IEEE/IES Int. Conference on Mechatronics (ICM 2015)

A Novel Intention Prediction Strategy for a Shared Control Tele-manipulation System in Unknown Environments

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***Abstract*—This paper addresses the problem of controlling a slave robot with a shared control scheme of a tele-manipulation system in unknown environments. Shared control schemes may be useful for reducing the communication delay in time-critical tele-manipulation systems. Shared control scheme consists of two key components: intention prediction and command arbitration. An intuitive and novel strategy under which the human operator intention could be extracted seamlessly from the hand point to point path during the tele-mnipulation process is developed in this paper. The new strategy is based on the environment scene awareness conducted at the remote side at the beginning of the tele-manipulation task. The developed strategy is tested experimentally with a simulation of a robot model in several remote environments to verify its accuracy and effectiveness. The results confirmed significant performance improvement in terms of reduced time using the proposed shared control scheme compared to the direct tele-manipulation scheme.**

I. Introduction

Performing tasks repetitively and precisely opens the door for robots to invade the field of industrial automation in different scenarios. At the beginning of 2014, around 179,000 industrial robots were sold worldwide [1]. This number is expected to be increased within the next few years with a noticeable growth in the industrial robotics market. Although this significant advance, robot's potential has not been fully realized as a key element to assist the factory automation. Once the robot is programmed, it is expected to interact with a relatively static working environment. To cope up with this limitation, the robotic research directions have focused on taking advantage of applying human-robot interaction (HRI) schemes in industrial applications [2]. Hence, numerous applications could benefit from the synergy between the human intelligence and the robot accuracy.

Tele-manipulation through a master-slave system is the dominant scenario that embodies the synergy between human and robots. It is defined as controlling a dexterous robotic manipulator (slave) at a distance by a human operator (master) to achieve manipulation tasks [3]. This distance implies a barrier that inhibits the co-existence of a human operator into the workplace. It could be a physical distance, which is imposed by working in hazardous and in accessible environments as in [4]. Moreover, the distance may be due to scale dissimilarity between the operator and the task workspace as in micro-telemanipulation systems [5].

Tele-manipulation of a robotic arm could be done in two different schemes: direct and shared control schemes. In direct control, the manipulator moves in such a way to copy the captured operator movements at the master side. On the other hand, the shared control permits the manipulator to support the operator in performing manipulation tasks while absolving him/her from some of the motion control work. Specifically, high level cognition tasks are assigned to the human while low level tedious tasks are assigned to the robot at the remote side. More than one motivation behind developing such a mode of control are reported [6]. For instance, in master-slave systems with large communication delay, robot can do critical tasks autonomously without waiting commands from human. Furthermore, shared control tele-manipulation eliminates the demand for continuous human attention. Thus, the operator workload can be scaled down.

To support human operator, shared control tele-manipulation systems have to solve two main problems; namely, predicting the operator intention, and deciding how to achieve this intention [7]. Generally, intention prediction is the ability of a system to predict what operator is intended to do next given some evidential actions within the context of the task he/she does. Several approaches had been studied extensively in the literature to facilitate the intention prediction capability for the shared control tele-manipulation. They can be broadly classified into the following three main streams:

1) Strategies in which the operator's intent is assumed to be known by the slave robot. Consequently, the robot has the authority to fully control its motion to achieve that intent. For example, in [8] the manipulator is required to achieve the operator intent which is assumed to be aligning the end-effector with the centroid of a near object. Such kinds of strategies are not applicable in real-world scenarios since both the environment and operator intent could be changed significantly.
2) Strategies which assume that the operator is following one of a set of predefined behaviors. Subsequently, a classifier has to be trained off-line to model the operator actions with these different behaviors. Afterwards, this classifier

will be used in the tele-manipulation runtime to predict the operator behavior based on the observed user actions [9]. These strategies are limited due the assumed per-defined behaviors. Additionally, they are not applicable in real-world scenarios for the same reason mentioned above.

3) Strategies in which it is allowed for the operator to communicate his intent explicitly to the robot. Intent communication could be done via one of other interfaces. For example, in [10] laser pointing was used by the operator to identify the intended goals to be grasped by the robot. Also, in [11] the operator identifies the intended goal including the exact grasp via a GUI interface.

