Characterizing Biometric Behavior through Haptics and Virtual Reality. *

2008


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Abstract - Haptics technology allows users to interact via the sense of touch by applying forces, vibrations and/or motions to users. With this technology, particularly by using force-feedback haptic devices (like stylus-based haptic devices), data directly generated by the user as he/she interacts with a system can be recorded and used – feature space – for authentication purposes.

In this paper, non-linear transformations are applied to the original feature space in order to produce Euclidean 3D spaces preserving the similarity structure of the samples, which are represented with Virtual Reality (VR) techniques. By using these new spaces, it is visualized how certain features (i.e. position, pressure and torque) contain more meaningful information that can characterize a biometric profile when virtually signing.

Index Terms — Biometrics, Data Visualization, Haptics, Virtual Reality, Visual Data Mining

I. INTRODUCTION

Nowadays, almost all systems involve an identity authentication process before a user can access requested services; such as, logging into a computer system, laptop or cell phone, online transactions, secure access to buildings and so on. Hence, authentication has been increasingly gaining interest over the last years to prevent impostors from a fraudulent and unauthorized use. Traditional authentication approaches are based on showing ID cards or passports and PIN numbers or passwords, which sometimes can be easily compromised or “hacked”. This scenario, where several possibilities of identity frauds can occur, leads to consider Biometrics as a promise to enhance security and improve identification.

Biometric systems recognize users based on behavioral (i.e. voice, signature or keystroke dynamics) or physiological characteristics (i.e. fingerprints, iris pattern, face image or hand geometry) [1]. The novel aspect of our approach is that we characterize biometric behavior through Haptics. Haptics technology allows users to interact via the sense of touch by applying forces, vibrations and/or motions to users. This is a state-of-the-art technology and examples are vibrating phones, gaming controllers, force-feedback control knobs in cars and the Nintendo Wii remote controller. This is an emerging technology expected to have a large impact on consumer society and services.

With this technology, particularly by using force-feedback haptic devices, data directly generated by the user as he/she interacts with a system can be recorded and used for authentication purposes. Therefore, Haptics can be seen as a mechanism to extract behavioral features that characterize a biometric profile for authentication.

The current integration of Haptics and digital technologies ensures a large application potential in authentication processes. It has been shown that identity recognition based on human-haptic interactions is feasible [2, 3]. Moreover, there are natural differences between the psychomotor patterns exhibited by individuals that can be exploited for constructing authentication procedures.

Many authors have attempted to address the problem of authenticating a user by hand signature verification [4]. Signatures can greatly vary depending on the type of pen used, whether or not the person is standing or sitting, how and with what body part the user is writing (i.e. by using wrist, elbow and shoulder or just the muscles of the hand itself). Moreover, all of these change over time. Despite their variability, the character of handwritings remains unmistakably the same and they are well-known recognized as proof of authenticity in different type of social transactions (i.e. official documents, cheques). On the other hand, signatures seem to be more vulnerable to be forged.

In this sense, haptic-based applications where users can produce their signature by means of a haptic device can have potential as an alternative mechanism to overcome traditional handwriting vulnerability. The wide range of physical attributes captured during a user-haptic-computer interaction (i.e. time, position, force, torque, pressure and so on) can be translated into a more careful selection of features to identify among them the features which provide richer information content and can improve a biometric identification
Moreover, haptic data are unlike to be faked, since it is impossible to precisely replicate the way a human produces a signature while preserving all of the physics involved.

In this paper, two samples of handwritten signatures of individuals on a virtual cheque are analyzed, where each sample is given by a collection of features obtained with a force-feedback haptic device, thus leading to high dimensional vectors. Nonlinear transformations are applied to the original feature space in order to produce Euclidean 3D spaces preserving the similarity structure of the samples, which are represented with VR techniques. In these new feature spaces, interesting patterns related to the distribution of the individuals and the discriminatory power of the nonlinearly generated features can be visually discovered and inspected. This paper is an extension of our previous research [5, 6] in the spirit of visual data mining.

