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Modeling and Defining Expert Handwriting Behavior

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Abstract— Computer based training has become an increasingly attractive alternative to traditional training methods for skill acquisition, and the topic of skill modeling has become one of great interest. One of the key problems in computer-based training is automatic skill evaluation, which requires precise and accurate skill modeling. In order to evaluate and model human skills it is necessary to identify a relevant set of attributes by which skill can be measured, interpreted and evaluated by computers. In this paper we present our work on attributed skill transfer and focus on the specific task of writing. Identifying the central attributes associated with writing and analyzing the consistencies of these attributes within and among subjects determines whether one unique expert model can be derived from a pool of experts. In our study key attributes of hand writing were identified and statistical analysis on subject data was conducted. In our analysis we found experts' behavior can be modeled using the parameters and the same could be used to distinguish between experts and novices, lending itself as an evaluation tool.

***Keywords*— Motor skill modeling, haptics, handwriting**

I. INTRODUCTION

Motor skills are typically learnt in direct interaction with a teacher or master. The primary challenge in training for any such motor skill is identification of a suitable master or teacher model. Given that there can be multiple experts for any motor skills, following question arises -- Is it possible to determine a generic expert model from a given population? (ii) Do any patterns exist in a population of such experts? Identification of such a generic expert model that encapsulates the so called skill attributes could prove beneficial for skill transfer and evaluation using haptic systems. Germain et al [1] incorporated a visuo-haptic device 'Telemaque' to increase the fluency of handwriting production of cursive letters in kindergarten children. Haptics has been used effectively for training for fine motor skills. Pemalete et al [2] used force feedback provided by a haptic device to improve handwriting. Mansour et al [3] discuss about learning and evaluation system using haptics to facilitate learning of alphabetical handwriting of various languages. Chen et al [4] describes human skill to be highly stochastic in nature, that not even an expert can consecutively exhibit the same "skill" with nil variation. While general patterns emerge, there will be inherent variability in the skill depicted. Wang et al [5] defined motor skill as the ability to execute a movement in an optimal fashion, or as an activity of a person involving a single or a group of movements performed with a high degree of precision and accuracy. From these two studies it can be deduced that an expert will show lower variability than a novice. Skill can also be depicted as the fluency of the task being performed. Elesa et al [6] measured fluency, movement time and axial pen forces involved in hand writing. According to their study deteriorated signal to noise ratio (SNR) resulted in less fluent writing.

In order to better understand skill it would be instructive to analyze the pattern of behavior being addressed. At the behavior level Rasmussen [7] describes skill as the perceptual motor system that acts as a multivariable continuous control system. In order to quantify skill, identification of attributes pertinent to the task being performed need be analyzed. While multiple groups have worked constructing handwriting /calligraphy trainers or simulators, modeling of expert skill or actions has been largely restricted to fitting models to written characters. There has been little work in identifying comprehensive expert models for writing that would combine force and position information. Srimathveeravalli et al [8] parameterized hand writing by building a force profile and defined a new paradigm called "Haptic Attributes" where they relate a unique haptic force profile to every task performed using motor skills. How to model human skill and its learning mechanism during tasks such as handwriting? The remainder of this paper is organized as follows. Section II gives the identification of attributes that deal with the handwriting. Section III analyzes the consistencies of handwriting writing behavior.

II. METHODOLOGY ANALYSIS OF ATTRIBUTED SKILL TRANSFER

In this work a method for determining an expert model for fine motor skill – handwriting, is proposed. In this approach skill was described through identification and quantization of attributes associated with writing and subsequent statistical analysis to estimate consistency, patterns and to finally derive a model from these attributes. This was executed as a three step process i) Collection of handwriting samples from expert writers (native language writers in English and Tamil selected as experts) ii) Preprocessing and filtering of data followed by extraction of skill attributes iii) Statistical analysis to characterize skill.

அ எ இ ந ய ண

S Q P O Δ *

Figure 1. Tamil characters (row above) and English alphabets and symbols (row below) used for data collection

Data Collection

An experimental procedure was conducted to collect handwriting samples that would represent expert skill. Data was collected for six Tamil characters, three English letters and three symbols. For testing the proposed methodology two of the nine letters one from Tamil and the other from English were randomly chosen. WACOM's Intuous tablet was used for obtaining data when writing the characters, including pressure and pen orientation information. Data was captured at 100 Hz (spatial accuracy 2500 dpi, temporal accuracy 1ms). Subjects (n = 22, 18 male and 4 female, age 18-28 years) who participated in the experiment were asked to provide six consecutive samples for each shape continuously. All subjects except one were left handed. Participants wrote on an A4 sheet that had a printed template, which was laid upon the tablet. There was no restraint on hand movement and anthropometric pen grip. Six reference boxes (1x1 inches) within each template was provided to ensure that all the subjects had the letters at the same fixed location with respect to their posture and arm position. The participants were given a separate sheet for each letter Fig 2. The parameters obtained with respect to time ***t*** was

