MDP-led Proactive Intention Recognition for Improved HRI Settings

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Summary
Increased appearance of robots in both the domestic and professional human life is no wonder today. It needs to improve human-intention recognition capabilities in a robot. Intention recognition is inevitable for effective Human Robot Interaction (HRI). Proactive intention recognition will improve the intuitiveness of HRI. In the presented research work use of reinforcement learning exhibits promising results. Markov Decision Process (MDP) has been used for early intention recognition with the condition of finite state and action space. Different real-time HRI scenarios are modeled using MDPs. A simple algorithm is proposed to identify pseudo destination state(s). Identification of these states is helpful for early intention recognition. An Arduino based robotic arm with a simple webcam is used to perform intention recognition experiments. Use of more sophisticated equipment would enhance the precision level along with the success rate.

Key words:
Intention Recognition; Human-Robot Interaction; Markov Decision Process, Reinforcement Learning, Pseudo Destination

1. Introduction

Modern applications in robotics have changed the human perception of a robot from a pre-planned mechanical apparatus working in a confined environment to a helping companion assisting in an interactive environment. In order to be effectively productive a human needs to interact with its environment. The environment means everything in one's limited surroundings. In most of the situations a human expects certain actions performed by the autonomous entities sharing the workspace with the human. The autonomous entities may correspond to other humans or autonomous machines. Humans expect certain actions by some of the objects in the environment by understanding the human intent. For example, a human expects certain actions performed by a trained pet against regular gestures. After spending a suitable chunk of time with the pet a human desires that the pet (object in the environment) should recognize the intention of the human proactively. If the humans interact with each other then most of the interactions take place just by recognizing the intention of each other. Hence in order to have a robot as a co-worker or as an assistant, it is of vital concern to offer relative means of interaction as used for Human-Human Interaction (HHI). Robots were being used in a confined environment at many different factories but with the rise in HRI applications it is necessary to make a robot capable of understanding behaviours and intentions of interacting human [1]. It is important to identify human intention proactively so that the robot may help in efficient completion of a task.

When it comes to have a robot as a physical assistant or a co-worker, it should minimize human stress level about doing a task and should improve pace and precision while working under the supervision of the human[2]. Early intention recognition can surely improve pace of doing a job in a HRI setting and it also reduces the stress level associated with the 'how to tell and all to tell' problems in HRI environments.

1.1 Problem scenarios

A variety of multi-stage/multi-state decision scenarios is based upon a destination-reach feature for intention recognition, hence MDP based solutions by overcoming late/destination-reach intention recognition problem, may benefit a number of sequential decision scenarios.

With the provision of early intention recognition or early destination estimation the work of a surveillance robot will become more effective by estimating the possible destination of an object in its vicinity. In a building all the paths are known to the robot and by observing the movement pattern of an object (may be human) it can be judged earlier that whether the object is heading towards some physically prohibited point(s) in the building or not?

An early estimation of the human intention can help a robot perform its job more accurately and efficiently. A robot can help in performing day to day house chores by predicting proactively the intention of the interacting human and to facilitate in a number of situations e.g. start washing used crockery while observing that the human is collecting used crockery from the dining table and next

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step is surely to wash them up, similarly turning off the electrical appliances while observing that the human is picking up the car's key and heading towards exit door, etc.

At a citrus cultivation farm different tasks are performed by the human labor and are now assisted by the robots also. With the early human intention recognition a robot can help in a variety of ways e.g. loading the fruit trays in the vehicle by observing that the human has parked the vehicle in the proper place for loading and next step is surely putting the trays in the vehicle. It can also start plucking fruit by observing earlier that the human is putting up the plucking gloves or collecting empty trays for plucking, etc.

Another interesting and well experimented setting is to have robot as a restaurant waiter and it moves between kitchen and the dining room to bring the order to the target Table [3]. With the inclusion of early and proactive intention recognition capabilities the robot may serve in a more effective way e.g. by observing an empty or about to empty glass of water it can fill it up before the customer explicitly makes a demand for refilling or it can bring the required item to the table by observing the about to finish item on the table specially for combinational dishes in buffet settings. Hence a number of situations may be improved by early intention recognition.

