Intuitive Human-Robot Interaction by Intention Recognition

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Zusammenfassung

Damit zwei Menschen miteinander interagieren können, um eine gemeinsame Aufgabe zu erfüllen, müssen sie die Erwartungen, die sie während der Interaktion aneinander haben, kennen. Betrachten wir das Beispiel eines Obers und eines Gastes. Kippt der Kellner eine Flasche, um dem Gast ein Getränk anzubieten, so kann er zwei mögliche Reaktionen des Gastes erwarten. Entweder reicht ihm der Gast sein Glas, um es füllen zu lassen oder er zieht es zurück um anzudeuten, dass er kein Getränk will. Hält er dem Kellner das Glas hin, so kann dieser damit rechnen, dass der Gast sein Glas solange an einem bestimmten Ort hält, bis er das Glas füllt. Zieht der Gast dagegen das Glas weg, so rechnet er damit, dass der Kellner sein Glas nicht füllen wird. Im Falle eines Missverständnisses kann ein Missgeschick geschehen. Für fast alle Fälle von Mensch-Mensch-Interaktion gilt, dass die Erkennung der Absicht eine Schlüsselrolle spielt. Für die Mensch-Roboter-Interaktion ist sie genau so wichtig.

Mit zunehmender Forschung auf dem Gebiet der Robotik sind und werden Roboter mehr und mehr Teil des menschlichen Lebens. Damit Roboter ein erfolgreicher Teil des menschlichen Lebens werden müssen sie nützlich für den Menschen sein. Hierfür sollen sie sich nach dem Menschen richten. Versucht der Roboter, einem Menschen zu helfen, ohne die Absicht der interagierenden Person zu kennen, so kann der Roboter selbst zu einem Problem werden, statt die Lösung der Probleme zu sein. Daher ist es notwendig, dass ein Roboter die Absicht eines Menschen, mit dem er interagieren soll um ihn zu unterstützen, kennt.

Das Ziel dieser Arbeit ist es, eine Lösung vorzuschlagen, die die intuitive Mensch-Roboter-Interaktion intuitiv macht. Um die Mensch-Roboter-Interaktion intuitiv zu machen sollte dem Roboter die Absicht des Menschen bekannt sein. Es wird ein wahrscheinlichkeitsbasierter Ansatz zur Erkennung der menschlichen Absicht eingeführt. Der Ansatz nutzt endliche Zustandsautomaten. Jeder endliche Automat stellt eine menschliche Absicht dar und besitzt einen Wahrscheinlichkeitswert, der als Gewicht des endlichen Automaten bezeichnet wird. Aus diesem Gewicht bestimmt der Roboter die momentane Absicht des Menschen.

Da es nicht möglich ist, alle möglichen Absichten, die der Roboter erkennen muss, in den Roboter einzubetten, bedarf es einer Maßnahme, damit der Roboter neue menschliche Absichten lernen kann. Für diesen Zweck wird ein Ansatz diskutiert.

Damit die Mensch-Roboter-Interaktion intelligent ist sollte der Roboter schnell in auf die menschliche Absicht reagieren. Hier wird ein Ansatz für eine schnelle (proaktive) Reaktion des Roboters beschrieben. Der Ansatz diskutiert auch das Szenario einer mehrdeutigen menschlichen Absicht. Dabei handelt es sich um eine Absicht, die mehr als einer menschlichen Absicht entspricht.

Es ist möglich, dass der Mensch eine völlig neue Intention hat, die der Roboter noch nicht kennt und auch noch nicht gelernt hat. In diesem Fall gibt es offensichtlich keine Mensch-Roboter-Interaktion. Für die Bewältigung dieses Problems wird ein Ansatz diskutiert, der es dem Roboter ermöglicht, eine geeignete Aktion auszuwählen, um mit dem Menschen zu interagieren.

Darüber hinaus wird ein Ansatz zur Verallgemeinerung der menschlichen Absicht diskutiert. Dadurch kann der Roboter seine Reaktion dem menschlichen Willen entsprechend ausweiten. Die Ausweitung der Reaktion bedeutet, dass der Roboter diejenigen Aktionen nimmt, die er nicht beauftragt wurde, bei einer menschlichen Intention zu nehmen.

Abstract

For two humans to interact with each other to perform a common task, they need to know the expectation of each other during interaction. For example if we consider an example of a waiter and a guest. If the waiter tilts the bottle to offer a drink to the guest then he may expect two actions from the guest, i.e., either the guest will forward his glass to get it filled or he will take his glass backward for not accepting the drink. If the guest forwards his glass then the waiter expects that the guest will keep his glass at a certain point until he pours the liquid into the glass. Similarly if the guest takes its glass backward then he expects from the waiter not to pour the liquid into his glass. In any case of misunderstanding an accident can occur. It applies to almost all the instances of human-human interaction. The recognition of the intention plays a key role in human-human interaction. It is equally important in human-robot interaction.

With the increase of research in the field of robotics, the robots are and will be becoming more and more part of human life. For the robots to be the effective part of the human life they should be helpful to the human. For a robot to be helpful to the human he should act according to the human. In case if the robot tries to help the human without knowing the intention of the interacting human then the robot can be itself a problem rather than a solution to the problems. Therefore it is necessary for a robot to know the intention of the human with whom the robot is supposed to interact to facilitate him.

The aim of this work is to propose a solution to make the human robot interaction intuitive. For making the human-robot interaction intuitive the intention of the human should be known to the interacting robot. A probabilistic approach is introduced to recognize the human intention. The approach uses the finite state machines. Each finite state machine representing a unique human intention carries a probabilistic value that is called the weight of the finite state machine. That weight tells the robot about the current human intention.

