Proceedings of the SICE Annual Conference 2016
Tsukuba, Japan, September 20-23, 2016

Synergistic human-robot shared control via human goal estimation

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Abstract: In this paper, we propose and implement a synergistic human-robot collaboration framework, where the robotic system estimates the intent or goal of the human operator while being controlled by the human in real-time. Having an estimate of the goal of the human operator, the system augments the human control signals by its own autonomous control output based on the goal estimate. Consequently, the net control command that drives the robot becomes a mixture of human and robot commands. The motivation for such a collaborative system is to obtain an improved task execution to surpass the performance levels that each party could achieve in solo. This is possible if the developed system can take advantage of the individual skills so as to cover the weakness of the other party. To test and validate the proposed system we realized the framework by using the 'ball balancing task' where an anthropomorphic robot arm was required to bring a ball on a tray attached to its end effector to a desired position. Task execution performance was quantified with completion time and positional accuracy. To test the validity of the framework, experiments were conducted in three conditions: full autonomous control, human-in-the-loop control, and shared control. Full autonomous control did not require any human subjects; whereas for the latter two conditions, 10 subjects for each condition were employed to measure task performance of naive solo operators and naive human-robot partners. The performance results indicate that the task can be completed more effectively by the human-robot system compared to human alone or autonomous robot execution in different performance measures.

Keywords: Synergistic Collaboration, Human Intent Prediction, Goal Estimation, Human-Robot Interaction, Human-Robot Interface

1. INTRODUCTION

Some tasks might be out of human physical capabilities due to environmental constraints or extreme precision and accuracy requirements. Sometimes, a task can be too dull to sustain the full attention of a human, which might have adverse and even fatal consequences. As some examples of such tasks, welding, operations in radioactive, undersea and space environments, lifting in construction sites and high precision medical surgery can be mentioned. Although robots are expected to be part of our daily life in the coming decades, it is hard or sometimes impossible to make some tasks perfectly and completely automated. However, many of such difficult tasks can be performed with human-robot cooperation.

The goal of synergistic human-robot collaboration is to make a team which takes advantage of each party's skills and deliver a high performance task execution [1]. On one hand, humans are good at creativity, flexibility and dexterity; on the other hand, robots are resistant to hazards, robust to fatigue and good at repetitive tasks. Thus, combining human and robot skills seems very appealing for taking advantage of these features. Therefore, the goal of synergistic human-robot collaboration is to develop methods and technologies enabling human-robot systems to surpass both robot and human performance. In this paper, we try to make an attempt towards this direction via creating an effective shared control system by combining human teleoperative control with robot autonomy guided by human goal estimation.

A simple way to control robots by human guidance is so called direct control [2-4], where the human controls the robot by physically holding and moving it through desired postures. Direct control is limited and not suitable for dynamic control tasks [5], and thus might be difficult to be widely adopted for shared control applications. In human-in-the-loop control [6-8], the human takes share in real-time control of the robot in order to make the robot perform a given task. However, no physical contact with the robot is needed. This paradigm has been successfully used to obtain robot skills such as ball manipulation [5] with a five fingered robotic hand, balanced inverse kinematics on a humanoid robot [7], and tasks involving force based policies [7, 8]. In the human-in-the-loop control framework, the main goal is to obtain an autonomous controller for the robot and eventually remove the human from the control loop. However, in assistive control, the robot takes share in control and helps the human accomplish the desired task by making it easier and more seamless [9]. So a synergistic cooperation is sustained as long as the task is there. For a fruitful collaboration knowing the human intent for the robot is critical as two systems should better have a common goal. Therefore, it makes sense to have the robot predict the human intention and then generate control commands to augment or correct the human commands.

† Negin Amirshirzad is the presenter of this paper.

In the prior work on assistive control, it is not uncommon to assume that the robot is given the human intention [10-15]. However, some other works use classifiers for goal prediction by assuming that the human is following a predefined path or behavior [16-20]. In this study, we follow a similar approach and propose a synergistic human-robot collaboration framework in which the human starts performing a task and then the robot takes share in control by predicting the human intent and augmenting the human control based on its prediction.

To be concrete, in this study, the proposed human-robot system was realized for a physical balancing task where an anthropomorphic robot arm holds a tray with a ball on it. The goal of the task is to bring the ball to the target position and stabilize it there. The effectiveness of the framework is examined by comparing the shared control performance with two other conditions: when the robot autonomously performs the task and when the human teleoperates the robot.

2. METHOD

In the proposed framework both human and robot are involved to accomplish the given task. The human starts performing the task, simultaneously the robot assists the human by predicting the human intent (a continuous two-dimensional position), taking share in control and augmenting the human control commands. The proposed framework is illustrated in Fig.1. For the net control command that drives the robot a convex combination of the human and robot commands is used (Eq. 1).

$$C = \omega C_H + (1 - \omega) C_R \tag{1}$$

Where ω is a parameter for tuning the command weights, C_H is the human command, C_R is the robot command and C is the net command that drives the robot. In the reported experiments ω is chosen as 0.5.

