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Human-Robot Interaction in an Unknown Human Intention scenario

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Abstract— **In this paper an approach is introduced to human-robot interaction in a known scenario with unknown human intentions. Initially, the robot reacts by copying the human action. As the human-robot interaction proceeds, the level of human-robot interaction improves. Before each reaction, the robot hypothesizes its potential actions and selects one that is found most suitable. The robot may also use the human-robot interaction history. Along with the history, the robot also considers the action randomness and heuristic based action predictions. As solution, a general Reinforcement Learning (RL) based algorithm is proposed that suggests learning of human-robot interaction in an unknown human intention scenario. A Particle Filter (PF) based algorithm is proposed to support the probabilistic action selection for human-robot interaction. The experiments for human-robot interaction are performed by a robotic arm involving the arrangement of known objects with unknown human intention. The task of the robot is to interact with the human according to the estimated human intention.**

I. INTRODUCTION

With the growth of robotic presence in the human community, the need of intuitiveness in the human-robot interaction has become inevitable. The human-robot coexistence with various degrees of restriction can be found in many areas, specifically in the industry. The most commonly used robots in the industry are the robotic arms. There exist many tasks in the industrial scenarios where the robots (robotic arms) work together with the humans. Therefore, it is necessary for the robots to interact smoothly and intuitively to solve the task effectively, successfully, and safely. The human-robot interaction can only be intuitive and thus effective if the robots can anticipate the human intention. A robot as a machine can not extend its interaction model to adapt to the changing human intention that is not already known to the robot. With a significant deviation from the basic focus of the human robot interaction, there exist a lot of such solutions under the umbrella of Programming by Demonstration (PbD) that is almost a complete field in itself. The approach of PbD tries to enable the robot to reproduce what has been performed before the robot. In the literature of RL many solutions exist with no human input. In some of RL-based solutions, human input exist, e.g., [9] and [3]. These are required to be trained. The presented solution is not required to be trained. In [2] RL is used to refine (teach) the robot behaviour.

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In the area of intention recognition for human-robot interaction, there exist a number of approaches [5, 10, 11] that use HMM, Dynamic Bayesian Network, and Hybrid Dynamic Bayesian Network to recognize the human intention. The approaches described in [4, 12], perform Ontology and Graph based intention recognition. The human-robot interaction based on the probabilistically weighted Finite State Machines (FSM) is described in [6]. Each FSM represents a potential human intention that is already known to the system. The approaches described in [1, 8] deal with the proactive recognition of the premature human intention. More specifically [7] describes about how to handle the totally new situation in intention recognition based human-robot interaction. The approach described in [7] does not suggest the robot how to react in the totally unseen situation. Rather it suggests first to learn how to react and then interact in that situation. In the literature of human-robot interaction, the topic of human-robot interaction in a known scenario with the unknown human intention is not considerably explored. The known scenario means that the objects present in the scene are known to the robotic system. The *inference parameters* are the features related to the objects present in the given scenario. The *associated operations* are the changes in the inference parameters, occurred due to the human actions. They are used to infer the human actions. The operations associated with the objects and related inference parameters of the scenario are known to the system. The *unknown human intention* describes what the human intends about the scene and that is not known already to the system. In this paper a solution is proposed for the human-robot interaction with the unknown human intention. In the proposed solution, the robot interacts with the human by selecting a suitable action. If the selected action is according to the human's intention then the robot continues. Otherwise, the human may correct the performed robotic action or may ask the robot to select another action. The robot hypothesizes all the possible seen actions and selects an action that is probabilistically suitable and has good history support if it exists. The remainder of this paper is organized as follows. In the Section II a general RL based human-robot interaction algorithm is given. In Section III the process of probabilistic action selection is explained in detail. Section IV describes the experiments performed using the proposed approach. Finally, Section V concludes the approach and discusses that the presented approach can be applied to different cooperation scenarios, other than the performed experiments.