Since it is not possible to embed all the possible intentions into the robot that the robot may need to recognize. Thus, there should be a measure that the robot can learn new human intentions. An approach is discussed for this purpose.

For the human-robot interaction to be intelligent the robot should be quick in his response towards the human intention. An approach is described that addresses the issue of quick (proactive) response of the robot. The proposed approach also discusses the scenario concerning the ambiguous human intention. An ambiguous intention is a human intention that apparently corresponds to more than one human intention.

There may be a scenario in which the human has a totally new intention that the robot does not know already and also has not learned that intention. In this case, apparently there is no human-robot interaction. In order to cope with this problem an approach is discussed that enables the robot to select an appropriate action to interact with the human.

An approach concerning the generalization of the human intention is also discussed. By generalizing the human intention, the robot can extend its response according to the human intention. The extension of the response means that the robot takes those actions that were not instructed to him to be taken concerning the human intention.

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Chapter 1

Introduction

The active research in the field of robotics and the increased presence of robots among the humans have made the Human-Robot Interaction (HRI) inevitable. HRI is one of the emerging areas of robotic research, with intuitiveness as an integral part of HRI. It may exist in the situations where the tasks to be performed are dangerous for the humans and require situation dependent responses. The robot is less vulnerable to destruction as compared to the human thus the dangerous part of the task can be performed by the robot and supervised by the human during HRI. In household chores, the robots may also interact with the humans by assisting them. HRI can be used in the situations where the precise and accurate operation is required along with the human expert knowledge. HRI can also be found in the problems where the tasks require enormous strength and intelligent decision making capabilities, i.e., power of the robot and intelligence of the human. The robots may also interact with the humans in the tasks including rescue operations in disasters and industrial tasks, e.g., in manufacturing industry, healthcare, e.g., surgery through robots, and in household chores, e.g., service robots.

HRI is an important issue in rescue robotics [107]. Rescue robots can be typically employed in the situations that are not easily accessible by the human rescue workers. The rescue related HRI is shown in Figure 1.1. The rescue robots are required to intuitively comfort the injured humans in the rescue operations. HRI is the combination of multiple disciplines, i.e., robotics, cognitive sciences, psychology, and communication experts [122].

Figure 1.1: Rescue robots. Left: All terrain rescue [124]. Right: Earthquake rescue [123]

There exist diverse forms of HRI in healthcare, e.g., surgical operations by HRI [117], rehabilitation robotics [39], robot assisted therapy [160], and robotized patient monitoring systems [28]. The surgical robots operate in combination with the human surgeons. The surgical operation is performed by combining the accuracy of the robot and the knowledge of the human surgeon. The advantages of HRI based surgical operations involve remote surgery, minimal invasive surgery, reduced blood loss and less pain [46]. The demonstration of robot assisted surgery is shown in Figure 1.2.

Figure 1.2: Robot assisted surgery [68]

There exist a few examples to date for HRI concerning household chores, e.g., Roomba [128] and Hybrid Assistive Limb (HAL) [67]. The level of HRI is very little as Roomba is a cleaning robot and considers the human as an obstacle and avoid him during the cleaning task. Honda's ASIMO is considered as a most sophisticated humanoid, can not perform the sophisticated household chores interacting with the human. The experiments are performed with ASIMO for handing over the special coffee cups in a tray to the human but it is not marketed yet. In Figure 1.3 the robots and the example of the HRI concerning the household chores are shown.

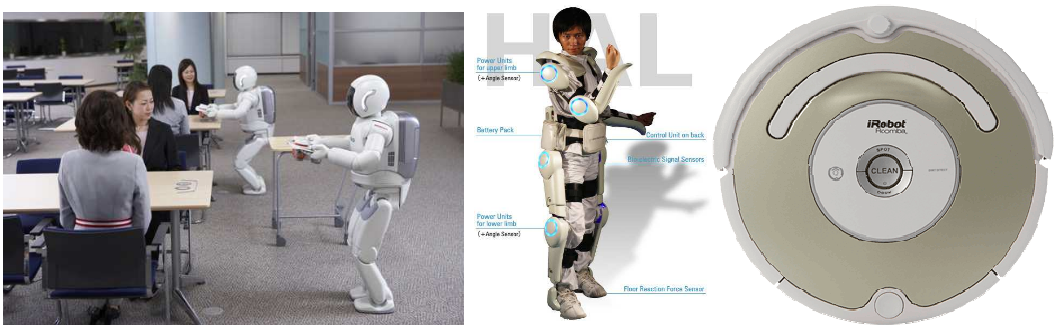


Figure 1.3: Household robotics. Left: ASIMO [2]. Middle: HAL [35]. Right: Roomba [128]

Industrial robots can be found in almost all automated manufacturing industry. They are used in many industrial applications, e.g., packaging, stacking, casting, painting, and welding. The industrial robots move very fast to be efficient and thus they are dangerous for persons working around them. The working areas of the human robots are separated by fences if the robots are operating autonomously as shown in Figure 1.5. The HRI safety is an active research area. Industrial HRI may involve manipulation of dangerous objects in the industry, controlling of complex operations, and movement of heavy objects in combination with the human. The robot application in industry with respect to HRI is increasing day by day [47]. Since a long time the industrial robots, especially robotic arms have been extensively used in the manufacturing industry including car making and assembling industry. Now the industry robots concerning HRI are introduced into the oil and gas industry [65]. The robots can be remotely handled by the human to avoid the harsh environment effect on the human and to improve the safety and efficiency [65]. The two industrial robots are shown in Figure 1.4.

