Haptic: The New Biometrics-embedded Media to Recognizing and Quantifying Human Patterns

ABSTRACT

Authentication for the purposes of security has taken giant strides since the introduction of Biometrics to help identify people by their behavioral and physiological features. From organizations and corporations to educational institutes, electronic resources, and even crime scenes, Biometrics offers a wide application scope to detect fraud attempts. This paper proposes a research path to achieve the task of authenticating users that are working in a haptic-based environment. The field of Biometrics can be divided into two main classes of human features. Fingerprints and facial features are characteristics that are birth-given and which cannot be developed or altered by humans. Behavioral characteristics such as hand signature and voice fall into the second class [1]. The work presented in this paper pursues the latter class and specifically studies how a person reacts to using daily devices or tools. The fact that we can exploit people's habits in handling devices to detect identity was the hypothesis that motivated this work.

Keywords

Biometrics, Haptic Systems, Hapto-task.

1. INTRODUCTION

Our society is rapidly becoming more computerized. Access to high-restricted areas, documents, privilege services and executions of tasks are, among others, the main concerns in terms of security in many organizations. Biometrics is contributing immensely to ease those concerns; related technology has already been implemented to help identify people via fingerprints, face images, iris, handwritten signatures, and voice signals. Many normal executions of daily tasks have been simulated in a completely virtual world that simulates applications of surgery, military training, tele-operation, and tele-manipulation. Such virtual environments require the installment of sense of touch and force feedback interaction scenarios to provide realism. Haptic systems provide a sensory channel to the human-computer interaction scenarios through tactile and kinesthetic. Haptics is a term that has its origins in the ancient Greek language that means "to touch" or "to handle". This technology requires a level of security that guarantees that the correct user gains control over the system. By using the physical output and facilities of the haptic devices, this study proposes a software system that could extract the user' characteristics when he/she performs a designed task using the haptic device in a particular session. These personal features are analyzed and compared with a reference or against others models in order to provide a level of authenticity.

As mentioned before, the field of Biometrics can be divided into two main classes: according to features that humans are born with, such as fingerprints or facial features, or behavioral characteristics, like a handwritten signature or voice [1]. We will pursue the latter class. Among the many examples of the potential use of this class of Biometrics is the particular force applied to the keys in a keyboard. There's also the time interval between each keypad when dialing a telephone number. Another example that can be extracted from the latter would be the map described by the fingers in the dialing operation. Extracting these features by using a haptic-based application and defining the subsequent individual pattern is the objective of this research. A framework that identifies behavioral patterns through physical parameters such as direction, force, pressure and velocity has been built. The set up for the experimental work consisted of a multi-sensory tool, using the Reachin API software and the Reachin Display hardware [7]. A virtual mobile phone was implemented where the user interacted through the haptic pen to complete a series of dialing trials. This study follows principles that have already been studied in the traditional biometric system, such as signature verification, speech processing and keystrokes dynamics [2,3,4]

This research has been motivated by the idea of using the haptic devices as mechanism for analyzing individual's biological and physical attributes such as hand-finger positions, velocity and force exerted during the haptic sessions [3,4,5].

2. RELATED WORK

This innovative concept of introducing haptics systems to the security systems for identify users has not been investigated yet. In other words, we would not exaggerate if we said that, to the best of our knowledge, no other work has examined haptics from a Biometric point of view. However, our concept is somewhat based on that of traditional behavioral biometric systems, such as keystroke dynamics, speaker recognition, and signature recognition [2,3]. In the past two decades, keystroke dynamics research has been studied in terms of latency timings [3]. These

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studies describe a particular pattern defined by a simple approach that the keystroke durations provide. It can be said that our study is a child of previous works, but it extends the concept by using the dynamic devices that provide real time physical parameters in order to obtain a biometric template for each user. This system adds parameters such as force exerted, speed of hand motion, and the pen's position during the haptic training.