II. INTERACTION IN AN UNKNOWN INTENTION SCENARIO

An algorithm is proposed on the basis of RL for human-robot interaction in the unknown intention scenario. In this

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algorithm, the robot learns to interact by human response while interacting with the human in the unknown intention scenario in a known environment. The robot's reactions are purified by the passage of time as the robot interacts more and more with the human with respect to an intention. This is the point where the algorithm has resemblance with the RL paradigm as the robot's interacting capability improves as the robot interacts with the human.

As RL allows the agent to decide what action to take in a specific state depending on a reward function, similarly in this algorithm the robot decides for an action depending on three factors that are: The randomness of that action, the history support of that action, and the weight of the that action. The reason for proposing a new RL-based algorithm is due to the fact that in the current RL algorithms, the agent (robot) interacts with the environment and gets the reward against his action. In the proposed algorithm, the rewards are directly given by the human. The human either gives reward to guide the robot to make a better reply or simply corrects the agent's action. Therefore, this is also semi-supervised approach in this sense that the agent may be corrected by the human but not necessarily in every case. Another reason that the proposed algorithm deviates from the core idea of RL is that the human can not wait for a long time for the agent to learn the optimal action and then perform that action. The algorithm is given in Figure 1.

Initially the action set A and state set S are empty. Each action $a_{F_1=f_1,\ldots,F_n=f_n}$ is characterized by n different features $F_1,\ldots,F_n$, where f_1 represents the value of feature F_1. The state set S consists of 3-tuple element. Each 3-tuple contains the state s_i before the action and the state s_{i+1} after the action and the action $a_{f_1,\ldots,f_n}$ with $f_1 \in F_1,\ldots,f_n \in F_n$ itself. It is assumed that the human starts the interaction and the robot responds. Therefore the robot waits for the human action. It is also reasonable to wait for the human action because the likelihood of success with respect to correct action is considerably low.

After the human has performed, an action 3-tuple is added to set S with state s_i before the human has performed the action, the performed action $a_{F_1=f_1,\ldots,F_n=f_n}$ and the state s_{i+1} of the system after the human has performed the action (Line 5). The robot reacts after making an educated guess. The process of selecting an appropriate reaction is discussed afterwards. If the reaction is according to the human intention and accepted by the human then another 3-tuple is added to the set S (Line 16). If the human gives negative reward then the robot reacts with the next likely action (Line 14), if there exist one. In case that the human performs the correction then the 3-tuple is added to the set S and the action $a_{F_1,\ldots,F_n}$ is added to the set A if the action is newly performed by the human (Lines 8-12). The output of the algorithm given in Figure 1 is the set S. The set S can be used to construct a probabilistic FSM [7]. The process continues until the goal state is reached. The goal state is reached if all the objects present in the scene are acted upon by the human and robot and the human does not perform any further action. The goal state is also reached if the human stops the robot from further interaction.

1 - Set $A = \{\}$
2 - Set $S = \{\}$, $i = 1$
3 - Wait for human action $a_{F_1,\ldots,F_n}$
4 - Add the taken action to A, i.e., $A = A \cup a_{F_1=f_1,\ldots,F_n=f_n}$
5 - Add s_0, s_1 and $a_{f_1,\ldots,f_n}$ with $f_1 \in F_1,\ldots,f_n \in F_n$ to S,
    i.e., $S = S \cup (s_0, a_{F_1=f_1,\ldots,F_n=f_n}, s_1)$
6 - **repeat**
7 - React with highly likely action
8 - **if** "the human corrects the action" **then**
9 - **if** $(a_{F_1,\ldots,F_n} \notin A)$ **then**
10 - Add the human action to A,
    i.e., $A = A \cup a_{F_1,\ldots,F_n}$
11 - **endif**
12 - Add s_i, $a_{F_1,\ldots,F_n}$ and s_{i+1} to S, i.e.,
    $S = S \cup (s_i, a_{F_1,\ldots,F_n}, s_{i+1})$
    $i = i + 1$
13 - **elseif** "human gives negative reward" **then**
14 - React with the next highly likely action
15 - **else**
16 - Add s_i, $a_{F_1,\ldots,F_n}$, s_{i+1} to S, i.e.,
    $S = S \cup (s_i, a_{F_1,\ldots,F_n}, s_{i+1})$
    $i = i + 1$
17 - **endif**
18 - **until** the goal state is reached.