Figure 1.4: Industrial robots. Right: Staeubli RX130 during HRI [159]. Left: Kuka LWR [158]

1.1 Motivation

The goal of the robotic presence among the humans is to make the human life as easy as possible. The robots are supposed to assist the humans in their activities. The provided services are appreciated if they are offered at the right time and need little input effort. Interaction characteristics make a robot more or less acceptable among the humans. The interface between the human and the robot describes the interacting capabilities of a robot, i.e., how much the robot is intuitive towards the interacting human. If the interacting human needs to know prerequisites in order to interact with the robot then the level of interaction is less acceptable as compared to the one that does not demand any prerequisite for interaction. The capability of adaption of the robot is also an important factor in HRI. The robot must adapt to the requirements of the interacting human. The requirement may directly concern the behaviour of the interacting human and / or the simple changes in the HRI workspace. Similarly proactiveness of the robot also plays an important role in the intuitiveness and improvement in HRI. The proactiveness is the understanding of a situation as early as possible. The described interacting qualities of a robot with a human directly relates to the fact that how much the robot is aware of the intention of the interacting human. The robot is required to assist the human rather than be assisted by the human thus the intention recognition is inevitable for a robot interacting with a human.

The robots exist in higher numbers in industry as compared to the other fields of life. Most of the robots used in the industry are the robotic arms. Mostly, the robots in the industry are automated and do not interact with the humans. The reason for no interaction is mostly the issue of HRI safety as the robot moving at high speed can harm the cooperating human. Therefore the human and robots are separated by fences as shown in Figure 1.5. There exist seldom cases where the human and robot interact with each other as the robot work more or less like a tool for the human [24].

A simple solution may be the usage of available sensors, i.e., vision sensors, range sensor, force sensors, etc. The perception of the sensors is always limited to the ability of the algorithms or the techniques that are used to interpret the data obtained from the sensors. The safety solution provided by the sensors does not ensure 100 % success.

Another reason that the robots are not employed in the industry to work in cooperation with the humans is that the robots do not take into account what the human is currently doing, what is his task, and what he will be doing in few moments. Mostly robots work like simple machines performing the already programmed tasks with very little flexibility.

Figure 1.5: Industrial robots separated from humans by fences [129]

For a robot to work with the human the robot needs to be flexible but also needs to be aware of what the interacting human intends to do so that both the human and the robot can work in collaboration. We motivate the importance of intention recognition in HRI by addressing the following issues concerning HRI, i.e. safety in HRI, robot as a tool, adaption, and robot in Small and Medium Enterprises (SME).

1.1.1 Safety in HRI

In the industry, HRI safety is a significant issue that restrains the human and the mighty industrial robot from interaction. The range and the vision sensors can be used to monitor the HRI workspace. With the presence of human, the speed of the robot may be decreased, the robot may be completely stopped or the robot's path from the source to the destination can be reconsidered and planned to avoid human robot collision in HRI workspace. Decreasing the speed of the robot or simply stopping the robot effects the efficiency of operation. The HRI is negatively affected due to slowing or stopping the operations of the robot. The changing and reconsidering of the path to avoid the collision between the human and robot is acceptable, but it is not risk-free. There may be a situation while the human and robot are moving in the HRI workspace that one or more parts of human body are occluded by the robot. Thus there may be a collision between the human and the robot due to the improper monitoring of the HRI workspace. The situation may be improved by predicting the human locations in HRI workspace, i.e., the robot can anticipate the future human actions and thus the robot can plan the path avoiding any expected collision. In order to anticipate the future human actions, the robot needs to know the human intention, i.e., what the human intends to do. Then the robot can infer in which direction the human can move, stay, bend, etc. Taking into account all the virtually occupied locations the robot can plan its collision-free path. Moreover, while path planning; the robot can consider the locations as virtually occupied that are frequently visited by the human during HRI. This can considerably improve the safety measurements but it can not fully guarantee the risk-free safe HRI.

1.1.2 Robot as a tool

In manufacturing industries, there may be tasks that require enormous power, intelligent decision making, and excellent sensors with efficient inference. The robots can help the humans with enormous power, but intelligent decision making and excellent sensors with efficient inference may not always be guaranteed by the robots in all the cases. The human can not perform such tasks alone too. Therefore the human and robot need to work together. In almost all such cases the robot is used as a tool by the human instead of an intuitive coworker.

As a tool the robot is very expensive unless the task is impossible without the robot. There exists other less intelligent machines that can be applied instead of the robot, e.g., in assembly line there exist less intelligent devices that help the coworkers to move the heavy objects, e.g., doors of the vehicles, dashboards, seats etc to the desired places as shown in Figure 1.6. These less intelligent machines are called CoBots [11]. They are used to assist the human coworkers on an assembly line.

Figure 1.6: CoBots. Left: Seat assembly [34]. Right: Door assembly [33]

The robot can only be appreciated in such conditions if the robot can perform that task with least human input as compared to the less intelligent devices, i.e., if the robot performs the task automatically recognizing the human intention and bring him the required component and cooperate intuitively to install that component into the vehicle.

The tasks of moving, assembling, and installation of the heavy components are repeatedly performed in the manufacturing industries. The intuitive execution of these tasks by the robots cooperating in accordance with the human intention can improve the efficiency of the human workers. The intelligent tool behaviour of the robot can be accepted in HRI if the robot acts according to the human intention for a task in the given situation. For example, consider a robot that can perform more than one operation. The robot interacts with the human while performing certain task and executes the specific operations according to the human intentions to complete the task. The robot as an intuitive tool with multiple capabilities is valuable if the robot selects and switches between the available capabilities according to the intention of cooperating human.