- Coordinates (*X(t), Y(t))* of the pen tip
- Pressure *P(t)* applied against the pen tip by the tablet. No pressure is recorded if the pen tip looses contact with the tablet.
- Orientations of the pen θ_1 *(t)* and θ_2 *(t)* where θ_1 is the angle between Z=0 plane and the orientation vector of the pen while θ_2 is the angle between the projection of the orientation vector on *Z = 0* plane and Y axis (shown in Fig. 3).

Preprocessing

The attributes that were identified and collected for this study for skill transfer were cumulative speed, RMSE of the X, Y coordinates (with respect to a straight line) of stylus tip for positional difference in writing samples and the axial pen forces (APF). The profiles obtained for each of the above attributes was segmented into 10 equal windows. This made inter-and intra subject comparison easier.

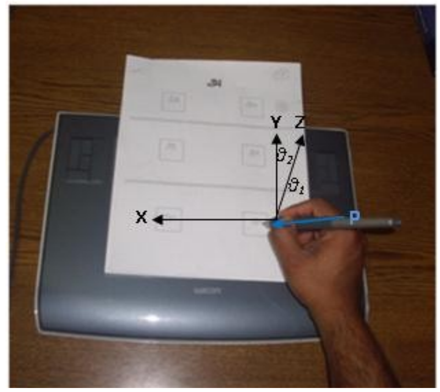


Figure 2. Data collection using WACOM™ of subject writing on template

Positional Error

Spatial comparison of each writing samples was performed by transposition of each writing sample to the origin followed by proportionate scaling where a fixed size bounding box is used and each sample proportionately scaled (PS) along its major axis Fig. 3 shows PS data of digitizer tablet pen tip. The PS data set was then normalized and interpolated such that all samples now contained the same number of data points.

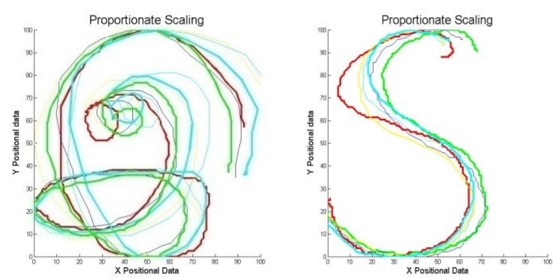


Figure 3. Proportionate scaling of Tamil character (left) English letter (right)

One of the common methods of finding the similarity between two profiles is to find the Root Mean Square Error (RMSE) between the profiles. The X (horizontal) and Y (vertical) profiles of the pen tip was divided into 10 windows and RMSE values were computed for each with respect to a predefined line.

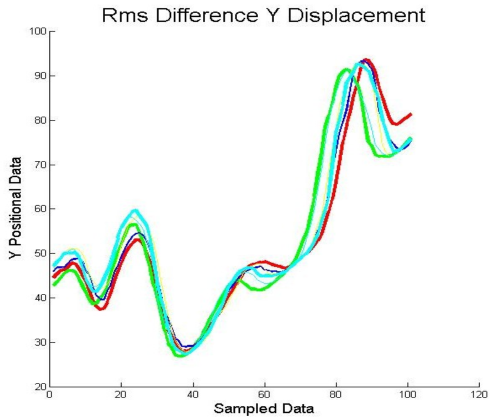
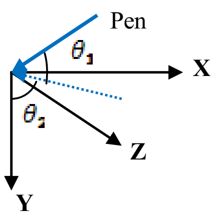


Figure 4. Plot of RMSE for Tamil character

Axial Pen Forces

The force profile generated for each writing sample was computed as follows. Force applied to the paper surface can be resolved into components, a force normal to the writing plane (NPF) and a frictional force along the writing plane. The normal pen force (NPF) at t is FN_t and the axial pen force (APF) at t FA_t are related as shown in equation (1)



$$FN_t = -FA_t \sin(\theta_1) \qquad (1)$$

Figure 5. Reference coordinates used for data collection

Calibration of the tablet to determine forces was done and a conversion factor C was determined. An experiment using a graduated sequence of known weights was used to do the same.

$$C = \frac{P}{F} \qquad (2)$$

Equation (2) gives that conversion actor C for force applied by digitizer table stylus tip, where P is the intensity level measured by tablet (1024 Pressure levels) and F is the force (Newton) measured by the load cell. In our experiment it was found out that 1pressure intensity equaled 0.0023N.

