A Two Party Haptic Guidance Controller Via a Hard Rein

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***Abstract*— In the case of human intervention in disaster response operations like indoor firefighting, where the environment perception is limited due to thick smoke, noise in the oxygen masks and clutter, not only limit the environmental perception of the human responders, but also causes distress. An intelligent agent (man/machine) with full environment perceptual capabilities is an alternative to enhance navigation in such unfavorable environments. Since haptic communication is the least affected mode of communication in such cases, we consider human demonstrations to use a hard rein to guide blindfolded followers with auditory distraction to be a good paradigm to extract salient features of guiding using hard reins. Based on numerical simulations and experimental systems identification based on demonstrations from eight pairs of human subjects, we show that, the relationship between the orientation difference between the follower and the guider, and the lateral swing patterns of the hard rein by the guider can be explained by a novel 3rd order auto regressive predictive controller. Moreover, by modeling the two party voluntary movement dynamics using a virtual damped inertial model, we were able to model the mutual trust between two parties. In the future, the novel controller extracted based on human demonstrations can be tested on a human-robot interaction scenario to guide a visually impaired person in various applications like fire fighting, search and rescue, medical surgery, etc.**

I. INTRODUCTION

The need for advanced Human Robot Interaction (HRI) algorithms that are responsive to real time variations in the physical and psychological states in a human counterpart in an uncalibrated environment has been felt in many applications like fire-fighting, disaster response, and search and rescue operations [1]. There have been some studies on guiding people with visual and auditory impairments using intelligent agents in cases such as indoor fire fighting [2] and guiding blind people using guide dogs [3]. In the case of indoor fire fighting, fire fighters have to work in low visibility conditions due to smoke or dust and high auditory distractions due to their Oxygen masks and other sounds in a typical firefighting environment. In the case of warehouse firefighting, it has been reported that, they depend on touch sensation of walls for localizing and ropes for finding the direction [2]. In [2], the authors propose a swarm robotic approach with ad-hoc network communication to direct the fire fighters. The main disadvantage of this approach is lack of bi-directional communication to estimate the behavioral and psychological state of the firefighters. Personal navigation system using Global Positioning System (GPS) and magnetic sensors were used to guide blind people by Marston [3]. One major drawback with this approach is, upon arriving at a decision making point, the user has to depend on gesture based visual communication with the navigation support system, which may not work in low visibility conditions. Moreover, the acoustic signals used by the navigation support system may not suit noisy environments.

Another robot called Rovi, with environment perception capability has been developed to replace a guide dog [4]. Rovi had digital encoders based on retro-reflective type infra red light that recorded errors with ambient light changes. Though Rovi could avoid obstacles and reach a target on a smooth indoor floor, it suffers from disadvantages in uncertain environments. An auditory navigation support system for the blind is discussed in [5], where, visually impaired human subjects (blind folded subjects) were given verbal commands by a speech synthesizer. However, speech synthesis is not a good choice to command a visually impaired person in a noisy situation with ground distractions like a real fire. A guide cane without acoustic feedback was developed by Ulrich in 2001 [6]. The guide cane analyzes the situation and determines appropriate direction to avoid the obstacle, and steers the wheels without requiring any conscious effort [6]. Perhaps the most serious disadvantage of this study is that it does not take feedback from the visually impaired follower. To the best of our knowledge, there has been no detailed characterization of the bi-directional communication for guiding the person with a limited perception in a hazard environment.

Any robotic assistant to a person with limited perception of the environment should monitor the level of confidence of mutual trust of the person in the robot for it to be relevant to the psychological context of the person being assisted. In a simulated game of fire-fighting, Stormont *et al* [7] showed that the fire-fighters become increasingly dependent upon robotic agents when the fire starts to spread along randomly changing wind directions. Freedy [8] has discussed how self confidence correlates with trust of automation in human robot collaboration. However, so far, there has been little discussion about mutual trust in the context of cooperative navigation in unstructured environments. The paper attempts to show that an optimal closed loop controller can be constructed by combining the mutual trust and the difference