1.1.3 Adaption

As an intuitive and intelligent machine the robot should also adapt to the small changes in HRI. The adaption may correspond to the workspace of HRI and to the cooperating human. Adaption to the workspace is to remember the knowledge gained in the workspace concerning intuitive HRI and to apply that knowledge in the next HRI situations in order to be more intuitive and helpful to the cooperating human. The adaption to the human coworker corresponds to adapt towards the human intention. There may be more than one aspect for adaption towards the human intention. For example, adaption may correspond to the solution of the conflict between the two nearly similar human demonstration concerning different intentions. Similarly the adaption aspect may also involve the robot adaption to the routine human tasks in the HRI workspace.

If the robot does not have the adaption capability then the robot needs to be explicitly programmed or the robot requires adding or update of related modules. In this case the difference between an intelligent robot and a simple machine is reduced. In every robot related industry making manual updates for small changes in HRI workspace is less acceptable for robots. Update for the robots will require extra trained manpower, stopping of production and extra costs. This is further problematic if the update is required to be performed after short intervals.

Thus the capability of adaption is necessary for an intuitive robot for HRI. The capability of adaption enables the robot to alter its response in HRI without the explicit human clarification and robotic expert intervention. In response to the little changes in the HRI the robot needs to adapt to the changes intuitively by performing accordingly.

The recognition of the human intention is the basic ingredient to adapt according to the interaction human. For example if the human has one of the two intentions while working in the HRI workspace. Then the collaborating robot can only adapt according to the human if he can recognize both of the intentions. Next time the robot can proactively interact with the human based on the adaption.

1.1.4 Robot in Small and Medium Enterprise (SME)

A SME consists of limited resources relating to manpower and finances. The production rate is also low due to the lack of resources and less demand. There may be a few or no robot experts in SME. The robotic tasks in the SME are quite different as compared to big manufacturing industries. In big manufacturing industries the robots are mostly working as automated machines without human interference, whereas in SME almost all the tasks are performed directly by the human workers or under the direct supervision of human workers. Thus the robot present in SME must have the capability to work in an environment concerning HRI. In order to justify a robot to be present in SME it must work as intelligent and intuitive machine. It must not require reprogramming for small amendments in different tasks, possessing the capability of adaption. The robot must be adaptive towards the small changes in the HRI workspace regarding human intention.

For better HRI regarding intuition and adaption it should anticipate the intention of the cooperating human. The ability of robot of being proactive is an extra advantage for HRI in SME. Similarly a robot with intuitive interacting capabilities with the human can act as helper for a craftsman and mechanic in their related workshops.

In industry ranging from SME to big manufacturing industry mostly the manufacturing pattern remains the same for quite a time. In big manufacturing industries like vehicle industries the manufacturing setup is established for longer time as compared to the SMEs. The production speed is increased by introducing the robots as well as less intelligent machines. The automated robots work mostly very fast, independent from each other. However, all the sections of the industry big or small do not contain the automated robots. The tasks in such sections are performed directly by the humans or under the direct supervision of the humans. The number of manual section vary from industry to industry depending on the concerning tasks in the industry. The employment of intuitive robots in such sections can improve the efficiency of cooperating humans. The intuitive robots should be capable to recognize the intention of cooperating human and should be able to act accordingly. These robots can perform the task better as compared to the less intelligent CoBots, requiring little human input. The CoBots require more focused human input as a tool to perform a task. The intuitive robots will work not as a simple tool, but like an intuitive coworker that can react according to the cooperating human.

The robot must know the answers of the following questions to be intuitive with respect to the human requirements and thus effective during HRI. The questions are given below

1. When to do?
2. What to do?
3. Where to do?

The question what to do corresponds to the robot actions in response to the human actions while interacting with the human. For this reason the robot needs to know the human intention. Knowing the human intention tells the robot when to do what, i.e., if the robot has recognized the human intention regarding a specific task. Then the robot must also know the cooperative actions in order to respond in an intuitive and cooperative way. That corresponds to the answer of second question that robot needs to know. The question three corresponds to a specific situation in which the selected robot action is to be taken. For example, if a human and a robot are cooperating in a HRI workspace. Two products are manufactured in the workspace. Manufacturing process is same for both the products except one operation. Thus the robot needs to take care what he needs to do where and when in order to be effective and intuitive.

1.2 Goals

The goal of the research work is to propose a solution for the intuitive HRI by human intention recognition. The robot should be aware of the intention of the cooperating human for intuitive HRI. The following points are considered to make the HRI intuitive regarding the intention of cooperating human.

A. Intuitive HRI by intention recognition
B. Intention learning by scene observation
C. Proactive intention estimation
D. Interaction in unknown human intention scenario
E. Rule-based intention generalization

1.2.1 Intuitive HRI by intention recognition

The Goal A involves the proposition of a probabilistic framework for intuitive HRI by intention recognition. The apprehension of the human intention is based on the human actions along with the scene changes that occur due to the human actions.
The given information corresponds to the human actions and the scene information of HRI workspace concerning the problem. The required is the recognition of human intention out of the already known human intentions.
The robotic tasks involve picking and placing of an object according to the human intention. Experimentation with the proposed probabilistic system involve the following

1. Picking and placing of an object according to the human intention
2. Handing over the intended object to the human
3. Pile up and unpile of objects according to the human intention
4. Picking up an object and holding that object and placing the held object at a human intended place.

1.2.2 Intention learning by scene observation

The input to the problem corresponds to the human actions, scene information, scene change information, and the human intentions in terms of scene information. The output corresponds to the modelling of a new human intention.
The Goal B corresponds to the inference of the human intention from the actions performed by the human as well as from the scene changes occurred due to the human actions. Each newly learned human intention is modelled using a finite state machine. The inference of the human intention is performed based on the already known features.
The expected experiments include the arrangements of the known objects with respect to a pattern according to the human intention. The robot responds by recognizing the newly learned human intention.

