Motor Skill Training Assistance Using Haptic Attributes

Govindarajan Srimathveeravalli Kesavadas Thenkurussi
VR Lab, State University of New York at Buffalo, USA
E-mail: gks2@eng.buffalo.edu,kesh@eng.buffalo.edu

Abstract

In this paper we describe our efforts to develop a new strategy for providing assistance using haptics in a virtual environment when training for a motor skill. Using a record and play strategy, the proposed assistance method will provide closest possible replication of expert's skill. We have defined a new paradigm called "Haptic Attributes" where we relate a unique haptic force profile to every task performed using motor skills. This has been combined with an earlier concept called Sympathetic Haptic to develop a new paradigm in training complex skill based tasks such as writing, surgery or playing musical instruments. As a demonstration, a virtual environment that can be used for training handwriting was designed and implemented. Position based feedback assistance and training with no assistance were tested against our method in a series of human subject tests. Results prove our method to be superior to training methods tested which use position based or no assistance.

1. Introduction

Motor skill can be defined as an activity of a person involving a single or a group of movements performed with a high degree of precision and accuracy [1]. Motor skill involves coordinated motion of various joints, nerves and limbs of the body to achieve the desired action; the skill can range from the complex (surgery) to more mundane ones (cutting). Consider handwriting, an essential motor skill which takes a number of childhood years (3-4) to acquire. There are two chief means of learning handwriting; through observation or through training by a teacher. Observation has generally been deemed inferior for learning most motor skills and the latter method of learning, which can be termed as skill transfer is more commonly used for teaching handwriting. Here learning and skill transfer can be seen as a transfer of an established strategy, which the trainee is then able to reproduce with his or her own understanding of it [2]. In a similar vein, it would be of great interest to see if skill of an expert can be captured in a 'record and play' fashion and be transferred entirely to another person, such that the student will be able to replicate the teacher's touch. The original idea of this approach was called "*Sympathetic Haptics*" and was proposed by Joshi and Kesavadas [3] [4]. The work presented here will further explore the concept of "*Sympathetic Haptics*". We have developed a system where a person can be trained to replicate an expert's handwriting in the closest possible fashion. Quoting one of the primary axioms of biometrics 'that no writing is ever completely replicated, even by the same person', in the proposed work the target is 'closest replication' and not 'exact replication'.

2. Contemporary work in Haptics for Skill Training

An expert's skill in the virtual environment can be represented using temporal position, velocity and force information. This information is then learned by the trainee in the form of proprioception and kinesthetics. Based on this form of the teacher's data, different types of training assistance can be designed and provided to the trainee. Yokokohji et al during their development of WYSIWYF interface [5] 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. However due to the nature of the problem they had undertaken to simulate, they were unable to provide any substantial results. Henmi et al [6] had developed a system for teaching Japanese calligraphy using a *record and play* strategy, primarily utilizing force information. While they reported transfer of skill, they had cited need for further experiments. Solis et al [7] had also developed a calligraphy system using reactive robot technology. While the system has been proven highly effective they have chosen to use a position based control method to serve their purposes. Gillespie et al [2] developed a virtual teacher to train students to balance a dynamic object. They used PD position control for training assistance. Their work reports that while the strategy was communicated from the teacher to the student, the implementation was student dependent. The application developed by Kikuuwe & Yoshikawa [8] is another example of a system that utilizes force information to teach a student on the correct method of pressing with a finger. The results of their experiments suggest that while precision reproduction of teacher's action is possible, accuracy is difficult.

From the discussed literature it becomes evident that most training assistance modes in a virtual environment depend on force or position information. For clarity and ease of comparison we chose to ignore hybrid assistance (which use both position and force information) in our literature survey.

3. Testbed Setup

Pen-paper interaction for the testbed was modeled with the major interaction forces as show in the figure (Figure 1). To simplify the model we ignored the user's grasp on the pen. The paper itself was assumed to be resting on a rigid body which is smooth and does not contribute to the friction of the paper We also assume zero slip between the paper and the surface.