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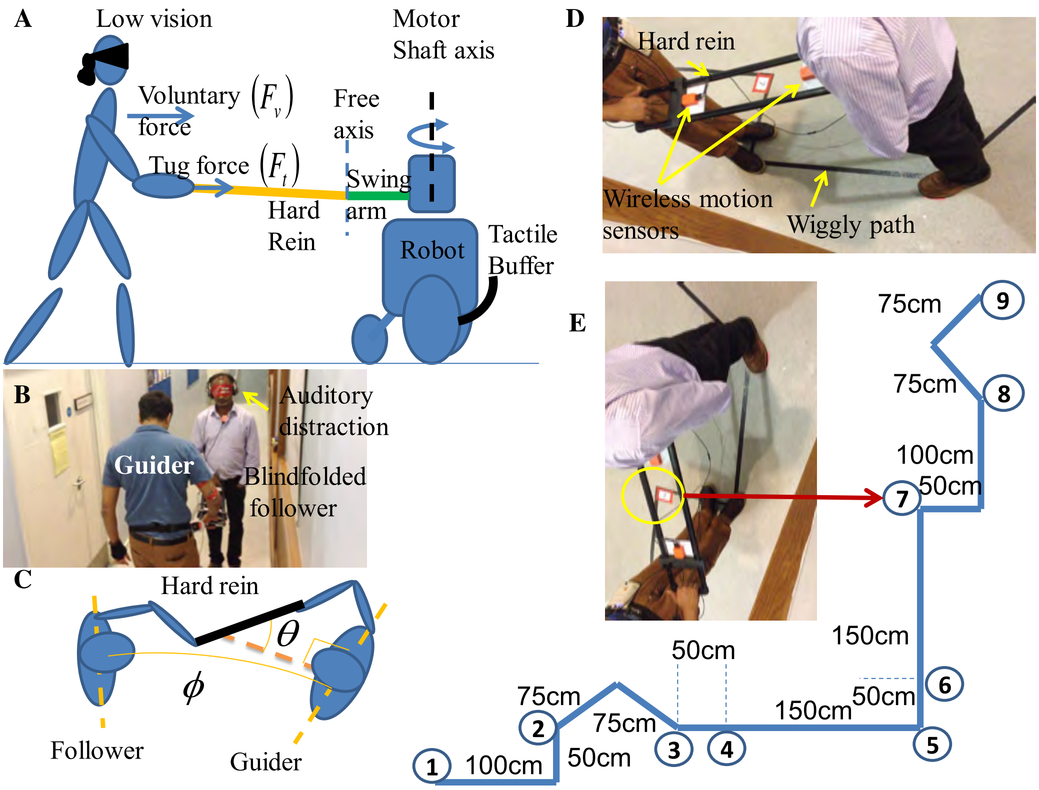

Fig. 1. A) Anticipated scenario of a human with visual impairment being guided by a robot. The mutual trust is high if the voluntary force (F_v) is much greater than the tug force (F_t), B) Tracking the path by human pair, C) The hard rein with wireless MTx motion sensors attached to measure the difference of heading direction ϕ and the action θ, D) The hard rein with wireless MTx motion trackers. pushing/pulling in horizontal plane to guide the follower, E) The detailed diagram of labeled wiggly path on a floor.

of heading directions of the two parties to generate corrective actions to guide the follower.

Recently studies have been conducted on complementary task specialization [9] between a human-human pair and a human-robot pair to achieve a cooperative goal. They suggested that complementary task specialization develops between the human-human haptic negotiation process but not in the human-robot haptic interaction process [10]. This indicates that there are subtle features that should be quantified in the closed loop haptic interaction process between a human pair in task sharing. Therefore, characterization of human-human interaction in a haptic communication scenario, where one human subject is blindfolded (limited perception of the environment) while the other human subject has full perceptual capabilities, can provide a viable basis to design optimal human-robot interaction algorithms to serve humans working in many hazardous/uncertain environments.

It is very important to understand the mathematical properties of closed loop haptic guidance that would in turn shed light on optimal robotic guidance of humans in low visibility conditions in a hazard or uncertain environments. Therefore, to the best of our knowledge, this is the first paper to characterize the closed loop state dependent haptic signaling policy of an agent with full perception capabilities to take a following human in an arbitrary path.

The rest of the paper is organized as follows: Section II elaborates the experimental methodology to collect data of human-human interaction via a hard rein while tracking an arbitrary path. Section III describes the mathematical model of the guider's control policy in detail. Section IV gives the experimental results of human subjects along with numerical simulation results to show the stability of the control policy identified through experiments on human subjects. It also discusses the virtual time varying damped inertial model to estimate the mutual trust between the visually and auditory limited follower and the guider. Finally, section V gives conclusions and future research directions.