Figure 1. Reinforcement-based human-robot interaction algorithm

III. PROBABILISTIC ACTION SELECTION

We motivate the problem of probabilistic action selection for human-robot interaction in an unknown human intention scenario by an example of interaction between two perfect strangers. They do not know a common language to communicate with each other. The person A is totally new to the work area, joins to collaborate with the person B who is already experienced with the tasks in the work area. At each new task, the person A observes person B and tries to help him by copying his action and amends his own reactions by the correction performed by the person B. Afterwards the person A may analyze the similarities in the actions performed in the new task and the actions performed previously. Depending on the similarities, person A may select an action to collaborate. The person A may select an action finding the similarity between the previous and current task. Similarly A can prefer an action over another action using some known heuristics. The person A keeps track of the complete action sequence concerning an intention of person B, for later use for the interaction in the unknown intention cases. We replace the person A with the robot and assume that the robot is already given the features that characterize the actions of the human (person B). Thus the robot can understand the human actions as well as correction with respect to features. The scene information is also known to the robot, i.e., the objects that exist in the scene. In order to collaborate with the human, the robot needs to follow the pattern of human activities simulating the person B. Similarly, at the start of each new task corresponding to unknown human intention, the robot repeats the human action. For simulating the human analysis of action selection, the robot needs to know how many times $P(a_i)$ an action a_i is performed, how many times $P(a_j \mid a_i)$ an action a_j is performed after action a_i, what kind of action sequences are performed already while collaboration, and what action should be preferred. The robot needs to take into account the following aspects in order to interact with the human in the unknown human intention case:

A. Action probability
B. Action prediction
C. Weighting of the predicted collaborative actions
D. History based collaborative actions predictions

A. Action probability

The action probabilities tell about the probabilistic suitability of an action. The conditional probability $P(a_j \mid a_i)$ describes the uncertainty involved in the currently performed action a_j with respect to the previously performed action a_i The robot first tries to find out if the actions a_j and a_i have already occurred in the same sequence. If yes then how many times. In case that the robot cannot find an already existing sequence of the actions a_j and a_i, then it simply tries to find out the prior probability $P(a_j)$ of the action a_j, i.e., how many times the action a_j has been performed by the human with respect to other actions. The robot uses one of these values while selecting an action for reaction.

B. Action prediction

The actions performed by the human and the accepted robot actions are used as input to predict the future actions. Each action corresponds to a set of known features, i.e. $a_{f_1,\ldots,f_n}$ with $f_1 \in F_1,\ldots,f_n \in F_n$. The future actions are predicted based on the human actions and accepted robot actions, observed during the human-robot interaction. After an action is performed, all the previously performed actions are considered for further action prediction. If the robot action is accepted then all the previous actions are used for new action prediction with respect to the performed action, shown in Figure 2 (above). If the robot's action is corrected by the newly performed human action then that action is added as new action hypothesis to the previously existing hypotheses and newly created hypotheses, shown in the Figure 2 (below). The Figure 2 (above & below) is further explained in next subsection with respect to weighting of actions. The prediction of actions is performed after each human-robot interaction step. The interaction step corresponds to the action performed by the robot. The interaction step is completed if the human accepts the robot action. Otherwise it is completed by the correction performed by the human.

C. Weighting of the predicted actions

All the expected scene changes produced due to the predicted actions are considered as hypotheses. Initially all the hypotheses are weighted uniformly. In the Figure 2 (above & below), the predicted hypotheses are represented by the encircled dots. The simple dots represent the acted upon hypotheses that were accepted.