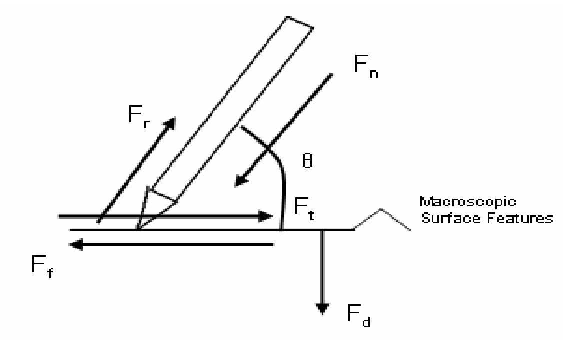

Figure 1: Model of Paper-Pen Interaction

If applied user force at time t_i ($i=1...T$) is $F(t)$, assuming the paper to be the XY plane, the current pen position to be the origin and the pen to be inclined with only the Y axis by θ then,

$F(t) = \Sigma F_n(t)+F_t(t)$, F_t – Tangential force component & F_n – Axial force component

$F_r(t) = F(t)*sin(\theta)$, F_r – Normal reaction force

$F_f(t) = \Sigma F_{static} |_{\Delta X(t)=0} + F_{dynamic}|_{\Delta X(t)>0}$, F_f – Total frictional force at any time t

$F_d(t) + K*\Delta X(t) + C*X'(t) = F_n(t)$, F_d – Dynamic Response of paper, X – Vertical displacement of paper surface, K – Spring constant for paper surface, C – Paper damping ratio.

The forces described above are sufficient to describe a simple but complete interaction model. The surface friction model for the paper was generated using a Gaussian distribution as described by Siira et al [10]. The macroscopic features on the paper are generated using a mesh triangulated from height fields. The triangulation was done using an algorithm described by Bourke [11]. 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 WYSIWYF interface for natural writing action. The picture (Figure 2) shows a user writing with the virtual interface. Haptics and graphics portion of the testbed was managed by GHOST SDK [12] and the Open Inventor API [13] respectively.

Figure 2: A user operating the virtual writing testbed

4. Training Modes

The training mode developed by us depends entirely on force information. A position information based assistance set up was also implemented for comparison with our training method. To compare the effectiveness of the two modes a base line mode was also included, where the user received no haptic assistance and was entirely dependent on their capability to replicate the expert's handwriting. The following training modes were designed and implemented in the testbed.

4.1. Basic Mode

In this mode the user received no haptic assistance and learning was dependent on their skill to replicate the trajectory presented to them. This training method represents the most rudimentary method of training for handwriting, where learning is through observation and physical repetition.

4.2. PD Position Control

In this mode PD position control feedback was added to minimize trajectory error during the training sessions. This is an iterative improvement over method one and can be seen as a virtual teacher actively correcting the student's positional error and can also be described as active assistance. In this mode the reference trajectory was provided to the user to practice and the position control assists the user in the training process. The position and derivative gains were theoretically modeled and experimentally fine tuned to 0.35 N/mm and 0.17 Ns/mm.

4.3. Haptic Attributes

Prior to discussing the next training methodology a new concept called "*Haptic Attributes*" is introduced. In biometrics writing pressure has been used for quite sometime now as one of the metrics for online signature and handwriting recognition. Initially pen pressure for a person's handwriting had been considered unique enough to be a biometric measure but not sufficient for identification by itself. Current literature shows that [14] that it may be possible to identify a person based on pen pressure alone. In a similar vein we propose that the haptic forces generated by a person for a given action is unique for a controlled environment. Though there may be variance over multiple samples, for a given person and for a given action it will be distributed over a sharp normal curve. The above statements can be explained as follows.

