Workshop on Robotic Co-workers 4.0: Human Safety and Comfort in Human-Robot Interactive Social Environments
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Human-Aware Robot Navigation by Behavioral Metrics Based on Predictive Model*

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***Abstract*— Human-aware robot navigation is very important in many applications in human-robot shared environments. There are some situations, people have to move with less visual and auditory perceptions. In that case, the robot can help to enhance the efficiency of navigation when moving in noisy and low visibility conditions. In that scenario, haptic is the best way to communicate when other modalities are less reliable. We used a rein to guide a human when 1-DoF robotic arm can perturb the humans' arm to guide into a desired point. The novelty of our work is presenting behavioral metrics based on novel predictive model to strategically position the humans in human-robot shared environment in low visibly and auditory conditions. We found that humans start with a second order reactive autoregressive following model and changes it to a predictive model with training. This result would help us to enhance humans' safety and comfort in robot leading navigation in shared environment.**

I. INTRODUCTION

Human-aware robot navigation has been studied in many years when visual and auditory perception are limited [1], [2], [3]. In that situation, human safety and comfort in human-robot shared environment must be well understood. Moreover, real time control parameters and algorithms would help us to make safe and comfort environment. There have been many studies in human-aware and context-aware navigation when the vision and audition are impaired recently [4], [5]. However, most of them lacking in managing/controlling parameters and algorithm in real time. In addition to navigation algorithm/techniques, it is important to understand the interplay between humans' muscle activity and haptic perception to make humans comfort when human arm is perturbed in haptic-based navigation. In this workshop paper, we presented behavioral metrics such as Rise Time (RT), the model order (N), and Steady State Variability (SSV) combined with Electromyography (EMG) data in eight arm muscles to understand humans' behavior and muscle activation in human-aware robot navigation in shared environment.

We have modelled humans' control policy when a human is guided by an intelligent agent (man/machine) in our previous human demonstration experiments (in Fig. 1A) [6], [7], [8] as shown in Eq. 1. We have found out the guiding agent (robot in navigation) gives more emphasis on 2^{nd} order predictive model [6], [7]. In this study, we implemented it on a planar 1-DoF robotic arm as shown in Fig. 1B to understand humans' safety and comfort in haptic-based guiding.

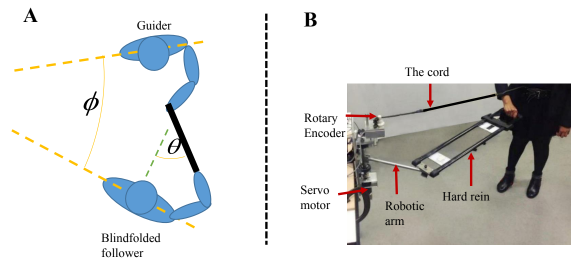

Fig. 1. Experimental set up, A) Human-human demonstration in haptic-based guiding in our previous studies [6], [7], B) The guiding policy, extracted from human demonstrations in Eq. 1 was implemented on the planar 1-DoF robotic arm. The cord was attached to the waist belt of the blindfolded subjects and the encoder on the robot to measure the relative error between the human and the motor shaft (ϕ).

in human-aware robot guiding, if it is a reactive controller,

$$\phi_f(k) = \sum_{r=0}^{N-1} a_r^{fRe}\theta_f(k-r) + c^{fRe} \quad (1)$$

where, the state is ϕ and the action is θ. ϕ is the orientation difference between the guider and the follower and θ is angle of the rein relative to the agent in Fig. 1A, k denotes the sampling step, N is the order of the polynomial, $a_r^{Re}, r = 0, 1, 2, \cdots, N-1$ is the polynomial coefficient corresponding to the r-th state in the reactive and predictive model respectively, and c^{Re}, are corresponding scalars. These linear controllers can be regressed with the experimental data obtained the R^2 values (coefficient of determination). The behavior of these coefficients for all human subjects across the learning trials will give us useful insights as to the predictive/reactive nature of the control policy. First, Eq. 1 was regressed to find the Coefficients of Eq. 1 for reaching six desired angles ($\pm 65°$, $\pm 45°$, and $\pm 25°$).

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II. Experimental Methodology

The schematic diagram of replication of human-human experiments in our previous studies [6], [7], [8] in Fig. 1A was replicated by human-robot physical experimental setup as shown in Fig. 1B. In Fig. 1B, the guider's arm was replaced by planar 1-DoF robotic arm to generate the swing arm action in horizontal plane. The cord was attached to the waist belt of the blindfolded subject and the encoder on the robot arm to measure the error between the human and the desired position (ϕ). The planar robot arm shaft was driven by a Maxon EC60 (ϕ) mm brush less 400 Watt with Hall sensors motor. An EPOS2 50/5 digital position controller was used to control the motor. Here, NI LabVIEW 2009 was used for programming and communicating with other hardware devices to control the robotic arm. The joint between the robotic arm and the hard rein was a passive joint to behave like a guider's arm in human-human interaction experiments in Fig. 1A. The other end of the hard rein was held by the human as shown in Fig. 1B. The experimental protocol was approved by the King's College London Biomedical Sciences, Medicine, Dentistry and Natural & Mathematical Sciences research ethics committee.

Moreover, before starting the experimental trials, subjects were trained to give an idea to move proportional to the given tug force. For the training, the desired angles were chosen different from experimental angles such as $-10°, -20°, -30°, +10°, +20°$, and $+30°$.