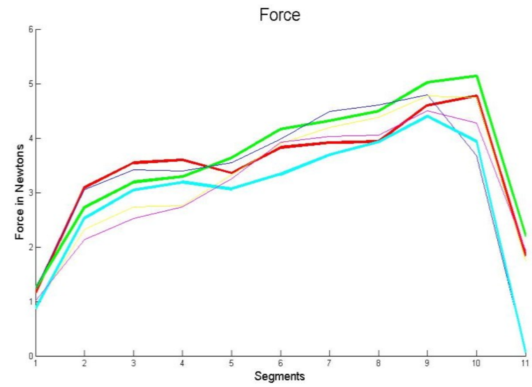


Figure 6. Force profile for letter S (six repetitive samples)

Cumulative Speed

The cumulative speed of writing Tamil character and English letter is depicted in Figure 3 (above). Each writing sample was segmented into 10 equal windows and the cumulative speed over windows was computed as the cumulative length of segments over total time. The fluency of writing was determined by comparing the consistency movement time profiles.

$$S_i = \frac{\sum_{i=0}^{n-1} |\overrightarrow{X}(t_{i+1}) - \overrightarrow{X}(t_i)|}{t_i} \qquad (3)$$

Here, S_i represents the cumulative speed, $\overrightarrow{X}(t_i)$ is the vector location of the pen tip at time t_i ,n is the number of segments of writing sample and t_i is the time stamp of the i^{th} segment. Equation (3) shows the cumulative speed by summation of speed in each i^{th} segment.

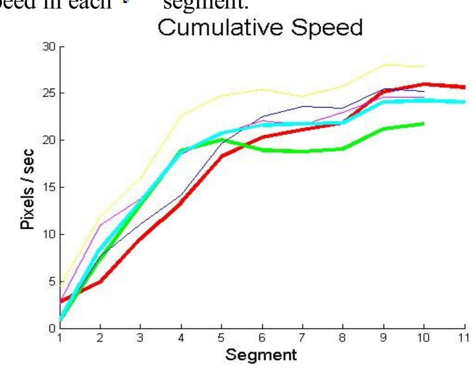


Figure 7. Cumulative Speed for Tamil character (six repetitive samples)

Based on graphical analysis of the force, position and speed plots consistent behavior and patterns within experts was observed.

III. RESULTS

Our primary goal of analyzing the data was to statistically test if the writing parameters (force, speed, position) were consistent across participants, for two different characters — the English letter "S" and a Tamil character. As discussed in the experiment section, the writing parameters of both the letters were extracted from two different sets of 11 experts. The data was normalized across the participants and was segmented into 10 time windows (the value of the writing parameter at every 10% of the total time to write the character). A three way ANOVA analysis was performed to test the consistency of the writing parameters against the independent variables of subject, time segment, trial (main effects), and their interactions, at a 95% confidence interval.

Results for the English character "S"

1) Main Effects

Table 1 summarizes the ANOVA main effects results run on the four writing parameters, between the variables – subject, segmented time, trial. The results indicate that all of the main effects were significant – thus rejecting the notion that handwriting parameters are consistent across participants, segments or trials. The mean values of speed, force and X, Y coordinates were not consistent among participants. This could be attributed to qualitative differences in learning and training. But, it is not surprising that the main effect of time segment is significant across the writing parameters (Figure 8). Across the time of writing the character, speed and force vary. For instance, speed tends to increase as the character is begun, but slows down towards the final time segments, when the character ends (Figure 8). A similar trend is observed with force (Figure 9). The application of force increases as the time segment increases, but finally slows down towards the end of the character. Similarly, it intuitively makes sense that X and Y positions are different at different time segments – the character "S" is not a straight line to hold similarity of positional coordinates. It is however interesting that all the parameters are different across the six trials. While the graph indicates differences across trials, there was no pattern that would suggest effects due to learning or fatigue as the trials progressed.