Let J be the moment of Inertia of the pen and C the friction co-efficient for the pen-paper surface, then the system can be modeled as shown below

$$Jx(t)'' + Cx(t)' = 0$$

Where $t = 0 \ldots T$ and the system is stable for all t, if J >> C. For a unit step force input $H(t)$ at $t = 0$, the system would track it giving a straight line with zero static error. That is,

$$Jx(t)'' + Cx(t)' = H(t), \text{ solving would give us}$$

$$x(t) = fn(t) \text{ , } t = 0 \ldots T$$

Let us consider the case where,

$$x(t) = \Phi(t) \text{ , } t = 0 \ldots T$$

Where $\Phi(t)$ is a function for generating any desired trajectory. For the described system, each input force generates a unique response. Thus $\Phi(t)$ will correspond to a unique force profile $\Psi(t)$. Let us now decompose $\Psi(t)$ as a series of impulses of form $I_t * \delta(t)$, where I_t is the magnitude of the impulse applied at time t. As each person has a unique handwriting, each character written by that person can be defined by a unique $\Phi(t)$, the generating force $\Psi(t)$ will also be unique to that person. The profile of $\Psi(t)$ depends on the I_t , wherein there are infinite combinations of I_t to obtain a given $\Psi(t)$. But due to physical limitations and laws of physics, this infinite set of impulses can be reduced to a finite set, which, however still represents a rather large set of choices. But in reality the person will choose a set of forces based on the following prior knowledge/experience, preference and environmental settings. This in effect may be called the *Haptic Attribute* of the person for the given action. This *Haptic Attribute* can then be looked at as a time series of force information. The profile obtained by plotting the individual X, Y and Z components of the *Haptic Attribute* can be called the *Haptic Profile* of the person.

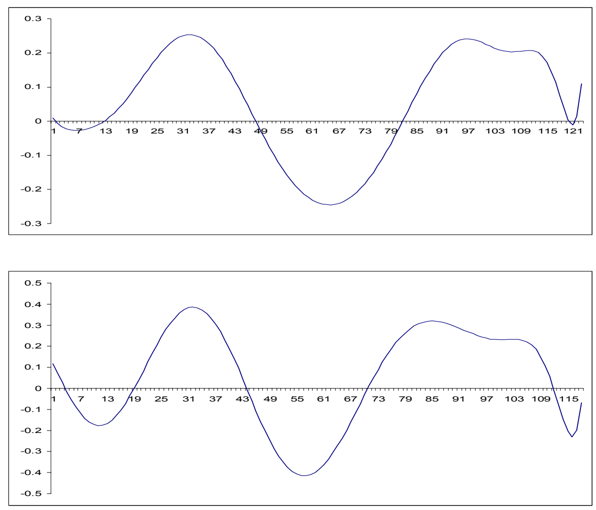

Figure 3: Haptic Profiles of a subject sampled with a 7 day time gap for the same alphabet

Just as in the case of pressure data, the *Haptic Profile* for different people performing the same task is different, but is unique for each individual (Figure 3). In these plots a trainee was asked to write the alphabet 'S', sampled at a week's interval. Looking at past literature Huang [15] and Mussa-Ivaldi [9] have touched upon a similar concept. In human control of dynamic systems, Huang refers to generation of control force profile for a given task being dependent on past experience or knowledge. The set of perturbing forces generated by Mussa-Ivaldi for training can be considered as the inverse set of the haptic profile generated for a desired trajectory. In most cases where a record and replay strategy was used in conjunction with force cueing, the researchers were actually displaying the force profile of the teacher to the students.