In this paper, a new strategy called inferred intention is proposed to cope up with the aforementioned limitations while working in unknown environments. The motivation behind this work is to enhance the tele-manipulation process in terms of the time delayed by exploiting the synergy between robot and human capabilities. The key principle of the proposed method is to be aware of the remote environment scene prior to the tele-manipulation process. Scene awareness will help the proposed system to predict what the operator is intending to do next based on his/her hand movements towards an object. Consequently, the operator intention is predicted at the run-time of the tele-manipulation process rather than being assumed to be one of a predefined behaviors. In contrast to the aforementioned strategies, predicting intention from hand movements allow natural, fast and seamless way of implicit communication. Moreover, the proposed tele-manipulation system has a much wider scope in terms of providing assistance in areas such as nuclear waste clean-up, space/undersea tele-robotics, and defense applications.

The remainder of this paper is organized as follows: In Section II, the proposed shared control tele-manipulation system is introduced and discussed in detail. In Section III, experimental work is provided to quantify both the inferred intention strategy and the system as a whole. Experimental results are detailed and discussed in Section IV. Finally, conclusion is given in Section V with remarks on the future directions.

II. System Description

The proposed system consists of a master-slave tele-manipulation scheme which operates in a shared control mode. This system allows the manipulator at the slave side to aid the operator at the master side in reaching an intended object precisely and promptly. The object that is intended to be grasped is intuitively predicted via the operator's hand movements. These movements were tracked prior to grasping the object. Having recognized this object with a high level of confidence, the master system commands the manipulator to reach this object directly without waiting the human operator to complete his/her reach-to-grasp movement. The motivation behind the usage of this scheme is to decrease the communication delay between the master-slave system. In particular, at a certain time of the whole runtime the manipulator can reach the intended target independently of the operator control. This is a significant feature, especially in critical tasks in which the robot is required to react promptly.

Figure 1 shows the proposed master-slave system block diagram with the developed inferred intention strategy. It is

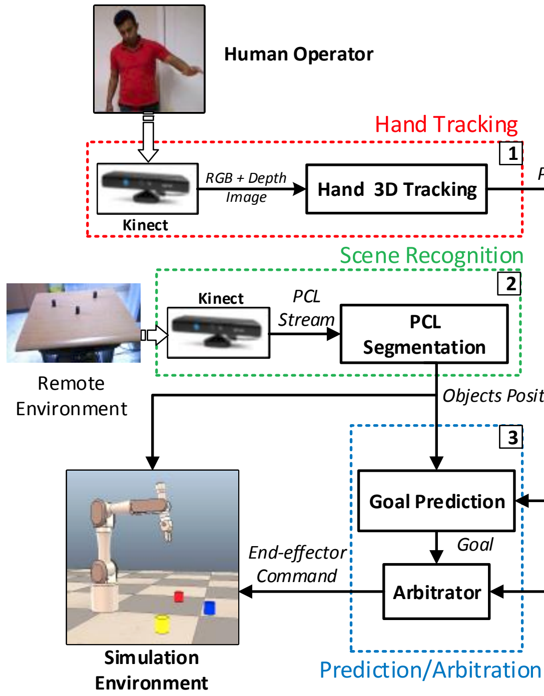

Fig. 1. Block diagram of the proposed master-slave tele-manipulation system.

divided into three principle sub-systems: (a) Hand Tracking (Block 1); (b) Scene Recognition (Block 2); and (c) Prediction/Arbitration (Block 3). The proposed system consists of several modules which communicate with each other under the Robot Operating System (ROS) framework [12].