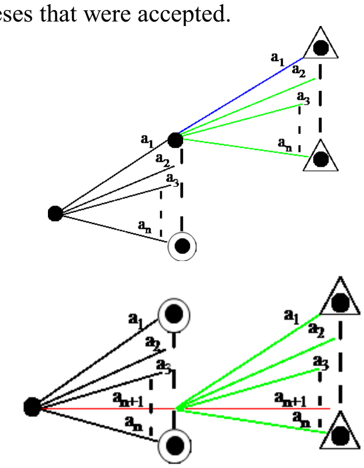

Figure 2. Generation and weighting of potential action hypotheses, a dot represent an acted upon hypothesis, an encircled dot represent the result of a previously created action hypothesis, a triangulated dot represent the result of a currently created action hypothesis and the lines represent the action that lead to result of that action, i.e., encircled dot and triangulated dot. Generation of hypotheses if robot action is accepted, (above). Generation of hypotheses if robot action is corrected, (below).

In case if the robot reaction is accepted by the human then the further action hypotheses are created only with respect to the that action, shown in Figure 2 (above). All the newly created hypotheses (represented as green) are weighted high with respect to the previously existing hypotheses. The accepted action represented as blue in Figure 2 (above) gets higher weight with respect to the newly generated (Green) hypotheses. In case if the human rejects the robot's response and corrects the action performed by the robot. Then the hypotheses are generated and updated with the addition of the new (correction by human) action, shown in Figure 2 (below). The new action (shown red in Figure 2 (below)) is added to the previously generated hypotheses (update) with comparatively higher weight from the already exiting hypotheses. The new hypotheses are generated with respect to the correction and get higher weight with respect to the previous hypotheses (shown green in Figure 2 (below)). In new hypotheses the newly added action (shown red) gets higher weight with respect to newly generated hypotheses.

D. History based actions predictions

As descried earlier that a human intention consists of a sequence of actions. Each action can be characterized by a set of *n* features.

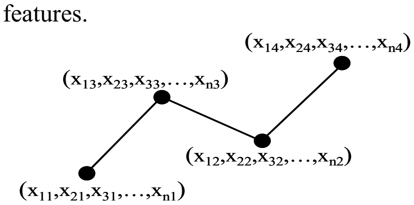

Figure 3. Action sequence trajectory concerning a human intention, each dot represents an action and a complete trajectory represents a task concerning a human intention

It means that each action can be represented as a point in the n dimensional plane. Thus each intention consisting of a sequence of action (represented as vectors in the n dimensional plane) is represented as an ordered set of vectors.

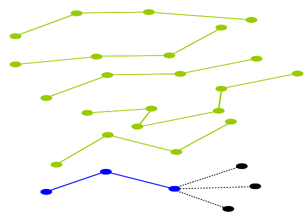

Figure 4. Hypothesis evaluation using previous intention trajectories, green trajectories represent previous action sequence and blue trajectory represent current action sequence and black dots represent the action hypotheses to be evaluated

A complete action sequence concerning an intention represents an *intention trajectory*. Graphically an intention can be represented as a trajectory in the n dimensional plane as shown in Figure 3. Using the trajectories of the different intentions the similarities between different intentions can be found. The future action hypotheses can be evaluated with respect to the previous trajectories. It is explained with the help of the Figure 4. The green trajectories represent the already performed action sequences concerning the human intentions. The blue trajectory represents the current interaction action sequence. The predicted action hypotheses are placed as black dots with dotted lines. The hypothesis with significant historical support gets higher weight with respect to others.

E. *Combination of action aspects for final action prediction*

The combination of the history support, randomness and the hypotheses weight is shown in the Figure 5.

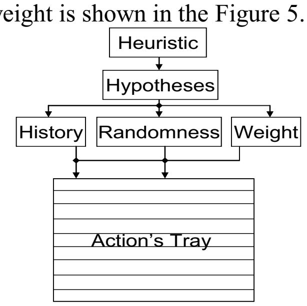

Figure 5. Final action selection for human-robot interaction by the combination of history support, and randomness of each action hypothesis with the weight of the hypothesis, resulting in a value, the action hypotheses are arranged in descending order with respect to the resulting value

The final selection out of all the action hypotheses is made by considering the randomness, history support, and the weight of each hypothesis. The history support and randomness of each action hypothesis is weighted by the hypothesis weight. For each action hypothesis a value is calculated by adding the weighted history support value and weighted action randomness. The calculated actions are stored in descending order with respect to their action values. The top action in the action list is selected for the robotic reaction. The next lower value actions are selected if the human asks the robot to switch its reaction.