4.4. Force Control

The third and final mode of training assistance utilizes the *Haptic Profile* information for providing force feedback control. This work tries to expand upon a prior concept called "*Sympathetic Haptics*" developed by Joshi and Kesavadas [3][4]. They explored the concept of sharing haptic sensation between two people over a network. The core of this concept depends upon the ability of one person to be able to position track the other person accurately in real time. As the position tracking error tends to zero the person tracking is able to feel the exact same haptic sensation as the leader. As accurate position tracking is a very complex task, an alternate approach is proposed here which consists of a PD force control in conjunction with visual trajectory tracking. Even if gross errors exist in the trajectory tracking, the haptic sensations felt by the user would be similar to what the expert felt during his interaction with the model. This is made possible by comparing the user's current force with the *Haptic Profile* of the expert for a given time step and providing a feedback of the scaled error value. The *Haptic Profile* information of the expert will help in augmenting or decreasing the trainee's force. The assumption here is that if the *Haptic Profile* of the trainee and the expert is similar, then by nature of the forces generated (described in section 4.3) the trajectories will be similar. The proportional and derivative gains used for the method were theoretically estimated and were set equal to 0.5 N/mm and 0.1 Ns/mm respectively.

5. Experimental Design

The three assistance modes discussed in the previous section were implemented in the experimental testbed. The modes were called BASIC for no assistance mode, PCONTROL for position feedback mode and ALPHA for force guidance mode. To avoid prior knowledge of trajectory from affecting the trainee performance, characters from a South Asian (Indian) regional language called Tamil was chosen [16]. To ensure similar conditions, all the subjects were trained on a particular character, pronounced 'Na'. The figure below shows the character that was used for providing the reference to the subject's during training (Figure 4)

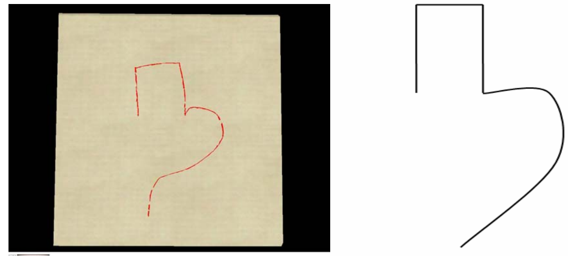

Figure 4: The character 'Na' as written by the expert, sample of the printed character.

The experiment was conducted on 10 subjects. The subjects were given instructions regarding the experiment and then the expert demonstrated the character to be written. The subjects were allowed to familiarize themselves with the apparatus and upon their consent to begin, a file containing the test character written by the expert was loaded. Each mode consisted a training phase of 11 trials with assistance which was followed by a recall mode where the subject was asked to reproduce what they had learned 11 times without any assistance. The reference trajectory was removed during the recall mode. At the end of each recall trial a short resting period was allowed. At the end of the session the subjects were asked for anecdotal feedback about their experience. The entire session lasted about 20-30 minutes.

5.1. Evaluation Criterion

The subjects were evaluated with 2 error criteria and the data from only the recall trials were used for analysis.

5.1.1. Data preprocessing. The number of time steps between the subject trial and the reference may not be equal. In order to compare data based on different time scales, the subject datasets were normalized and linearly time scaled to match the timeframe of the expert. Linear interpolation was performed to convert all the subject data in terms of reference time steps.

5.1.2. Character shape match. The character shape matching between the reference character and the subject recall character was done using Dynamic Time Warping (DTW) [17]. The DTW algorithm was implemented for each axis separately. DTW operates by constructing a global cost matrix with a function defined using the two time series that need to be aligned. In this case we chose finite difference as the cost function. After populating the matrix, a minimum path is determined and the final value of the minimum path provides an estimate of the global cost associated with the warping of the subject time series with respect to the reference time series. The global cost is a sufficient metric for comparison of shapes- lesser the value, better the match.

5.1.3. Haptic profile shape match. In this metric we try to determine the shape match between the *Haptic Profile* generated by the subject with that of the reference. The DTW algorithm defined in the previous section is used for determining the shape match.

6. Results

For calculating the final results we used 10 of the 11 recall trials for each mode. A balanced ANOVA with factors being the training mode and subject was done with each of the two error metrics. The ANOVA was performed using MINITAB. The null hypothesis was chosen that 1) There is no significant effect of training on the recalled trial and 2) There is no significant difference between the performances of the subjects for the given training assistance.

