IMTC 2005 - Instrumentation and Measurement
Technology Conference
Ottawa, Canada, 17-19 May 2005

Automatic Identification of Participants in Haptic Systems

Mauricio Orozco, Yednek Asfaw, Andy Adler, Shervin Shirmohammadi, and Abdulmotaleb El Saddik
School of Information Technology and Engineering
University of Ottawa, Ottawa, Canada
{morozco,shervin,abed}@discover.uottawa.ca, {adler,yasfaw}@site.uottawa.ca

Abstract – *Biometric systems identify of users based on behavioral or physiological characteristics. This paper explores the feasibility of automatically identifying participants in Haptic systems. Such a biometric system would lead to important and interesting applications such as continuous authentication in tele-operation. In order to test this feasibility, we designed a Haptic system in which position, velocity, force and torque data from the tool was continuously measured and stored. Using this system, users navigated a simple maze where the user generates a continuous path from start to finish. Subsequently, several algorithms were developed to extract characteristic biometric features from the measured data. A 78.8% probability of verification was observed for data from trained users. Overall, the paper suggests the possibility of extracting identity information in a real world Haptic system.*

Keywords *–Biometrics, Haptic Systems, Measurement of Haptic Interaction, Biologically-inspired Instrumentation.*

I. INTRODUCTION

Biometric systems allow identification of individuals based on behavioral or physiological characteristics [7]. The most common implementations of such technology are to recognize people based on their fingerprint, voice, iris or face image. Applications for such systems are vast, and range from national security applications to access control.

In this paper, we are particularly interested in access control for Haptic systems. Haptics, derived from the Greek verb "to touch", introduces the complex sense of touch, force, and hand-kinaesthetic in human-computer interaction. The potential of this emerging technology is significant for interactive virtual reality, tele-presence, tele-medicine and tele-manipulation applications. This technology has already been explored in contexts as diverse as modeling and animation, geophysical analysis, dentistry training, virtual museums, assembly planning, surgical simulation, and remote control of scientific instrumentation. Other examples of sensitive haptic systems are for military and industrial applications. To control access, such sensitive systems have some type of login requirement, which may be based on a password, token, or perhaps a physical biometric. However, 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 paper, we propose an avenue of research to overcome this problem, by allowing continuous authentication of participants in a Haptic system. This continuous authentication is based on the characteristic pattern with which participants perform their work. We assume that it is possible to automatically characterize and differentiate participants based on these data. To the best of our knowledge, no other work has examined haptics from a Biometric aspect, and this work is novel in presenting a new approach for authentication of users with Haptic instruments. This concept is somewhat similar to that of traditional behavioral biometric systems, such as keystroke dynamics, speaker recognition and signature recognition [1, 2].

We believe that, similar to user interactions with a signature pad, user interactions with a Haptic device are also characteristic of an individual's biological and physical attributes [5, 6]. By measuring the position, velocity, and force exerted in those interactions, one should be able to identify an individual with a certain degree of certainty. The instrumentation and measurement approach presented in this paper is an initial evaluation of the feasibility of this idea. As we shall see, the test results support our idea that Haptic instruments can be used for authentication purposes. Such authentication can be beneficial in scenarios where haptics are used to carry tele-collaboration and tele-operation tasks [3, 4]. By using the existing Haptic instrument, the user can be authenticated both prior to gaining access to the session and during the execution of the session by monitoring Haptic interactions: something that is currently not done in other authentication applications.

Our goal in this work is to develop a Haptic system and software algorithms with which we can evaluate the possibility of authentication of Haptic system participants.

II. METHOD

A. Data Capture

The possible data for authentication offered in a Haptic environment are larger than that of the traditional authentication tools. For our tests, we have chosen to construct a Haptic maze built on an elastic membrane surface (Fig. 1). The user is asked to navigate the stylus through a maze, which has sticky walls and an elastic floor. Such a task allows many different behavioral attributes of the user to be measured, such as reaction time (to release from a sticky wall), the route and velocity, and the pressure applied to the floor.

