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Neural-Network-Based Human Intention Estimation for Physical Human-Robot Interaction

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Abstract - To realize physical human-robot interaction, it is essential for the robot to understand the motion intention of its human partner. In this paper, human motion intention is defined as the desired trajectory in human limb model, of which the estimation is obtained based on neural network. The proposed method employs measured interaction force, position and velocity at the interaction point. The estimated human motion intention is integrated to the control design of the robot arm. The validity of the proposed method is verified through simulation.

Keywords - Motion intention estimation; neural network; physical human-robot interaction

1. Introduction

Nowadays, robots are expected to participate in and learn from intuitive, long term interaction with humans, and be safely deployed in myriad social applications ranging from entertainment, health care to education. In many applications, the demand of physical human-robot interaction, such as hand-shaking, hugging and human-robot cooperation, is increasing. It brings along many challenging problems to control engineers and researchers.

To realize natural physical interaction, position control method, which is designed to track a predefined trajectory, is not applicable. On one hand, the reference trajectory for position control is usually not available. On the other hand, the position control objective, i.e., to obtain a fast and accurate position or velocity tracking performance, is not as essential as in most industrial applications. Instead, safety becomes a main concern. One way to guarantee the safety is to maintain the interaction force in an acceptable scale. In this regard, force control is a possible option. Force controller is designed so that for a known environment (including human partner) stiffness, rapid rise times of forces, low or zero force overshoot, and good rejection of external force disturbances can be achieved [1], [2]. However, as discussed in [3], the same force controller typically exhibits sluggish response in contact with softer environments, and goes unstable in contact with stiffer environments. In [4], a more robust method, impedance control, is proposed. It does not regulate the position or force but rather to regulate the dynamic behavior at the interaction port. As proved in [5], if the environment is passive, then imposing a passive impedance model to a robot will guarantee the stability of the coupled environment-robot interaction system. The passivity assumption is applicable to a large set of environments and thus many research results have been achieved under the passivity assumption, such as [6], [7], [8], [9]. In the latest literature [10], [11], researchers point out that impedance control is only able to achieve modest performance with the passivity assumption. In other words, to make the robot to be a follower is insufficient in some applications.

From human-human interaction experience, we notice that understanding the partner's intention is essential for natural and efficient interaction. Partners usually keep communicating with each other during the interaction. In physical interaction, haptic and position sensors represent the communication medias. How to observe human partner's intention from available sensory information becomes an important issue. In the literature, one way is to find the dynamic model of the human partner and then the intention of the human partner is predicted based on this model. In [12], human intention state is taken as a stochastic process and Hidden Markov Model (HMM) is employed for the intention estimation. In this method, human limb model parameters are estimated online, and two intention states (active and passive) are defined, which indicate the human partner leads and follows, respectively. In [13], under the assumption that the momentum is preserved during an interaction task, motion intention of the human limb is represented by the change of the interaction force, which is estimated by the change of the control effort. Under this scheme, if the magnitude of the filtered-control-force vector exceeds a defined threshold for a defined continuous duration, the impedance control mode is switched to interactive control mode, in which the estimated motion intention is integrated. The above illustration indicates that there is an inherent delay from the intention estimation to the beginning of the interactive control mode.

In this paper, we employ the human limb model as in [14], [15], and define the desired trajectory in the model as the human motion intention. Related work can be found in [16], in which the desired trajectory in human limb model is estimated by using reactive and predictive approaches. Considering the complicated nonlinearity

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and time-varying property of the human limb model, the desired trajectory in the model is estimated based on supervised neural networks (NN). Due to the excellent universal approximation ability of NN to unknown complicated nonlinearities, NN based control is particularly suitable for controlling highly uncertain, nonlinear and complex systems [17]. During the training phase, the robot is controlled in a compliant way by using impedance control to follow human partner's motion. Interaction force, position and velocity at the interaction port are used to estimate the human limb model. During the predicting phase, the trained model is used to estimate the human motion intention, according to which different control schemes for robot can be developed, so that the robot is able to play either a leader or a follower role.

The rest of the paper is organized as follows. In Section 2, human-robot interaction system is investigated and unknown desired trajectory problem is formulated. In Section 3 and 4, the details of the proposed NN-based estimation method are given and the interactive controller based on the estimated intention is developed. In Section 5, an intensive simulation study is used to verify the effectiveness of the proposed method. Concluding remarks are given in Section 6.

