Prompt Human to Robot Handovers by Estimation of Object Transfer Point based on Human Partner's Motion

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***Abstract*— Handing over objects is the foundation of many human-robot interaction and collaboration tasks. In the scenario of human handing over an object to the robot, the human chooses where the object needs to be transferred. The robot needs to accurately predict this point of transfer to reach out proactively, instead of waiting for the final position to be presented. This work investigates an efficient method for predicting the Object Transfer Point (OTP), which synthesizes (1) an offline OTP calculated based on the safety, comfort and reachability of the human partner with (2) a dynamic OTP prediction based on the observed human motion. Our proposed OTP predictor is implemented on a humanoid nursing robot and experimentally validated in human-robot handover tasks.**

I. INTRODUCTION

The study of fluent and natural-looking human-robot handovers has been motivated by the need for intimate physical interactions between assistive robots and their human partners [1]. For instance, a nursing robot needs to hand over food, beverage and medicines to patients, and hand over medical supplies when assisting a human nurse. Such handover tasks are frequent and therefore disproportionately affect the overall task performance. In this paper, we focus on how to predict where the object will be transferred in a handover process and how to render a proactive and natural robot response.

Studies of human-human handovers have provided insights on the premeditated prediction of the object transfer point (OTP) in human-robot handover tasks. An analysis of handing over objects on a table [2] showed the reaching motion of the receiver to be based on experience and not on the visual feedback of the giver's arm motion. The giver usually chooses a direct path to the OTP without deviating from it. Similarly, the giver's arm motion in a vertical 2D plane [3] is pre-planned feed forward with a fixed maximum velocity. The motion of the giver's arm is also independent of the receiver [4], with similar velocity profiles observed for handing over an object to a human and for placing the object on a table at the same distance. Moreover, the handovers occur halfway between the giver and the receiver. Apart from interpersonal distance, even safety, visibility and arm comfort can be considered to postulate the point of object transfer [5]. Therefore the receiver can have a fairly good guess of where the OTP would be, even before any handover motion is initiated.

Accurate estimation of the OTP requires knowledge of the tempo-spatial coordination observed in individual and interactive human motion. A simple but effective method to react is to control the robot hand velocity to be proportional to the hand velocity of the human partner [1]. Knowing that natural human reaching motions follow minimum-jerk trajectories, the timing and location of the object transfer can be predicted after peak velocity of the human partner's hand has been observed [6]. A novel technique is developed in [7] which achieves real-time performance by early prediction of the goal location, having greater than 70% classification accuracy in less than 500 ms by observing the first one-third of the human's trajectory.

Methods for robot learning from human teachers directly benefit real-time motion prediction in human-robot interactions. In the case of human-robot handover, the human-initiated handover is more challenging compared than robot-initiated handover [8], [9], [10], because it is difficult to predict the object transfer point based on observing only a small part of the human partner's motion. To address interactive intent and motion coordination during handover, Maeda et al. proposed probabilistic models for learning and reproducing the phase matching between human and robot hands [11]. Superior to the minimal jerk model, the phase estimation model can reliably predict the object transfer point earlier in the process, yet, the robot is unsure about how to move until a portion of human partner's hand motion has been observed. In addition, this model predicts the handover motion phase based on the absolute hand positions of the human and robot, and therefore will not be valid in cases where the human-robot distance and relative pose are different from the learned demonstrations.

In this paper, we propose an improved model for estimating the object transfer point by integrating a pre-computed OTP which addresses giver's tendency and receiver's comfort, safety, and social acceptability, with a dynamic OTP predictor which updates the OTP based on real-time handover motion phase estimation. Our integrated OTP predictor initiates the robot reaching motion in the appropriate direction before the human partner's motions are observed and adjusts the robot motion by dynamic handover phase matching. To improve model generality, we demonstrate the importance of using the coordinate frame defined by the human's orientation relative to the robot. Our proposed OTP-estimation strategy is implemented on a humanoid mobile nursing platform. Initial experimental results show that handover time is decreased by 16% and position accuracy is increased by 50% after observing 30% of the human trajectory.