3. METHODOLOGY

3.1 Experiment

3.1.1 Using a stylus to dial telephone numbers

Every day, people interact with different devices, whether it be while checking e-mail messages via the computer, driving a car, or using a mobile phone. These devices have become part of our daily environment. It would not be an understatement to say that almost everybody has a unique way of opening a door or typing a message using a keyboard. In order to discover such patterns, we designed an experiment to conduct a simple hapto-task operation. Users dial a set of five different telephone numbers by using a virtual mobile phone with some form of force feedback stimuli. There are two modes of dialing; using given numbers, or telephone numbers that are familiar to the user in order to test skills and habits. Pen's position, force exerted, and velocity computed from the haptic-based application provide the results that will become the input to obtain the user's patterns.

3.1.2. Subjects

For our subjects, we chose 20 students from the University of Ottawa. There were 7 females and 13 males. Being that most of them were unaware of haptics, the selected students were introduced to such scenarios through some demos that familiarized them with the device. This helped to eventually immerse them successfully into the virtual environment. Also, written instructions were prepared to explain the task requirements.

3.1.3 Apparatus and Stimuli

To create the all important force feedback, a haptic set and stereo viewing were utilized to provide a highly realistic visual stimulation. The visual display was provided by the Reachin Technologies AB, which integrated a PHANTOM™ force feedback device (from Sensable Technologies [8]) with stereo monitor and supporting systems. For haptic rendering, a workspace of 16x13x13 cm with a maximum applied force of 7.9 Newton by the stylus End Effector, 6 Degrees of Freedom (DOF) positioning and 3 DOF force feedback was used. A semi-transparent mirror and a 17" monitor integrated the visual display. To manipulate the 3D computer graphics models, a 3D stereo with 6 DOF Magellan/Mouse was used. And lastly, users were immersed in the virtual environment by using a wireless set of liquid crystal shutter eyewear for Stereo3D™ [9].

3.1.4 Software Application

The haptic application were developed using the Reachin® API [7], which captures raw data. This application-programming interface provided direct access to the tracking device via various position (Θ), orientation, time (t), force (F) and torque (T), etc events. These data were captured and sent to a haptic database, where the measurements for the classification such as the mean and standard deviations for these events, for example, are extracted. The haptic software application was developed in a combination of VRML-based scene and Python scripting programming language. The VRML-node fields' approach created the 3D virtual environment. The other hand Python provided the procedural process to handle the programmed events and registered the output data to a file. The haptic stimuli were provided by accessing a special API [7], which handled the complex calculations for the touch simulation and the synchronization with the graphic rendering in the haptic loop process.

3.1.4 Procedure

The subjects wore stereo glasses to be able to see through the semi-transparent mirror. The glasses and the mirror became the interface where the graphics and the haptics were co-located so that users could feel and see the object. The virtual environment depicted a realistic mobile phone with haptic characteristics. Its key buttons were dynamically deformable and provided a real pressing sensation.

Before each trial, subjects were instructed to explore the scenario and get used to the haptic device and its feedback sensations. The trial started when the subject dialed the 5 telephone numbers. When carrying out the skill mode test, the numbers appeared on the right side of the screen. To signify a call, the subject had to press the "green-phone" key. Then, after a short interval of time, the subject pressed the "red-phone" to terminate the call and consequently, be able to carry on with the next telephone number until the fifth number was dialed. In the second testing mode, the user dialed a familiar number several times.

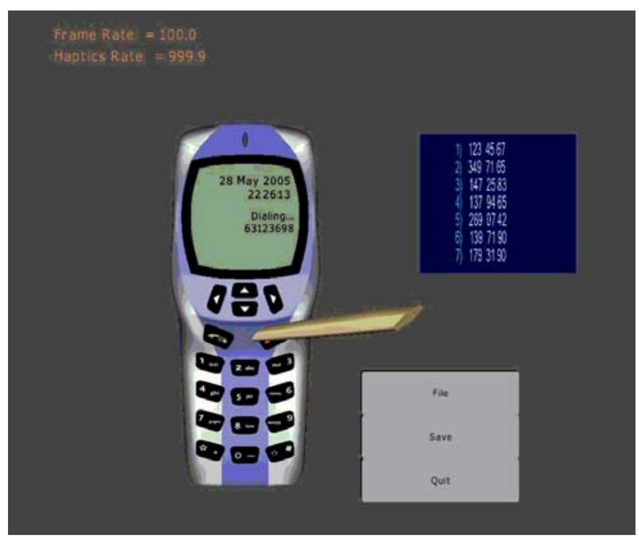

Figure 1. Screenshot of the user dialing code process. The user is required to dial the 7 numbers that appear on the right side of the screen.

