Haptic Attributes and Human Motor Skills

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ABSTRACT

Most human fine motor skills involve the use of a tool to complete the given task. The task to be completed is often defined in terms of some desired trajectory and humans generate certain forces to achieve the desired trajectory. In this paper we describe our efforts to experimentally and theoretically classify forces associated with these skilled tasks. The idea is then to develop a system that can capture and playback exhibition of skill through haptics from person to person. Our preliminary results from experiments show that the forces generated by an individual are unique for a given task. Furthermore, for a given person, these forces show little variance over repeated exhibition of the same task. A virtual writing simulator was used to collect data from human subjects. The significance of this research is that not only was the forces generated by a person for a given skill unique, but is also verifiably different from another human subject performing the same task.

Keywords: Motor skill, training, dynamic models, haptic attributes

1. Introduction

Many human fine motor skills involve the use of a tool to complete some desired action. These motor skills range from those, which are vital for day to day life, like sewing, writing, handling a fork and knife to those which are considered highly valuable, like playing a musical instrument or wielding a scalpel. Traditionally, these skills had been passed from teacher to student by teaching through direct contact and/or demonstration. With the advent of high fidelity virtual reality simulations, enhanced with force feedback devices, the training of these skills has been taken to the next level. There has been continuing research in improving the quality and effectiveness of training in such environments. As haptics or the sensation of touch and force plays a key role in the effective learning of these motor skills, much attention has been given to utilizing the modality to a greater extent.

Looking at some key definitions, human motor action can be defined as the movement of the limbs in response to some external stimulus to achieve some defined result. In a similar vein human motor control can be defined as the careful, controlled use of muscles to move limbs in a purposeful manner or in essence controlling the human motor action [1].

Considering a skilled motor task in conjunction with a tool, the task can be defined in terms of a desired trajectory that the tool needs to be taken through. A person is said to be highly skilled at a motor task when the person is able to recreate a closely defined trajectory, multiple times to achieve a clearly defined objective, with a high degree of precision. The desired trajectory together with certain added temporal constraints (f.e. motion with certain velocity rates) can be defined as a metric for evaluation and comparison of the skill exhibited. We hypothesize that the interacting or haptic forces generated during the exhibition of skill can also prove to be a vital source of information that can be used for assistance and training methods using haptics. In conjunction to this, we present some key definitions and theoretical developments which we think would prove vital in the way haptics is used in the design of trainers for fine motor skill transfer and teaching.

For a unique motor skill task performed in conjunction with a tool, the following parameters can be used to completely define the skill being performed: a) The objective, or the trajectory of the tool tip being manipulated, b) The lumped system, given by the combined dynamics of the tool operator’s hand and the tool and, c) The interaction forces, i.e. the forces exerted by the person on the tool and the haptic forces experienced by the person in return.

One or more of the above given parameters are generally used for devising assistance methodologies using haptic force feedback. In most previous studies the focus has been on using (a) for assistance design. In this study we focus on evaluating and understanding the importance of (b) and (c) in the exhibition of human motor skill. We study and present the variations in the forces generated by the subject when writing on our virtual writing simulator. We use pattern recognition algorithms, system identification procedures and statistical analysis to achieve the same.