F. *Particle Filter based Probabilistic action selection*

The mechanism used in Particle Filter (PF) considers all the possible solutions as particles. PF is a recursive algorithm and operates in two phases, i.e., prediction and update. In the prediction phase each particle is modified according to the given prediction model. Each particle has weight that represents the significance of the particle. In the update phase the particle weights are updated based on the incoming sensory information. According to the weight the particles are re-sampled. Using the particles the solution is estimated. PF is used to track and estimate the solution of a problem with respect to time. The current problem of the robotic reaction in the unknown human intention scenario also corresponds to the prediction and update of the current belief of the reacting agent about the unknown human intention. The robot uses its history knowledge as well as the immediate previous human action to predict the human intention and react accordingly. The update is performed on the basis of human response. If the human accepts the reaction then the predicted human intention is considered as correct and the agent goes on with the possible reaction. In case if the reaction is not accepted then the robot changes its reaction if possible. Otherwise the human may respond by simply correcting the robot's reaction. That human correction helps the agent to purify his prediction about the human intention. The difference between the application of PF algorithm for current problem and the problems where PF is normally applied is spatial. As PF is mostly applied in the robot localization and normally the state space involves the two dimensional (2D) space in which the robot exist. For more accuracy the orientation of the robot is considered. In the current case the state space corresponds to the human actions. If the human actions are represented in a n-dimensional plane. Then the future actions can also not be predicted based on the location of the current action. It is reasonable in robot localization problem because if it is assumed that the robot is at *x, y* location rotated at an angle θ. The robot moves and the displacement can be described with the help of a motion model. Therefore on basis of the relation between different coordinate points the robot location can be predicted. Since there is no action model for human action prediction as the motion model for robots. Thus we have to assume all the possible actions as hypotheses and then the evaluation of the hypotheses can be performed on the basis of currently performed action and the history of performed action sequences concerning the intentions and the actions probabilities. Therefore the PF algorithm can not be applied directly to the current problem. The modified PF algorithm is described in Figures 6, 7, 8 and 9. In the initialization phase, all the action particles are created with equal weights as shown in Figure 6 (1-6).

1 - Initialization()

2 - $S_t = \phi$

3 - **for** $i = 1 \ldots n$ **do**

4 - Sample A_t^k from $p(\mathrm{A}_t | \mathrm{A}_{t-1})$

5 - $S_t = S_t \cup \{ < \mathrm{A}_t^k, 1/n, 0 > \}$

6 - **end for**

Figure 6. Initialization of the action particles

In the probabilistic action selection described in Figure 7 the action values of all the existing action particles are calculated as shown in line 4.

In case if the conditional probability of a predicted action with respect to the previously performed action is not available then the prior of that action is used. At the step 6 all the expected actions are sorted with respect to their values and stored. The highest value action is selected for reaction. The system loops from step 7 to 21 until a suitable action is selected or all the actions are tried or the human performs a correction.

$S_t = \{ \langle A_1, w_1, v_1 \rangle, \langle A_2, w_2, v_2 \rangle, ..., \langle A_n, w_n, v_n \rangle \}$

