis approach, the EER of the system is quite high: 18.8%. This result motivates us to propose two different methods for signature verification, among them, the dynamic time warping, whose effectiveness in the dynamic signature verification is well known.

6.7.2.2 Dynamic Time Warping Analysis

The DTW algorithm produces a MS between two biometric profiles by computing the minimum cost of aligning two sets of time-series measurements. We use two-dimensional time-series position data to characterize the virtual signature, and thus to be used in the DTW calculations. The identity of a user is verified by the system if their sample signature produces a MS, less than a predetermined threshold, with at least two of the associated template signatures. As depicted in Figure 6.13, the performance of DTW supersedes that of the spectral analysis. We also took another approach towards the virtual signature verification, where the MSs are produced via a simple calculation of the Euclidean distance between the 2nd and 3rd virtual 3D world coordinates of the template and sample signatures. The results of employing this method for user verification are quite good, considering its simplicity. These results are also depicted in Figure 41.

The FARs shown in Figure 41 are generated by the acceptance of 'random' forgeries. A random forgery is a signature that is falsely verified, despite the fact that no such verification was intentionally sought. We also evaluated the FARs generated by 'skilled' forgeries – intentionally fraudulent submissions. These skilled forgeries were made, by using -like a visual reference- handwritten signatures of five participants who signed the virtual cheque. At an operation level of 97% PV, the Euclidean method falsely accepted 20% of the skilled forgeries. Using the DTW algorithm, the 26% of the skilled forgeries were accepted at an operation level of 93.8% PV. The 'Euclidean' method allows for the highest (98%) PV at 25% FAR; however, the DTW algorithm is more reliable at low FAR operating levels.

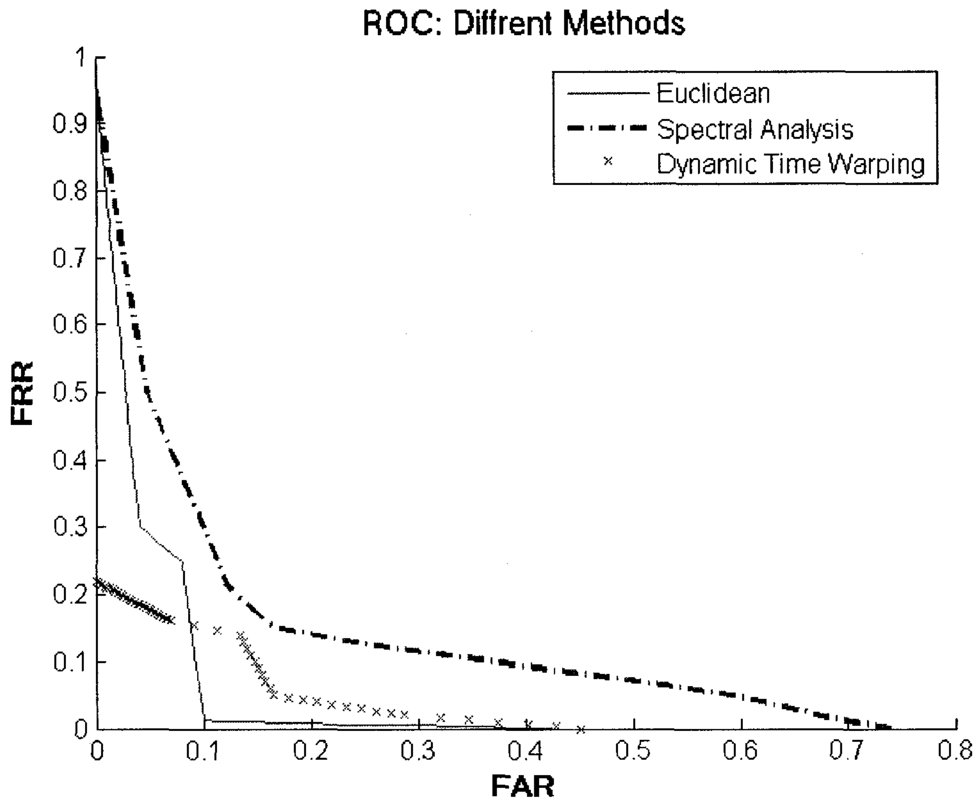


Figure 41: Receiver Operating Curves depicting the performance of several verification algorithms.