II. Experimental Methodology

Fig. 1(B) shows how the guider and the follower held both ends of a hard rein to track the wiggly path. We conducted two separate experiments to understand: 1) The guider's control policy in an arbitrary complex path, 2) The coefficients of the follower's time varying virtual damped inertial system over different paths.

In the first experiment, eight pairs of subjects participated in the experiment after giving informed consent. They were healthy and in the age group of 23 - 43 years. One of the

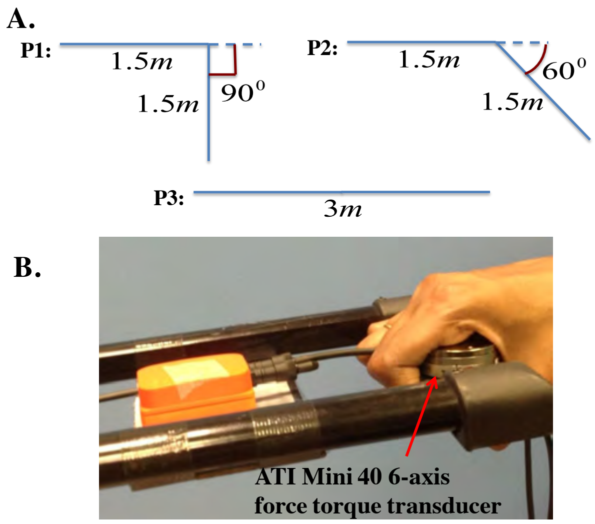

Fig. 2. A. The three different paths used to study mutual trust between the guider and the follower - P1: 90° turn, P2: 60° turn, and P3: Straight path, B. In this experiment, additional ATI Mini 40 6-axis force torque transducer sampled at 1000Hz was attached to the hard rein to measure pushing/pulling force .

subjects (an agent with full perceptual capabilities) lead the other (a person with limited visual and auditory perceptions) using a hard rein as shown in Fig. 1(C). Visual feedback to the follower was cut off by blindfolding, while the auditory feedback was cut off by playing a sound track of less than 70dB as shown in Fig. 1(B). Fig. 1(C) shows the relative orientation difference between the guider and the follower (ϕ). Two MTx sensors were attached on the chest of the guider and the follower to measure the rate of change of the orientation difference between them (error of following). The angle of the rein relative to the agent (θ) was taken as an action. A MTx motion tracker was mounted on the hard rein to measure θ. MTx motion capture sensors (3-axis acceleration, 3-axis magnetic field strengths, 3-axis Gyroscope readings - roll, pitch, yaw) were used to measure the orientation difference ϕ and actions θ. We sampled data from the MTx sensors at 25Hz to stay within hardware design limits. For clarity, the detailed wiggly path is shown in Fig. 1(E). The path of total length 9m was divided into nine milestones as shown in Fig. 1(E).

In any given trial, the guider was asked to take the follower from one milestone to another at six milestones up or down (ex. 1-7, 2-8, 3-9, 9-3, 8-2, and 7-1). The starting milestone was pseudo-randomly changed from trial to trial in order to eliminate the effect of any memory of the path. Moreover, the follower's initial direction was randomly started. At the end of the experiment subjects confirmed that they did not have any clue of the initial orientation or location. The guider was instructed to move the handle of the hard rein only on the horizontal plane to generate left and right turn commands. Furthermore, the guider was instructed to use push and pull commands for forwards and backwards movements. The follower was instructed to pay attention to the commands via hard rein to follow the guider. The follower started to follow the guider once a gentle tug was given via the rein.

A second experiment was conducted to study the mutual trust between the guider and the follower through 10 trials each for three different paths as shown in Fig. 2 (A). An ATI Mini 40 6-axis force torque transducer was attached to the hard rein to measure resistive force felt at the guider's end (tug force) sampled at 1000Hz along the horizontal plane to guide the follower as shown in Fig. 2 (B). The acceleration of the follower was measured by MTx sensors as shown in Fig. 1(B).

The experimental protocol was approved by the King's College London Biomedical Sciences, Medicine, Dentistry and Natural & Mathematical Sciences research ethics committee.

III. Modeling

A. The guider's closed loop control policy

We model the guider's control policy as an N-th order discrete linear controller. The order N depends on the number of past states used to calculate the current action.

Let the state be the relative orientation between the guider and the follower given by ϕ, and the action be the angle of the rein relative to the sensor on the chest of the guider given by θ as shown in Fig. 1(C).