2.1. Experimental Setup

We realized the proposed framework by using the ball balancing task where an anthropomorphic robot arm (6DOF Kuka Agilus R6000) was to move two of its joints to balance the ball placed on the tray ($70_{cm} \times 70_{cm}$), attached to its end effector, on the target position.

To teleoperate the robotic arm, the human input is captured by a standard computer mouse and converted to control commands. The horizontal and vertical displacements of the mouse are linearly mapped as the desired angular movements of the 4th and 5th joints, respectively (Eq.2), which tilt the tray in two axes. The linear scale used to map mouse movements to robot movements was tuned experimentally to provide an intuitive teleoperation.

$$\begin{aligned} \theta_{4_{desired}} &= \theta_{4_{current}} + k_1 \Delta x \\ \theta_{5_{desired}} &= \theta_{5_{current}} + k_2 \Delta y \end{aligned} \tag{2}$$

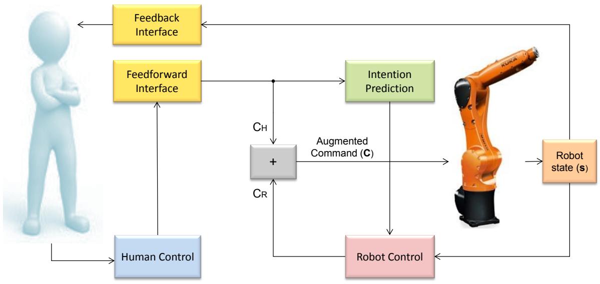

Fig. 1 : The shared control framework is illustrated. Human demonstrator controls the robot in real-time to achieve the desired goal. Simultaneously, the robot infers the human intent and generates commands based on its predicted goal to assist the human in achieving the goal. Eventually, the control command that the robot receives is obtained by a convex combination of the human and the robot generated commands.

Here θ_4 and θ_5 denote 4th and 5th joint angles of the robot, k_1 and k_2 are mouse scale constants and Δx and Δy are recorded horizontal and vertical displacements of the mouse.

For tracking the position of the ball and the tray frame accurately, an infrared camera that oversees the tray is used. The experimental setup is shown in Fig.2. Using camera data, the relative position of the ball with respect to the tray frame is calculated. Image processing and robot control are handled on separate computers and ball positions are sent to the main computer asynchronously. A new set of desired joint angles are sent to the robot whenever a mouse event happens or a vision input is captured. The desired joint angles are then converted into low-level velocity commands by a low-level controller that commands the robot synchronously at 250Hz. Also, a leveling bias is added to the control loop to ensure the frame levels horizontally when no input is created.

2.2. Autonomous Controller

The goal of autonomous controller is to move and balance the ball on the target position on the tray. This controller is obtained by imitation learning. The system state is defined with eight parameters (Eq.3):

$$S = [x, y, x', y', j_1, j_2, j_1', j_2'] \tag{3}$$

Where $(x\ ,\ y)$ and $(x'\ ,\ y')$ indicate ball position and ball velocity respectively, j_1 , j_2 are joint angles and j_1', j_2' are angular velocities.

We assume that correct commands issued at the states experienced by the system will be sufficient for successful execution of the task. For the ball balancing task, if we assume that the relation between the control command and the state is linear, the control policy for ball balancing can be approximated by linear regression. To obtain

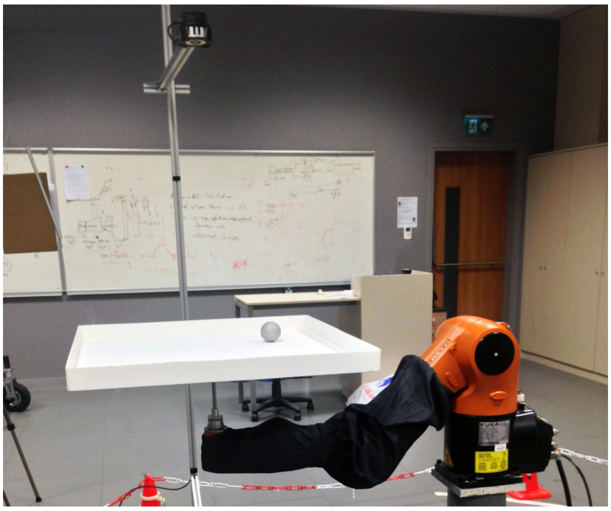

Fig. 2 The Experimental Setup; The tray is held by Kuka Agilus R6000 and the infrared camera is located, where it can oversee the tray.