TABLE I. MAIN EFFECTS RESULTS FOR CHARACTER "S" WITH F STATISTICS

Parameter	Subject	Trial	Time Segment
Speed	149.08*	7.30*	170.97*
Force	317.75*	5.56*	539.58*
X	83.65*	43.60*	1192.39*
Y	*56.50**	*10.04**	1122.38*

2) Interaction Effects

The interaction effects between each of the three variables have also mostly yielded significant results (Table 2), showing significant participant x time segment, participant x trial, and trial x time segment interactions. These interactions suggest that participants' had different patterns of performance across time segments or trials. However, although there are inter-subject variations between most of the parameters, the overall pattern of each parameter's distribution is similar across subjects for different time segments (Figures 10). This suggests that although experts differ quantitatively in terms of the values of each handwriting parameter, the general trend of the parameters across time segments is qualitatively similar. Hence a mean value of each parameter within each time segment across subjects would yield us with a reasonable prototypical pattern of the distribution of expert parameters across time.

TABLE II. INTERACTION EFFECTS FORCHARACTER "S" WITH F STATISTICS

Parameter	Subject*Time Segment	Subject*Trial	Time Segment *Trial
Speed	4.49*	7.29*	1.15
Force	4.37*	5.64*	1.71*
X	11.73*	8.78*	1.88*
Y	18.87*	4.77*	0.91

TABLE III. MAIN EFFECTS RESULTS ON TAMIL CHARACTER WITH F STATISTICS

Parameter	Subject	Trial	Time Segment
Speed	324.10*	19.14*	728.58*
Force	2289.85*	18.52*	747.19*
X	259.45*	6.31*	851.95*
Y	6.43*	6.66*	337.95*

Results for the Tamil character

3) Main Effects

Table 3 summarizes the ANOVA main effects results run on the four writing parameters, between the variables – subject, segmented time, trial. The results obtained are very similar to the main effects on the English character "S". This lends more credence to the hypothesis that participants' handwriting attributes tend to differ across time segments and trials, regardless of the type of character/language. Also note that, in addition to the main effect of time segment being significant across the parameters (Figures 8, 9), the trend of speed and force increasing with progression in time segment, and finally tapering at the final segments of time, matches that of the English character. This is a positive indication of the potential similarity in trends of handwriting parameters across different types of characters. And similar to the English character, the Tamil letter is not a simple straight line and hence it makes that the X and Y positional coordinates vary at different time segments. Finally, while the parameters are significantly different across trials, there was no pattern that would indicate an effect of learning or fatigue.

4) Interaction Effects

Table 4 indicates the results of the interaction effects on the combination of the three variables run against the writing parameters. Similar to the results on the character "S", the interaction effects between participants across time segments and participants across trials have yielded significant results on all writing parameters. Thus it reinforces the result that among different experts', writing parameters significantly differ within each time segment and within each trial. However, some parameters seem to be consistent across time segments, with each trial. The character "S" had two such instances, in this case three parameters – force, X and Y positional coordinates are similar. This seems to imply that within each trial, the force and shape (X and Y coordinates) of the character show a consistent pattern with progression of time segments.

TABLE IV. INTERACTION RESULTS ON TAMIL CHARACTER S WITH F STATISTICS

Parameter	Subject*Time Segment	Subject*Trial	Time Segment *Trial
Speed	28.72*	17.49*	1.43*
Force	35.77*	5.72*	1.23
X	12.04*	4.65*	0.88
Y	6.56*	4.16*	1.19

Finally, despite the inter-subject variations between the parameters, the general trend of the parameters' distribution across different time segments is similar (Figures 11, 13). Therefore, it is reasonable to plot a prototypical distribution of expert parameters across time, similar to the English letter.

IV. IMPLICATIONS/DICUSSION

Handwriting is a fine motor-skill that goes through three stages of learning — 1) initial skill acquisition, 2) skill compilation and 3) automaticity [9], [10]. The participants analyzed in this paper are experts operating at the skill level of automaticity, i.e., their writing is through smooth integration of their motor skills, without conscious attention or control [7]. This autonomous motor behavior is evident from the results; despite differences in the quantitative variations of the mean values of the writing parameters, the general qualitative pattern of the distribution is the same across all the participants. For the sake of brevity, we have presented the results of only two randomly selected characters in this paper, but the original study collected data on 14 different characters and the results and trends in the data was similar. This is indicative of the similarity of the motor program employed by all the experts without attributing conscious control. Therefore it implies that experts use a similar strategy for writing the characters. If the graphs showed no patters or trends it would have suggested not just quantitative differences in parameters but also employed different writing strategies. From the results, it is evident that this similarity in trends is present in two different scripts written by two different sets of experts, thus lending credence to validity of the results.