II. THE BIOHAPTIC SYSTEM

This section briefly describes the biometric haptic system used in the present paper (BioHaptic) that was designed and developed elsewhere [7, 6].

A. Architecture of the BioHaptic system

Fig. 1. High level architecture for the BioHaptic system

Fig. 1 characterizes a high level architecture view of the BioHaptic system. The Adaptive Haptic Framework (AHF) and Haptic-Data Repository (HDR) subsystems can characterize a biometric enrollment process, that is, haptic raw data is captured through haptic applications (i.e., virtual cheque, maze or cell phone). A user is able to work in a virtual environment (VE) with haptic feedback while the system is recording his behavioral performance. The HDR subsystem is capable of recording haptic data (biometric raw data in an unprocessed format) and accessing recorded haptic data. The recorded data includes a variety of physical attributes such as the 3D world coordinates of the haptic device's position, force exerted, torque, or angle of the end-effector. In the Feature Generation/Selection FGS subsystem, for accurate identity recognition, features are to be chosen so that they are unique for each individual. In the Classifier Design/Evaluation CDE subsystem, we employ pattern recognition methods to authenticate the identity of these users. These methods include k-means, Neural Network, Principal Component Analysis (PCA), Dynamic Time Warping (DTW) or Fourier spectral analysis.

B. Haptic-biometric applications

Three different haptic-biometric tasks have been designed and tested (Fig. 2). These tasks are based on the well-known dynamic signature verification and keystroke dynamics [8]. These methods comprise the most important biometric systems based on behavioral attributes.

Fig. 2. Three applications in the BioHaptic system: (a) the virtual cheque, (b) the virtual maze and (c) the virtual phone.

The three applications were used with the ReachIn system [9] — combining the single-point interaction Desktop PHANTOM device [10] and stereo viewing. The virtual cheque emulates users performing a signature on paper; one can feel 'friction' between the end-effector of the haptic device and the virtual cheque. The virtual maze involves the user completing a flat 2D maze. To prevent a user from passing through the maze walls, a 'sticky' haptic sensation is provided. The virtual phone allows users to virtually call someone: dialing the number, pressing the "green-phone" key and later pressing the "red-phone" key to terminate the call.

III. RELATED WORK

A. Haptic-based authentication

The first question of this haptic-biometric research is whether users can be authenticated by using haptics. Recently, it has been shown that identity recognition based on user-haptic interactions is feasible [2, 11].

On the other hand, the precision of this biometric system depends on the choice of behavioral features (haptic data) used to form user biometric profiles. An important question is which are the most relevant features for classifying behavioral patterns. It was found that physical attributes, such as force (pressure), torque and angular orientation of the end-effector seemed to provide richer content with regard
to other variables, however the information content of the attributes differed amongst the different users and it poses a problem [3]. To overcome this problem, a novel concept was introduced; the entropic signature that characterizes the identity of an individual by how unique their attributes are [3].

Throughout different experimental tests, it was shown that haptic-based authentication is best suited in biometric verification rather than in biometric identification [3]. Recent research has improved these previous results on haptic-biometric identification where 16 users were successfully identified at a rate of 81% by using multilayer perceptron neural networks [12].

With regard to verification mode, the best preliminary results were for the virtual cheque (probability of verification of around 98.4%) [3]. Furthermore, an equal error rate of 6.0% for the virtual signature verification with a threshold of 1.6 compared to the tasks of ‘dialing phone numbers’ and ‘navigating the maze’ was achieved [13]. As a result, it suggested the decreasing accuracy of the system, when mental interference was involved (‘dialing phone numbers’ and ‘navigating the maze’).