data for linear regression, an expert subject performed the task multiple times while task states and corresponding commands were being recorded. In total, 4 hours of teleoperation data was captured. The recorded states and commands are collected in the rows of S, C matrices, respectively. With the assumption that SW = C, the weight matrix W that maps states to commands, can be found by:

$$W = S^{\dagger}C \tag{4}$$

where $S^{\dagger}$ is the pseudo inverse of S

Once W is found, having the current state (s), autonomous controller command (c), can be obtained by $c = sW$. The predicted commands and actual commands of the expert subject are illustrated in Fig.3

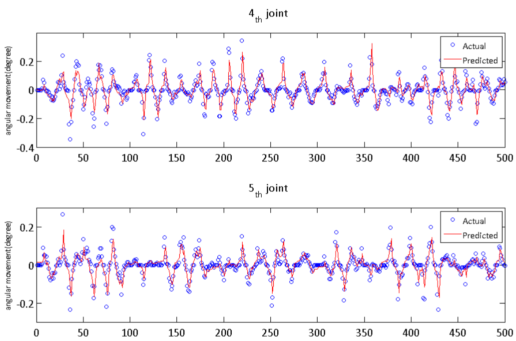

Fig. 3 Actual commands and predicted commands obtained by imitation learning are shown (only 500 points are displayed for clarity).

Although the obtained autonomous controller can perform the ball balancing task, it is not perfect due to nonlinearities in the control and the noise in the environment. We did not spend effort to improve the performance of this controller since we wished to investigate the synergistic effect of shared control.

2.3. Human Intent Prediction

For a successful collaboration knowing the human intent is critical for the robot to assist in accomplishing the goal. Therefore, it needs to have an estimate of the goal and then generate control commands to augment the human commands. Hence, a simple goal prediction method has been developed, in which the robot predicts the human target position on the tray, based on the position histogram of the ball (Fig.4). The histogram is calculated within a predefined time windowed and the predicted goal position is updated based on histogram changes. The goal prediction continues until the end of the session.

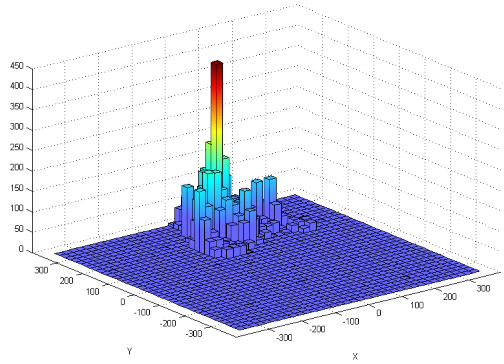

Fig. 4 Position histogram of the ball on the tray for a successful attempt is shown. The subject's target position is $(0_{mm}, 200_{mm})$ which is also the maximum of histogram in the figure.

3. EXPERIMENTS AND RESULT

The proposed shared control framework was implemented and evaluated on a physical ball balancing task on a $70_{cm} \times 70_{cm}$ tray held by a 6-DOF Kuka Agilus R6000 arm. At the beginning of the experimental session, the ball is positioned at the center of the tray with zero velocity and robot joints in their initial positions. As the joints of the robot move, the tray tilts and the ball starts moving. The session continues until the ball is positioned and balanced with zero velocity at the target position.

Experiments were conducted under 3 different conditions. Full autonomous robot control, human-in-the-loop control and shared control. 20 naive subjects were divided into 2 groups to perform the task in shared control and human-in-the-loop control to provide the first trial result for a set of target points selected on the tray.

Two success measures were defined for this experiment: task completion time and the distance of the final ball position to the target position. Each of the subjects had two minutes maximum to balance the ball on the target position and finish the task. The final ball position distance to the target position should not be more than 3cm, in order that an attempt is considered as successful (3cm is chosen based on the radius of the ball, which is 3cm).

In full autonomous robot control, the controller generates robot control commands; in human-in-the-loop control, the human has full control over the task, while in shared control both human and robot take share in generating control commands.

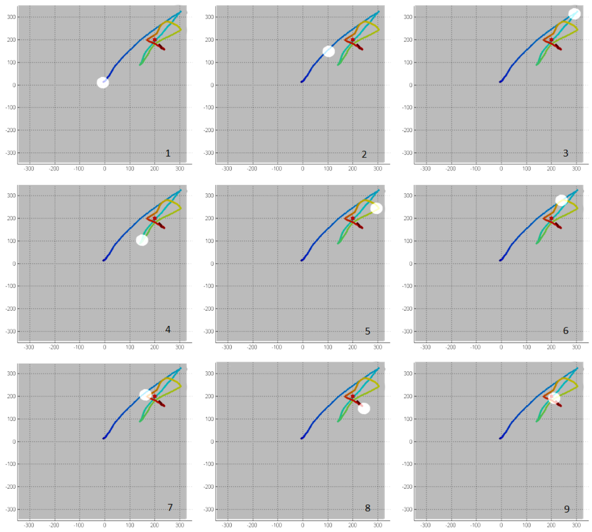

Fig. 5 These frames depict ball movement trajectory from starting point $(0_{mm}, 0_{mm})$ to the target point $(0_{mm}, 200_{mm})$ of a successful attempt. Camera frames are superimposed with the ball trajectory.