1.2.3 Proactive intention estimation

The Goal C corresponds to quick recognition of a human intention. It includes the premature recognition of an intention in an ambiguous situation that may lead to two or more human intentions.
The Goal C includes the proposition of probability-based approach that helps the system to adapt towards the human behaviour and to react proactively in the intermixed human intentions scenario. The system can either wait for disambiguation of the intention, requiring extra human actions or it can proactively react depending on its previous knowledge about the human behaviour.
Proactive intention estimation task includes the proposition of the mechanism to update the intention recognition trigger states for the probabilistic finite state machines that model the human intentions. A state of a state machine is assigned as the *trigger state*. If the trigger state of a finite state machine is reached then the human intention concerning the finite state machine is recognized. The online trigger state update corresponds to the online selection of a state of a finite state machine as the trigger state.
The experiments involve the arrangements of objects that represent different human intention but have similar portion too, e.g., the objects placed in a square pattern and the objects placed

along a line. There exists a pattern (placement along the line pattern) that is similar in both patterns. The objects placed in different patterns are shown in Figure 1.7.

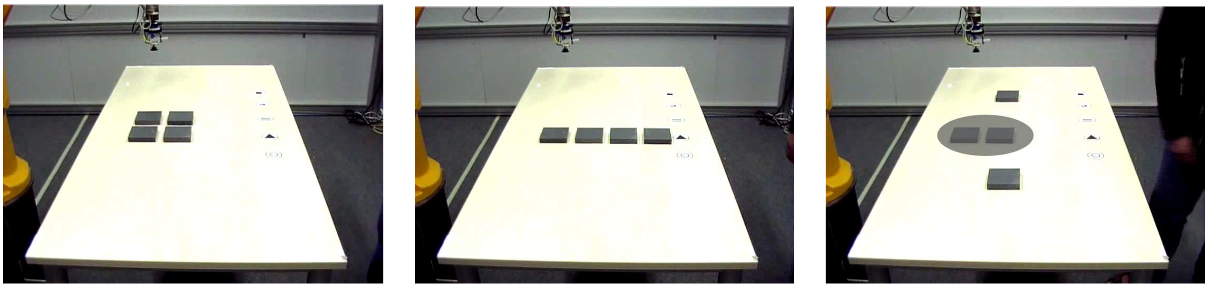


Figure 1.7: Left: Square pattern. Middle: Line pattern Right: Similarity in both the patterns

1.2.4 Interaction in unknown human intention scenario

The Goal D corresponds to the solution of HRI in case if the robot does not know the human intention, i.e., by no means the robot can recognize the exact human intention. Based on the current actions and the history of the actions the robot tries to estimate the next most likely action. The solution corresponds to a reinforcement based probabilistic action selection for HRI. The HRI environment is already known to the robot.
The sub tasks for the Goal D consist of the following

1. Action hypotheses generation based on the known actions
2. Prediction of the actions based on the previous action in the current task
3. Weighting of the predicted actions
4. Calculating the history support of the action hypotheses
5. Calculating the conditional probability (P($Action_t$ | $Action_{t-1}$)) and the prior probability (P($Action_t$)) for the predicted actions
6. Related implementations

The experiments involve 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 action.

1.2.5 Rule-based intention generalization

The input to this problem corresponds to the rules inferred from the human actions. The required is the reduction of antecedents of the rules by HRI. The task in the Goal E is to enable the robot to generalize its HRI capabilities. The robot infers rules and generalizes them to extend its interaction capabilities with the cooperating human. The extension means that the robot performs the known actions that were not instructed to him to perform concerning a human intention. The rule-based intention generalization is divided into the following sub tasks

1. Rule generation
2. Rule application
3. Rule generalization

Rule generation concerns the rule inference that describes an action performed on an object having certain known characteristics. During the rule generation, the system knows the

objects present in the scene, the change in the scene occurred due to the human action and different properties / characteristics of the objects present in the scene.
Rule application corresponds to the selection of the objects on which the rule can be applied. Rule generalization corresponds to the elimination of maximum number of unnecessary antecedents from the inferred rule.
The anticipated intention generalization experiments involve the following

1. Picking and placing speckled object into the container for the speckled object
2. Picking and placing broken object into the container for the broken object
3. Picking and placing non speckled object into the concerning container

Generalizing the above defined operations on the other related (match with respect to property / characteristic) objects will enable the robot to perform a task that the robot has neither observed nor been instructed, e.g., the robot only knows to place a speckled object of a specific type into the speckled container. After the generalization, it can place all types of the speckled objects into the container for the speckled objects. The generalization enables the system to respond in an unknown situation (with known objects). Unknown means that system is not explicitly taught that how to react in case of a certain known object.