2. Contemporary work in force and system analysis for fine motor skills

In the previous section, we had said that tool trajectory had been given primary importance when constructing a haptics based motor skill training set up; however, there is a large body of work looking at the role of interacting forces in the same context. Yokokohji et al during their development of WYSIWYF interface [2] had looked at using it to transfer recorded expert’s skill. They displayed the teacher’s forces to the user and expected the student to identify and adopt a strategy based on the force displayed. Henmi et al [3] had developed a system for teaching Japanese calligraphy using a record and play strategy, primarily utilizing force information. Joshi and Kesavadas [4] developed a framework called Sympathetic Haptics, where, based on position tracking a trainee would be able to experience the haptic forces generated by an expert’s interaction with a haptic model. Huang
and Mussa-Ivaldi [6] have also looked upon the role of input forces and had devised training methodologies that utilized this information. However, in all the cases discussed the use of input forces were done at a most rudimentary level. No specific analysis was done in order to determine if any patterns existed in these input forces. Neither was the input force used as a comparison metric to determine the success of a learning program. In most cases the forces recorded were displayed directly or used in a simple control loop. The application developed by Kikuuwe & Yoshikawa [7] is an example of a system that utilizes force information to teach a student the correct method of pressing with a finger. As opposed to body of work discussed previously, here, a trainee specific force analysis was done and a model was created. This model was then used for further training purposes. The above discussed body of work is by no means exhaustive with respect to analyzing and using input forces in a haptics based motor skill trainer. This set is merely intended to illustrate what we found to be a general short coming in the body of research. Prior work done by Srimathveeravalli et al [8] dealt with both force and tool trajectory data being used in the design and evaluation assistance methodologies to promote interpersonal skill transfer. The work reported here is a direct extension of their prior work. In a similar sense there is not much concerted effort in identifying motor models and modeling dynamic systems connecting input forces and trajectories in a haptics set up. System modeling of minimally invasive surgery along with the associated force collection and analysis has been done by Rosen et al. [9]. However, their attempt was more towards establishing a metric of comparison of skill between novice and expert surgeons and less towards establishing a dynamic model relating the input forces with the tool trajectory. Similar work in quantization of forces and its graphical analysis has also been done by Greenish et al [10]. Again, this group did not go in depth and establish any dynamic models, but restricted themselves to collection and graphical analysis of the collected data. A formal system identification procedure has been carried out by Hasser et al [11] for the identification of a human grasping a knob. Their work represents a very valuable piece to help better design training interfaces.

A vast amount of literature can be found in the area of pattern recognition and biometrics pertinent to the analysis of forces during writing. However, most of that literature is not directly relevant to the task attempted here. The first reason being the primary metric used in biometrics is pen pressure and not triaxial forces. Secondly, pen pressure is used in conjunction with trajectory information and is not analyzed independently. Due to the divergence of goals we sustain from citing literature related to handwriting analysis in pattern recognition and biometrics.

3. Testbed Setup

For this research a virtual reality based writing simulator was built. A simple pen-paper interaction model was used for determining the forces to be provided at the tool tip. The haptic environment to simulate writing was implemented using a PHANToM™ desktop device. The PHANToM’s stylus served as the pen and a special apparatus was fabricated to facilitate a WYSIWYG interface for natural writing action. The picture (Figure 1) shows user writing with the virtual interface. Further details regarding the testbed construction can be found in prior work done by Srimathveeravalli et al [8].

4. Concept

The primary objective of this study is to verify a previously introduced concept called “Haptic Attributes and Haptic Profiles” [8] to the domain of motor skill training using haptics. We believe that the theoretical developments along with the definitions that we provide here provide a useful tool for designing newer and better methods of training. A look at contemporary description of haptic profiles or attributes would show that the terms were invariably used to describe properties of mechanical objects and surfaces. Nesbitt [12] had used the term haptic attributes to describe the properties of a given surface and had defined it through surface hardness, surface roughness and object inertia.

Looking in terms of compliant objects, the term haptic profile was used by Weir et al [13] to describe the temporal haptic feel of a mechanical device, in their case, switches. It can be said that there has been no formal attempt to look at the same from the perspective of human motor actions. We explain the motivation to extend the concept of haptic attributes to humans in this section.