The results of our study suggest that haptic-based biometric systems are best suited to verification applications. At 25% FAR, the PV of our maze-based identification system was at best 75.5%, while the PV of the verification system was at best 95% at 4.5% FAR.

The ERR of the identification function was 27%, compared to the 4.5% EER of the verification function.

Since the results have been improved remarkably, we also faced the issue that the haptic data generated from the haptic interface is very demanding, especially at the moment of synchronizing the haptic and graphic rendering processes. We decided to overcome this issue by incorporating a method that can reduce the load of haptic information but at the same time does not affect the performance of the verification system. Therefore, we opted to choose the Principal Component Algorithm to decrease computational cost.

6.7.2.3 The Quantized PCA –DTW Algorithm

As we choose to project physical parameter matrices onto only their first principal component axis, some information loss is inevitable. Moreover, as these projections undergo quantization and discrete sequence extraction, we expect the information content to degrade further. Such transformations are depicted in Figure 6.9, where we see the virtual 'size' of the signature representation is reduced to 4.1% of its initial value. This data compression suits the goal of our present experiment: to reduce both the dimensionality and size of a virtual signature. In order to test the magnitude of the information loss, we used the DTW technique to generate 5120 MSs. These scores are drawn between 144 signatures created by 16 different haptic users in the virtual domain. The imposter and genuine distributions of these scores are shown in Figure 42, on the left and right respectively. If we impose the condition that a signature must match with at least two 'reference' signatures, the probability of successful of the virtual signature verification is 92% at 25% FAR. Clearly, this result shows that our proposed approach removes a significant portion of useful information from the large data sets, which fully characterizes the virtual signatures. Moreover, due to the extreme compression we impose on signature features, a PV of 92% seems somewhat surprising. Therefore, we believe that there exists an optimal balance between the magnitude of feature compression and corresponding reductions of the computational cost of dynamic alignments.

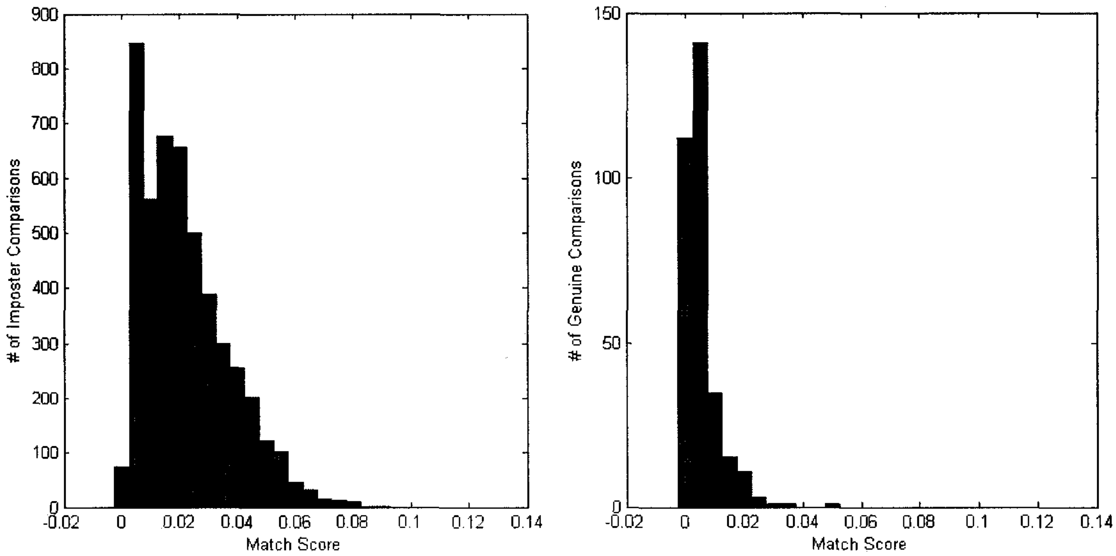


Figure 42 : Left: Distribution of Imposter Match Scores. Right: Distribution of Genuine Match Scores

6.7.2.4 Neural Network: Dynamic Signature Verification

As a figure of merit, the FAR of our ANN, when operating in verification-mode, is 0.4%; this is a remarkable improvement on previous haptic-based biometric FARs of, approximately 10% to date. The low FAR of the ANN is because only one output neuron is excited when the input layer receives a pattern. Unlike other systems, a pattern is never decided to belong to more than one user. On the other hand, a pattern is always associated with at least one user; hence, the lowest possible bound on the probability of a successful attack by a non-registered user is 4.5%. This probability can be reduced by increasing the size of the output layer, and thus the number of enrolled users.