Then the linear discrete control policy of the guider is given by

$$\theta(k) = \sum_{r=0}^{N-1} a_r^{Re} \phi(k-r) + c^{Re} \tag{1}$$

if it is a reactive controller, and

$$\theta(k) = \sum_{r=0}^{N-1} a_r^{Pre} \phi(k+r) + c^{Pre} \tag{2}$$

if it is a predictive controller, where, k denotes the sampling step, N is the order of the polynomial, $a_r^{Re}, a_r^{Pre}, r = 0,1,2,\cdots,N-1$ is the polynomial coefficient corresponding to the r-th state in the reactive and predictive model respectively, and c^{Re}, c^{Pre} are corresponding scalars. These linear controllers can be regressed with the experimental data obtained in the guider-follower experiments above to obtain the behavior of the polynomial coefficients across trials. The behavior of these coefficients for all human subjects across the learning trials will give us useful insights as to the predictive/reactive nature, variability, and stability of the control policy learned by human guiders. Furthermore, a linear control policy given in equations 1 and 2 would make it easy to transfer the fully learned control policy to a robotic guider in a low visibility condition.

B. Virtual time varying damped inertial system reflecting mutual trust

In order to study how the above control policy would interact with the follower in an arbitrary path tracking task, we model the voluntary movement of the blindfolded human