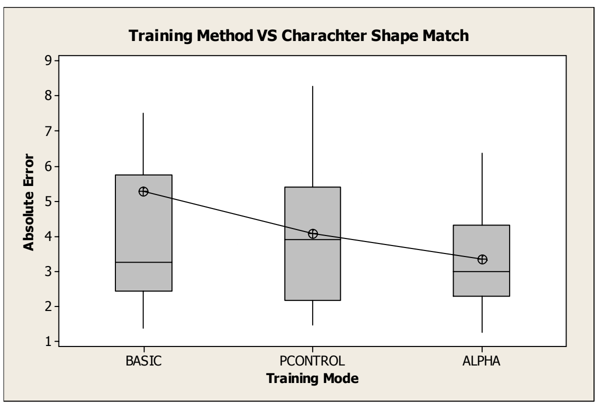

Figure 5: Variance and mean for character shape match

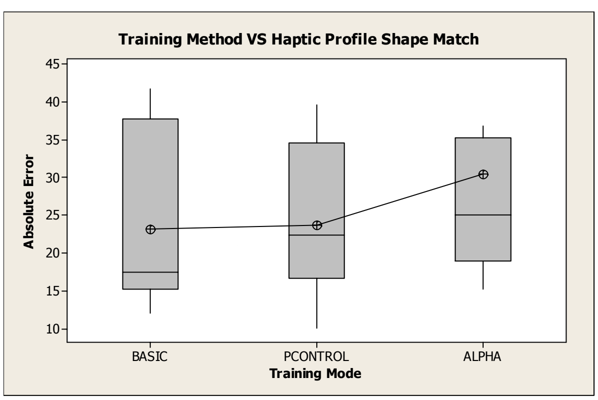

Figure 6: Variance and mean for haptic profile shape match

Character Shape Match: Figure 5 shows the results of the ANOVA performed for character shape match. For the BASIC mode, there was insignificant effect of training and significant difference between performances of the subjects ($p<0.001$). For the PCONTROL mode there was insignificant effect of training and there was no significant difference between performances of subjects. For the ALPHA mode there was insignificant effect of training and there was no significant difference in performance between subjects. The overall inter subject variance in performance was least for ALPHA mode.

Haptic Profile Shape Match: Figure 6 shows the results of the ANOVA performed for haptic profile shape match. For the BASIC mode, there was insignificant effect of training and significant difference between performances of the subjects ($p<0.001$). For the PCONTROL mode there was a significant effect of training ($p<.003$) and there was no significant difference between performances of subjects. For the ALPHA mode there was marginally significant effect of training ($p<0.01$) and the trainees performed similarly. The overall inter subject variance in performance was least for ALPHA mode. An anecdotal finding in this category was that most of the subjects found ALPHA assistance mode new and took a number of trials to get accustomed to it. Post trial the subjects reported some difficulty in identifying the reference forces that were generated. For conclusive results we felt that separate experiments with larger trial sets must be performed for the ALPHA assistance mode. The mode in which each subject showed best performance for each metric is tabulated below. It can be seen that while ANOVA suggested that none of the modes have any significant impact on character shape matching, we find that ALPHA mode has dominated that column.

Table 1: Best performance mode for every metric for each subject

Trainee No.	Character Shape Match	Haptic Profile Match
Person 1	**ALPHA**	ALPHA
Person 2	PCONTROL	ALPHA
Person 3	**ALPHA**	PCONTROL
Person 4	**ALPHA**	BASIC
Person 5	**ALPHA**	PCONTROL
Person 6	BASIC	PCONTROL
Person 7	**ALPHA**	BASIC
Person 8	**ALPHA**	PCONTROL
Person 9	**ALPHA**	BASIC
Person 10	BASIC	ALPHA