A. Hand Tracking Subsystem

At the master side, human hand positioning is tracked and conducted by continuously processing RGB and depth images acquired from a RGB-depth camera. A Microsoft kinect sensor is used to provide these types of images. It is placed in front of a human operator to acquire his/her hand movements. Firstly, the OpenNI tracker package [13] is used to extract the human skeleton joints. After that, the upper torso joints are identified as shown in Fig. 2. To neglect the transformation between the operator hand and the Kinect sensor, the relative hand position $\boldsymbol{p}_h = [x \quad y \quad z]^T$ is defined as the location of the left/right hand joint, $\boldsymbol{p}_{lh}/\boldsymbol{p}_{rh}$, relative to the torso joint location $\boldsymbol{p}_t$. In this research, the operator left hand is extracted. Furthermore, the relative hand location $\boldsymbol{p}_h$ is smoothed among different frames to minimize jittering and stabilize the joint positions over time. The smoothing process is achieved via an exponential moving average filter [14] as follows:

$$\widehat{\boldsymbol{p}}_h(t) = (1-\alpha).\widehat{\boldsymbol{p}}_h(t-1) + \alpha.\boldsymbol{p}_h(t) \tag{1}$$

where $\widehat{\boldsymbol{p}}_h(t)$ is the smoothed relative hand location at time t, $\boldsymbol{p}_h(t)$ is the actual relative hand location at time t while $0 \leq \alpha \leq 1$ is a damping factor that is empirically selected.

B. Scene Recognition Subsystem

To achieve the human intention recognition in unknown working environment, the proposed system has to be aware

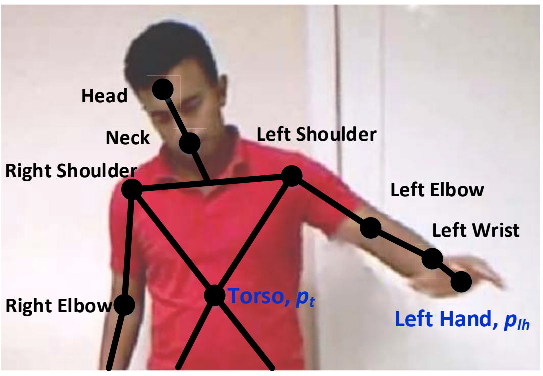

Fig. 2. Human upper part joints extracted from OpenNI skeleton tracker.

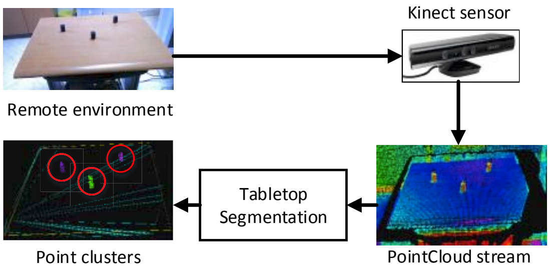

Fig. 3. PCL segmentation process to extract the set of graspable objects rest on a table.

of the remote environment at the beginning of the tele-manipulation process. This permits the robot to recognize in real-time the set of all graspable objects (objects that are applicable to be grasped by the human). Remote scene awareness is carried out by a secondary Kinect sensor placed in the remote environment. This sensor provides a 3D world representation of this environment in the form of a stream of point clouds (PCL) data [15]. Having the PCL representation, the graspable objects could be realized by means of PCL segmentation. It is done by breaking the cloud apart in different pieces or groups of points called clusters. Ideally, every cluster would belong to the logical notion of ”object”. For example, for a cloud that shows 4 boxes on a table, 5 clusters would be created; one for the table, and one for each of the boxes.

In this regard, the available ROS Tabletop object detection package [16] is used to perform object segmentation for the working environment scene. A modification to this segmentation process is developed here to extract centroids of these segmented objects. PCL points stream of the remote scene is fed to this package to extract the clusters of the objects placed on a table as shown in Fig. 3. The object detection package is based on the following assumptions:

- Objects are resting on a table, which is the dominant plane in the scene.
- The minimum distance between two objects exceeds a given threshold (around $3cm$).

In the remote environment, the 3D location of a certain graspable object i within a cluster C_i with respect to Kinect frame $\{K\}$ is obtained by simply calculating the centroid of the cloud points within that cluster as follows:

$$^K\boldsymbol{p}_{Oi} = \frac{1}{N_i}\sum_{j=0}^{N_i}\boldsymbol{p}_{C_{ij}} \tag{2}$$

where N_i is the number of points associated with a cluster C_i and each point j has a location $\boldsymbol{p}_{C_{ij}}$. However, these values should be expressed with respect to the base frame of the robot manipulator to facilitate the prediction process. Since a simulation model for the robot manipulator is used, a virtual frame $\{B\}$ is placed somewhere on the remote environment to represent the manipulator base. Thus, the Kinect has a relative transformation with respect to the virtual base frame ^BT_K which is used to express the object locations with respect to the manipulator base as follows:

$$^B\boldsymbol{p}_i =^B T_K * (^K\boldsymbol{p}_{Oi}) \tag{3}$$

where $^B\boldsymbol{p}_i$ is the location of the object i with respect to the virtual frame $\{B\}$ of the manipulator base.