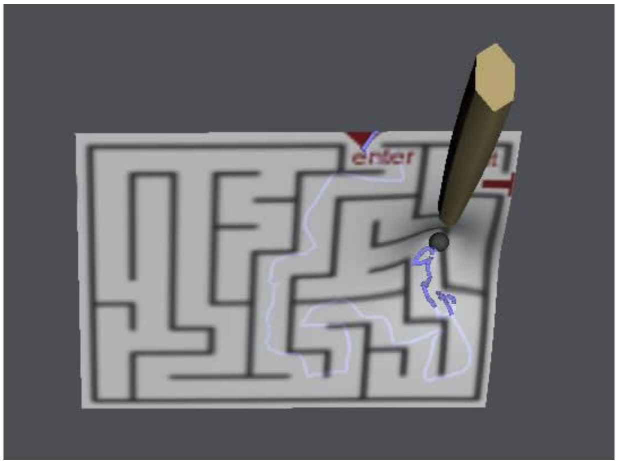

Figure 1. Screenshot of a user navigating the maze. The user is required to begin at “enter” and follow a path to “exit” without crossing any walls. The stylus path is indicated with the blue line.

A total of 22 different participants’ movements were captured for the purposes of analysis. Each person performed the exact same maze 10 times, one trial immediately after the other. Participants were given the opportunity to practice the maze before the trials were actually recorded. Since there is only one correct path through the maze and the ability to solve the maze was not being judged, it was important to ensure participants knew how to correctly solve the maze in advance.

A maze was used as a mean of testing individual abilities and describing a psychomotor pattern through the path followed and performance speed. The user must move the stylus from the entry to the exit arrow without crossing walls.

The haptic software application was developed in a combination of Python script code and VRML-based scene graph module. The 3D environment was defined by using VRML-node-fields approach, while Python provided the procedural process to handle certain events and output the data to a file. The haptic stimuli are provided by accessing to a special API [9] which handles the complex calculations for the touch simulation and the synchronization with graphic rendering.

As can be seen in Figure 2, the process starts recording data when the users make contact through the pen device within a reasonable radius of the starting point of the maze. The trail ends when the user reaches the end point of the maze, at which point the process stops recording data and the maze changes color to indicate this. The software application is able to record two types of 3D world coordinates, the weighted-position and the device position. The weighted-position is calculated as an average of the pen’s real location versus its position on the maze if it was not elastic. The device position is a format for expressing the real position of the pen. The data files also recorded the force and torque applied by the pen on the maze as 3D vectors, and the pen rotation angle.

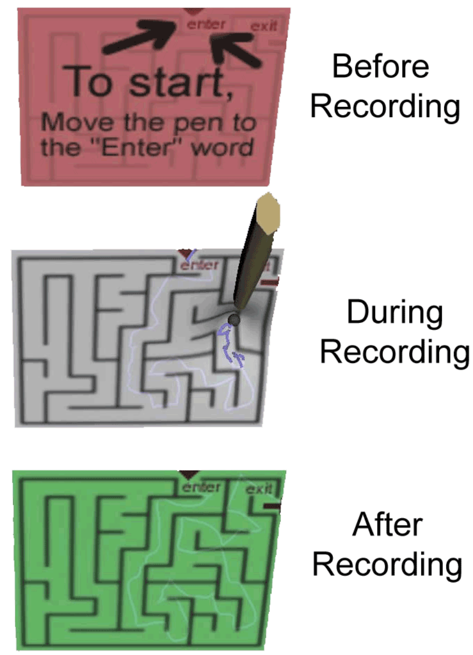

Figure 2: The color Codes of the Maze Recording Process

B. Analysis algorithms

In order to explore the feasibility of biometric identification from these data, several algorithms were implemented to analyze the data from the Haptic system: 1) first order statistics such as total time, speed, and velocity, 2) stroke based identification by using dynamic time warping, and 3) spectral analysis.

First order statistic:

The present experiment provides data that describe particular user behavior. Firstly, the 3D world location of the pen reflects how consistently the user handles the pen device. Each subject’s comparable positions through the maze were evaluated, by calculating a user’s mean normalized path, and velocity in units traveled /per second. Based on these data the set of trials for each subject showed a high standard deviation making it difficult to discriminate subjects. Although on the other hand, such variability in velocity on the set of trials could characterize the subject. The average speed defines a particular “character” to each subject’s handling a task. While speed is generally relatively steady for each subject, it appears that subjects with higher stylus speeds showed more variability in speeds across different trails than those performing in lower speed. These results are shown in Fig. 3. Mean velocity and mean standard deviation in velocity across trials were compared among participants. There is a direct correlation between speed and standard deviation with slope of 0.433. In other words, the quickest subject completed the maze path with the highest unpredictability in speed and the other hand the lowest had the steadiest speed to complete the task.