7. Closing Remarks

The BASIC mode where no training assistance was provided to the subjects showed the worst performance in the tests. Training using BASIC mode showed a high amount of dependence on the individual subject's capability to replicate the expert's action. An interesting facet of PCONTROL mode was that it also influenced the haptic profile shape of the trainee. Finally, looking at ALPHA mode we found that it had significant impact on the haptic profile metric. This essentially suggests that the subject was able to identify the reference forces and was able to match those forces. This brings us to the next question, if the haptic profile accuracy is known to exist, then by our derivations in section 4.3, this mode must also exhibit good shape accuracy. From Table 1 it can be seen that the ALPHA mode brought about the best shape accuracy too! However for complete character shape accuracy the haptic profile must be matched in discrete time to the original reference, which is very difficult to achieve. From our experiments we conclude that training given using force information in the form of *Haptic Attributes* gives superior results as compared to training using position information. We also plan on conducting a more in depth analysis into *Haptic Attributes* for various tasks and aggregating a library of *Haptic Profiles* for various motor skills

8. References

[1] Singer R. N., "Motor Learning and Human Performance: An Application to Motor Skills and Movement Behavior" Macmillan Publications, 3rd Edition, 1980

[2] Gillespie R, M. O'Modhrain, P. Tang, D. Zaretzky and C. Pham, "The Virtual Teacher" Proceedings of the ASME Dynamic Systems and Control Division, (Anaheim, CA) ,1998 , pp 171-178

[3] Joshi D. and T. Kesavadas, "Framework For Network Based Manufacturing Training Through Telehaptics" In Proceedings of ASME International Mechanical Engineering Congress And R&D Expo, Washington D.C., 2003

[4] Joshi D., "Development and Experimental Analysis of a Framework for the Communication of Haptic Experience Over a Network", Master's Thesis, SUNY Buffalo, 2003

[5] Yokokohji Y., R. Hollis, T. Kanade and K. Henmi, "Toward machine mediated training of motor skill" Proceedings of the IEEE International Workshop on Robot and Human Communication, 1996, pp 32-37

[6] Henmi, K. and T. Yoshikawa, "Virtual Lesson and its Application to Virtual Calligraphy System." Proceedings of the IEEE International Conference on Robotics and Automation, 1998

[7] Solis J., C. A. Avizzano and M. Bergamasco, "Teaching to Write Japanese Characters using a Haptic Interface" Proceedings of the 10th Symposium On Haptic Interfaces For Virtual Envir. & Teleoperator Systs. 2002

[8] Kikuuwe R. and T. Yoshikawa "Haptic Display Device with Fingertip Presser for Motion/Force Teaching to Human" Proceedings of the 2000 IEEE International Conference on Robotics and Automation. ,2001

[9] Mussa-Ivaldi F. A. and J. L. Patton "Robots can teach people how to move their arm" Proceedings of the IEEE International Conference on Robotics and Automation., 2000

[10] Siira J. and D. Pai, "Fast Haptic Textures", Proceedings of Conference of Human Factors on Computing Sys., 1996

[11] Bourke, "An Algorithm for Interpolating Irregularly-Spaced Data with Applications in Terrain Modeling" Pan Pacific Computer Conference, Beijing, 1989

[12] GHOST SDK, "General Haptics Open Software Toolkit" www.senable.com, Sensable, 2004

[13] Open Inventor, "Open Inventor API", www.coin3d.org, Systems In Motion, Norway, 2004

[14] Nakai M., T. Sudo, H. Shimodaira and S. Sagayama , "Pen Pressure Features for Writer Independent Online Handwriting Recognition Based on Substroke HMM", Proceedings of 16th International Conference on Pattern Recognition, Vol. 3, 2002, pp 220-223

[15] Huang F., R. B. Gillespie and A. Kuo "Haptic Feedback and Human Performance in a Dynamic Task" Proceedings of the 10th Symposium on Haptic Interfaces for Virtual Envir. & Teleoperator Systs. ,2001

[16] Tamil, Indian Language, www.ta.wikipedia.org, Dec 2004

[17] Wang K. and T. Gasser, "Alignment of Curves by Dynamic Time Warping" The Annals of Statistics, Vol.25, No. 3, 1997, pp 1251-1276