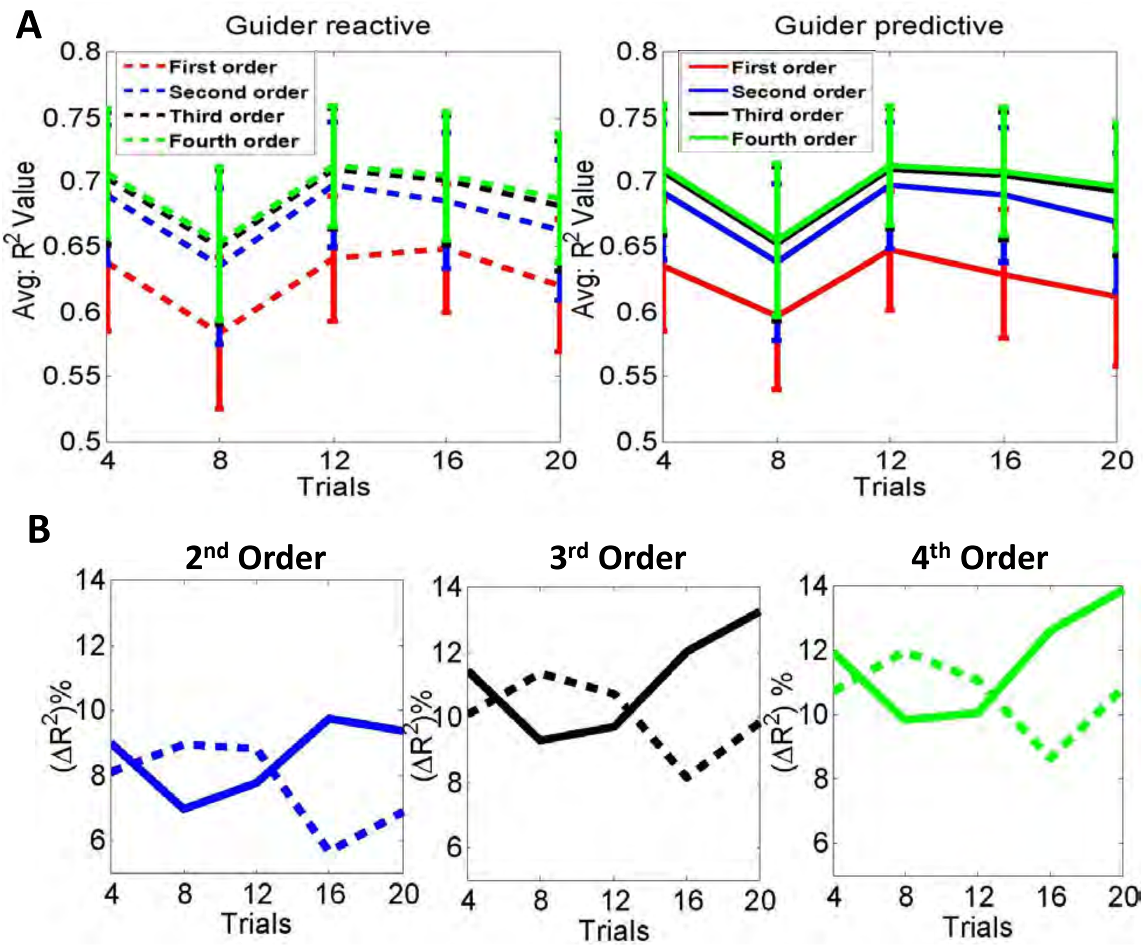

Fig. 3. Control policy model orders over the guider reactive (dashed line) and predictive (solid line): (A) The R^2 value variation of the guider reactive and predictive from 1^{st} to 4^{th} order polynomials over trials. (B) The % differences of R^2 values of 2^{nd} to 4^{th} order polynomials with respect to 1^{st} order polynomial: 2^{nd} order (blue), 3^{rd} order (black), 4^{th} order (green). Dashed line for the guider reactive and solid line for the guider predictive.

subject (follower) as a damped inertial system, where a force $F(k)$ applied along the follower's heading direction at sampling step k would result in a transition of position given by $F(k) = M\ddot{P}_f(k) + \zeta\dot{P}_f(k)$, where M is the virtual mass, P_f is the position vector in the horizontal plane, and ζ is the virtual damping coefficient. It should be noted that the virtual mass and damping coefficients are not those real coefficients of the follower's stationary body, but the mass and damping coefficients felt by the guider while the duo is in voluntary movement. This dynamic equation can be approximated by a discrete state-space equation given by

$$x(k) = Ax(k-1) + Bu(k) \tag{3}$$

where , $x(k) = \begin{bmatrix} P_f(k) \\ P_f(k-1) \end{bmatrix}$, $x(k-1) = \begin{bmatrix} P_f(k-1) \\ P_f(k-2) \end{bmatrix}$, $A = \begin{bmatrix} (2M+T\zeta)/(M+T\zeta) & -M/(M+T\zeta) \\ 1 & 0 \end{bmatrix}$,

B = $\begin{bmatrix} T^2/(M+T\zeta) \\ 0 \end{bmatrix}$, $u(k) = F(k)$,

k is the sampling step and T is the sampling time.

Given the updated position of the follower $P_f(k)$, the new position of the guider $P_g(k)$ can be easily calculated by imposing the constraint $\|P_f(k) - P_g(k)\| = L$, where L is the length of the hard rein. Our intension is to incorporate the instantaneous mutual trust level between the follower and the guider in the state-space of the closed loop controller. Here, we suspect that the mutual trust in any given context should be reflected in the compliance of his/her voluntary movements to follow the instructions of the guider. By modeling the impedance of the voluntary movement of the follower using a time varying virtual damped inertial system, we observe the variability of the impedance parameters - virtual mass and damping coefficients - in paths with different complexities (context). The three paths are shown in Fig. 2.

IV. Experimental results

A. Determination of the salient features of the g control policy

We conducted experiments with human subjects derstand how the coefficients of the control policy r difference of heading directions ϕ and action θ gi equations 1 and 2 settle down across learning trials. I to have a deeper insight into how the coefficients discrete linear controller in equations 1 and 2 change learning trials, we ask 1) whether the guider and the fo tend to learn predictive/reactive controller across tr whether the order of the control policy in equations 1 change over trials, and if so, 3) what its steady stat would be.

First, we used experimental data for action θ a ference of heading directions ϕ in equations 1 an find regression coefficients. Since the raw motion da contaminated with noise, we use the 4th decompositic of Daubechies wave family in Wavelet Toolbox (Th Works, Inc) for the profiles of θ and ϕ, for reg analysis. Since the guider generates swinging actions in the horizontal plane, the Daubechies wave family best suits such continuous swing movements [11].