2. Related work

A robot's motion not only in case of humanoid robots, creates a social engagement between a robot and a human[4], hence in case of multipurpose HRI environment this social bond expects certain intelligent behaviour(s) presented by the robot. HRI can improve our living in multiple ways[5]. In order to improve HRI it is desirable to add new and improve existing interacting capabilities in this potential area of research. The basic requirement in this regard is to identify and explore the natural ways through which a human can interact with a robot[6]. Intention recognition plays a vital role for a smooth and error free communication and dealing between two humans.

A number of intention recognition approaches have been presented in literature [7,8,9] with a common limitation of providing solutions for specific problem(s). Youn et al. [10] presented a generalized but theoretical approach for intention recognition using graph representations but without any experimentation. Dynamic Bayesian Network (DBN) with cycle removal has also been suggested in [11] and in a home environment service scenario as an assistant robot in [12] with a major problem of complexity as it needs a huge number of prior and conditional probabilities[13]. Hybrid Dynamic Bayesian Networks (HDBN) have been proposed for intention recognition by Schrempf et al. [14] with the same limitation of requiring a big number of prior and conditional probabilities[13]. For the approaches of [11] and [14] techniques have been proposed for modeling reduction[15]. A study presented in [16] used Hidden Markov Models (HMM) for the same with the limitation of recognizing the human intention if they meet, cross, drop or pick something, further robot does not take part in active HRI and simply works as an observer. Another study discussed in [17] uses HMM to recognize the human intention by discussing in detail the usage of HMM for modelling the human intention. Moreover the focus of [17] is both on hardware (implementation of response using actuators, end effectors, etc.) as well as on software (intention recognition). In the technique of HMM, each observation corresponds to a hidden state and in case of intention recognition if the human performs more than one actions corresponding to the same intention then all the hidden states should belong to the same human intention. HMM suits well for speech recognition where each phonic corresponds to a distinct phonogram. Awais et al. [18] used Finite State Machines (FSM) in collaboration with the particle filtering for intention recognition but the learning mechanism of this approach considers simple modeling of the actions leaving more computation on the vision techniques to understand the action. Another approach presented by Ashraf et al. [19] uses the FSM to estimate the human intention and on the bases of current human intention it divides the HRI workspace into safe and unsafe zones. The approach may avoid a possible collision between human and the robot but it suffers the similar problems as of [18]. Intention based HRI safety has been ensured but the technique is limited to only collision avoidance.

Takahashi et al. [20] proposed on the basis of a neurophysiology study of the mirror neurons that intention inference and behavior acquisition can be done using similar models/techniques as previously both the jobs were considered independent. Reinforcement learning has been used to get both the jobs done with the assumption that state values of all possible behaviors are already known.

The study exhibits the core limitation where a node in the MDP leads to more than one intention graphs. Now what is the intention of the agent?. Increase in reward is the only thing suggested for intention recognition. But in case of more than one intention graphs, reward value is increased on all the paths. Hence early intention recognition is not possible. Further it has not been proposed that at which state and with what value the intention is considered to be recognized. It is also assumed in this study that the state values are already known for all possible behaviors that is not possible in an interactive environment.

3. Methodology

3.1 Markov Decision Processes (MDPs) in Reinforcement Learning

Stochastic dynamic programs or Markov Decision Processes are the models that help us to make sequential decisions interestingly with the uncertain outcomes[21]. In probabilistic environments, MDPs offer a standard formalism for multi-stage decisions[22]. Among the machine learning techniques including supervised learning, unsupervised learning, learning to learn and reinforcement learning the reinforcement learning is selected for intention recognition as it is closest to the human technique of learning[23]. Reinforcement learning is the technique of learning through interaction to achieve a goal, learner is called the agent(robot in HRI environment) and everything around the agent is called environment. As the agent performs different actions and changes its states, the environment(human in this case) gives rewards or penalties in response and the goal of the agent is to maximize the long-term reward known as return. This technique suites well to HRI environments where during interaction robot learns by exploring new paths and populates its knowledgebase for exploitation in future.