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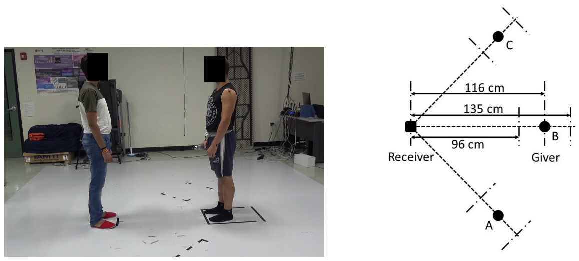
II. PILOT STUDY

A human motion study was performed with the $receiver$ standing at a fixed location and orientation, while the $giver$ would stand at positions A, B and C as shown in Fig. 1b. These positions are at a distance of 96 cm to 135 cm [4] from the $receiver$ with A and C at $45°$ to the $receiver$'s orientation. Markers were placed on the wrists, shoulders, head and torso of both the subjects and tracked with the Vicon Motion Capture system. From each position the $giver$ would hand over a bottle to the $receiver$, 5 times. This motion data was used to find the reaction and handover time for human-human handover as a baseline and the correlations between the subject's relative pose and the OTP.



(a) Subjects with Markers (b) Giver Positions

Fig. 1: Recording of human-human handover in motion capture space for giver standing 116 cm from the receiver and in 3 different positions each $45°$ apart.

A. Response Time of Receiver

The response time for a handover was measured from the instant the giver started moving his hand, to the instant the receiver started his reaching motion. The reaction time was observed to be 0.425 ± 0.187 $secs$. The observed handover time, which was the time from the giver starting his motion to the receiver reaching to grasp the object, was 1.212 ± 0.225 $secs$. For a robot to respond this quickly it is vital to predict the OTP and begin its motion early.

B. OTP Parameters

The OTP was found to lie at the mid-point of the distance between the subjects and at a height that was between the hip and the head of the receiver. Therefore this correlation can be used to obtain an initial guess of the OTP.

III. METHODOLOGY

This paper proposes a fast and reliable method to deliver proactive and natural robot motion in response to an object handover initiated by a human. Shown in Fig. 2, the **autonomous control module** takes input from the **sensing module** which observes the robot states and human partner's motions in real-time. Within the autonomous control module, the *offline training* components are responsible for (1) training a Probabilistic Movement Primitives (Pro-MP) model to reproduce legible robot motion using demonstrations of human-robot handovers, as well as (2) generating an off-line OTP estimation before the handover starts. As soon as the human partner starts a handover, the dynamic OTP generator takes in the offline OTP estimation and continuously updates

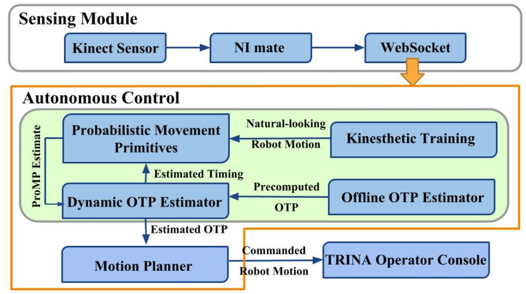


Fig. 2: Handover System Architecture

the OTP estimation based on the observed human partner's motion. The dynamic OTP generator also sends its estimation of the phase of the human partner's motion to the Pro-MP, in order to match the robot motion to the observed human motion in timing. The motion planner receives the estimated OTP and controls the robot end-effector to reach toward it. The planned motion is then sent to the robot for execution.

A. Natural-looking Motion Generation

The core of our method is to train a Multi-dimensional Interaction Probabilistic Movement Primitives (Pro-MP) with multiple human-robot handover demonstrations [11]. Here we briefly describe the algorithms of motion learning and reproduction using Pro-MP:

Learning phase: During the learning phase, the sensing module observes both human and robot arms during a handover demonstration. At each time step t, the 7 observed degrees-of-freedom (DOF) of the robot end-effector and the 3 observed DOFs of the human hand are concatenated into the following human-robot state vector:

$$\mathbf{y}_t = [y^H_{1,t}, \cdots, y^H_{3,t}, y^R_{1,t}, \cdots, y^R_{7,t}]^T \tag{1}$$

The trajectory of each DOF is further parameterized by weights such that:

$$p(\mathbf{y}_t|\bar{\mathbf{w}}) = \mathcal{N}(\mathbf{y_t}|\mathbf{H_t}^{\mathcal{T}}\bar{\mathbf{w}}, \mathbf{\Sigma}_{\dagger}) \tag{2}$$

where $\mathbf{H}^T_t = diag((\Psi^T_t)_1, \cdots, (\Psi^T_t)_3, (\Psi^T_t)_1, \cdots, (\Psi^T_t)_7)$ is the diagonal matrix of the Gaussian basis functions. Among the M handover demonstrations, the i-th demonstration correlates the observed DOFs of human and robot in the handover such that:

$$\bar{\mathbf{w}}_i = [(\mathbf{w}^H_1)^T, \cdots, (\mathbf{w}^H_3)^T, (\mathbf{w}^R_1)^T, \cdots, (\mathbf{w}^R_7)^T]^T \tag{3}$$

Reproduction phase: Using the learned Pro-MP model, the robot end-effector trajectory can be inferred by computing the posterior probability distribution of the weights $\mathbf{w}$ conditioned on the observed human motion. The inferred trajectory not only matches the human partner's reaching in phase but also updates the dynamic estimation of the OTP as more human motion is observed. For algorithm details, please refer to [11].