To select best fit policies, coefficients of (Eqs. (1) and (2)) were estimated from 1st order to 4th order polynomials shown in Fig. 3 (A). Dashed line and solid line were used to denote reactive and predictive models respectively. From binned trials in Fig. 3 (A), we can notice that the R^2 values (percentage of variability of the dependent variability explained by the model) corresponding to the 1st order model in both Eqs. (1) and (2) are the lowest. The relatively high R^2 values of the higher order models suggest that the control policy is of order > 1. Therefore, we take the percentage (%) differences of R^2 values of higher order polynomials relative to the 1st order polynomial for both Eqs. (1) and (2) to assess the fitness of the predictive control policy given in Eq. (2) relative to the reactive policy given in Eq. (1). Fig. 3 (B) shows that the marginal percentage (%) gain in R^2 value (%$\triangle$R^2) of 2nd, 3rd, and 4th order polynomials in Eq. (2) predictive control policy, (solid line) grows compared to those of the reactive control (dashed line) policy in Eq. (1). Therefore, we conclude that the guider gradually gives more emphasis on a predictive control policy than a reactive one. Statistical significance was tested by Mann Whitney U test to find the guider's model order. There is a statistically significant improvement from 2nd $\rightarrow$3rd order models ($p < 0.03$), while there is not significant information gain from 3rd $\rightarrow$4th order models ($p > 0.6$). It means that the guider predictive control policy is more explained when the order is $N = 3$. Therefore, hereafter, we consider 3rd order predictive control policy to explain the guider's control policy. However, at this stage, we do not quantify the relative mixing of the two policies - predictive and reactive - across learning trials if at all.

Our next attempt is to understand how the polynomial parameters of a 3rd order linear controller in equation 2

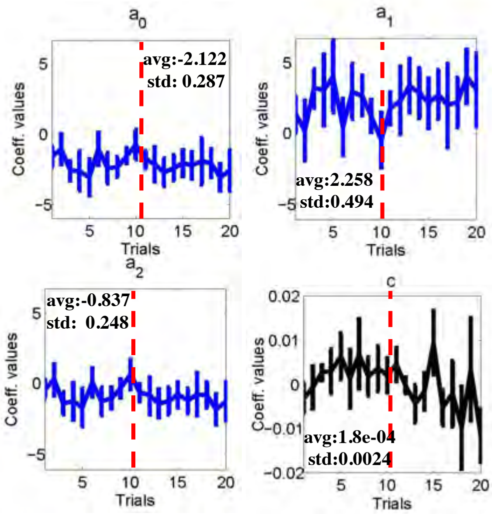

Fig. 4. The evolution of coefficients of the 3rd order auto regressive predictive controller of the guider (for eight guider-follower pairs). The average and S.D values of the coefficients are labeled. a_0^{Pre}, a_1^{Pre}, and a_2^{Pre} by blue. c^{Pre} by black with different scale. 10^{th} trial is marked by vertical dashed red line.

would evolve across learning trials. We notice in Fig. 4 that the history of the polynomial coefficients fluctuates within bounds. This could come from the variability across subjects and variability of the parameters across trials itself. Therefore, we estimate the above control policy as a bounded stochastic decision making process.

B. The mutual trust level of the guider and the follower in different contexts

Then we address the question of how the mutual trust between the guider and the follower should be accounted for in designing a closed loop controller. When a human is guided by another agent (human/machine), human confidence to follow the guiding agent depends on mutual understanding between each other. As shown in Fig 1(A), the follower's locomotion is mostly driven by his/her own voluntary force ($Fv >>> Ft$). Therefore any change in mutual trust that leads to a change in the voluntary force (Fv) should be reflected in a change of (Ft), assuming $Fv+Ft$ is a constant in steady state movement. The experimental results of eight pairs of subjects in three types of paths - a 90° turn, a 60° turn, and a straight - are shown in Fig. 5. Here we extracted motion data within a window of 10 seconds around the 90 and 60 degree turns, and for fairness of comparison, we took the same window for the straight path for our regression analysis to observe the virtual damping coefficient and the virtual mass in three different paths. We can notice from Fig. 5(A) that the variability of the virtual damping coefficient is highest in the path with a 90° turn, with relatively less variability in that with a 60° turn, and least variability in the straight path. However, we do not notice a significant variability in the virtual mass across the three contexts.

In Fig. 5 the variability of the virtual mass distribution and the virtual damping coefficient in straight path are lc This shows that the mutual trust level of the follow greater in the straight path. Statistical significance was t by of Mann Whitney U test for different paths (90° 60° turn, straight path) of coefficients in Eq.4. Re show that the virtual damping coefficient in 90° turr significantly different from that in straight path ($p < 0$ Moreover, virtual damping coefficient in 60° turn was significantly different from that in straight path ($p < 0$ There was no statistically significant difference betwee virtual damping coefficient in path 90° turn and 60° t $p > 0.60$). The virtual mass distribution in Eq. (4) is s in Fig. 5 (B). Interestingly, only straight path was statist significantly different from 90° turn ($p < 0.01$). Hov the Mann Whitney U test in between 60° turn and str path is not significantly different ($p > 0.70$). This come from the fact that the follower and the guider more mutual trust to move in a straight path than othe paths. Therefore these results confirm that mutual tru the follower and the guider is reflected in the time varying parameter of the virtual damped inertial system. We also note that the virtual damping coefficient presents itself to be more sensitive parameter to the level of mutual trust than the virtual mass.