6.8 Conclusions

As can be seen from the previous first order statistical approach to analyze the means and variances of the temporal functions separately, we cannot characterize uniqueness in the same way as mutual information approaches for evaluating dependency among outputs (i.e. relative entropy) [Lexa_04][Masulli & Valentini_01] .The magnitude of the mean velocity is directly proportional to the variance. Put otherwise, the user with the fastest mean speed exhibited the most variability in their behavior. Suppose now that two users have the same mean velocity. Then, from a first order statistical perspective, they are identical users. On the other hand, the user with the slowest mean velocity exhibited the least variability in their behavior. It turns out that we get more information from the slower user. The slow user's behavior is a more consistent characteristic, since a higher level of relative entropy exists between that user and the population.

The purpose of following the study is to analyze among the haptically captured features which of those play a critical role in defining the haptic system state/identifier by providing richer content. Hence, we assess the uniqueness of each biometric identifier. To measure the uniqueness of the identifiers, we follow the relative entropy approach of different users' biometric feature distributions with respect to the population distribution [Lexa_04]. Such a measure reveals the information content of each user's haptic interaction feature. Our analysis shows that the information content of identifiers varies among the users. We concluded that the construction of entropic signatures is relevant to characterize both the way in which an individual is unique, and the magnitude of that uniqueness [Orozco et al_07].

Given raw data generated directly from the haptic interface, we have explored the idea of haptic-biometrics. Using the relative entropy as a pseudo-metric and the chi-squared test for independence, we extracted unique-to-the-individual parameters describing patterns exhibited by users in the virtual domain. The results of our study suggest that haptic-based biometric systems seem to be best suited to verification applications.

The above-mentioned results are based on the behavior of users who had never interacted with our specific set of haptic-based applications before; moreover, the psychomotor patterns of these users were captured over a relatively short period of time (on the order of minutes). Nevertheless, these users exhibited remarkably consistent distinguishing characteristics. We know that the variation of a user's patterns diminishes throughout the hapto-task session [El Saddik et al_07]. Therefore, we believe that our results place a lower bound on the possible performance of haptic-biometrics with the current haptic technology. In the future, there will most probably be environments where users can interact with haptics on a daily basis. Within such environments, the uniqueness and consistency of user patterns would be significantly greater than 'first-time' or novel haptic users. In these environments, continuous verification by using haptic-biometrics would be commonplace.

Finally, the majority of conventional biometric systems (i.e. iris scanners, voice recognition, fingerprint/hand geometry and so on) can only assure that the correct user is present at the time of login. Indeed, such conventional systems perform the identification process much better than the haptic identification systems studied in [El Saddik et al_07]; however, after a user logs in, these systems have no way to detect if the correct user is still present. The Haptic-Biometric AuThentication System (HaBiTs) overcomes this difficulty. After the completion of tasks using haptic devices, the HaBiTs system determines whether or not the user who logged in is still the same user operating the system. This operation is applicable to high-security environments, where each manipulation of the system would ideally be followed by identity confirmation/rejection.

Chapter 7

Conclusions and Future Work

7.1 Conclusion

In conclusion, this thesis has investigated the possibility of authenticating users based on haptic data. Previously to this thesis, to our knowledge, no attention had been paid to research on issues pertaining to pattern recognition with the usage of haptic systems. To this purpose, a Haptic-Biometric auThentication System, called HaBiTs, has been successfully implemented and tested. The results obtained suggest that the haptic technology is suitable as a mechanism to authenticate individuals through VEs.