B. Visualizing Human Behavioral Features

Generally, the haptic information captured during an individual interaction is very large (measured every few milliseconds) and with a high number of attributes. In our case, the number of attributes were 18: time, Pw, Pw, PR, PR, PR, PR, Pw, Pw, Pw, Pw, Fz, Fz, Fz, force magnitude, nx, ny, nz and angle orientation of the end-effector, where the subscripts x, y, z indicates spatial dimensions, Pw, PR and P are different positions that provide the haptic device used and F and n denote forces and torques, respectively. Therefore, the behavioral haptic data that describe users are defined in terms of a large number of features which adds complexity to the analysis. Moreover, post-processing and examination of haptic data is usually addressed manually which is a time-consuming and tedious task. Virtual Reality (VR) is a suitable paradigm for visual data mining. The creation of a 3D virtual space by using a nonlinear dimensionality reduction technique provides a tool where one can navigate and visually inspect the main features of the data. Different studies have shown the feasibility of this technique to understand and discover new information [14, 15].

In our previous research [5, 6], different 3D VR spaces were created that showed the similarity of users’ haptic data during different trials, as well as the existing relationship among other users’ features for the three different tasks. Non linear transformations were applied to the original feature space in order to produce Euclidean 3D spaces preserving the similarity structure of the samples. In these new spaces, interesting patterns and relationships were found:

- Haptic data had certain uniqueness for each user
- Human hand behavioral patterns depend on the application
- Haptic data corresponding to the signature shows the least variability (as expected due to no mental interference)

These conclusions confirm what had been found by different pattern recognition techniques in previous works.

However, by inspecting the 3D virtual space some interesting relationships -which were somewhat hidden in the original data- were found. For example, the pressure that the users applied during the three different experiments exhibited the smallest variability across different trials. Moreover, the pressure and torque attributes that a user applied were more similar when ‘navigating a maze’ and ‘signing a cheque’ than in the case of ‘dialing phone numbers’.

As per the virtual cheque task it was seen that some users’ haptic data showed striking dissimilarity amongst other users, so their haptic signature could be easily verified. On the other hand, some showed certain similarity among them.

This research is an extension of [5, 6] which, to our knowledge, pioneering the visualization of human behavioral features. This paper focuses on haptic signature data from two different users and the identification of attribute subsets sensitive to sample discrimination.

IV. THE VIRTUAL REALITY SPACE

In this section the creation of this VR space and how to visualize and inspect it will be described. This 3D virtual space will allow a rapid assessment of pattern distributions for single users and for the two of them.

A. Creation of the VR space

The idea is to maximize some metric/non-metric structure preservation criteria. In an unsupervised approach, it can be done by minimizing some measure of information loss. If δij is a dissimilarity measure between any two objects i, j, and ξij is another dissimilarity measure defined on objects
An error measure frequently used is the Sammon error [16] given by

\[
\text{Sammon error} = \frac{1}{\sum_{i<j} \delta_{ij}} \left( \sum_{i<j} \frac{\delta_{ij} - \delta_{ij}}{\delta_{ij}} \right)^2
\]

(1)

In this paper, \( \delta_{ij} \) is the Euclidean distance in the VR space and \( \delta_{ij} = (1 - s_{ij}) / s_{ij} \) is a dissimilarity measure derived from \( s_{ij} \) which is Gower's similarity coefficient [17].

As a preprocessing step a kernel set is computed by clustering the objects according to a predefined similarity threshold (objects with a pairwise similarity greater or equal to the threshold are merged and represented by a single element from the subset). Then, the VR space is computed for the kernel set using (1). VR objects (subsets of the original dataset) are represented using different geometries and with a size proportional to the cardinality of each subset.

Fig. 3 represents the creation of the VR space.

B. Visualizing and interacting with the VR space

In our study, the VR space is comprised of cubes, which are data objects/features/attributes from the original space. Each cube represents a set of objects that are mapped to it from the original user data objects (Fig. 4). These data can belong to the same or a different user, and that information is visually displayed when the mouse is placed on a cube. On the other hand, each cube is colored differently corresponding to the user. Some clues to visualize and interact with the VR space:

- Semi-transparent cubes: non-singleton subsets.
- The closer the cubes, the more similar the represented objects are with respect to all of the features in the original space.
- Placing the mouse on a cube additional information is provided (Fig. 4).