C. Prediction/Arbitration Subsystem

The Predication/Arbitration block is the key component for the proposed system. It is in charge of achieving two tasks: (1) Human intention prediction and (2) Robot command arbitration. A ROS package is implemented to achieve these tasks as follows:

1) Human Intention Prediction: In shared control tele-manipulation system, the robot is required to support the human in achieving the manipulation task accurately. Such a collaboration could be realized if only the system has the ability to predict what the human is aiming to do in earlier stages of the manipulation process. Ideally, prediction of human intention has to be conducted intuitively and smoothly without interrupting the human operator. Here, intention prediction strategy called inferred prediction is proposed. It is based on estimating the most probable object that the operator is intended to grasp in real-time. Namely, the developed strategy eliminates both the need for training a classifier off-line and the need of another modality to express the intention explicitly. In the proposed strategy, once having this intended object, the manipulator is required to move towards it without waiting the operator to complete his command and hence reduce the total communication delay.

Letting G represents the set of all graspable objects that are obtained from the scene recognition block (Sub-Section II-B), the estimated goal g^* that maximizes the posterior probability to be grasped $P(g|\boldsymbol{p}_h(t))$ is formulated as follows:

$$g^* = \arg\max_{g\in G} P(g|\boldsymbol{p}_h(t)) \tag{4}$$

where $\boldsymbol{p}_h(t)$ is the human hand trajectory acquired from the hand motion block (Sub-Section II-A) from the start to the current time t. From the neuroscience of grasping, the reach-to-grasp movement is divided into two subsequent steps: an initial fast movement towards the goal, then a slow fine movement while approaching the goal to match the geometry of this goal [17]. During the first step, the point-to-point hand paths in planar Cartesian space are approximately straight [18]. Based on these knowledge, the posterior probability could be estimated from the operator hand trajectory towards the

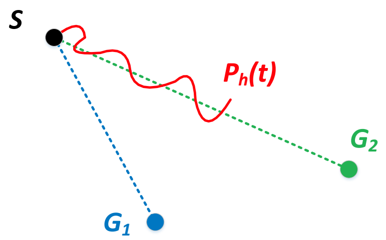

Fig. 4. An example of operator hand's trajectory leading to two possible goals. Operator's trajectory $\boldsymbol{p}_h(t)$ has the minimum deviation from the optimum trajectory to G_2 rather than to G_1

intended object. Operator hand is assumed to follow a certain path that minimizes the deviation from the optimal line leading to the intended object. In other words, among the set of all graspable objects, the intended goal is the object which has minimum deviation between the goal optimum line and the operator hand trajectory. This is illustrated in Fig.4, where G_2 has the minimum deviation between its optimum line and the hand trajectory $\boldsymbol{p}_h(t)$ compared with G_1. Subsequently, the object G_2 is the object that is likely to be grasped. Generally, this can be formulated as follows:

$$P(g|\boldsymbol{p}_h(t)) \propto \sum \frac{1}{d(\boldsymbol{p}_h(t), L_{s\to g})} \tag{5}$$

so,

$$g^* = \arg\min_{g\in G} \sum d(\boldsymbol{p}_h(t), L_{s\to g}) \tag{6}$$

where $\sum d(\boldsymbol{p}_h(t), L_{s\to g})$ is the accumulated piecewise orthogonal 3D point-to-line distance between the current operator hand trajectory $\boldsymbol{p}_h(t)$ and the optimum line $L_{s\to g}$ to a certain goal g which is calculated as follows:

$$d(\boldsymbol{p}_h(t), L_{s\to g}) = \frac{\|(\boldsymbol{p}_h(t) - \boldsymbol{p}_s) \times (\boldsymbol{p}_h(t) - \boldsymbol{p}_g)\|}{\|\boldsymbol{p}_s - \boldsymbol{p}_g\|} \tag{7}$$

where $\|.\|$ is the norm of a vector, $\boldsymbol{p}_h(t)$, $\boldsymbol{p}_s$ and $\boldsymbol{p}_g$ are the location vectors of the operator hand, starting point and goal position respectively, which are received to the Prediction/Arbitration block continuously.