A fundamental assumption made in this thesis is that there are natural differences between the psychomotor patterns exhibited by individuals in virtual domains when using haptics devices. This assumption emerges from the analogue principle in pattern recognition, which assumes that everybody has a unique way of handwriting a note or typing a message using a keyboard. According to that, the haptic tasks used for capturing individuals' psychomotor features are based on actions which involve hand dexterity interactions in daily life tasks – writing, dialing and typing. These haptic-biometric applications are the virtual maze, the virtual phone and the virtual cheque.

The *HaBiTs* system is based essentially on a pattern recognition methodology that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data (feature selection process), and finally comparing this feature set against the template set in the database. Therefore, such haptic applications are tested and analyzed to calculate parameters that characterize the uniqueness of individual participants. The goal is to evaluate the suitability of haptic systems for authentication based on behavioral haptic biometrics.

The haptic-biometric experimental set consisted of 131 different participants for the three applications. Handwriting, dynamic signature verification and keystroke dynamics literature have suggested a number of approaches that consider local and global attributes based on measurements, such as velocity, distance encoding, timing and shape features, pressure, and angle functions. For the signature verification on the virtual cheque, a 35-parameter feature set was built to achieve a 6% ERR of application, which indeed enhanced the performance of the system with regard to previous results. Further research was carried out to improve these results from the relative entropy approach.

Position (p), velocity (v), force (f), torque (n), and angular orientation of the end-effector (θ), among other features, were extracted from the haptic interfaces used. To study which features can be consider as biometric identifiers, that is, to measure the uniqueness of identifiers, the relative entropy of different users' biometric feature distributions were calculated with respect to the population distribution. In view of the variability of the haptic features which characterize each individual, a new concept, called entropic signature, was introduced considering these psychomotor features. This entropic signature confirmed that the chosen biometric identifiers are at least somewhat unique to an individual. From a statistical perspective, an entropic signature is a vector $S = (D(p_1||q_1), D(p_2||q_2)\dots D(p_n||q_n))$, whose components are a feature distribution's relative entropy. By its definition, S characterizes the uniqueness of each individual's various biometric features, because it considers both the mean and variance of a distribution with respect to the population distribution. From a geometrical perspective, an entropic signature can be modeled as a curve in the plane. The shape of letters in a handwritten signature is analogous to the distribution of information content in an entropic signature. Overall, the results, based on the entropic signature, suggest that haptic-based biometric systems are best suited to verification applications. For instance, at 25% FAR, the PV of the maze-based identification system was at best 75.5%, while the PV of the virtual cheque system was at best 95% at 4.5% FAR. The EER of the identification system was 27%, compared to the 4.5% EER of the verification system. Similar results were obtained from the virtual phone application (80% PV).

HaBiTs has the potential to offer continuous identification of users throughout their session. The majority of conventional biometric systems can only assure that the correct user is present at the time of login; however, after a user logs in, these systems have no way of detecting if the correct user is still present. Continuous identification is becoming increasingly more important and the majority of the pattern recognition approaches – for instance, fingerprints, face recognition, iris scan or voice biometrics- do not fulfill the requirements of this challenging issue. The haptic patterns (behavioral biometrics) cannot be foiled by copying and they do not require specific ambient conditions, such as lighting or low background noise. This operation is applicable to high-security environments, where each manipulation of the system would ideally be followed by identity conformation/rejection.

From the experimental evaluation, several guidelines for better performance of a haptic-biometric system are suggested:

- Training users with the haptic tasks before creating each user's pattern template is required to avoid undesired effects and increase the system's efficiency.
- The choice of a feature set or classificatory set is required. Current haptic devices are capable to capture and record a great variety of physical parameters depending on the application and the haptic interface. Combining globally specific characteristics of the signing action (i.e. the total time taken, the average speed, acceleration, force, pressure or the initial orientation) could lead to better performance, however, several issues must be taken into account:
  - A single haptic measurement (i.e. force, torque, angular orientation and so on) does not characterize an individual identity. This is due to the variability of the results for the same users among different trials; therefore, choosing a single identifier would not be the most effective approach in identifying individuals.
  - Due to the vast number of possible selections, first of all, the selection of those which contain the greatest user-classificatory worth is required.
  - Moreover, the level of dependency among the features needs to be studied. There are some variables that are correlated with others and there is little gain if they are present in the feature set.
  - The stability of the feature set is necessary. Haptic-based user's performances vary with repetition; therefore behavioral biometrics relies on such stability so that it characterizes the human behavioral trait.