2. Problem Statement

The system under study in this paper is shown in Fig. 1, where the robot arm is physically interacting with the human limb. Particularly, it is assumed that there exists only one interaction point, which is at the end-effector of the robot arm, as well as at the end of the human limb. In what follows, all positions and orientations of the object, the coordinates of the robot arm and the human limb are expressed relative to a common reference frame unless otherwise stated. Besides, the dependence of the system parameters and signals on time is implied unless otherwise specified.

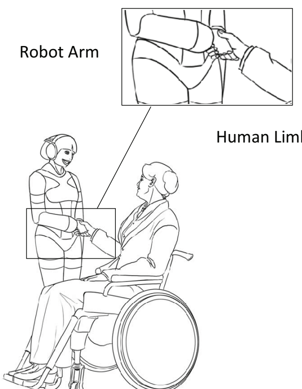

Fig. 1 Physical Human-Robot Interaction.

Suppose that the robot arm kinematics is given by

$$x(t) = \phi(q) \tag{1}$$

where $x(t),\ q \in \mathbb{R}^n$ and n are the positions/oritations in Cartesian space (operational space), joint coordinates in joint space and the degree of the freedom (DoF), respectively. Differentiating (1) with respect to time results in

$$\dot{x}(t) = J(q)\dot{q} \tag{2}$$

where $J(q) \in \mathbb{R}^{n\times n}$ is the Jacobian matrix and assumed to be nonsingular in finite workspace. Further differentiating (2) with respect to time results in

$$\ddot{x}(t) = \dot{J}(q)\dot{q} + J(q)\ddot{q} \tag{3}$$

The robot arm dynamics in the joint space is described as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau - J^T(q)f(t) \tag{4}$$

where $M(q) \in \mathbb{R}^{n\times n}$ is the symmetric bounded positive definite inertia matrix; $C(q,\dot{q})\dot{q} \in \mathbb{R}^n$ denotes the Coriolis and Centrifugal force; $G(q) \in \mathbb{R}^n$ is the gravitational force; $\tau \in \mathbb{R}^n$ is the vector of control input; $f(t) \in \mathbb{R}^n$ denotes the vector of constraint force exerted by the human limb, which is 0 when there is no contact between the robot arm and human limb.

Since the interaction is in the operational space, by considering the kinematics constraints (1)-(3) and dynamics (4), we obtain the robot arm dynamics in the operational space:

$$M_R(q)\ddot{x} + C_R(q,\dot{q})\dot{x} + G_R(q) = u - f \tag{5}$$

where

$$\begin{aligned} M_R(q) &= J^{-T}(q)M(q)J^{-1}(q), \\ C_R(q,\dot{q}) &= J^{-T}(q)(C(q,\dot{q}) - M(q)\dot{J}(q))J^{-1}(q), \\ G_R(q) &= J^{-T}(q)G(q),\ u = J^{-T}(q)\tau \end{aligned} \tag{6}$$

It is well-known that model (5) has the following properties, which will be used in the control design.

Property 1: The matrix $M_R(q)$ is symmetric and positive definite.

Property 2: [18] The matrix $2C_R(q,\dot{q}) - \dot{M}_R(q)$ is a skew-symmetric matrix if $C_R(q,\dot{q})$ is in the Christoffel form, i.e., $\xi^T(2C_R(q,\dot{q}) - \dot{M}_R(q))\xi = 0,\ \forall\xi \in \mathbb{R}^n$.

Property 3: $M_R(q),\ C_R(q,\dot{q}),\ G_R(q)$ are linear in terms of a suitable selected set of the physical parameters of the robot arm, i.e.,

$$M_R(q)\ddot{x} + C_R(q,\dot{q})\dot{x} + G_R(q) = Y(\ddot{x}_r, \dot{x}_r, \dot{x}, x)\theta \tag{7}$$

where $\theta \in \mathbb{R}^{n_\theta}$ is a vector of the physical parameters of the robot arm; n_θ is a positive integer denoting the number of these parameters; $Y(\ddot{x}_r, \dot{x}_r, \dot{x}, x) \in \mathbb{R}^{n\times n_\theta}$ is the regression matrix, which is independent of the physical parameters; $\ddot{x}_r$ and $\dot{x}_r$ are defined in (15).