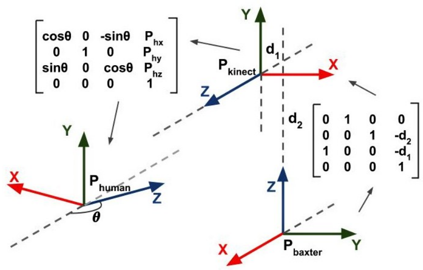


Fig. 3: Reference Frame Transformations

B. Reference Frame Transformation

In [11], the demonstrations for training the Pro-MPs are recorded in the robot's body frame or the world frame depending on the sensor placement. As a result, the motion of the human arm differs from the training demonstrations if the human stands in a new position. This causes the ProMP estimation of the OTP to be inaccurate. To resolve this problem by training the Pro-MP with many demonstrations of all possible handover configurations is highly inefficient.

We avoid this problem by learning from demonstrations in a user-adaptive reference frame. The Z-axis of this reference frame is aligned with the direction in which the human is facing and the Y-axis is set perpendicular to the ground. In this reference frame, the robot's end effector and human wrist positions are recorded and saved from the perspective of the human partner. Since the object transfer points can be calculated with respect to the human partner's pose, the accuracy of the predicted points is not affected by the changes in position and distance of the human partner with respect to the robot. Overall, using a user-adaptive reference improves the generalization capability of the Pro-MP model.

C. OTP Estimation

To reduce the robot response time during handover, it is useful to begin the robot motion as early as possible based on an initial estimate of the OTP. As a result, we synthesize:

Offline OTP estimation: Before handover is initiated, the offline OTP-estimator computes the initial object transfer point (OTP_{off}) in the task space based on three criteria: (a) the "Initial Pose" criterion constrains the handover region to be bounded in a trapezoidal prism whose edges are the vectors joining the human's and robot's head positions and initial wrist positions; (b) the "Midpoint of Actors" and (c) the "Reachability", based on the motion study data.

Dynamic OTP estimation: When the human partner initiates the handover, dynamic OTP is activated and will be updated until its prediction converges as depicted in Algorithm 1. As more of the human partner's motion is observed, the trust factor w which indicates the phase of the human arm motion is updated according to the expected time to the goal location. This time estimate is re-calculated based on the speed of the human's arm and its distance to the current OTP estimate and provided to the ProMP for slicing the trained data.

A Pro-MP by itself requires 40-50% of the human's motion to be observed for accurate estimation of goal states.

Data: $P_{obj}, OTP_{off}, OTP_{pmp}$
$w \leftarrow 1, t_{goal} \leftarrow t_{init}$;
while $w \geq 0$ **do**
  if *moving* **then**
    $w \leftarrow w - K * (\frac{dt}{t_{goal}})$;
    $OTP_d \leftarrow (w * OTP_{off}) + (1 - w) * OTP_{pmp}$;
    $t_{goal} \leftarrow \frac{OTP_d - P_{obj}}{V_{obj}}$;
    return $OTP_{dynamic}$;
  end
end

Algorithm 1: Dynamic OTP generator

This setup allows the robot to initiate its motion as soon as the human starts moving without compromising the legibility of the trajectory, thus leading to faster handovers.

IV. EXPERIMENTS & RESULTS

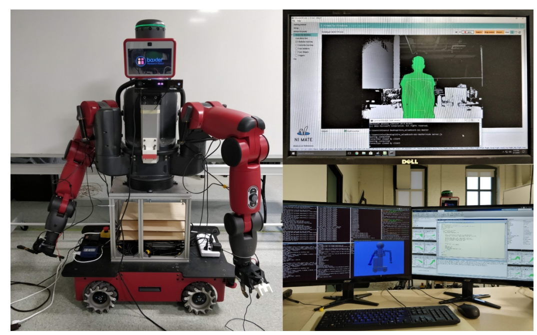


Fig. 4: (Left) The Tele-robotic Intelligent Nursing Assistant (TRINA) system. (Right top) The sensing server computer that runs skeleton tracking system, and (Right Bottom) the operator console displayed on the robot control computer.