Moreover, a user can interact with the objects, change their representation and obtain additional textual information which helps in analyzing the data.

V. RESULTS AND ANALYSIS

Two participants' haptic signatures were selected out of 14 users available. These users presented the haptic data signatures more stable than the others (with less variability) and they had certain similarities in their haptic signature data. The variability for each participant during different trials was analyzed and several subsets of attributes for their description were tried.

A. Haptic data set

Both users signed the virtual cheque 9 times on different days. The original objects for user 1 were 1,495 and the VR space is depicted in Fig. 4 a); whereas the original objects for User 2 were 2930 and Fig. 4 b) illustrates the VR space for that user.

B. Signature position, pressure and xy-axis torque

Fig. 5 shows the signature position, pressure and torque on the xy-plane for both users on a trial. It can be seen that those attributes behave differently for both users. However, we will see that their signature haptic data in the VR space can have certain similarity when analyzing all the attributes captured while signing.
C. Single user spaces

For both users (Fig. 4) cubes appeared occupying well-separated spaces, moreover large cubes contain information from different trials (see textual information Fig. 4 HETEROGENEOUS[S]) which means that some samples from the same user behave similarly, therefore lying on the same location in the VR space. Particularly, user 2 showed more similarity among trials than user 1’s trials.

D. A space with two users

Fig. 6 a) is the VR space corresponding to both users’ data which contains 4,425 objects and 18 attributes, called 18-feature space. The data was maintained with a similarity threshold of 0.95. Fig. 6 b) illustrates the VR space representing both users’ haptic data with the same number of objects but using only 6 attributes (x, y and z-axis position, pressure and x and y-axis torque) (it is called 6-feature space). The similarity threshold for this latter one was 0.97 (the threshold value for computing the kernel set).

The VR space in Fig. 6. a) contains 228 objects with 17 of them that are unique samples, mainly belonging to user 1. In addition, some cubes of user 1 contain information about user 2, which means that some data are common between them. Despite this fact, since the cubes representing both users appear compact and separated between them, in the overall their haptic signatures are different.

The VR space in Fig. 6. b) contains 260 objects and 27 representing unique samples. In this space, each sample has a similarity with its represented cube of at least 0.97 the threshold value). Since this similarity is higher than the corresponding to the 18-feature space, there is an increase in the number of objects. The representation of the 18-feature space with a similarity of 0.97 showed many overlapping cubes from both users.

In this VR space (Fig. 6 b), since cubes are closer to each other for the same user and there are larger cubes than in the 18-feature space, data (position, pressure and x- and y-axis torque) seem to keep more similarity during the trials.
Moreover, only two cubes represent information from both users. Therefore, the 6-feature virtual space is clearer and more discriminative than for the original one with 18-features.

Different VR spaces created by taking into account other features were created, however none of them provided a VR space where the dissimilarity of haptic signature data were shown as rich as it is shown in the 6-feature space. For example, when only pressure and torque on xy-plane were considered, more users’ haptic data were overlapped. Although in [3] it was stated that pressure, torque and angular orientation of the end-effector seemed to provide richer-classificatory worth, in the present study they did not provide better results.

IV. CONCLUSIONS

This paper shows the role of a VR space representation for the understanding of haptic data used for authentication purposes. Haptic data (9 trials on different days) from two users were analyzed and exhibited VR spaces where the similarity structure of the data was maintained (using 0.95 and 0.97 as thresholds).

The results suggest that position, pressure and torque on xy-axis can visually characterize a biometric. Both users’ haptic data were represented in the VR space with a similarity threshold of 0.97 using a reduced number of attributes and also exhibiting good discrimination. Moreover, with these features, less variability among trials was observed for the investigated users.

As per future work, we will continue the assessment of unique-to-the individual behavioral attributes using different approaches. The discovery of more discriminative attribute subsets will contribute decisively to the success of individual authentication using haptic information.

VI. REFERENCES