As mentioned in Introduction, in a pre-defined task, the desired trajectory x_d is available for the robot arm control design, while in an interaction task, x_d is usually unknown or has to be refined according to a certain criterion, e.g., to realize the human-robot motion synchronization. In this regard, it is important to understand the motion intention of the human limb.

3. Human Intention Estimation

3.1 Human Limb Model

To estimate the motion intention of the human limb, one way is to employ the human limb model, as discussed in Introduction. To describe the human limb dynamics, the following mass-damper-spring model (in the operational space) is acknowledged to be a good candidate [14], [15]:

$$M_H(\ddot{x} - \ddot{x}_{Hd}) + C_H(\dot{x} - \dot{x}_{Hd}) + G_H(x - x_{Hd}) \\ = f \tag{8}$$

where $M_H,\ C_H,\ G_H$ are the inertia, damping and stiffness matrices, respectively, and x_{Hd} is the desired trajectory as planned in the central nervous system of the human. Note that when there is no contact, i.e., the interaction force $f = 0$, (8) will lead to $x \rightarrow x_{Hd}$. Thus, x_{Hd} is defined as the motion intention of the human limb in this paper. In the following, we aim to obtain x_{Hd} in model (8).

Using a simplified version of the above model (8) usually helps in simplifying the problem formulation. For example, in [19], the inertia and damping parts are not used and an "equilibrium point control model" is developed. This model suggests that the central nervous system utilizes the spring-like property of the neuromuscular system in coordinating multi-DoF human limb movements. In this work, motivated by (8) and human-human interaction experience, we have the following assumption:

Assumption 1: In a specific scenario, human's motion intention (in every possible direction), i.e., x_{Hd} in (8), is determined by the interaction force, position and velocity at the interaction point (in the corresponding direction) of the human limb and robot arm. To be short, we may estimate the motion intention of the human limb by

$$\hat{x}_{Hd} = \hat{x}_{Hd}(f, x, \dot{x}) \tag{9}$$

where $\hat{x}_{Hd}$ is the estimated value of x_{Hd}.

3.2 NN-based Intention Estimation

From (8) and Assumption 1, we find that if parameters M_H, C_H, G_H are available, it is possible to obtain x_{Hd} from collected data $f, x, \dot{x}, \ddot{x}$. However, due to the nonlinearity and uncertainty, it is impossible to estimate these parameters through off-line experiments and also difficult, if not impossible, to conduct the online experiments. In this section, we utilize machine learning algorithms to solve this problem.

Machine learning algorithms can discover intrinsic information, map unknown relationship and approximate functions. As one of popular machine learning algorithms, radial basis function neural network (RBFNN) is explained in this paper. By adopting RBFNN instead of other NNs, the modes of the system can be easily described and the training process is boosted up with different patterns of the interaction. The structure of RBFNN is expressed as follows:

$$\begin{aligned} &\phi(W, z) = W^T S(z),\ W, S(z) \in R^l, \\ &S(z) = [s_1(z),\ s_2(z), \ldots, s_l(z)]^T, \\ &s_i(z) = exp[\frac{-(z - \mu_i)^T (z - \mu_i)}{\eta_i^2}], \\ &i = 1, 2, \ldots, l \end{aligned} \tag{10}$$

where $z \in \Omega_z \subset R^m$ is the input to RBFNN, l is the NN nodes number, $\mu_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{im}]^T$ is the center of the receptive field and η_i is the width of the Gaussian function, and W is an adjustable synaptic weight vector. For a smooth function $\varphi(z)$ over a compact set $\Omega_z \subset R^m$, given a small constant real number $\mu^* > 0$, if l is sufficiently large, there exist a set of ideal bounded weights W^* such that

$$\max |\varphi(z) - \phi(W^*, z)| < \mu(z),\ \ |\mu(z)| < \mu^* \tag{11}$$

This work to predict the motion intention of the human limb falls under the category of supervised learning. In the training phase, interaction force f, position x and velocity $\dot{x}$ at the interaction port, as well as the given desired trajectory x_{Hd}, are supplied to RBFNN to approximate the mapping from $f, x, \dot{x}$ to human's desired trajectory x_{Hd}. In the predicting phase, measured signals $f, x, \dot{x}$ are supplied to the trained RBFNN to determine the estimated value of x_{Hd}.

Denote the input of RBFNN as a vector $z = [f^T, x^T, \dot{x}^T]^T$, then the estimation of the desired trajectory x_{Hd} is given by

$$\hat{x}_{Hd} = W^T S(z) \tag{12}$$

where W and $S(z)$ have the same meanings as in (10).