We implemented the proposed autonomous control method on the Tele-robotic Intelligent Nursing Assistant (TRINA) system shown in Fig. 4, which was developed for remote patient-caring tasks [12]. A Microsoft Kinect 2 sensor is attached to the robot's chest and interfaced with a sensing server computer with Windows 10, which uses *NI Mate* [13] to stream the human partner's skeleton data. The Pro-MP model is trained using 25 human-robot handover demonstrations, in which the robot motion is controlled through kinesthetic teaching. During these demonstrations, the human partner stood at a fixed position with respect to the nursing robot and intended to hand over the object at five different object transfer points. For each demonstration, we recorded the arm joint angles, and end-effector pose (position and orientation) of the robot, as well as the shoulder, elbow and wrist trajectories of the human partner's reaching arm.

A. Faster Handover Response

In Experiment 1, the subject stands at the same position as in the training demonstration and initiates natural handovers to arbitrary positions. The total OTP prediction accuracy (difference between the observed and the estimated

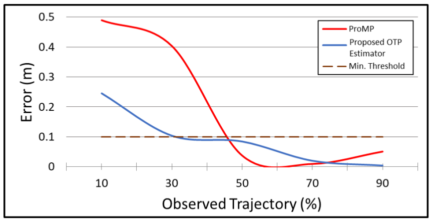


Fig. 5: Comparison of the prediction error between the baseline (red) and the proposed system (blue).

OTP) was measured when $10\%, 20\%, \cdots, 90\%$ of the human partner's hand motion was observed. Shown in Fig. 5, the proposed method only needs to observe about 30% of human partner's hand motion to render accurate predictions, while the $baseline$ (original ProMP) [14] can achieve the same prediction accuracy after 45% of human motion has been observed. After 70% of the human motion has been observed, both the proposed method and the $baseline$ method can predict the OTP with less than $5cm$ error.

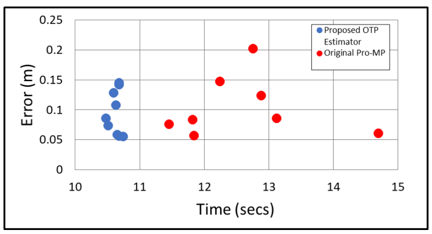


Fig. 6: Comparison of the handover time between the baseline (red) and the proposed system (blue).

Fig. 6 compares the two methods by handover time, with the robot operated at a safe and slow speed. Overall, the robot can respond faster by about 1.97 sec. with the proposed method. Considering the total handover process takes about 12.6 sec for the $baseline$ method, the proposed method improves the robot response time by 16%.

B. Better OTP Estimation at Different Positions

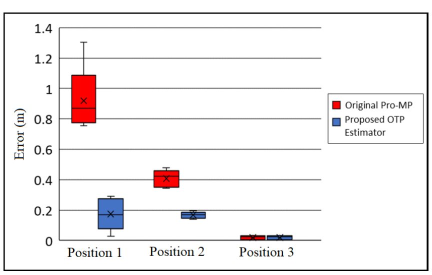


Fig. 7: Comparison of the generalization capability between the baseline (red) and proposed method (blue).

Experiment 2 compares the prediction errors of the proposed and $baseline$ method for three different standing positions within the visible workspace. When the subject stands close to the edges of the robot's vision range (positions 1 and 2), the proposed method has significantly smaller prediction errors. The prediction error for the right extreme is smaller because the field of view of the Kinect camera is asymmetric. In human-robot handover demonstrations, the subject was standing at position 3 (centre), which is closer to the right edge of the Kinect vision range, which is why the $baseline$ method can generalize better for the extreme right of the visible workspace. Through Experiment 2, we demonstrate that the proposed method has better generalization capability across the robot's visible workspace given the same training demonstrations.

V. CONCLUSION & FUTURE WORK

The need for a prompt handover was determined from the pilot study which demonstrated that $receiver$ should respond in 0.425 $secs$ to the handover initiated by the $giver$, whose OTP depends on the initial head and wrist position of the $receiver$. This justifies a full-fledged human motion study to be conducted for validating the claim of a pre-computed OTP. Further, a human-robot motion study is required to verify if the $giver$ chooses the same OTP when the $receiver$ is a robot. The results clearly show the improvement in handover time and estimation accuracy by using the proposed method. Further tests are required for faster handovers and for comparison with other existing methods implemented on the same system.

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