- The actual single-point interaction devices seem to satisfy the requirements for authentication; however, current hand haptic exoskeleton devices still seem to be far from being used in such terms. Although there is still some hardware and software limitations in commercial single-point contact devices for accurate measurements of haptic data, these seem to have no effect on recognizing user patterns to be used as biometric identifiers. In the case of the CyberGrasp unit, the low performance of the hand posture measurements combined with limited collision detection approaches resulted in poor performance.
- Mental interference while performing the tasks makes the performance more variable. The haptic-virtual tasks, where no mental interference was involved, provided less classification error; whereas the tasks that involved some kind of mental concentration requirements, such as dialing a set of unknown phone codes or navigating though a maze, revealed low performances if compared with the virtual cheque application.
- The slow user's behavior is a more consistent characteristic. During the experiments, the user with the fastest mean velocity exhibited the most variability in their behavior; whereas the user with the slowest mean velocity exhibited the least variability. It turns out that we get more information from the slower user, since a higher level of relative entropy exists between that user and the population.

7.2 Future Work

As per future work, we believe that the *HaBiTs* system can be improved by incorporating adaptive feedback between the feature extraction and the feature selection processes to improve its classificatory performance. Adaptive feedback can be developed based on the nature of the requirements of the haptic based application but also by the analysis from the relative entropy approach. It can be conceived as a verification system by designing a set of haptic-based tasks within a game-based VE. Users could navigate the VE and perform the different haptic-tasks. Therefore, the combination of all interactions and actions would serve as a login password. We believe it would not only be a better user-classificatory biometric identifier but also difficult to be copied. On the other hand, from the viewpoint of continuous identification, the face and voice recognition, along with a haptic-biometric system, would provide consistent and reliable recognition.

The captured psychomotor features can result in relatively large data files. Therefore, another research avenue would be the development of a data repository that is capable of retrieving, filtering, and storing the compacted data sets (reducing the size of haptic data) in a local database. This problem is still difficult to handle, especially when faced with haptic data; several problematic issues arise such as data accuracy and relevance, data filtration and presentation. The idea can be addressed as an adaptive filtering algorithm with capabilities to handle the threat of data, as well as by using an I/O optimization approach.

Appendix A – Class diagram of the Adaptive Haptic Framework component (AHF) and HDR architecture