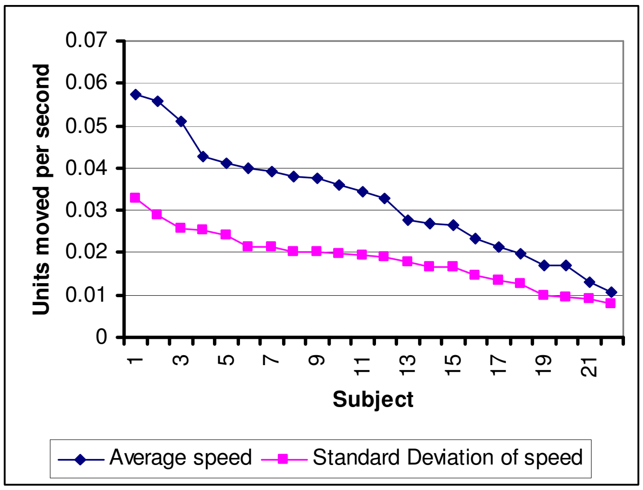

Figure 3: Comparison of individual's mean velocity and its standard deviation.

Dynamic time warping:

Dynamic time warping analysis creates a match score (*MS*) of two data sets, d^1 and d^2, by comparing their respective strokes: sudden changes in direction on the xy plane. Initially, the approach matches the time scale of d^1 to d^2 through interpolation so that the data points represent similar xyz location. The data of l^2 is the interpolated version of d^2 matched to d^1 based on linear interpolation.

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

The best interpolation match is selected based on the Nelder-Mead non-linear minimization [8] used to determine the appropriate p value. The initial p value is set to be 1 and non-linear minimization determines a local p that provides the lowest square difference.

Finally, the *MS* is determined as shown in eq. 1 on 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 data sets of the same user, while stylus velocity would be more constant.

This technique is used in our calculations of false reject rate and false accept rate (FRR/FAR) results discussed in section III.

Spectral analysis:

This algorithm calculates a match score based on the spectral analysis of d^1 and d^2. The analysis is carried out after first matching the time scales using linear interpolation and Nelder-Mead non-linear minimization as described in the previous section. Subsequently, the frequency content of the xyz position data was analyzed based on windowed discreet time Fourier transforms. Due to the low frequency content of the data, a large hanning window size of length 256 with non-overlap data points of 128 is applied. The Fourier Transform of d^1 and d^2 is calculated (Fig. 4) and the square of the difference is calculated as in eq. 1. Fig. 4 shows an example of the frequency content of three data sets. Data 1 and 2 are of the same user data acquired at different times, whereas data 3 is from a different user. The frequency profile of data 1 and 2 are better matched than data 3. *MS* decreases when the spectral content of the two data sets are similar.

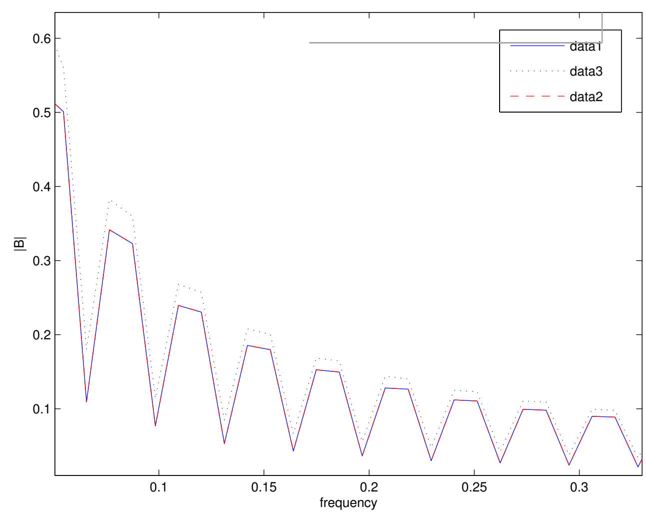

Figure 4: Spectral content of data from three data sets. Data1 and Data2 are from a single user and Data3 from a different user. There is a significant in magnitude between data from different users and near perfect match between data from the same user.

III. RESULTS

Eight participants were asked to use this system ten times each. While solving the maze, the stylus position (in x,y,z was measured and recorded at 100 samples/sec). Each participant was first allowed to become familiar with the Haptic instrument by a few minutes of free practice. Measurements were taken after the user felt comfortable with the device. Each participant solved the maze ten times in one sitting.