3.2 Framework

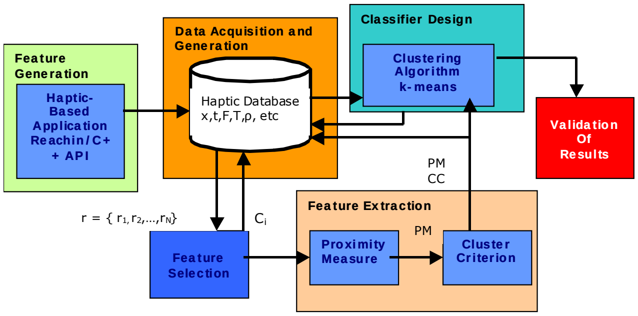

Figure 2. The proposed dynamic haptic-based authentication system.

The proposed haptic-based authentication system is illustrated in the Figure 2 and is composed of four modules: 1) data acquisition 2) Feature Extraction; 3) Feature Selection; and 4) Classifier Design and 5) Verification.

In the data acquisition module, the dialing code sessions are acquired and digitized by the software application. The keystroke duration, pen's position, force exerted parameters are recorded according the programmed application of the haptic device API [7]. The discrete signals of the mentioned variables are computed in the feature selection process module. Then, they are normalized before sent to the feature extraction module. In the feature extraction module, pre-configured feature extractors calculate the key information of the input dynamic dialing code. For the training dialing codes, the extracted sampling feature vectors are clustered and sent to the verification module be compared with others templates by a signature classifier.

3.3 Data Acquisition

The performance results reported here are based on a database of profiles collected over a period of 4 weeks. The data had been collected on workstation MS-OS 2000 with a XENON processor at the Discover Lab of the University of Ottawa, where the Reachin system had been installed. We used a virtual phone model provided by the Reachin technologies, and then configured it to be used in a set of trials where the users were asked to dial the 7 telephone numbers that appeared in the right side of the screen. This virtual environment provided a mechanism to test individual skills in dialing and handling concentration in such a process. The software application implemented for capturing particular characteristics recorded data only when users made contact through the pen device with each of the key buttons of the virtual telephone. Volunteers who took part in this experiment performed the same dialing code 10 times. The data files recorded 3D world coordinates, the force and torque applied by the stylus on the virtual keys of the phone, as well as the pen rotation angle. An example of users' profile of the force exerted during the dialing code is illustrated in the Figure 3.

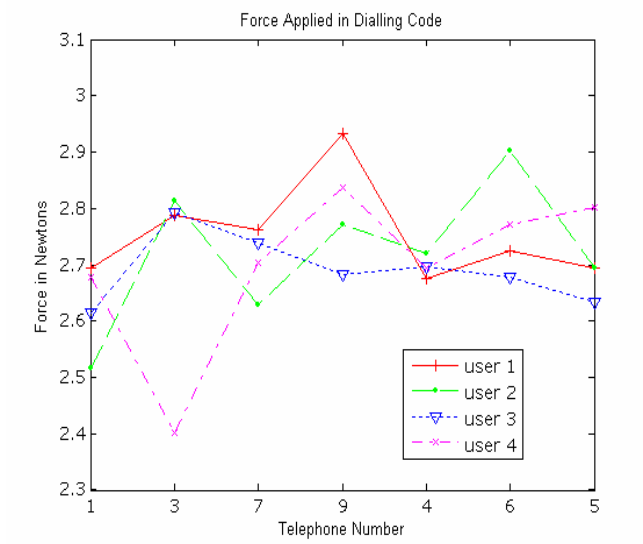

Figure 3. Profile of the force exerted during the dialing code for 4 users from the group.