This generic pattern of the handwriting parameters for the different characters can be used as evaluation criteria while training novices, since the prototypical trends define expert behavior in each of the handwriting parameters. Novices will go through the initial stage of skill acquisition by viewing the script of a language as a diagram to be replicated. Hence they are likely to follow declarative production rules with a heavy reliance on working memory to write the script [7]. With lack of autonomous, trained motor behavior, the differences in the trainees' handwriting parameters and the overall trend of the distribution are expected to be markedly different from the model of the experts'. As the training of the novices' progress, we expect the distribution of the trainees' writing parameters to follow a trend similar to the shape of the experts'. We believe that this principle can be extended to other manual skills requiring motor control and not just be restricted to handwriting.

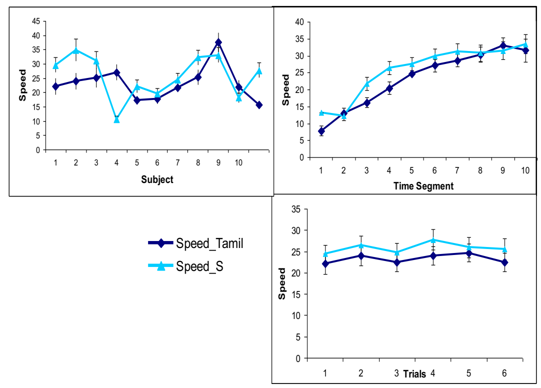


Figure 8. Main Effects plots on speed for Tamil character and English letter

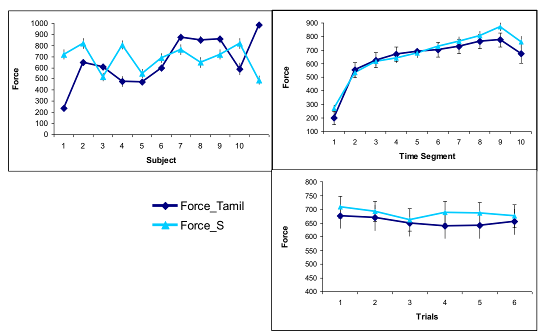


Figure 9. Main Effects plots on force for Tamil character and English letter

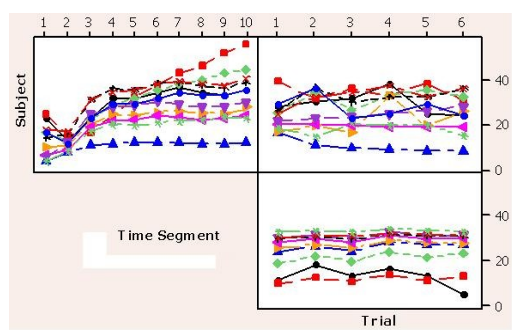


Figure 10. Interaction plots on Speed for letter S

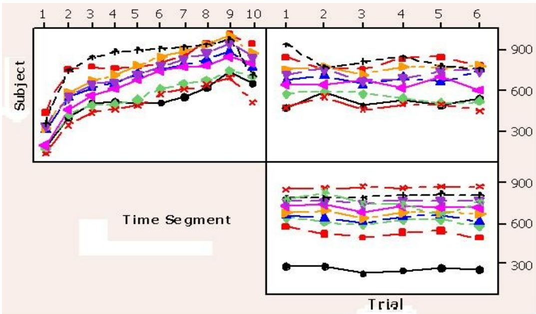


Figure 11. Interaction plots on Force for letter S

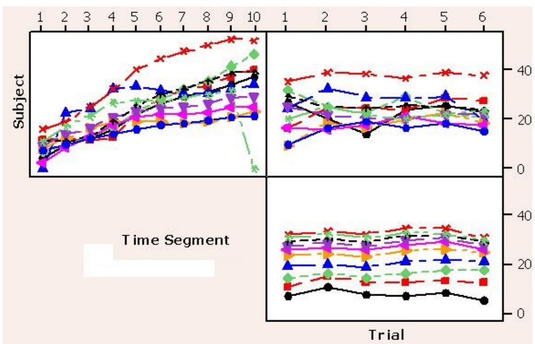


Figure 12. Interaction plots on Speed for Tamil character

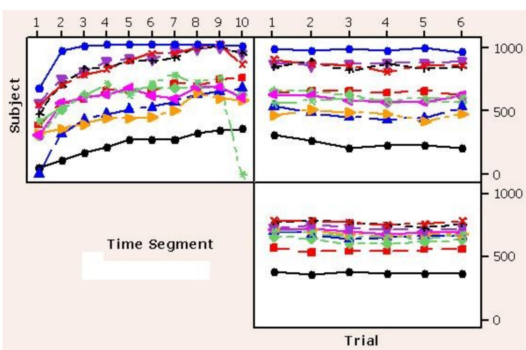


Figure 13. :Interaction plots on Force for Tamil character

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