The result of our experiments shows that in the human-in-the-loop control group, 5 out of 10 subjects failed to balance the ball on the target position in the given time; in the autonomous robot control out of 10 trials, 2 were unsuccessful, since the distance of the final position to the target position was out of acceptable range, due to surface irregularities. In shared control group, out of 10 subjects only 1 subject failed to achieve the goal in the given time.

Overall, we found 5 target points which could be achieved successfully in all the 3 conditions. We analyzed the performance for these 5 points, by using the success measure parameters. The results can be seen in Fig.6 and Fig.7

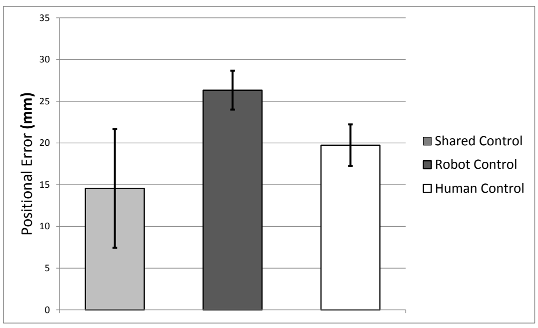

Fig. 6 Mean of positional error (the distance of ball final position to the target position) for the 3 conditions, vertical error bars indicate Standard Deviation.

According to Completion Time (Fig.7) and Positional Error (Fig.6), and T-test results (Table.1 and Table.2), we

Table 1 T-test result on positional error data

	Shared	Robot
Robot	0.036668	
Human	0.256616	0.0011847

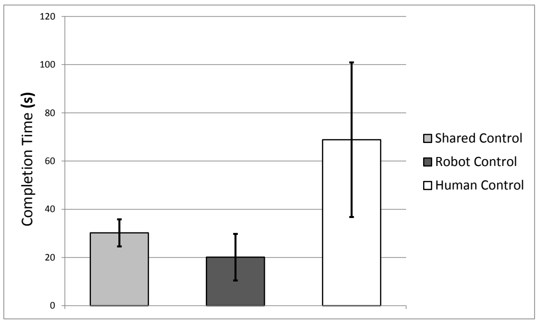

Fig. 7 Mean of completion time for the 3 conditions, vertical error bars indicate Standard Deviation.

Table 2 T-test result on completion time data

	Shared	Robot
Robot	0.108723	
Human	0.041547	0.01948

can infer that the robot control and shared control did not have significant difference in completion time and both were better than human control, however, shared control was significantly better than robot in positional accuracy. Considering both success measure parameters, shared control presents better performance than the other two controllers, which is almost as fast as the robot and more accurate than both the robot and the human.

4. CONCLUSION AND DISCUSSION

In this paper, we introduced a synergistic human-robot collaboration framework and investigated its performance by implementing it on a designed 'ball balancing task' on a tray held by an anthropomorphic robot arm. Three different control scenarios were considered for this task: full autonomous controller, where only the robot generates control commands; a human-in-the-loop controller, where the robot does not interfere with the control and a human-robot shared controller in which the human starts performing the task while the robot attempts to predict the human intent and then take share in control by augmenting human control commands. For this purpose a goal prediction mechanism was developed to be used by the robot, since pursuing a common goal is necessary for a successful collaboration. The effectiveness of the proposed framework was examined by comparing the performance of shared controller with the other two conditions, namely, when the robot autonomously performed the task and when the human teleoperated the robot. 10

subjects were employed for each condition to measure task completion performance of naive solo operators and naive human-robot teams.

According to the performance comparisons, the human-robot shared controller appears to be the best. The result suggests that the proposed system can take advantage of the individual skills so as to cover the weakness of the other party and yield a higher performance controller. Thus, synergistic human-robot collaboration seems to be a promising approach to obtain higher performances than possible with one party alone.

As future work, adaptive weight sharing must be investigated, and the usage of more advanced robot control interfaces, such as haptic feedback devices, should be considered. Moreover other general goal prediction methods must be sought. Finally it is of interest to know how this synergistic human-robot collaboration can affect the performance of the human operator after gaining experience in this shared control framework.

5. ACKNOWLEDGMENTS

We sincerely thank Dr. Ozkan Bebek for his help in the experimental setup.

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