Results were analyzed to assess the possibility of identifying participants based on these data. Fig. 5 on the next page shows representative data from two participants. The path taken by the stylus is shown, illustrating the difference in motion between them; one user makes more angular turns of the stylus, while the other shows a more rounded path. These participants' data are more visually distinct than others, but all show differences.

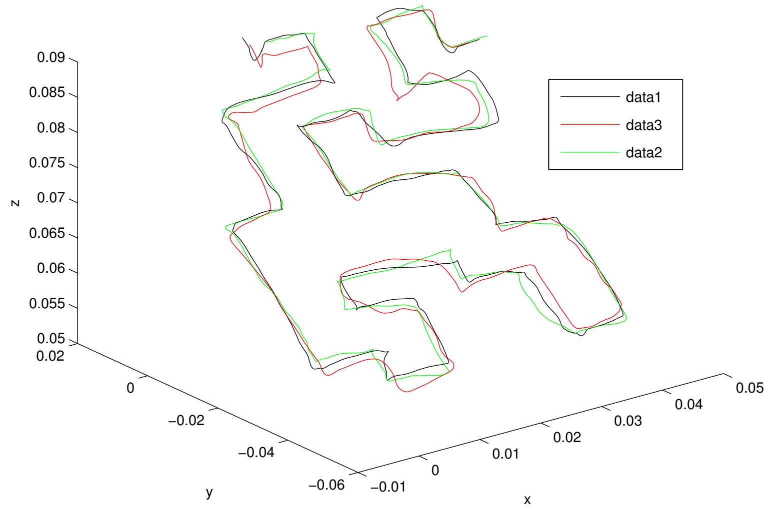

Figure 5. Representative paths taken navigating the maze. Data1 and Data2 are from two different tests by the same user, while Data3 is a different participant. Note the stylistic difference in pattern. Data1 and Data2 has a more angular trajectory, while Data3 shows a more rounded path.

In order to quantify the performance of the proposed algorithms, standard biometric verification analysis was applied [7]. Since each analysis between d^1 and d^2 produces match score, this can be compared with a decision threshold to calculate the biometric receiver operating curve (ROC) statistics: the false accept rate (FAR) is the probability that a comparison between different users exceeds the match threshold, while the false reject rate (FRR) is the probability that a comparison between samples from the same uses is below the match threshold. We also define the probability of verification (PV) as 1-FRR.

We performed this analysis based on match score generated for dynamic time warping and spectral analysis algorithms from the last five maze solutions. The first five maze solutions were discarded to avoid variability due to training effects. As a figure of merit we calculate PV at FAR=25%.

Fig. 6 on the next page shows the PV is 78.8% at 25% FAR when the first 5 data sets are removed for each individual participant. The Equal Error Rate (EER) stands at 22.3 % with a threshold *MS* of 0.195. When all the data sets are considered the PV is 67.6% at 25% FAR. The time warping algorithm results in PV of 60.1 with the first 5 data sets removed for each individual participant. When all data sets are considered PV of 49.0% is observed.

Table 1 Summarizes the PV results for both algorithms. The difference in PV value can be attributed to the training effect. The spectral analysis algorithm provides an increase in PV of approximately 18% compared to the time warping algorithm with or without training effect.

Table 1. Summary of PV results at 25% FAR. The spectral analysis algorithm shows better results than the time warping algorithm. Removal of training data improves the PV regardless of the algorithm.

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

IV. DISCUSSION

We have investigated the possibility of automatic identification in Haptic systems. Our goal was to implement a simple Haptic task which was instrumented to capture the actions of participants. These data were then analyzed to calculate parameters to identify the individual participants. This system was successfully implemented and tested, allowing us to evaluate the suitability of Haptic systems for this kind of identification.

Our results are mixed. Naive algorithms appear to show relatively low PV for a simple maze test. On the other hand, more complex of algorithms , such as spectral analysis, appear to show improvements in system performance, suggesting that more sophisticated approaches may be able to perform better. Additionally, analysis of the training effect shows that PV increases significantly as users become familiar with the system. In an operational Haptic application, all users will be trained.

Additionally, real world Haptic applications are considerably more complex than the maze system of this paper. Such applications will offer more sophisticated data from which to extract identity information and may thus show improved PV.

In conclusion, we have investigated the possibility of identifying users from Haptic data. Our results suggest that this may indeed be possible, especially for trained users. Such authentication would offer the possibility of continuous identification of users in such applications as high-value tele-operation Haptic technology.