1.3 Demarcation

HRI is a multiple domain research field. It contains the computer vision to monitor the HRI workspace for safety reasons concerning the avoidance of human robot collision. It contains the robot path planning, revising of the previously planned path, and collision avoidance for optimal movement from source to destination. It may also contain image reconstruction for scene monitoring. Along with human behaviour modelling, recognition of emotional states of the cooperating human and related fields can be part of the HRI. Similarly learning in HRI is also a complete subfield of HRI. The presented approach does not contribute to any of the above mentioned areas.
The presented probabilistic approach to intention recognition for HRI is general and does not correspond to a specific environment. There is no strict connection between the presented approach and any specific HRI scenario.
The presented approach does not propose an image-processing-based method for scene understanding. The process of scene understanding corresponds to the apprehension of scene.
The approach also does not address the issue of apprehension of any performed human actions, operation on the objects in the scene, changing in the scene and related scene inferring parameters. The inferring parameters correspond to the known features for inferring the scene information. The recognition of human gestures is also not included in the focus of the presented approach. Moreover, the presented research work does not consider the issues concerning the resource sharing in the common HRI workspace.
The proposed approach can be applied on humanoids and other robots for HRI. There is no robot specific operation proposed along with the given approach. There is also no sensor specification in the presented approach. Any kind of sensor can be used to monitor the HRI workspace. The selection of sensor depends on the current type of HRI workspace and the expected operations in the workspace.
There is no specification about the respective robot actions in response to the human actions. Like the scene understanding the robotic action information depends on the current robot in HRI.

1.4 Overview

The research work is organized as follows: Chapter 2 describes the already existing approaches for HRI. The discussed approaches correspond to the social issues concerning HRI, variable autonomy HRI, HRI approaches concerning robot as an assistant, and tactile HRI. At the end of Chapter 2, the differences are discussed between the existing approaches and the presented research work.

In Chapter 3 the proposed approach for intention recognition is described in detail. The modelling of different human intentions using the finite state machines is described in this chapter. Chapter 3 also discusses the algorithm for the probabilistic intention selection. At the end of Chapter 3, the experiments concerning the intention recognition using the proposed approach are described.

In Chapter 4 an online intention learning approach is introduced. The introduced approach is based on the intention recognition approach described in Chapter 3. Three types of intention learning methods are discussed. At the end of Chapter 4, the experiments are discussed that are performed for online intention learning.

In Chapter 5 premature and proactive intention recognition is described. The described approach is based on the approaches discussed in Chapter 3 and 4. The described approach takes into account the HRI scenarios that are similar to an extent but lead to different human intentions. Additionally an algorithm is introduced for the finite state machines representing the human intentions. The algorithm enables the finite state machines to recognize the human intention as early as possible. At the end of Chapter 5, the experiments are discussed that illustrate the proactive and premature intention recognition.

Chapter 6 discusses the HRI in a known environment with unknown human intention. The proposed algorithm hypothesizes the potential human actions and selects the most suitable action for HRI. The robot may be corrected by the human. The robot can reselect the next most suitable action for HRI depending on the interacting human. At the end of Chapter 6, the experiments are discussed, performed using the proposed approach.

In Chapter 7, an approach concerning the generalization of human intention is discussed. The approach describes the rule based human intention generalization. This approach corresponds to the concept generalization. The rule-based generalization uses the approaches of Chapter 3 and 4 to implement the human intention generalization. The generalization procedure is performed by HRI. The generalization methods using HRI and the rule conflict resolutions are discussed in detail in the Chapter 7. At the end of Chapter 7, the performed experiments are discussed that demonstrate the generalization result obtained through the proposed approach.

In the end, Chapter 8 summarizes the presented research work and provides an out look on future work.

Chapter 2

Related work

In this chapter most of the discussed approaches relate to the HRI in which the human interacts with a robot in the vicinity of the robot. In Section 2.1 the overview of the existing approaches concerning HRI is given. The existing approaches are discussed with respect different aspects of HRI, i.e., social HRI, robot as an assistant, and tactile HRI. In Section 2.2, the approaches concerning the social issues of HRI are discussed. Section 2.3 corresponds to the HRI in which the robot acts as assistant to the human to complete the task. The discussed approaches correspond to robot as tour guide in museum, a harvester, assistant in rescue operation, etc. The third aspect in Section 2.4 discusses different types of approaches concerning sensors that are used for tactile HRI and the types of tactile HRI. The sensor based approaches correspond to interpretation of sensor data and the types of application of sensors in the tactile HRI.

2.1 Overview

HRI is a mixture of many fields, e.g., psychology, cognitive science, social science, artificial intelligence, computer science, robots, engineering, and human-computer interaction [43]. The field of HRI corresponds to the research concerning understanding, designing, evaluation and the improvement of the robots that interact with the humans. One of the core issues in HRI is the effective communication between the interacting human and the robot. The motive of the HRI field is to consider all the possible communication channels and to improve them for better interaction. The HRI can be broadly classified into two classes [60], i.e., the teleoperation and the direct HRI. The class of *teleoperation* corresponds to the HRI in which the human and the interacting robot are separated. The separation concerns the temporal and / or spatial difference. In teleoperation the human and the robot are not required to exist at the same location. In *direct HRI* the human and the robot are present at a same location and physically interact with each other.

The described classes can be further classified into sub classes taking into account the design issues, application fields, nature of information exchange, level of the autonomy required in the HRI, emotions based HRI, control issues, etc.

A survey based on teleoperation is available in [132] and [69]. The survey in [132] discusses the teleoperation based on supervisory control and Human-machine interaction. A survey concerning the control theory of teleoperation is given in [69]. The space oriented teleoperation is surveyed by NASA given in [116].

The here presented literature focuses on the research work in the field of direct HRI. The direct HRI has two important aspects that may exist in almost all the categories of direct HRI, i.e., short term HRI and long term HRI. A HRI in which the human and the robot interact for short time and are not required to interact again and again is termed as *short term HRI*. If the human and the robot interact with each other many times then it is termed as *long term HRI*. In case if the robot has to perform long term interactions with a human as a part of his personal life then the robot is required to specialize according to the interacting person [41].

An extensive survey is performed for direct HRI concerning social interaction capabilities of the robots in [54]. The robots that engage the humans socially and interact with them to be helpful need to possess complex social skills and know the social values.