1- Algorithm Particle_filter(S_t)
2- $\eta = 0 \quad index = 0$
3- **for** $i = 1, ..., n$ **do**
4- $\quad v_i = w_t * p(A_t \mid A_{t-1}) + w_t * p(A_t \mid H)$
5- **end for**
6- $\Lambda = Descending\ Order(S_t.v)$
7- **do**{
8- $\quad \hat{A} = \Lambda.at(index^{++}).A$
9- $\quad$ *Execute* $\hat{A}$
10- $\quad$ **if** $(Accepted(\hat{A}))$ **then**
11- $\quad\quad$ Sample A^k_{t+1} from $p(A_{t+1} | \hat{A})$
12- $\quad\quad S_t = S_t \cup \{ < A^k_{t+1}, w_{\text{high}} > \}$
13- $\quad$ **elseif**$(Change(\hat{A}))$ **then**
14- $\quad\quad \hat{A} = \Lambda.at(index^{++}).A$
15- $\quad$ **elseif** $(A_{human\_correction} \in \Lambda)$ **then**
16- $\quad\quad$ Sample A^k_{t+1} from $p(A_{t+1} | A_{human\_correction})$
17- $\quad\quad S_t = S_t \cup \{ < A^k_{t+1}, w_{\text{high}} > \}$
18- $\quad$ **elseif** $(A_{human\_correction} \notin \Lambda)$
19- $\quad\quad$ Re_Initialization($A_{human\_correction}, S_t$)
20- $\quad$ **end if**
21- }**while**$(\hat{A} != A_{optimal} \,\|\, \hat{A} == \phi \,\|\, A_{human\_correction})$;

Figure 7. Probabilistic action selection for human-robot interaction

If the robotic reaction is accepted, i.e., the robot performs a suitable action then the particles are generated with respect to the performed action with higher weight as compared to the previously existing particles (Lines 10-12), Figure 2 (above). If the robotic reaction is not accepted by the human then the human may ask the robot to change its reaction. Then the robot selects the next highest value action for reaction (Lines 13-14). The human may also correct the robotic reaction without asking the robot to change its reaction. If the human correction belongs to the set of the predicted action then the particles are created with respect to that action with higher weight as compared to the exiting action particles (Lines 15-17)), Figure 2 (above). In case if the human corrected action does not belong to the set of predicted actions then re-initialization of the particles is performed, described in Figure 8. The new action is added to the list of known actions and new action particles are created with respect to the newly added action. The new particles are created for the newly added action with respect to previously existing actions with high weight as compared to the previously exiting particles (Lines 3-6), Figure 2 (below) (red line along with black lines). The new action particles are also created using the previous actions with respect to the newly added action (Lines 7-10). The weight of these new action particles is higher than the previously created (Lines 3-6) new action particles Figure 2 (below) (green lines).

$\mathcal{A}_t$: human correction

1- Re_Initialization($\mathcal{A}_t, S_t$)
2- $\eta = 0$
3- **for** $i = 1...n$ **do**
4- $\quad$ Sample A^k_t from $p(\mathcal{A}_t | A_{t-1})$
5- $\quad S_t = S_t \cup \{ < A^k_t, w_1, 0 > \} \quad // \ w_1 > w_{previous\_particles}$
6- **end for**
7- **for** $i = 1...n$ **do**
8- $\quad$ Sample A^k_t from $p(A_{t+1} \mid \mathcal{A}_t)$
9- $\quad S_t = S_t \cup \{ < A^k_t, w_2, 0 > \} \quad // \ w_2 > w_1$
10- **end for**
11- Sample A^k_t from $p(\mathcal{A}_t \mid \mathcal{A}_t)$
12- $S_t = S_t \cup \{ < A^k_t, w_3, 0 > \} \quad // \ w_3 > w_2$
13- **for** $i = 1...m$ **do** $\quad // \ m > n$
14- $\quad \eta = w_i + \eta$
15- **end for**
16- **for** $i = 1...m$ **do** $\quad // \ m > n$
17- $\quad w_i = w_i / \eta$
18- **end for**

Figure 8. Creation and weighting of the new action particles

The new action particle representing the repetition of newly added action (Lines 11-12) Figure 2 (below) (red line among green lines) is given the highest weight with respect to the all newly created particles.