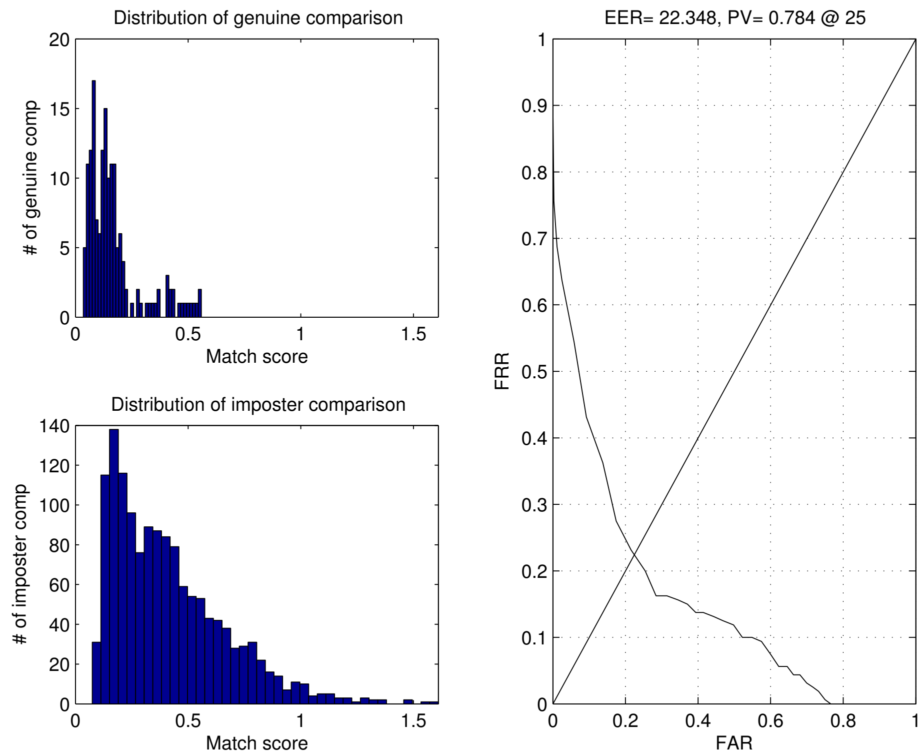

Figure 6. Biometric statistics for the spectral analysis algorithm. **Upper left:** distribution of genuine (within data from same individual) match scores**. Lower left**: distribution of impostor (between data from different individuals) matches scores. **Right:** FRR vs FAR calculated by varying the decision threshold. The line of identity is used to show the equal error rate (EER). Data were analyzed on the latter half of the data to reduce the effect of training.

REFERENCES

[1] V. S. Nalwa, "Automatic on-line signature verification" Proc. IEEE, 85:215-240, 1997.

[2] R. Plamondon, S.N. Srihari, "On-Line and Off-Line Handwriting Recognition: A Comprehensive Survey" IEEE Trans. Pattern Analysis and Machine Intelligence, 22: 63-84, 2000.

[3] S. Shirmohammadi and Nancy Ho Woo, "Evaluating Decorators for Haptic Collaboration over Internet", Proc. IEEE Workshop on Haptic Audio Visual Environments and their Applications (IEEE HAVE ‘04), Ottawa, Canada, October 2004, pp. 105-110.

[4] S. Dodeller and N.D. Georganas, "Transport Layer Protocols for Telehaptics Update Messages", Proc. Biennial Symposium on Communications, Kingston, Canada, June 2004.

[5] T. Qu, A. El Saddik, A. Adler "A Stroke Based Algorithm for Dynamic Signature Verification", Can. Conf. Electrical Computer Eng. (CCECE). pp. 461-464 Niagara Falls, Canada, 2-5 May 2004.

[6] T. Qu, A, El Saddik, A. Adler, "Dynamic Signature Verification System Using Stroke Based Features", IEEE Int. Workshop on Haptic Virtual Environments and their Applications, Ottawa, Canada, Sept. 2003. pp. 83-88

[7] J.L. Wayman, "Fundamentals of Biometric Authentication Technologies", Proc. Card Tech/Secure Tech, 1999. http://www.engr.sjsu.edu/biometrics/nbtccw.pdf

[8] P. E. Gill, W. Murray, M. H. Wright, “Practical Optimization”, Section 4.2.2, pages 94-96, Academic Press, New York, 1981

[9] Reachin Technologies http://www.reachin.se/