2) Command Arbitration: Having the operator hand trajectory $\boldsymbol{p}_h(t)$ and an estimated goal g^*, the arbitrator should choose the appropriate command for the robot manipulator. The arbitrator sub-block commands the manipulator end-effector to move either to follow the operator trajectory or to reach the intended goal directly. Commands arbitration is a challenge in the tele-manipulation scenarios, since the robot autonomy should contribute to the manipulation process in earlier stages. A simple binary policy is used to switch between operator following or goal reaching commands. Intuitively, the switching criteria depends on the confidence level ϵ the system has about the predicted goal at time t. In other words, if the system is more confident with the intended goal estimation by a certain threshold $\epsilon_{th.}$, the arbitrator switch to command the robot end-effector to reach this gaol g^* directly. Otherwise, if this confidence level is less than that threshold, the arbitrator will let the robot just follow the operator hand trajectory $\boldsymbol{p}_h(t)$ continuously. Formally, The current end-effector command $P_e(t)$ is calculated as follow:

$$P_e(t) = \begin{cases} g^* & \text{if } \epsilon \geq \epsilon_{th.} \\ \boldsymbol{p}_h(t) & \text{otherwise} \end{cases} \tag{8}$$

Confidence level ϵ is calculated as the posterior probability that the system has about the intended object at certain judgment point. In this work the judgment point is heuristically selected in such a way that the operator hand has traveled an enough distance to predict the intended goal robustly. On other hand, this point should be selected to be early to permit the contribution of the robot autonomy at earlier stages. Specifically, the confidence level is determined at the point that the operator hand has approximately passed 60% of any path length towards one of the graspable object:

$$\epsilon = P(g*)|_{\max(D)\approx 60\%} \tag{9}$$

where $D = \{d_1, d_2, \ldots, d_N\}$ is the set of all the percentage of distance d_i traversed by the operator hand over the total path lengths towards the object g_i. This obtained confidence value is compared to a certain threshold value $\epsilon_{th.}$. This threshold is selected to be any value greater than the initial uniform distribution over N graspable objects, i.e. $\epsilon_{th.} > \frac{1}{N}$.

III. Experiments

A. Experimental Test Bed

Two Kinect sensors, K_1 and K_2 are employed in the proposed scheme. K_1 is located in front of a human operator to track and capture the hand position over time, while K_2 is located in the remote side for scene recognition as shown in Fig. 5. The hand tracking sub-system acquires the hand positions at frequency of 30 frame/sec. A Mitsubishi PA-10 redundant manipulator is simulated in V-REP simulation environment [19] representing the slave manipulator. A visual feedback of the simulation environment of the slave robot is provided for the human operator via a front screen S to be aware of the controlled robot.

B. Experiment Methodology

Two types of experiments are conducted to quantify the proposed intention/arbitration strategy in terms of accuracy and effectiveness. Accuracy of the inferred intention strategy is assessed in terms of the success rate in predicting the human intention during the tele-manipulation process. Three human subjects are asked to perform a reach-to-grasp movement five times towards a certain object which is known to the human subject prior to the experiment.

Moreover, the effectiveness of the proposed tele-manipulation scheme is measured in terms of reduced execution time. In this case, three human subjects are asked to tele-manipulate the slave robot end-effector to reach an object via

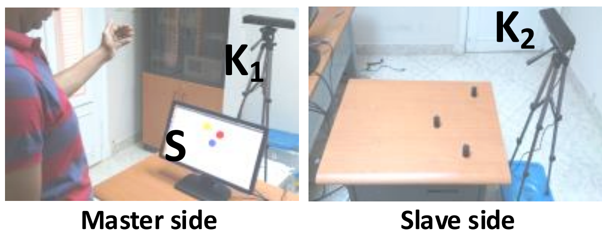

Fig. 5. Test bed of master and slave sides.