During the experiment, eight (4-male, 4-female) naive and ten (4-male, 4-female) trained right-handed subjects participated in the experiment after giving informed consent for the experiment. They were healthy and in the age group of 21 - 30 years. Subjects were instructed to move proportional to the force they felt and to the direction of the tug force. Here, the guider's control policy from human demonstration [6], [7], [8] was imported to compute the action command from the robotic arm. Once the trial was started, the encoder read instantaneous error of the follower's position relation to a desired angle (ϕ). Then the robotic arm computed the commands to minimize the following error between the human subject and the robotic arm.

Furthermore, five naive subjects (2-male, 3-female) and ten (4-male, 4-female) trained subjects' surface EMGs were recorded by using the EMG (Noraxon, USA) sensors. The was to study humans' arm muscle responses when the subject's arm is perturbed from leftward/rightward directions. For simplicity, $-45°$ and $+45°$ were taken as the desired angular positions and the subject's most dominant arm was perturbed by a single tug to study arm muscles actuation immediately after the arm perturbation.

III. Results

It would be interesting to test the subjects' model order and the nature in human-robot shared environments. In our previous experiments [9], [7], it was found that on average

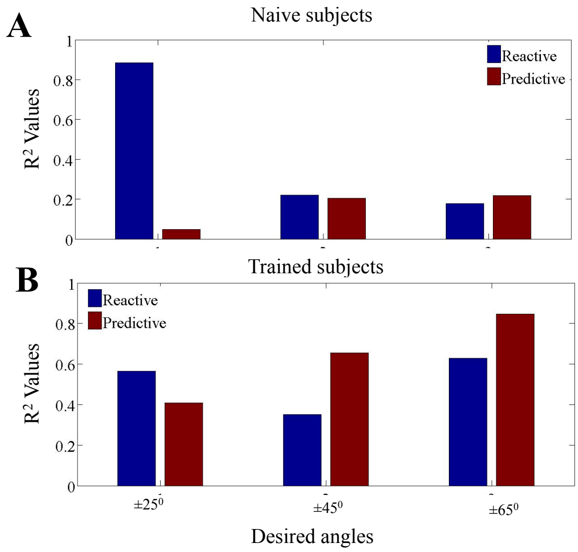

Fig. 2. Experiment 1: Reactive and predictive model nature (reactive/predictive) in reaching desired angles of $\pm65°$, $\pm45°$, and $\pm25°$:A) Average R^2 for naive subjects' model nature, and B) Average R^2 for trained subjects' model nature.

the naive follower used a 2^{nd} order reactive model. Here, our aim is to find out whether this would change with training for the same guiding control algorithm.

To test that, the gradient of R^2 values of reactive and predictive models in reaching $\pm65°$, $\pm45°$, and $\pm25°$ desired angles over trials were tested. Polyfit in Polynomial curve fitting (MATLAB 2014a) was used to fit the linear curves to find the gradients. On average the positive trend in reactive model in naive subjects shows that, naive subjects emphasize more on reactive than predictive following behaviors. However, after training the positive gradient for predictive model shows that trained subjects give more emphasis on predictive nature than reactive. Moreover, by selecting reactive/predictive nature, we summarize the model nature in reaching $\pm65°$, $\pm45°$, and $\pm25°$ desired angles for naive and trained in Fig. 2A and Fig. 2B respectively. Both naive and trained subjects have mixed reactive and predictive nature in reaching desired angles as shown in Fig. 2. However, naive subjects have more dominant reactive nature as shown in Fig. 2A. Interestingly trained subjects' most dominant model nature is predictive as shown in Fig. 2B. The results show that the predictive nature is more dominant than reactive after training. This model nature in human-aware robot navigation can be taken into account designing algorithms in navigation.

Next, we have tested behavioral matrices RT, N, and SSV in reaching six desired angles for naive and trained subjects. We moved to test whether there is a behavioral symmetry in moving leftward and rightward directions after arm perturbation in RT, N, and SSV [10]. The ratio in moving leftward/rightward directions in reaching desired angles for RT, N, and SSV were taken. Our argument is, if the subjects move leftward and rightward symmetrically, the ratio ≈ 1. However, none of the values in RT, N, and SSV are equal to 1.

Since the distributions of behavioral metrics are not symmetric, one tailed t-test was performed to test whether there is a statistically significant difference between the distributions of each metric in leftward vs rightward movements. We used a significance level of $P = 0.05$. However, significance values show that the asymmetry in moving leftward/ rightward directions.

After that, we moved to understand to test whether the asymmetry of perception noticed in behavioral metrics come from different activation of muscles in leftward and rightward arm perturbation, based on the hypothesis that haptic perception depends on how muscles are activated by restoring reflex after the perturbation. The results show that on average the muscle activation is significantly different just after the leftward/rightward arm perturbations. Therefore, the results confirm that asymmetry in behavioral metrics could accompany difference in muscle activation in EMG. Therefore, we conclude that humans' muscle activation and perception are coupled in haptic-based navigation.

IV. Discussion

This workshop paper presents an overview of haptic-based guiding in human-aware robotic navigation in uncertain environments. We presented the model nature changes of the human after training in robotic guiding. Moreover, we showed behavior metrics that can be used to understand humans' movement symmetry in real time. Experimental results show that the subjects develop a predictive behavior accompanied by a reduction in muscle co-contraction with training. These findings provide a valuable basis to design training protocols for robot assisted guiding in shared environments. In our previous studies in [8], we have found out humans' trust on robot can be modelled by voluntry dynamics using a virtual damped inertial model. Therefore, our findings in [8], [10], [9] and [7] would be combined to design safety and comfort human-aware robot navigation in low visual and auditory perceptions. Moreover, monitoring behavioral metric index in real time would give us an idea how those could be varied in navigation algorithms to enhance humans' safety and comfort. The behavioral metrics presented in this paper to quantify the effect of model based predictive controllers will also provide a new basis to monitor the quality of training in a human-robot interactions in shared environment.

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