We address the limitations of the study presented in [20] and overcome the problem of more than one intention graphs from any given state e.g. S6 in Fig. 1. The proposed solution disambiguates the situation by selecting the earliest node on the path that corresponds to a distinct intention. In our sample MDP graph presented in Fig. 1 we consider S2 a destination state as there is no other path along the way till the final state on this path. We claim to have recognized the intention that is actually the S10 but recognized earlier. S2 is considered destination state on this very path and same is true for S8 and S7. State S6 leads to two different destinations and with the explored state values and its possible transitions(S8 and S7 in this case) early intention recognition is done. Actions a7, a4 and a5 represent no state change while all other actions in the graph cause some state transition.

Table 1 elaborates the Fig. 1 by defining state transitions of the agent along with the action, probability of the action occurrence and reward of the transition. First row of Table 1 shows the start state as S1, reach/landing state as S2 by taking action a1 with the probability 1 – (Pa2 + Pa3) and earned reward RS1S2. All subsequent rows may be read accordingly.

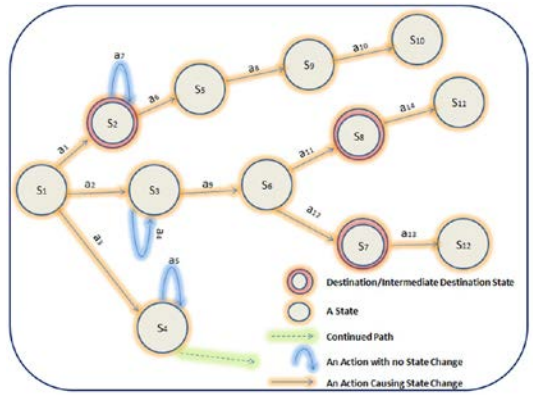

Fig. 1 A Sample MDP Graph for Intention Recognition

3.2 Early Intention Recognition

Here with the early intention recognition we mean recognizing future steps of a multi-step task where robot helps in performing subtasks or individual steps of a multi-step task by recognizing earlier the next step most likely to be performed by the observed human. More precisely it can be said that the prediction or intention recognition is limited to the destination state of the current MDP at a maximum.

3.3 MDP-Led Early Intention Recognition

We suggest Algo.1 for finding pseudo destination state(s) proactively:

Algo. 1 Finding Pseudo-Destination State(s)

Input:

1. A global 2D array representing state values
2. A local start state St_S
3. A global integer variable 'a' initially set to 1

Processing:

```
4.  FOR all states From Si To Dj
5.          Nx_S[ ] = arg_max(Nb_S[ ])
6.    IF (Size(Nx_S[ ] == 0)
7.          EXIT FOR
8.    ELSE IF (Size(Nx_S[ ] == 1)
9.          Ps_D[a] = Cr_S
10.         a = a + 1
11.   ELSE IF (Size(Nx_S[ ] > 1)
12.         a = 1
13.         Pseudo_Search(Cr_S)
14.   END IF
15. END FOR
16.   Return(Ps_D[ ])
```

Output:

17. An array representing pseudo destination state(s)

Algo.1 is demarcated as 1) A two dimensional array is supplied as input that holds state(node) values for all the states in the graph 2) An start state in the form of an array element is supplied 3) A binary variable named ‘a’ is initialized to 1 in order to set position of the states in pseudo destination states(Ps_D [ ]) array 4) A for loop to traverse all the states(nodes) from start state(Si) to destination state(Dj) in order to find the pseudo destination state if any on the path 5) Set the next state to be traversed by finding the one or more with the maximum state value using function arg_max() from among the neighbour states(Nb_S[ ]) of the current state 6) Check if there are no next state(s) in case current state is the actual destination state 7) Get out of the loop body as there is nothing more to explore 8) Check if the current state has only

Table 1: Transition probabilities and expected rewards for the finite MDP of Fig. 1