Considering an argument of linearity of the systems, consider two systems given by $S_1$ and $S_2$ (Figure 2) to define the lumped parameters of two subjects, with $m_i$ and $c_i$ being the mass and damping parameter values for the two systems. If the subject were asked to write out a character, say defined by the time series $Y(t)$, $t = 0...T$ Given similar initial conditions $[ic_1ic_2]^T$, unless $[m ic_1]$ are identically similar to $[m c_2]$, two different inputs $U_1(t)$ and $U_2(t)$ will be required to make the system generate the same output. Assuming the inputs $U_1(t)$ and $U_2(t)$ to be the interacting forces when the subject defined by the lumped system is trying to perform some skilled task, the outputs would be defined by the generated trajectory. For the above given set up, it would be of interest to investigate the following,

1) Can a generic system identification/modeling technique be employed to determine the dynamic models for the subjects?

2) Will the system parameters be distinct for each subject, will there be tangible variations in the system parameters between subjects performing the same motor skill task?

Now consider a situation where each subject is asked to provide a sample in their handwriting. We call the trajectory defined by these samples as $Y_1(t)$ and $Y_2(t)$. Assuming that the dynamic systems defining the individual subjects may have unique parameters, The following needs to be looked at, for a given person writing a consistent and repeated trajectory, are the

Figure 1: A user operating the virtual writing testbed
Consider a single subject, the system parameter \( \{ m, c \} \) being invariant for the subject. The subject generates a distinct trajectory \( Y(t) \) with \( U(t) \) as the corresponding input force. Among the assumptions given here, it has been proved by many research groups that the trajectories are invariant and closely bounded. The other two questions, namely concerning the system parameters and the interacting forces need to be experimentally evaluated and answered.

Knowing the two times series defining the input forces and the output trajectories along with knowledge of the system, we can establish the Markov parameters as follows. The model defined for the subject can be rewritten in discrete time state space form,

\[
\begin{align*}
x(k + 1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(k) + Du(k)
\end{align*}
\]

Where \( A, B, C \) and \( D \) are the state matrices, \( x(k), y(k) \) and \( u(k) \) are the states, input and output of the system at the \( k^{th} \) time step respectively. Let zero initial condition be assumed for this system (i.e. the subject is at rest and starts the action at \( k=0 \)). As the input and output profiles are in discrete time, let the input be represented by a series of delta functions, where \( S \) is some scaling factor.

\[
u(k) = S \ast \delta
\]

Now it can be said that to obtain a specific output given by \( y \), a series of impulses given by the RHS of the above equation has to be generated by the human. If there be a case where \( S=1, u(0) = I \) and \( u(k) = 0 \) for all \( k > 0 \). Then the following relation can be derived,

\[
Y_k = CA^{k-1}B
\]

Where \( Y_k \) is nothing but the Markov Parameter for the system. The value of \( S \) has no effect on the dynamics of the final output of the system. It merely acts to scale the output trajectory of the system linearly.

**Definition:** Now we proceed to define what we term “Haptic Attributes” for human motor skills. We define that for human motor actions with distinct trajectories, the input forces also follow a certain distinct pattern and a unique set of Markov parameters can be used to relate the input forces with the output trajectory. The Markov parameters will also be invariant and will define the lumped human-tool system. The combined three sets of information will completely define the given motor skill.

The definition given above is based on the previously stated assumptions and subject to the questions posed previously. In this experimental work, these assumptions were validated and the results are discussed in the following sections.

5. Experimental Design

The experiment was aimed at collecting input force profiles for varying output trajectories from a group of twelve test subjects. The PHANToM was used for obtaining the experimental data, i.e. the forces computed by the device at the interacting point were recorded and used for our experiments. Variable factors like ambient environment and factors which affect the handwriting directly like fatigue and pen dynamics were made accounted for by using a specially built virtual set up described in section 3. The other set of undesired factors which affected the experiment were allographic variation, sequence variability, neuro-biomechanical variability and affine transforms. The former two were controlled by predefining the character trajectories. The biomechanical variability is limited to the subject’s processing speed and bandwidth. Taking that in to consideration, we have made the experimental testbed as comfortable as possible to simulate the real writing posture. The affine transforms are variations that the writer imposes on the handwriting which includes scale, shear and rotation. The affine transforms are taken care of by noise reduction and normalization. Noise reduction was done by separate smoothing of \( X \) and \( Y \) coordinate sequences using a 5-tap low pass Gaussian filter. Also each segment or stroke was smoothed independently.