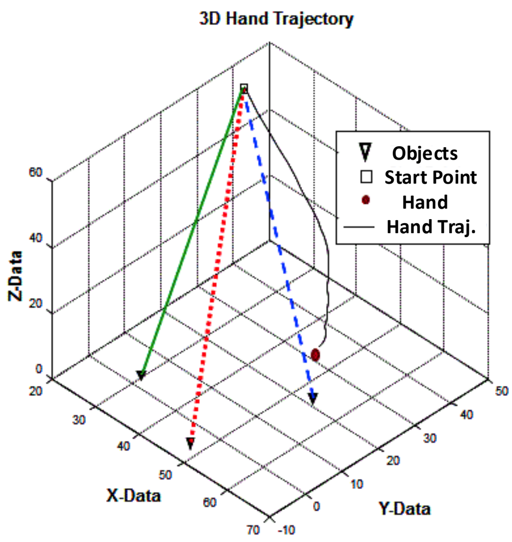

Fig. 6. 3D trajectory of the operator hand in black while approaching a certain goal in blue.

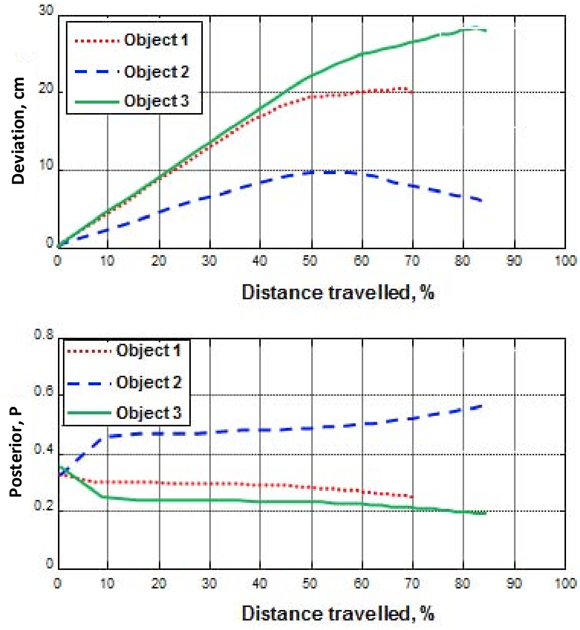

Fig. 7. Three objects scenario results: (top) the deviation in cm between the hand trajectory and the optimum paths towards the object, (bottom) the posterior probability of an object to be grasped.

the proposed master-slave system. Experiments are carried out in two different modes: the direct control mode and the shared control mode. In the direct control mode, the subject is required to achieve the task without any assistance, no shared control is used, except the visual feedback of the simulated environment. On the other hand, in shared control the manipulator will assist the human subject to achieve the task based on the inferred intention strategy. Before starting the experiments, subjects are given sufficient time to get familiar with the system. It is important to mention that, this paper focuses on just reaching an object rather than grasping the object. Force-closure grasps, finding optimal grasping points etc. are out of scope of this paper.

IV. Results and Discussion

The proposed inferred intention strategy is evaluated over five different environment scenarios. Namely, the number of objects are changed in each scenario from three to six objects with different distribution. A human subject is asked to manipulate the simulated manipulator to reach a certain object. Once the operator hand has reached the judgment point, the probability of the estimated object is recorded. For instance, Fig. 6 shows the operator hand trajectory while approaching one of objects in the three objects scenario. Figure 7 demonstrates the successive deviations between the operator hand and the three optimum line according to eq. (7). In addition, the successive posterior probability is plotted in Fig. 7 (bottom). It can be noted that the estimated object to be grasped has a minimum deviation between its optimum line and hand trajectory. Consequently, it has the maximum posterior probability among others. To evaluate the performance of the inferred intention strategy, confusion matrix C for each configuration scenario is constructed. For instance, Table I shows the confusion matrix for the three objects scenario which is averaged over five trials. Each element c_{ij} of the matrix represents the average posterior probabilities of an actual object j to be estimated as an object i by the intention strategy. Furthermore, the standard deviation is accompanied in the table. Indeed, these values are obtained at the judgment point once the operator hand has traversed 60% of the total distance. To measure the intention prediction accuracy, the probabilities of predicting an intended object truly positive (TP), truly negative (TN), falsely positive (FP) and falsely negative (FN) are obtained. Then accuracy η can be calculated using the following index [20]:

$$\eta = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

An average accuracy over four different scenarios is obtained as 65% which is a quite acceptable value especially in HRI applications where the human is in the loop and prediction is not required to be perfect [7].

