WILL YOUR PERFORMANCE BE IMPROVED BY A CUSTOMIZED HAPTIC ASSISTANCE? CHECK THE TEMPOROSPATIAL CHARACTERISTICS OUT!

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INTRODUCTION

In haptic assistive/shared control, various approaches to adapting haptic assistance level to user's skill level have been presented. However, most approaches, e.g., shared-control proxy model [1], assistance policy module [2], and haptic error field [3], did not facilitate the customization of the haptic assistive control that can adjust the assistance level based on both expert's strategy and user performance. To address this problem, we present an approach to customizing haptic assistance utilizing expert's strategy as well as user performance in [4] [5].

Although there have been ample considerations about adjusting assistance level, the efficacy of these methods on user performance has still remained inconclusive. Even when the assistance was customized based on various user characteristics, the improvements of user performance were not always observed explicitly [1] [5]. In this study, we propose an approach to predicting the potential improvement of user performance under a customized haptic assistance for each user. Specifically, we claim that user's temporal and spatial characteristics measured when no haptic assistance was provided would determine whether or not the user performance will enhance when customized haptic assistance for the user is provided. A relationship between the proposed metrics and performance improvement is defined and validated via using machine learning techniques.

METHODS

Thirty nine young adults (31 male and 8 female, age=20-35 yrs) who regularly play a video game (at least once a week) participated in this study. We developed a driving simulator of a power-wheelchair using Unity3D (Unity Technologies, San Francisco, CA) since we considered the driving simulator as a good target application for rehabilitation. Subjects were seated at the virtual power-wheelchair simulator platform which provides visual display and force feedback by a 50 inch monitor screen and a 2D haptic interface, respectively (For more information see [4]). The subjects were given tasks in which they drive a virtual power-wheelchair as fast and safe as possible while monitoring the visual display under various scenarios. Each scenario provides a road with different curvatures and obstacles. All subjects gave informed consent prior to their participation and this research was proved by the University Institutional Review Board.

The experiment consisted of two separate sessions. During the first session, no force feedback was applied to the subjects' hand by the haptic joystick while the virtual power-wheelchair was being controlled. After the first session, each subject's driving strategy was analyzed and represented by three parameters that describe 1) the curvature of the generated path, 2) its proximity to boundaries, and 3) the ratio between control effort and boundary collision avoidance. Then, haptic assistance was customized for each user based on three parameters that characterize their behaviors (For detailed explanation of our haptic assistance customization, please refer to [4] [5]). The second session was performed a week apart from the first session, and the customized haptic assistance was applied. For both sessions, there were four scenarios, and each scenario (road curvature and obstacle) was repeated three times. The sequence of presented scenario was randomized. The virtual wheelchair's (x, y) position, heading direction, and task-completion time were recorded from the start line to the finish line. Sampling frequency was 60Hz.

After completing the two experimental sessions, the subjects' performances in both sessions, under no assistance and the customized haptic assistance, were examined in terms of variability that was computed as the summed standard deviation of mean completion time of each scenario, $\sum_{i=1}^{4}(\mathrm{std}(\mathrm{mean}(\sum_{j=1}^{3} T_{i,j})))$ where i and j are indices for scenario and repetition. Then, we examined those subjects whose performance (i.e., variability) was improved when the customized

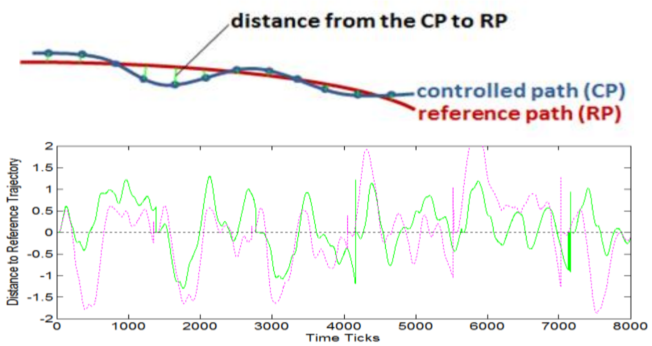

Figure 1: DFA example. Top: Controlled path (CP), reference path (RP), and distance from the CP and RP. Bottom: The reference path is employed as a baseline, and the distances from the reference path under no-assistance (magenta-dotted) and the customized haptic (green-solid) are depicted.