1- $S = \phi, \eta = 0$
2- **for** $i = 1, ..., n$ **do**
3- $\quad$ **if** $(w_i > \tau)$ **do** $\quad \tau \in]0, 1/n]$
4- $\quad\quad S \cup \{ < A_i, w_i, v_i > \}$
5- $\quad$ **end if**
6- **end for**
7- **for** $i = 1, ..., n$ **do**
8- $\quad \eta = \eta + w_i$
9- **end for**
10- **for** $i = 1, ..., n$ **do**
11- $\quad w_i = w_i / \eta$
12- **end for**

Figure 9. Re-sampling of the action particles

Afterwards the particles weight is normalized. The high weighting of the latest actions biases the robotic reaction towards the currently performed action. The re-sampling of the particles is described in Figure 9. A threshold value τ is selected between 0 and 1 / n, including 1 / n. The value n is equal to the total number of the particles. If the weight of a particle is less than τ then that particle is eliminated. The other particles are kept. Then the weights of the particles are normalized.

IV. Experiments

The experiments are performed with a robotic arm with 6 degrees of freedom. The human and the robot interact in a human-robot interaction workspace as shown in Figure 10. The workspace consists of a table with objects on the table along with the robotic arm. The video data is captured with an over head FireWire digital camera with the standard frame size of 640 x 480 at a frame rate of 30 frames / sec. The robot is communicated the cooperative instructions using the TCP/IP connection for performing different operation, e.g., pick, place and move to a certain location, etc. The performed experiments involve actions that are characterized by two features, i.e., the distance and the orientation. The performed human actions are inferred in terms of the change of distance between the objects and the orientation of the objects with respect to each other. The objects in the experiments involve the blocks on a table as shown in the Figure 10. The performed experiments concern different arrangements of the objects according to the human intention.

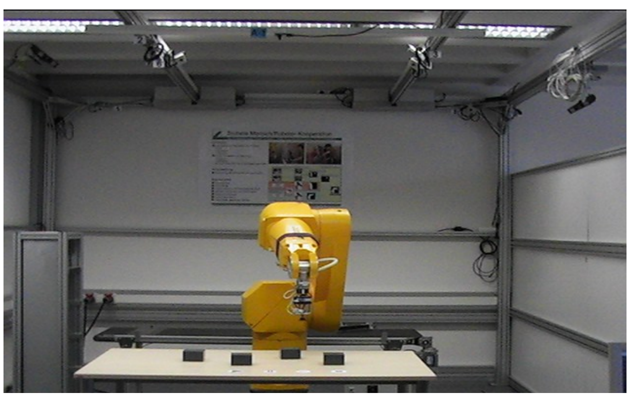

Figure 10. Workspace for the human-robot interaction

V. Conclusions

In this paper, we presented a probabilistic approach for the robotic reaction in the human-robot interaction scenario with unknown human intention. The discussed algorithm (Section II and III) can be applied to the cooperation scenarios other than picking and placing of objects, e.g., washing, opening, cutting, pouring, etc. The application to different interaction scenarios corresponds to different known heuristics for action prediction. It is explained with examples. We consider the placement of the kitchen utensils in a cupboard on each other, e.g., plate, jug, and glass. The robot is required to place the objects in the right order over each other. The order of the objects is used as the heuristic to hypothesize the new actions. Similarly another interaction example between intelligent cutting-machine and the human worker is discussed. The worker intends to cut the objects (metal rod, sheet etc) of variable length. The intelligent machine can adapt itself to the human worker to provide the predicted length for cutting. The heuristic in this case can be the length to hypothesize different actions. More complex tasks can be modeled using one or more complex heuristics.

The reaction can be more effective if biased with respect to the already given domain knowledge, e.g., in the presented experiments case if the potential box arrangements are already known then the reaction can be more robust. The domain knowledge can be used to weight the action hypotheses according to the nearest known arrangement. This can reduce the weight for insignificant hypotheses and increase the weight for significant hypotheses. The domain knowledge can also improve the action prediction by predicting the action hypotheses that robot does not know. In case if the human performs totally new actions while human-robot interaction then the new actions can not be estimated by the robot as the actions are unknown to the robot. The robot can react in that case intuitively if the robot is given the domain knowledge.

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