Another example of 3D trajectory of the PA-10 manipulator model is shown in Fig. 8. It could be observed that at the judgment point the manipulator will reach the target directly without waiting the command from the human operator. Subsequently, the total execution time is reduced. To measure the effectiveness of the proposed system in terms of reduced time, the total execution time for the reach-to-grasp process is obtained. This time is measured and compared for both control modes: direct and shared. As shown in Fig. 9, the averaged time over objects for the shared control is 34.9% less than the one of the direct control. This inferred that the time delay in communication is reduced.

TABLE I. Confusion matrix at judgment point of three object scenario.

Estimated	Actual		
	Object 1	Object 2	Object 3
Object 1	0.54±.02	0.34±.13	0.22±.06
Object 2	0.24±.01	0.34±.03	0.24±.05
Object 3	0.21±.03	0.32±.16	0.53±.10

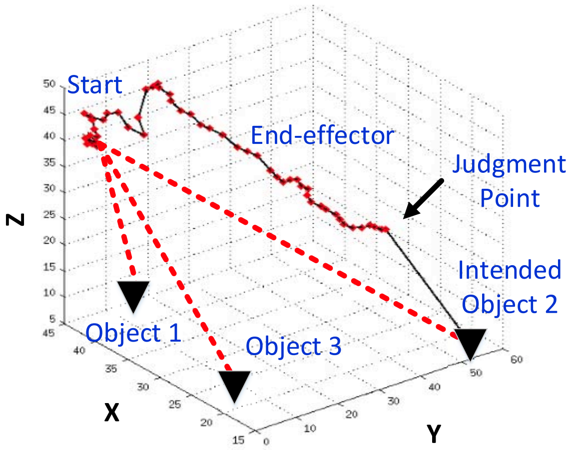

Fig. 8. 3D trajectory of the slave manipulator in the proposed shared control scheme.

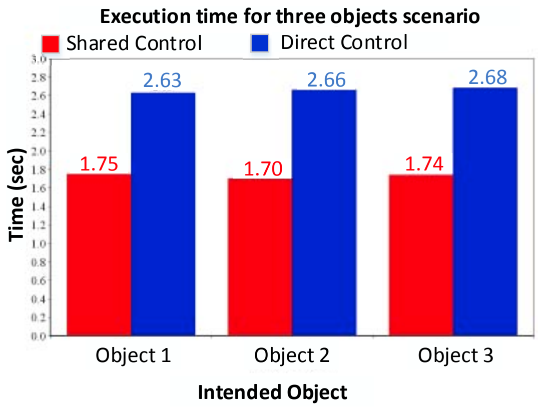

Fig. 9. Three objects scenario execution time plots for reach-to-grasp task.

V. Conclusion

A novel intention prediction strategy called inferred intention has been developed for tele-manipulating a robot arm in unknown environments. To reduce the total time delay in time-critical applications, the proposed strategy is combined with an arbitrator to provide a shared control tele-mainpulation scheme. The new approach is based on the remote scene awareness at the beginning of the tele-manipulation process. The accuracy and the effectiveness of the proposed inferred intention strategy has been confirmed through conducting several experiments in different scenarios of the remote environment. The obtained results prove that the total communication time delay is reduced in the master-slave system with unknown remote environments. Future work should include experiments on more complex environments. As well as, we intend to integrate more features to enhance the accuracy of the proposed inferred intention strategy. Such as operator hand distance and the bearing angle to the object.

Acknowledgments

The first author is supported by a PhD scholarship from the Mission Department, Ministry of Higher Education (MoHE) of the Government of Egypt which is gratefully acknowledged. Also, I would like to thank the administration of Egypt-Japan University of Science and Technology for their efforts to build the university as a model research university.

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