Start State	Next State	Action	Probability	Reward
S_1	S_2	a1	$1 - (P_{a2} + P_{a3})$	R_{S1S2}
S_1	S_3	a2	$1 - (P_{a1} + P_{a3})$	R_{S1S3}
S_1	S_4	a3	$1 - (P_{a1} + P_{a2})$	R_{S1S4}
S_2	S_2	a7	$1 - P_{a6}$	R_{S2S2}
S_3	S_3	a4	$1 - P_{a9}$	R_{S3S3}
S_4	S_4	a5	1	R_{S4S4}
S_2	S_5	a6	$1 - P_{a7}$	R_{S2S5}
S_5	S_9	a8	1	R_{S5S9}
S_9	S_{10}	a10	1	R_{S9S10}
S_3	S_6	a9	$1 - P_{a4}$	R_{S3S6}
S_6	S_8	a11	$1 - P_{a12}$	R_{S6S8}
S_8	S_{11}	a14	1	R_{S8S11}
S_6	S_7	a12	$1 - P_{a11}$	R_{S6S7}
S_7	S_{12}	a13	1	R_{S7S12}

one neighbor with maximum state value 9) Add the current state to the array containing pseudo destination state(s) 10) Move the pointer ‘a’ by one to hold the next pseudo destination state 11) Check if there are more than one neighboring states holding same maximum value 12) Set the pointer ‘a’ back to 1, as now we have the new start point to find the pseudo destination state(s) 13) Make a recursive call to the Pseudo_Search() by setting the current state as start state 14) Ending the If body 15) Ending the For body 16) Returning the pseudo destination(Ps_D[ ]) array 17) Output of the Pseudo_Search in the form of an array containing pseudo destination state(s) to be used for early intention recognition.

The linear complexity of the algorithm $O(n)$ indicates its efficiency as there is finite number of states.

4. Experimental Consideration

4.1 Workspace and Equipment

The HRI workspace is monitored using a simple 480x640 webcam to keep the experimentation viable. Any better option for image capturing may also be used like Microsoft Kinect sensor, an advanced sensor with RGB camera, depth sensor, microphone, motorized pivot and is capable of capturing motion and gestures. For the simple experiments of this study, webcam served well and did not exhibit any limitations. The camera is mounted at the top center of the customized metal stand. The calibrated camera is used to detect and locate the objects in the HRI workspace. Calibration is performed using standard techniques[24].

A customized aluminum stand is designed for the experimental setup. The stand can hold webcam shown hanging at the top of the stand looking downward in Fig. 2. The stand is a 4 x 3 x 3 feet in length, width and height respectively. All objects except the webcam are placed at the bottom of the stand.

A frequently felt need in robotics is to implement the valuable contributions practically. HRI researchers waste plenty of time finding engineering solutions for a particular hardware setup. To deal with the problem a number of robotic platforms have emerged[25]. Arduino-based platform provides user friendly interface in the shape of its programming language which is derived from C++. Arduino is a low cost and open source platform.

A plastic made 4DOF (degree of freedom) Arduino controlled robotic arm equipped with four DC servo motors is capable of holding, moving and placing small, lightweight objects. Fig. 2 shows the robotic arm in the middle exactly under the webcam. All four servo motors work using inverse kinematics to move the arm gripper to the defined destination in a 3D experimental workspace.

A bunch of image processing techniques is used to remove imperfections or noise in the data that arrives during segmentation. Two basic operations of morphology include erosion, dilation, opening and closing.

Human action understanding is performed using skin detection. The co-worker manipulates the workspace through his/her bare hands, visible to camera. The distance and time measures are used to infer the human actions, e.g. if the human hand is detected near to an object for specific corrective image frames then the grasping action is considered to be performed. Similarly the detection of displaced object is considered to be placing action performed by the human.

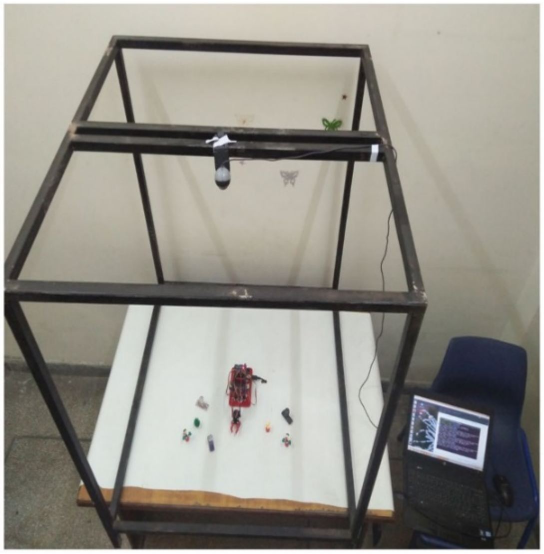

Fig. 2 HRI Workspace showing Camera, Metal Stand, Robotic Arm etc.