It is important to mention that each user provided a remarkable profile for the force applied to each of the virtual keys, but it is equally, if not more important to note that there were some difficulties encountered in discriminating one user from another.

3.4 Analysis

In order to explore and ultimately provide an index of reliability, a method of classification of the data was implemented. The data generated was analyzed with principles of the pattern recognition discipline in mind [6]. As a result, an unsupervised pattern recognition methodology was implemented.

3.4.1 Feature Extraction

The 'theme' of this experiment is somewhat related to the keystroke dynamics. The exercise of dialing a telephone number sets the stage to a similar pattern, where a user types on a keyboard or autographs a handwritten signature. Therefore, the design of the feature set is a hybrid approach. It considers the dynamic signature verification point of view [5], and authentication based on keystrokes dynamics [4]. It crucially takes advantage of the physical output recorded by the haptic device [7]. Understanding that dialing a telephone number describes keystroke information, we extended the concept introduced in [4] and modified it by adding the physical measurements such as force, speed, and pen's angle position captured by the software application.

A simple and promising approach for tackling the authentication issue by applying keystroke dynamics was introduced by Joyce and Gupta [3]. The basic idea was to build a set of mean vector values that were based on the users' signature of the username, password, first name, and last name incorporated into the system as reference signatures. These studies only considered the information that was provided by the keystroke performance, such as latencies, duration, and speed of typing. In the work of Q Tong [5], an algorithm based on observing the keystrokes characteristics in terms of gradients of pressure, velocity, and pen's angles was introduced. Local correlations comparisons were computed between those variables as a measure of similarity. This analysis scenario generated the feature set based on the speed, acceleration, and pen's position during the signature autographing process. By combing both approaches and taking advantage of the haptic device in terms of the physical data output, a feature generation process was designed by observing four variables of the keystroke information generated during the dialing code session. These are the duration between phone keys, the speed of dialing, force exerted by pressing each key, and the pen's position of the haptic device during the dialing code process. The mean values of each variable were calculated and an outliner removal process was applied to remove the values that were far off from the mean. A removal threshold set between 3 and 5 times the standard deviation was selected to reduce errors. A set of 4 vectors for the mentioned variables, based on mean and standard deviation of each keystroke of the particular code number dialed, were built. Therefore, feature set (S) was integrated by 24 parameters according with the following:

$$S = \{s_1, s_2, \ldots s_N\} \quad \text{For} \quad i = 1,2\ldots, N$$

$s_i = \{t, v, F, \theta\}$ Where, for example, the sub vector of the features of duration is defined as follow:

$$t = [\bar{t}_1, \ldots, \bar{t}_m, \sigma_1, \ldots \sigma_m]^T \quad \text{For } m = 1, 2, 3$$

Due to the characteristics of the physical data captured, and the nature of the experimental set which exhibited data falling under different domains, a preprocessing stage was introduced. In order to apply the same significant values for the feature set, data normalization was required. This technique limits the feature values in the range of mean equal to zero and unit variance [6] by proper scaling. It is carried out by calculating the mean and variance values for a *k*th feature from a set of N available data.

$$\bar{x}_k = \frac{1}{N} \sum_{i=1}^{N} x_{ik} \quad k = 1, 2, \ldots l$$

$$\sigma_k^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_{ik} - \bar{x}_k)^2$$

$$\hat{x} = \frac{x_{ik} - \bar{x}_k}{\sigma_k}$$

At the end of the data acquisition process, we noticed that some of the user's data sets were missing in the overall experiment. As the experiment was set to run 10 times, enough numbers of training data for each volunteer were collected, resultantly offering us the privilege to discard a pair of trail data sets in order to homogenize the trial domain to form the feature vectors.

3.4.2 Clustering Stage

In the following stage, we face the task of disclosing the organization of the user's templates into sensitive groups or clusters, in order to explore dissimilarities and similarities among them. Partitioning the data set can provide a quick overview for adding useful conclusions. Any unsupervised learning algorithm, such as K-means algorithm or Self-Organized Map, can fit in this first clustering stage.