Table 6: The class diagram of AHF

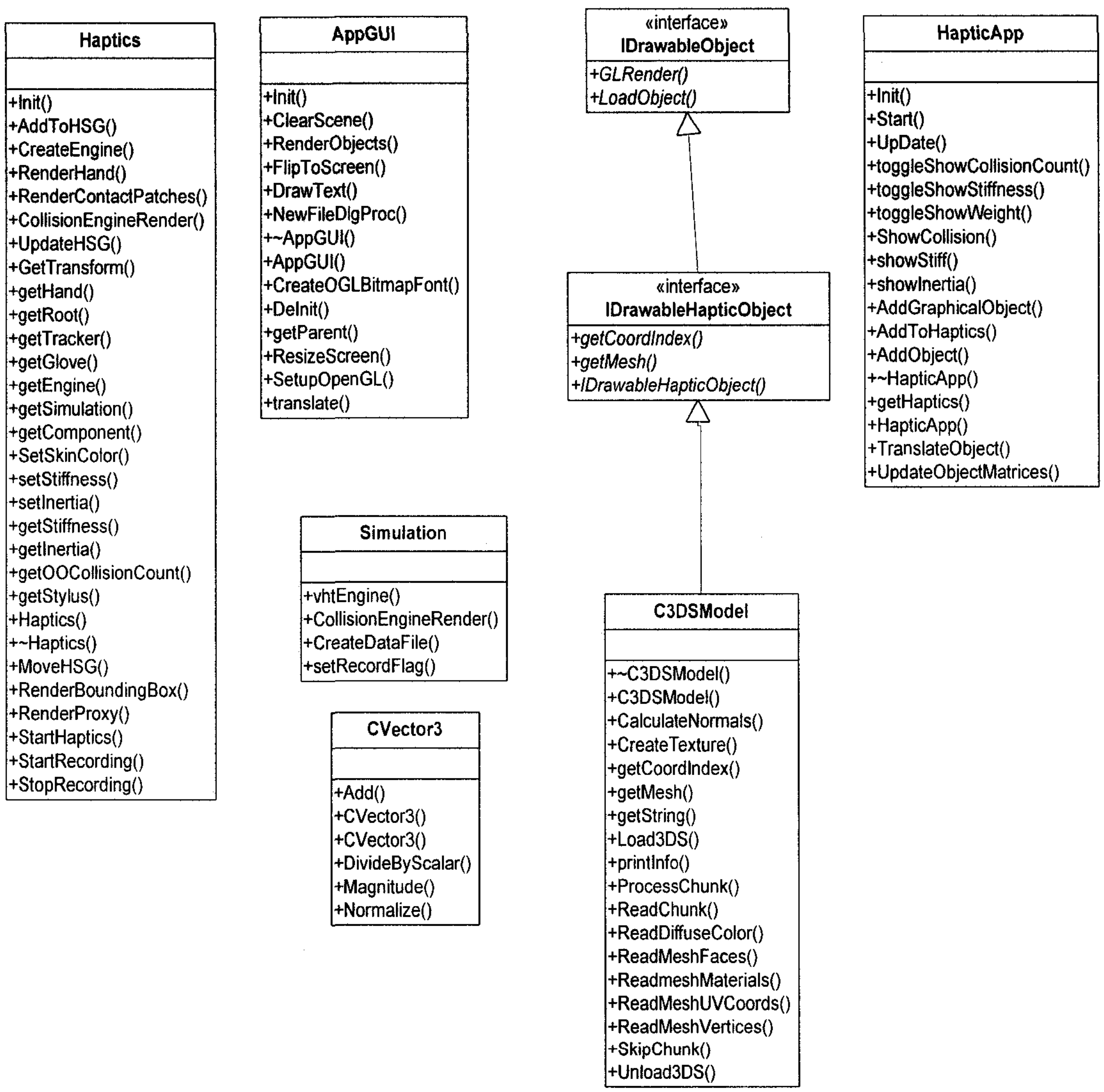
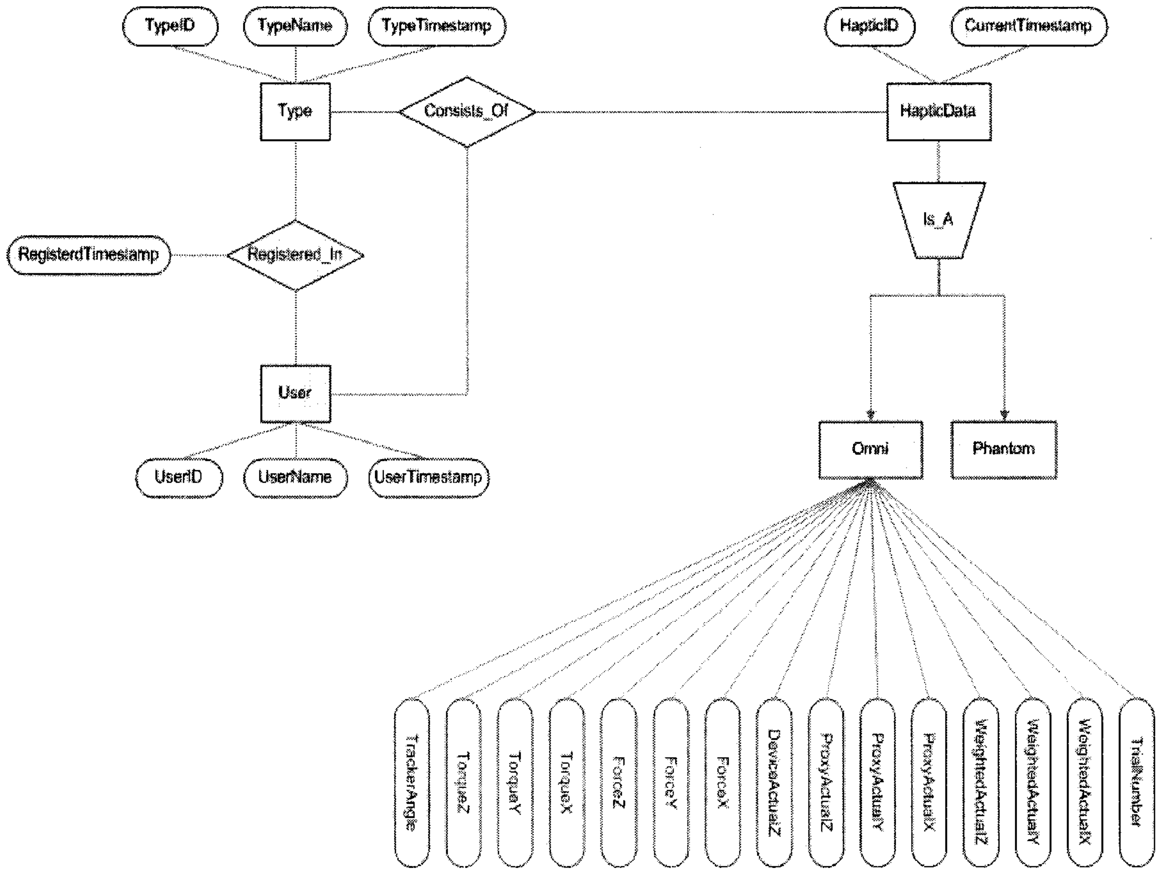