Remark 1: In [12], the motion intention of the human limb is divided to two states: active and passive. It is assumed to be a stochastic process and thus can be estimated by an HMM. Then the robot is controlled in the following manner: if the motion intention of the human limb is passive, which indicates the robot's current motion is coherent with the motion intention, then the robot is in an active state (stiff position control); if the motion intention is active, which indicates the human limb wants to lead the task or to change its intention, then the robot complies to the limb motion (compliant control). Under this framework, the estimation of motion intention is obtained based on the estimation of $M_H,\ C_H,\ G_H$ in (8). Instead of that, the method proposed in this paper is direct and straightforward from the data collection to the intention estimation.

4. Interactive Control Design

In this section, the interactive control design including training NN and integrating the estimated motion intention is proposed. The control design includes two components: impedance controller employed in the training phase and a proposed controller used in the predicting phase.

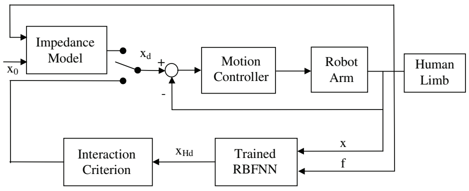

Fig. 2 Control Framework with Estimated Human Motion Intention.

The control framework including two components is shown in Fig. 2, in which the desired trajectory x_d switches between training and predicting phases.

In the training phase, the human limb is leading the task and the robot arm is following in a compliant manner. In this case, the robot dynamics is governed by a given impedance model:

$$M_d(\ddot{x}_d - \ddot{x}_0) + C_d(\dot{x}_d - \dot{x}_0) + G_d(x_d - x_0) = -f \quad (13)$$

where $M_d,\ C_d,\ G_d$ are the desired inertia, damping and stiffness matrices, respectively, and x_0 is the rest position of the robot arm.

An approach to implement impedance control is to use a fast, inner motion control loop in conjunction with an outer force control loop [20]. In this architecture, the force loop is usually used to determine the virtual desired trajectory, i.e., x_d in (13). The output of this loop serves as the input to the motion control loop, as shown in Fig. 2.

During this phase, the desired trajectory x_{Hd} of the human limb is pre-defined, and the interaction force f, position x and velocity $\dot{x}$ are measured. These data are used to train the NN.

In the predicting phase, the trained NN is employed. Given the measured $z = [f^T, x^T, \dot{x}^T]^T$, the estimated motion intention $\hat{x}_{Hd}$ is obtained according to (12). Then, the desired trajectory for the robot control x_d is obtained by following a certain criterion according to different interaction requirements, e.g., motion synchronization, which leads to $x_d = \hat{x}_{Hd}$.

When the desired trajectory x_d is available, in both training and predicting phases, the following computed torque control law is applied to make $x \to x_d$ as $t \to \infty$:

$$u = M_R(q)\ddot{x}_r + C_R(q,\dot{q})\dot{x}_r + G_R(q) + Kr + f \quad (14)$$

where K is a positive definite matrix, and

$$\begin{aligned} \dot{x}_r &= \dot{x}_d + \gamma e \text{ with } e = x_d - x \\ r &= \dot{e} + \gamma e \end{aligned} \quad (15)$$

with $\gamma > 0$.

The dynamics of the closed-loop system is:

$$M_R(q)\dot{r} + (C_R(q,\dot{q}) + K)r = 0 \quad (16)$$

Considering Property 1 and Property 2, it is trivial to prove that $r \to 0$ as $t \to \infty$, and thus $e \to 0$, $\dot{e} \to 0$ as $t \to \infty$.

When the robot dynamics parameters $M_R(q), C_R(q,\dot{q}), G_R(q)$ are unknown, by considering Property 3, the adaptive approach in [21] is employed with

$$u = Y(\ddot{x}_r, \dot{x}_r, \dot{x}, x)\hat{\theta} + Kr + f \quad (17)$$

where $\hat{\theta}$ is the estimation of θ, and updated as follows:

$$\dot{\hat{\theta}} = \Gamma Y^T(\ddot{x}_r, \dot{x}_r, \dot{x}, x)r \quad (18)$$

where Γ is a positive definite matrix.