The survey performed in [61] discusses the robot's role as an assistant to the human. The HRI survey in [60] mainly focuses on autonomy of robot concerning the robot's role as an assistant to the human. The robots may be required to interact as an assistant with one or more than one person. There exist certain applications, e.g., robotic tour around the museum [154], mobile-robot guide in the hospital [135], etc.

The survey provided in [6] discusses the HRI by taking into account tactile interaction. The article discusses the tactile HRI with respect to two aspects, i.e., type of direct HRI in tactile HRI and the sensors used in tactile HRI. The research work performed in the area of HRI is discussed according to the following topics. The topics correspond to different perspectives of HRI.

2.2 Social HRI
2.3 Robot as an assistant
2.4 Tactile HRI

2.2 Social HRI

The survey article [54] focuses different aspects of social HRI. The socially motivated design concerns the development of robot for interaction with the human. The robots can be developed based on the two types of objectives, i.e., biological inspirations and functional design. The biologically inspired robots internally simulate or mimic the social intelligence present in the living creatures. The biological inspiration is based on two arguments. The first argument describes that a robot must possess certain characteristics for interaction with the human. The outlook of the robot should be naturalistic. The robot should mimic the perception capabilities of the human [170]. The second argument corresponds to the testing and refining of concerning scientific theories [10]. The functionally designed robots are required to have socially intelligent outlook. It means that the appearance of the robot should be according to the social context. The design is not required to have basis in science. It means the actions of the robot should correspond to the artificial social agent for the concerning task. The internal mechanism is not required to be the same as in the living creatures. The mechanism corresponds to the reasoning capability of the robot. The functionally designed robots for HRI have constrained operational and performance objectives as compared to the biologically inspired robots.

The humans are expert in social interaction. The technology that adheres to the expectation of human makes the HRI intuitive and easy for the humans [121]. Therefore the anthromorphic robots are applied in situations that expect the outlook of the robot like a human. The robots are equipped with the speech recognition, face recognition, gaze tracking, and other such capabilities. These capabilities help the robot to make the HRI as human-human interaction [42]. The embodiment of the robot plays an important role in the concerning HRI scenario

[54]. The embodiment of a robot corresponds to the morphological aspects of the robot including anthropomorphic, zoomorphic, and caricatured. If a robot is supposed to imitate like a human then it must have the anthropomorphic capabilities [18].
Emotions have significant importance in the human-human communication. They are closely related to the context [7]. There exist literature concerning emotions embedded into electronic games, toys, and software agents [16]. In HRI the emotions play also an important role for social communication [29] [114]. Suzuki investigated the HRI based on emotions in [142]. A mobile robot was used with the artificial emotions. The emotion states of the robot are changed by the interaction with the humans. The change in the emotional states of the robot causes the change in its actions. In [26] detailed information is provided over the robot named Kismet. Kismet is a robot that is specially designed to interact emotionally with the human. A detailed discussion of software and hardware is also provided. The emotional system of Kismet is described concerning the influence of emotions on the motivational system of Kismet and affect of this on interaction with human. The robot Kismet is shown in Figure 2.1.
In Section 2.2, most of the described approaches emphasize on the appearance of the robot to positively affect the social issues of HRI. Along with the appearance, the understanding of the intention of the interacting person can also positively affect the social HRI.

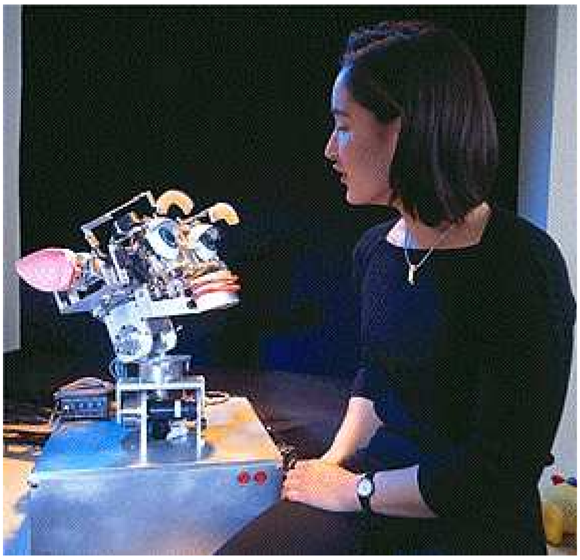


Figure 2.1: Emotion-based HRI by facial expressions [25]

2.3 Robot as an assistant

There exist many examples in which the robot act as a tool for the interacting human [23]. The examples vary based on the difference of applications as well as the robot autonomy while interacting with the human or along with the human. Horiguchi [70] proposed a force feedback based HRI in teleoperation of robots.
The HRI discussed in [27] corresponds to the application of a harvester robot along with the human. The experiment was performed for harvesting melons. A variable level of robot autonomy was applied during HRI. The detection rates of melons were increased by collaborative harvesting. The success rate of harvesting also depends on the complexity of situation.