Table 7: High level architecture representing the components of the Haptic Data Repository (HDR) component



Appendix B – A FEATURE SET: Parametric analysis

Table 8: A feature set

Parameter name	Index	Symbol	Description
Max v	1	X_1	Maximum handling speed
T max v	2	X_2	Time of maximum speed
Avg F	3	X_3	Average force applied
Ttime	4	X_4	Total stylus' handling duration
Max-Fx	5	X_5	Maximum horizontal force applied
Min-Vx	6	X_6	Minimum horizontal movement speed
T(min Vx)	7	X_7	Time of the minimum horizontal movement speed
Avg acc	8	X_8	Average acceleration
Max acc x	9	X_9	Maximum Horizontal Acceleration
Min acc x	10	X_{10}	Minimum Horizontal Acceleration
Avg θ	11	X_{11}	Average direction (Device angle tracker)
Xo	12	X_{12}	Initial direction
Max X	13	X_{13}	Maximum direction
Avg T	14	X_{14}	Average Torque applied
Max T	15	X_{15}	Maximum Torque applied
Min Tx	16	X_{16}	Minimum Horizontal Torque Applied
$t(v_{x+})$	17	X_{17}	Duration of $v_x > 0$
$t(v_{x-})$	18	X_{18}	Duration of $v_x < 0$
$T(v_{y+})$	19	X_{19}	Duration of $v_y > 0$
$t(v_{y-})$	20	X_{20}	Duration of $v_y < 0$
Avg v_{x+}	21	X_{21}	Average positive v_x
Avg v_{x-}	22	X_{22}	Average negative v_x
Avg v_{y+}	23	X_{23}	Average positive v_y
Avg v_{y-}	24	X_{24}	Average negative v_y
$N(v_x = 0)$	25	X_{25}	Number $v_x = 0$ events recorded
$N(v_y = 0)$	26	X_{26}	Number $v_y = 0$ events recorded
Max v_x - avg v_x	27	X_{27}	Max v_x - avg v_x
Max v_y - avg v_y	28	X_{28}	Max v_y - avg v_y
Max v_x - min v_x	29	X_{29}	Max v_x - min v_x
Max v_x - min v_y	30	X_{30}	Max v_x - min v_y
Max v_y - min v_y	31	X_{31}	Max v_y - min v_y
Time $t(x_{max})\ T_s$	32	X_{32}	Time $t(x_{max})\ T_s$
Time $t(x_{min}) / T_s$	33	X_{33}	Time $t(x_{min}) / T_s$
$(x_{max} - x_{min}) \times (y_{max} - y_{min})$	34	X_{34}	$(x_{max} - x_{min}) \times (y_{max} - y_{min})$
Max v	35	X_{35}	Maximum handling speed

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