4.2 Application

Two types of objects have been used in the HRI workspace (see Fig. 2) including plants and stamps. Both are light weight and easily graspable by the gripper of our 4DOF robotic arm. Experiment is designed to pick similar objects and place them at a set point recognized through the human intention. It is already learnt that after collecting the plants(pseudo destination) at some point in the workspace the next step surely is to collect empty pots (mapped as stamps for ease of grasping through available equipment) in order to place one plant in each pot. When the robot observes through camera presence of human hand in the HRI work space (Fig. 3a), it keeps observing till it recognizes the human intention of moving plants to some point (Fig. 3b) in the HRI workspace. Coordinates are calculated and robot starts helping human by putting the available plants (Fig. 3c-f) close to the human's set location (where the first plant is placed by the human). Subsequently robot starts the next MDP of collecting the empty pots (stamps) available in the workspace just by estimating the human intention of planting the plants in the pots (Fig. 4 a-d).

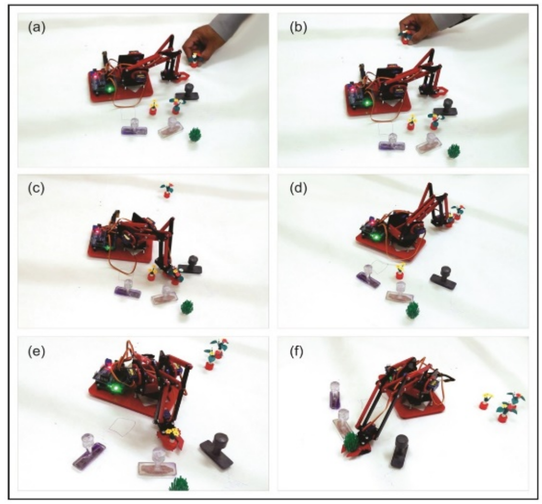

Fig. 3 a. Detecting human hand, b. Recognizing intention of placing plant at a specific location, c. Start picking second plant, d. Placing second plant near the human set location, e. Picking and placing third plant, f. picking and placing last plant.

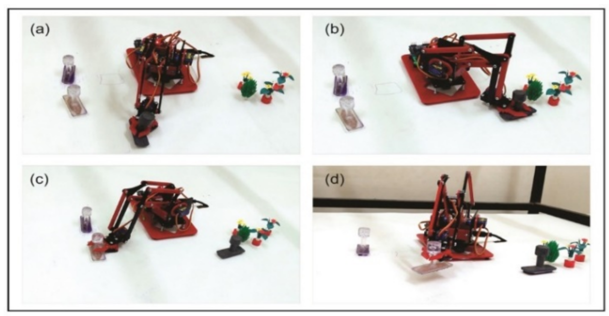

Fig. 4 a. Start next MDP automatically by picking first stamp, b. Placing first stamp near plants, c. Picking second stamp, d. Moving second stamp to specified location.

5. Conclusion

A proactive intention estimation approach based on MDP has been discussed in the presented research work. An algorithm is proposed to select the pseudo destination states of the related MDP network. The selection of pseudo destination states allows estimating the human intention as proactive as possible without intermixing with the other relating human intentions. In order to evaluate the proposed approach different experiments have been performed. The experiments are designed using simple objects easy to pick and place using a 4DoF robotic arm. It shows the extendibility of the scheme to other real-life situations using more sophisticated and purpose-built equipment. Experiment supports the importance of pseudo destination states in proactive HRI. Mood making by proactively executing an independent MDP and construction of MDPs through habit learning in HRI settings is the next focus of the research work. Monitoring the human activity and taking into consideration the human habit may improve the HRI. The future work also involves the auto selection of pseudo destination states.

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