haptic assistance was applied. For the improved subjects, the temporal (time) and the spatial (geometric) characteristics of power-wheelchair path during the first session were expressed by two metrics: the designed *variability* and *Hurst exponent* obtained from detrended fluctuation analysis (DFA). Hurst exponent was utilized as the metric to tell us how well the controlled power-wheelchair path followed the reference trajectory since it represents the slow/fast varying characteristic of time course data [6] (see Fig. 1). Consequently, each subject was associated with two metrics as the following format: *subject#*{V, H} where V and H represent variability and Hurst exponent value, respectively, from the first session.

With the associated two metrics above, a *performance improvement predictor (PIP) function*, denoted by f_{PIP}, could be defined by the following steps. First, among the subjects, 80% of the subjects' metric data were randomly selected as a training set, and the other 20% as a test set. Second, the distribution of improved subjects, $\varphi(H)$, along with H was estimated by a kernel density estimation. Third, logistic sigmoid function, $\sigma(V)$, was trained so that it could classify improved/non-improved subjects with V. Finally, f_{PIP} was defined by

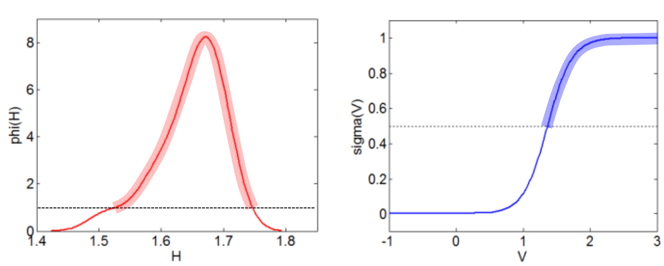

Figure 2: Example of the estimated $\varphi(H)$ and trained $\sigma(V)$. Shaded regions are related to a prediction for improvement.

$$f_{PIP}(\varphi(H), \sigma(V)) = \begin{cases} \text{yes}, & \text{if } \varphi(H) \geq 1 \text{ and } \sigma(V) \geq 0.5 \\ \text{no}, & \text{oherwise} \end{cases}$$

Figure 2 shows an example of $\varphi(H)$ and $\sigma(V)$ functions. The estimation of $\varphi(H)$ and the training of $\sigma(V)$ were repeated 100 times. The evaluation result of f_{PIP} with the test set will be presented in the next section.

RESULTS AND DISCUSSION

To validate the defined f_{PIP}, the evaluation result is presented in terms of Youden's index [7], J, which is defined by J = *sensitivity* + *specificity* – 1. Hence, the maximum J is 1. Figure 3 shows J values obtained from the 100 evaluations of f_{PIP}. The average J is 0.803 meaning the f_{PIP} has 80.3% of accuracy in average. Also, the further investigation on H and V value revealed that the subjects whose $V \geq 1.4$ and $1.55 \leq H \leq 1.72$ have the greater probability of performance improvement under the customized haptic assistance.

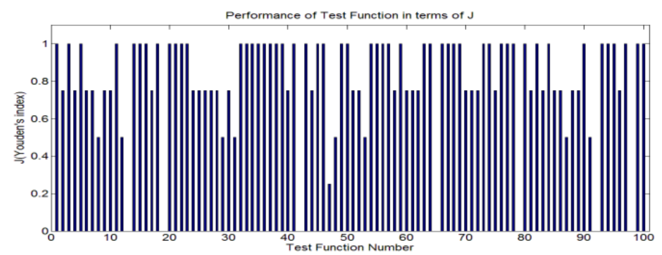

Figure 3: Youden's index J resulted from 100 evaluations of f_{PIP}. The average is 0.803.

CONCLUSION

User's performance improvement under customized haptic assistance could be predicted by investigating the temporospatial characteristics of controlled object trajectory. Further research should be followed in ways of comparing the predicted user performance improvement to actual performance improvement.

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