The variability of virtual damping coefficient is higher in the 90° turn, than the 60° turn and the straight path. Therefore, we conclude the virtual damping coefficient is a good indicator to show mutual trust of the duo. We would use the virtual damping coefficient as an indicator to control the push/pull behavior of an intelligent guider using a feedback controller of the form given in Eq. (4), where F(k) is the pushing and /pulling tug force along the rein from the human guider at k^{th} sampling step, M is the time varying virtual mass, M_0 is its desired value, ζ is the time varying virtual damping coefficient, k is the sampling step, and ζ_0 is its desired value.

$$F(k+1) = F(k) - (M - M_0)\ddot{P}_f(k) - (\zeta - \zeta_0)\dot{P}_f(k) \quad (4)$$

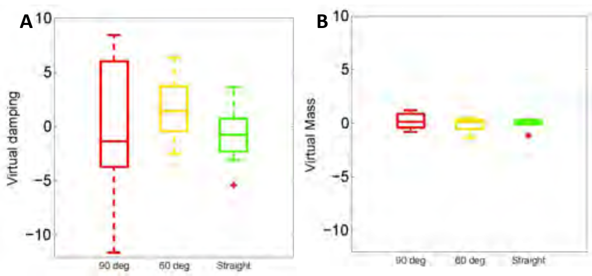

Fig. 5. Regression coefficients in equation 4 of different paths : (A) Virtual damping coefficient for paths: 90° turn (red), 60° (yellow) turn, and straight path (green).The average values are 3.055, 1.605 and-0.586 for 90° turn, 60° turn and straight path respectively. (B) Virtual mass coefficient for paths: 90° turn (red), 60° turn (yellow), and straight path (green). The average values are 2.066, -0.083 and 0.002 for 90° turn, 60° turn and straight path respectively.

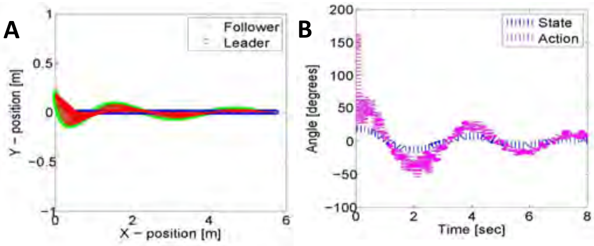

Fig. 6. Simulation results: (A) Stable behavior of trajectories of the follower (green) for where the guider tries to get the follower to move along a straight line from a different initial location. The control policy was based on the coefficients extracted from the experiments on human subjects. (B) The behavior of the difference of heading direction and the guider's action for the simulated guider-follower scenario. The control policy was based on the coefficients extracted from the experiments on human subjects.

C. Developing a closed loop path tracking controller incorporating the mutual trust between the guider and the follower

In order to ascertain whether the control policy obtained by this systems identification process is stable for an arbitrarily different scenario, we conducted numerical simulation studies forming a closed loop dynamic control system of the guider and the follower using the control policy given in equation 2 together with the discrete state space equation of the follower dynamics given in equation 3. The length of the hard rein $L = 0.5$m, the follower's position $P_f(0)$ was given an initial error of 0.2m at $\phi(0) = 45°$, the mass of the follower $M = 10$[kg] with the damping coefficient $\zeta = 4$[Nsec/m], the magnitude of the force exerted along the rein was 5N, and the sampling step $T = 0.02$. The model parameters of the last 10 trials were then found to be: $a_0 = N(-2.3152, 0.2933^2)$, $a_1 = N(2.6474, 0.5098^2)$, $a_2 = N(2.6474, 0.5098^2)$ and $c = N(1.0604e-04, 0.2543^2)$.