For Q: -

\[
\text{Figure 3: Sample writing instruction for letter 'Q'}
\]

Great care has to be taken in the selection of the alphabet to be used in the data collection for the experiments. So a carefully chosen character set was used in conducting the experiment. The 26 English alphabets were divided into three major groups based on their construction, example straight lines, closed curves, open ended curves etc. The final chosen set consisted of 4 alphabets P,
Q, S and X. To ensure similar conditions, an instruction sheet containing a predefined representation of the character set was used. The figure 3 shows the predefined representation of a character (Q) used for the experiment.

The experiment was conducted on 12 subjects. The subjects were given instructions regarding the experiment and the process was demonstrated to them. The subjects were allowed to familiarize themselves with the apparatus before the actual data collection. The data collection phase consisted of writing 5 samples of the four alphabets mentioned above both in capital and cursive style. A fixed sequence of writing, as mentioned in the instruction sheet, was used for all test subjects. At the end of the session, the subject was asked for anecdotal feedback about their experience. The entire session lasted about 15-20 minutes.

6. Evaluation Criterion and Tools

There were two categories under which the evaluation of the collected data was carried out. The data was evaluated with respect to the input force and the identified system parameters and the markov parameters of the system. In this paper the result pertaining to force analysis is presented, we will be presenting the results for the markov parameters in the future. For the analysis of the input force a special pattern recognition algorithm called Dynamic Time Warping [DTW] was used [14].

6.1 Force Analysis

The dynamic time warping algorithm is an algorithm primarily used in the fields of pattern recognition and voice analysis. The algorithm allows data association of time series of varying lengths. The algorithms works by constructing a cost matrix using the two time series along with a chosen weighting function. With the help of the weighting function, the algorithm forms a “path” of associating the data points in the two times series. The associating path gives the amount of skewing required to associate the two time series. If the path is along the diagonal of the matrix with all values equal to zero, then both the time series are said to possess an exact match. In our case we use the algorithm to perform a shape comparison for the input forces Fx and Fy between various samples taken from the same user and samples taken from different users. Looking back at the definition of Haptic Attributes the assertion was that the scaling factor ‘S’ of the input time series has no effect on the trajectory. So, as long as the net shape of the input series is maintained, the output trajectory will also retain its shape. If there exists any skewing in the input time series or variation in its net shape, then according to our definition the output trajectory would vary accordingly. This definition should work vice versa too, that is if the writing is skewed from some given mean, the input force should vary too. From the force analysis algorithms we hypothesize the following,

1) The shape of the input forces from the same person should have a very close match.
2) The shape of the characters from the same person must have a close match

An interesting anecdotal evidence that can be presented here is the raw input force values from two different subjects. Presented in the figure (Figure 4) are force values Fx and Fy from two subjects writing the same character. It can be seen that while the input force graphs are dissimilar between the two subjects, while the forces seem to follow a pattern for the same subject. That is force pattern remains consistent within the same subject.

6.2 Markov Parameters and System Identification

Apart from the force analysis, the other major analysis conducted on the data from the experiments is determining the Markov parameters of the system and performing a system identification procedure on the data to obtain a model of the subject. Here we discuss the system identification procedure adopted, the results of the procedure are not included in this publication. The Markov parameters of the system are obtained using the Fourier transform and the procedure are not included in this publication. The Markov parameters of the system are obtained using the Fourier transform and performing a system identification procedure on the data from the experiments is determining the Markov parameters of the system and performing a system identification procedure on the data to obtain a model of the subject. Here we discuss the system identification procedure adopted, the results of the procedure are not included in this publication. The Markov parameters of the system are obtained using the Fourier transform method given like so,
\[ M_p = \text{ifft}(t.f) \]
\[ t.f = \frac{Y'}{U} \]
\[ Y' = \text{fft}(y) \text{ conj} (\text{fft}(u)) \]
\[ U = \text{fft}(u) \text{ conj} (\text{fft}(u)) \]