5. Simulation Study

5.1 System Description

To verify the validity of the proposed method, we consider a scenario where a 2-DOF robot arm with two revolute joints interacting with the human limb in a horizontal plane. The control objective is to realize the synchronization of the human limb and the robot arm.

The robot arm parameters are: $m_1 = m_2 = 1.0$ kg, $l_1 = l_2 = 0.2$ m, $I_1 = I_2 = 0.003$ kgm^2,$l_{c1} = l_{c2} = 0.1$ m, where m_i, l_i, I_i, l_{ci}, $i = 1, 2$, represent the mass, the length, the inertia about the z-axis that comes out of the page passing through the center of mass, and the distance from the previous joint to the center of mass of link i, respectively.

For the convenience, we use the following abbreviation:

$$\begin{aligned} s_{12} &= \sin(q_1 + q_2), c_{12} = \cos(q_1 + q_2),\ c_1 = \cos(q_1), \\ s_1 &= \sin(q_1),\ s_2 = \sin(q_2),\ c_2 = \cos(q_2) \end{aligned} \quad (19)$$

The dynamics of the robot arm in the joint space is given as (4) with $G(q) = 0$ and

$$M(q) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix},\ C(q,\dot{q}) = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} \quad (20)$$

where

$$\begin{aligned} M_{11} &= m_1 l_{c1}^2 + m_2(l_1^2 + l_{c2}^2 + 2l_1 l_{c2} c_2) + I_1 + I_2, \\ M_{12} &= M_{21} = m_2(l_{c2}^2 + l_1 l_{c2} c_2) + I_2, \\ M_{22} &= m_2 l_{c2}^2 + I_2, \\ C_{11} &= -m_2 l_1 l_{c2} s_2 \dot{q}_2,\ C_{12} = -m_2 l_1 l_{c2} s_2(\dot{q}_1 + \dot{q}_2), \\ C_{21} &= m_2 l_1 l_{c2} s_2 \dot{q}_1,\ C_{22} = 0 \end{aligned} \quad (21)$$

By limiting the interaction to one direction, the model of the human limb is only described in the interaction direction, i.e., $\sin x(x - x_{Hd}) = f$. This equilibrium point model shows that the human limb has a spring-like property with position-dependent stiffness.

Note that in the beginning of the interaction, the initial positions of the robot arm and the human limb are the same, which are set as $q_1 = \pi/6$ and $q_2 = \pi/6$.

5.2 Simulation Results

During the training phase, the human limb is leading the interaction task with the desired trajectory $x_{Hd} = 1 + 0.5\sin(2t)$, and the robot arm is in a compliant manner with the target impedance model $0.01(\ddot{x}_d - \ddot{x}_0) + 0.1(\dot{x}_d - \dot{x}_0) = f$, where the rest position $x_0 = 1(t)$. Under this impedance control scheme, the robot will be compliant to the human limb motion when there is interaction force and stay at the rest position when the interaction force is zero. The results under this scheme are shown in Figs. 3 and 4. From Fig. 3, it can be found that the robot arm follows the desired trajectory of the human limb with an obvious time delay, which is mainly caused by the phase delay of the impedance function, i.e., $\frac{1}{0.01s^2+0.1s}$. The interaction force as shown in Fig. 4 will be compared with the result obtained with the proposed method.

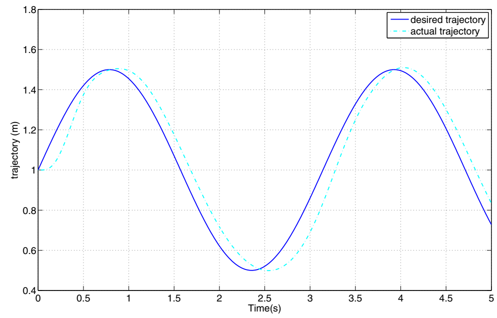

Fig. 3 Desired and Actual Trajectory with the Impedance Method

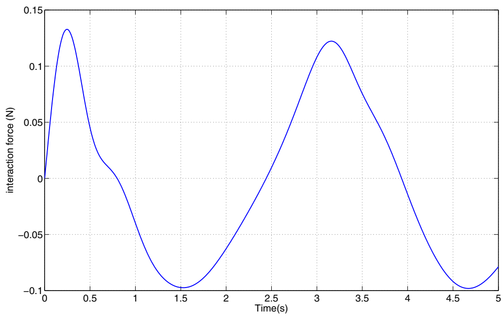

Fig. 4 Interaction Force with the Impedance Method

The employed NN has three inputs (interaction force, position and velocity of the robot arm) and one output (desired trajectory of the human limb). A number of 1000 epochs are proceeded until most networks reach the desired mean-square error 10^{-8}.