From Fig. 6(A) we notice that the follower asymptotically converges to the guider's path within a reasonable distance. The corresponding behavior of the difference of heading direction and the resulting control action shown in Fig. 6 (B) further illustrates that the above control policy can

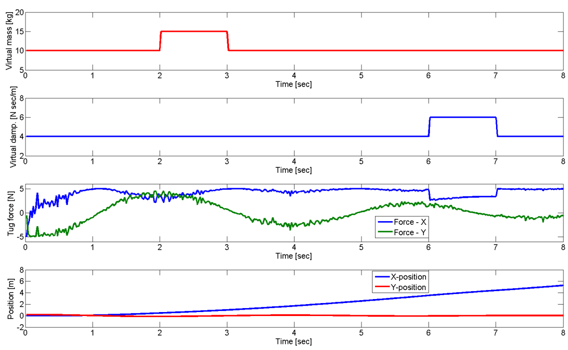

Fig. 7. Simulation results: The tug force and position variation of the follower in order to sudden change of the virtual mass $M = 15$[kg] from $t = 2$s to $t = 3$s and the virtual damping coefficient $\zeta = 6$[Nsec/m] from $t = 6$s to $t = 7$s.

generate bounded control actions given an arbitrary difference of heading direction. Next, we set the the virtual mass $M = 15$[kg] from $t = 2$s to $t = 3$s and the virtual damping coefficient $\zeta = 6$[Nsec/m] from $t = 6$s to $t = 7$s to observe tug force variation in equation 3 as shown in Fig. 7. The tug force variation Fig. 7 shows that, the virtual damping coefficient more influenced to vary the tug force than the virtual mass.

Combining the 3rd order autoregressive model for swinging the hard rein on the lateral plane to make path corrections, with resistive force felt at the guider's end modulation in response to the varying confidence level of the follower with mutual trust, we can now compose the combined controller given by

$$\begin{aligned} \begin{bmatrix} F(k+1) \\ \theta(k+1) \end{bmatrix} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} F(k) \\ \theta(k) \end{bmatrix} \\ &+ \begin{bmatrix} (M-M_0)\ddot{P}_f(k) - (\zeta - \zeta_0)\dot{P}_f(k) \\ \sum_{r=0}^{N-1} a_r^{Pre}\phi(k+r) + C^{Pre} \end{bmatrix} \end{aligned} \tag{5}$$

V. CONCLUSIONS AND FUTURE WORKS

In this study we could understand three major features in the haptic communication between a guider and a follower described in Fig. 1: The features are 1) the control policy of the guider can be approximated by a 3rd order autoregressive model without loss of generality, 2) when the duo learns to track a path, the guider gradually develops a predictive controller across learning trials, 3) the varying mutual trust level of the follower with visual and auditory impairment can be estimated by the variation of a virtual damping coefficient of a virtual damped inertial model that relates the tug force along the hard rein to the voluntary movement of the follower.

A novel controller was developed based on the above findings. To the best of the author's knowledge, this is the first publication that shows how to combine the confidence level of a follower with mutual trust in the context of being guided by a predictive controller based on a hard rein. The transient and steady state properties of the controller and its responsiveness to sudden changes in the voluntary movement of the follower was demonstrated using numerical simulations, demonstrating that it is ready to be exported to a mobile robot to guide a follower along an arbitrarily complex path using a hard rein.

In the future, we plan to uncover the cost functions that are minimized by the duo, during learning to track a path. This would help us to develop a reward based learning algorithm to enable a mobile robot to continuously improve the controller while interacting with a human follower. Moreover, we plan to have a closer look at how the guider maybe adaptively combining a reactive controller with a predictive one, in order to stabilize learning. It will also be interesting to explore for broader factors affecting the mutual trust, so that predictive action can be taken to maintain a good mutual trust level within the follower in the context of guiding.

The motivation of this study is to implement the proposed novel control policy on a robot when the human is guided by a robot as shown in Fig 1 (A) in future. Our intention is to develop a haptic based guidance algorithm that a robot could use to optimally facilitate human voluntary movements in a low visibility environment. In that case, a robotic arm that can swing on the horizontal plane as shown in Fig 1 (A), could implement what was demonstrated by the human guider's arm movements. In the future, we would study other possible modes of haptic feedback such as cutaneous feedback through a wireless link, and haptic feedback through a soft rein.

In addition to applications in robotic guidance of a person in a low visibility environment, our findings shed light on human-robot interaction applications in other areas like robot-assisted minimally invasive surgery (RMIS). Surgical tele-manipulation robot could use better predictive algorithms to estimate the parameters of remote environment for the surgeon with more accurate adaption of control parameters by constructing internal models of interaction dynamics between tools and tissues in order to improve clinical outcomes [12]. Therefore, we will continue to discover a generic robotic learning strategy/algorithm that can be generalized across RMIS as well as robotic assisted guidance in low visibility environments.

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