Where \( M_p \) is the Markov parameters of the system, \( t.f \) the transfer function of the system, \( u \) and \( y \) are the input and output of the system respectively. \( \text{fft} \) gives the discrete Fourier transform and \( \text{ifft} \) the inverse Fourier transform. Apart from this we perform a system identification procedure using an Auto Regressive Exogenous (ARX) algorithm using the Matlab system identification tool box. The form of the ARX model is like so,
\[ y(t) = G(q, \theta)u(t) + H(q, \theta)e(t) \]
Where,
\[ G(q, \theta) = \frac{B(q)}{A(q)}; H(q, \theta) = \frac{1}{A(q)} \]

The new terms in this equation are \( q \), the states of the system, \( e(t) \) the error function and \( \theta \) being the parameters of the system being identified. The system we are considering is a Multi-Input and Multi-Output (MIMO) system, hence the choice of ARX for the system identification procedure.

7. Results

The shape comparison using the DTW algorithm was carried out on two levels, between samples taken from the same subject and between samples of two subjects chosen at random from the subject population. The comparison was made on input forces \( F_x \) and \( F_y \) and the shape of the trajectory.

7.1 Comparison of force values

Same subject samples: (Figure 5) The metric on the Y axis is the percentage error in the shape match between two adjacent samples. The X axis gives the subject number. It can be seen that the maximum error and hence variation in shape is around 13% for all users. Some users tended to show a greater variation in the force values than others. On an average the variation of the shape match was at 9.2% with a standard deviation of 0.24. In general it can be noticed that there is an almost consistent amount of variation about the mean.

Comparison between subjects: (Figure 6) It can be seen that the maximum error shape for all users was around 70%. On an average the variation of the shape match was 44.31% with a standard deviation of 3.67.

From the two sets of analysis conducted for the input forces it can be observed that in general the shape of the input force values are generally well defined and bounded for a given subject. The subjects seem to use a similar looking force profile for a given task. Different subjects seem to use differently shaped force profiles to write a given alphabet (as can be seen in fig. 5).
This leads us to question, how a comparative analysis of the character shape for a given subject would look like. Looking at the results presented in figure 7, we find that for a given subject the shape of the output trajectory (in this case for the letter X) has a higher error and variation than the input force for the same subject (and letter). The reason for this is not quite obvious at this time because it would seem that for a given force attribute the matching shape trajectory should demonstrate a similar level of error and variations. This may also reflect the data collection and filtering technique used in collecting the force and position values.

7.2 ANOVA

An ANOVA test was conducted on the two analysis sets discussed here, i.e. the analysis of variation of input force profile’s shape when compared within the same user and between users. A one way ANOVA was performed using Minitab, the factors being the samples compared and the error in shape.

Same Subject Samples: The null hypothesis considered here was that the variation in the shape matching error metric was significant. The table given below provides the results of that comparison. It was found that for most of the subjects the null hypothesis got rejected. That is there was no significant variation in the amount of mismatch between input profiles of different subjects. It can be assumed that the mismatch between the subjects was high with little variation. (the highlighted cells show the cases where the hypothesis was not rejected). (Table 1)

Table 1: Results of ANOVA performed to test if there was a significant variation in the shape of the input force profiles for the same subject.

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Table 2: Results of ANOVA performed to test if there was a significant variation in the amount of mismatch of input force profiles between subjects

8. Closing Remarks

We have presented here some early results showing the uniqueness of force attributes in skilled tasks. While we found promising results to support our theories and definitions, the variability and the size of the population of subjects is not large enough to draw any concrete conclusions. We are planning a more exhaustive study on a larger population set. Also, the concept was tested on a virtual set up in a limited sense- the same needs to be replicated in a real world setting with a wider set of tasks that require motor skills.

REFERENCES