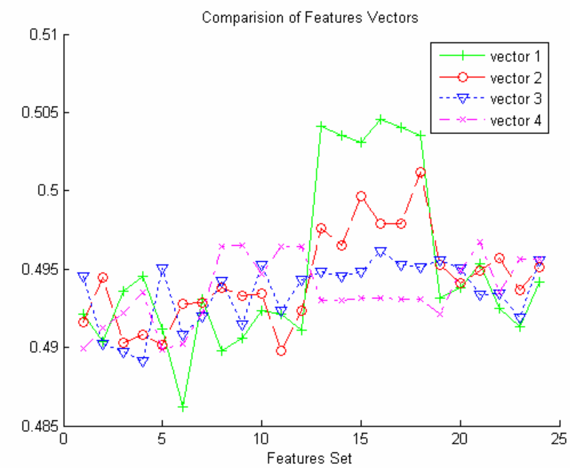

Figure 3. Profile of the force exerted during the dialing code for 4 users from the group.

The goal of clustering is to determine the intrinsic of grouping in a set of unlabelled data. It is important to identify common attributes between users, according to the way they handle the pen or the dialing code speed or by the force applied. The nature of the experiment dictates that the users' templates be organized into more sensible groups or domains. We are currently incorporating the K-means method to observe the mentioned user attributes in terms of differences and similarities among patterns. Following the clustering task, a proximity measure should be suggested. The well-known Euclidean distance, D, is selected as a proximity measure. It considers a metric based on a dissimilarity measure between two vectors X and Y of l dimension, where D is defined as:

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

With the proximity measure already selected, our major concern now is to determine a clustering criterion. Heuristically, we believe that in this experiment, the way that user's stylus is handled in terms of position is considered as a good measure for the sensibility of classification of the information.

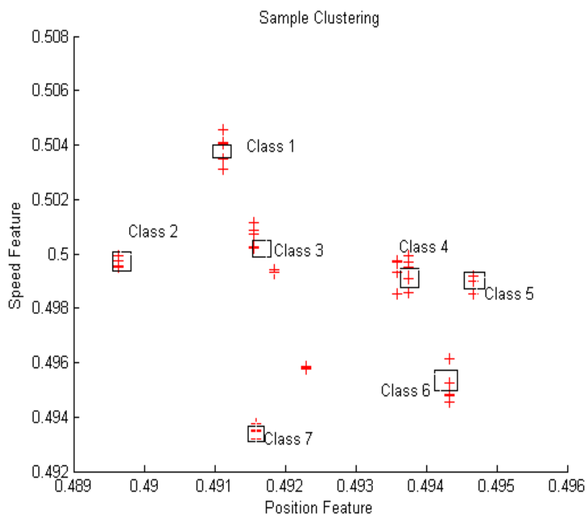

Figure 4. Clustering profile in two-dimension of user's pens position against the speed performed features. Here, the cluster algorithm identifies 7 different groups.

The K-means algorithm is implemented by considering the measurements known as features, which form the feature vector ***S*** = { s_1, s_2, …,s_N} in the feature selection step. Then, proximity measure (PM), which is based on the Euclidean Distance and cluster criterion (CC), which was also considered, were selected in order to quantify how "similar" or "dis-similar" two feature vectors were and how sensible they turned out to be, respectively. With these two variables in mind, the *K-means algorithm* finds the K vectors $\boldsymbol{\mu}_i$ (for i =1,…, N) that represent an entire dataset. This learning method converges quickly and hence can be used as an initial stage for testing the proposed framework due to its flexibility in developing into more sophisticated methods. This method works with a random initial partition of the data. The iterative process consists of two steps:

Firstly, the mean vectors $\boldsymbol{\mu}_i$ for each cluster is calculated as follows:

$$\mu_i = \frac{1}{N_i} \sum_{n \in S_i} x^n$$

Then, each data point is assigned to the cluster containing the closest mean vector. This process carries on until no further change to the error is observed. The error function is the total within-cluster sum of squares:

$$E = \sum_{i=1}^{K} \sum\nolimits_{n \in S_i} \| x^n - \mu_i \|^2$$

Pairwise dissimilarities were calculated using the Normalized Euclidean distance sample of a comparison process in order to provide an intuitive representation of the data embedded in high dimensional space. Figure 3 shows a graphical comparison of some of the feature vectors obtained.