During the testing process, the desired trajectory of the human limb is still $x_{Hd} = 1+0.5\sin(2t)$ in Case 1. Note that this time the desired trajectory is only used in the simulation and unknown to the robot arm, i.e., it is not available for the robot arm control. Instead, the estimated trajectory will be used as the reference trajectory of the robot arm control, as shown in Fig. 2. The results are given in Figs. 5 and 6. As shown in Fig. 5, the estimated trajectory follows the desired trajectory. And the actual trajectory of the robot arm tracks the estimated trajectory and thus follows the desired trajectory of the human limb. The interaction force between the robot arm and human limb is shown in Fig. 6, which is used to further indicate the synchronization of the robot arm and human limb. To illustrate this, impedance control method in the training phase is used as a benchmark to be compared with. It can be found in Fig. 4 that there is a larger interaction force between the robot arm and the human limb with the impedance control method, compared to that in Fig. 6, with integrating the estimated human motion intention. Therefore, the synchronization is better achieved with the proposed method than the impedance control method.

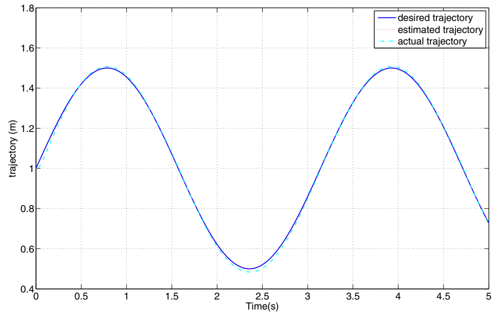

Fig. 5 Desired, Estimated and Actual Trajectory with the Proposed Method, Case 1

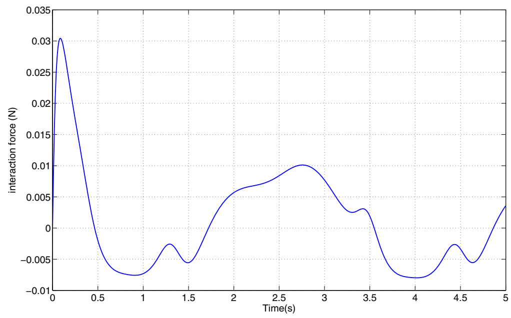

Fig. 6 Interaction Force with the Proposed Method, Case 1

In some applications, the robot is ”taught” to follow human partner’s motion in this manner: in the training phase, the robot is in a compliant control model and records the human limb motion, and then in the predicting phase, the robot is able to repeat the recorded motion, so that the synchronization can be realized to some extent. However, this method is limited by the change of the human limb motion, i.e., if there is any change in human limb motion in the predicting phase, then the synchronization will fail. In this regard, the proposed method is more favorable because the synchronization can be guaranteed subject to enough training. To explain this, we change the desired trajectory of the human limb to $x_{Hd} = 1 + 0.4\sin(t)$ in Case 2. And the tracking performance is shown in Fig. 7, which has clearly shown that similar results are achieved and the synchronization is still guaranteed, although the desired trajectory of the human limb has been changed.

6. Conclusion

In this work, human-robot interaction system has been investigated. Human motion intention has been observed by employing a human limb model and estimating the desired trajectory in this model. An NN method has been developed for the estimation. The estimated desired trajectory of the human limb has been integrated into robot arm control to improve the interaction performance. The simulation results have shown the validity of the proposed method.

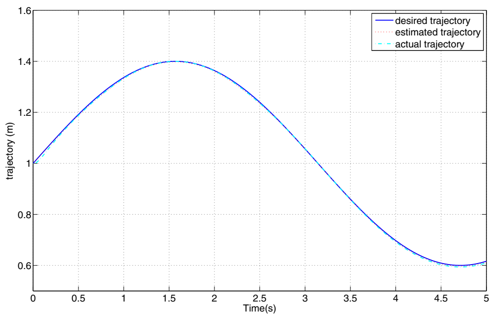

Fig. 7 Desired, Estimated and Actual Trajectory with the Proposed Method, Case 2

7. Acknowledgment

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