3.4.2 Classification

In order to obtain an intuitive representation of the data set, a clustering sample procedure was obtained in two-dimensional space by comparing the user's pen angle position against the speed performed during the trial. The results obtained in Figure 4 shows the scenario of recognizing a particular profile *X* with a given angle position against all members in the set of 7 different neighboring classes. The real problems however, involve clustering methods with high dimension which is applied in this case.

4. RESULTS

The results obtained through this clustering technique need to be materialized in order to find a compact description of each cluster. Suitable methods for quantitative evaluation of the results of a clustering algorithm have been studied exhaustively. Therefore, a term denominated cluster validity is in charge of the assessment of the clustering procedure's output. In this preliminary study, we follow an approach of validating a single clustering scheme based on an additional index matrix. The main idea in this technique is to find the degree of match score between a given clustering scheme *S*, consisting of *N*, clusters, and the proximity matrix *P*. The defined index for this approach is Hubert's F statistic (or normalized F statistic) [10]. The proximity scheme defined by the Euclidean distance, which is a measure of proximity and consideration of the cluster criterion, we define a set of scores for each feature vector. These sets of scores were used to make comparisons between results of different users and even those of the same user itself. With these comparison results, distribution functions that define two types of errors false rejection rate (FRR) and false acceptance rate (FAR) were defined. Both rates were used to evaluate the performance of our approach and depicted in figure 6.

The performance of the classifier and the statistical analysis obtained by comparing different feature sets show an acceptable performance with a probability of verification (PV) of the nearly 80% of the users that took part in the experiment, with a threshold of 3 times the standard deviation over the mean. The experimental results reveal that the best performance was that of features related to pen's position. These features provided the weighted value for recognizing individuals. The variables such as velocity (v) and keystroke duration (t) provided rare behavioral schemes in the definition of the patterns from the same user. Force measurement (F) did not provide the remarkable dissimilarity weight that we expected into to features definition. In addition force applied for most of the users fall in very compact band of values where the error rate was high.

In addition the speed profile for each user varied considerably in the first two trials then it shows more stable performance that we can conclude that dialing speed is an important parameter to define a user pattern applied to the haptic systems.

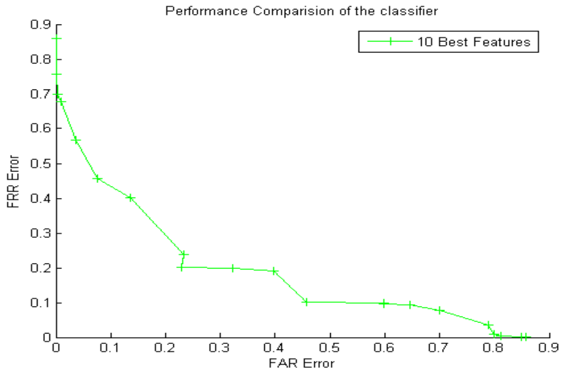

Figure 6. The output of the clustering analysis identify two classes of errors False Acceptance Rate (FAR) and False Rejection Rate (FRR) obtained by the performance with 10 of the best features

5. DISCUSION

This study has presented a proof that there is a possibility of using haptic devices for authentication of users working in a process, which involves Haptic systems. The data generated for the purposed experiment was the key point to finding the valuable parameters which define individuals' behavior. In overall view of the parameters captured to generate the participant's templates, some show highly remarkable differences from keystroke information from the same user. This observation suggests analyzing this haptic data from different perspectives, like removing the mental interference in the dialing process. In other words, it suggests designing an experimental set similar to the scenario represented when a person perform his/her handwriting signature spontaneously. We would to extend this study by considering other behavior characteristics for different test conditions such as tiredness, happiness, time stress for analyzing this behavioral data.

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