The task of the robot described in [156] corresponds to teleoperation. The robot operation concerns the placement of radioactive waste in a central storage. The robot is taught the task. The teaching is performed through the teleoperation. A functional architecture is proposed in [156]. The robot is monitored while performing a task. The human can interrupt the robot if a new situation arises while the robot operation. The robot can only perform what he has been taught but can not react intuitively in an unknown situation. For this purpose the human guides the robot.
In [73] the level of autonomy of the robot is similar as discussed in the [156]. The robot patrols a nuclear plant. The robot works autonomously in the normal situations. The normal situations correspond to the situations in which the robot knows how to react. In an unknown situation the robot is guided by the human to solve the problem. In unknown situation the level of autonomy is zero and the robot totally depends on the human instructions. In known situation the robot is fully autonomous in performing the tasks.
There exist research work on HRI in the domain of urban search and rescue (USAR). Mostly the mobile robots are used in USAR. The robots are used as a tool to search and rescue the humans. The situations awareness plays an important role in USAR [167]. The USAR issue discussed in [102] concerns the operator situation awareness and HRI. The variation in the level of autonomy between the human operator and the robot is discussed in [31]. The approaches in [143] and [146] proposed that with the use of an overhead camera and automatic mapping techniques the situational awareness can be improved by reducing the navigational errors.
Another teleoperation approach is discussed in [113]. In this approach multiple operators present at different locations control multiple robots in a collision free collaborative manner in a common working environment. The collision can occur due to the fact that the operators are separately located from each other and do not know the intention of each other. A graphic display is used to avoid the collisions. In the continuation of work in [113], the time delay for the sent commands to the robots was handled by simultaneously sending to the graphic display and the robots [30]. These commands are used as virtual force feedback by the operators to avoid the collisions.
Autonomy is a significant aspect in HRI. The level of autonomy varies between fully autonomous to teleoperation, based on the fragility and the delicacy of the task and the working environment. It also depends on the artificial intelligence present in the robot and the nature of the working environment. The nature of the working environment describes that with which likelihood the new conditions can arise.

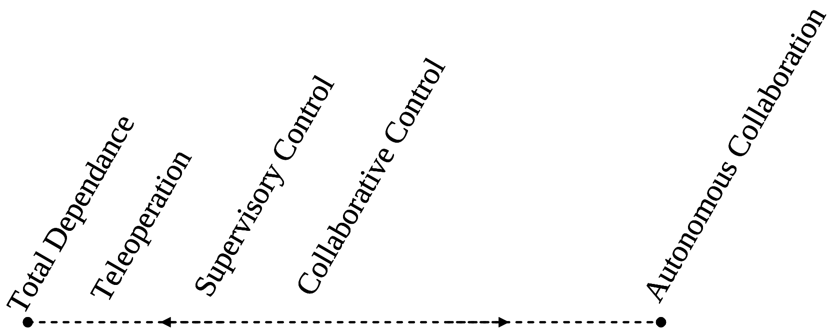


Figure 2.2: Levels of robot autonomy in HRI [63]

The autonomy corresponds to the mappings of environment input to the actuator movements or the representational schemas [61]. The autonomy of a robot is the amount of time a robot can be neglected [31]. The term neglected means unsupervised. The levels of autonomy discussed in [147] are divided in different levels from total dependence to total autonomy. The overview of levels of autonomy can be described as shown in Figure 2.2.

Fong [55] discussed the variability of autonomy in HRI. The robot operates autonomously until it faces a problem that can not be solved by him. The robot requests teleoperation in case of problem. The performance of the robots depends on the numbers of the robots and the teleoperators. If one human operator is present for more robots then the performance of the robots declines.

Autonomy is enabled in the robots with the help of artificial intelligence, signal processing, control theory, cognitive science, linguistics, and the situation dependent algorithms [61]. There existed different approaches for autonomy, e.g., sense-plan-act of decision-making [108] and behaviour-based robotics [8].

A mobile robot named Sage interacts with the people as a tour guide in a museum [111]. The change in the modes of the robot due to the HRI is discussed in [111]. The change in the mode of Sage causes the change in his behaviour with the interacting humans. The communication channels utilized by Sage in HRI include speech and emotions. Sage interacts with the humans through a LCD screen and audio as shown in Figure 2.3. The robot stops and asks for help in a troubled situation during HRI.

Figure 2.3: A museum guide mobile robot Sage [111]

A humanoid robot interacts with the humans using speech, gesture, and gaze tracking [81]. The robot works as a guide. The experiment with the robot showed the importance of gaze in the HRI. The interacting people spent more than half of the interacting time focusing on the robot’s face.

In [87] a study is performed on HRI where the robot acts as a guide to the human. It is discussed in the study that only speech can not help the robot to predict the future events concerning HRI. It is also important to understand the body language of the interacting human. The gaze of interacting human also gives a clue about his interest.

In [71] the importance of robot feedback is described during HRI. The robot feedback means that the robot acknowledges during HRI. The experiments showed that the robot feedback produced ease in HRI. The robot is designed to interact in office environment with the people having physical disabilities. The results of the experiments correspond to the fact that speech alone is not enough for human-robot communication.

The penguin robot interacts with the human as a host [144]. It is emphasized that a robot should not only exhibit gestures, but also interpret the gestures of interacting human. The robot uses the two channels of communication, i.e., vision and speech. The robot monitors the conveyed messages to the human by tracking the gaze of human.

Inagaki proposed HRI by perception, recognition and intention inference [75]. They used time dependent information along with the fuzzy rules for HRI. The approach in [75] is specialized with respect to the application of time dependent information in HRI. The human and robot cooperate to achieve a common goal.

Morita emphasized on the dialogue based HRI [101]. Their robot carries an object from one location to another location based on visual and audio inputs. Tversky [157] discussed the importance of understanding the spatial reference for HRI. Tenbrink [152] proposed a spatial understanding based HRI method. The robot is given the interaction commands through a keyboard. The interaction commands given to the robot considered the robot’s perspective.

Rani [120] proposed and performed the experiments concerning HRI that considers the human anxiety while HRI. The physiological knowledge is used to generalize the anxiety state of the interacting human. The anxiety state is independent of the age, culture, and gender of interacting human.

Fernandez [50] proposed HRI based on intention recognition. The experiments correspond to the transportation of a rigid object by human and the robot. They used spectral patterns in the force signal measured in the gripper arm.

The approaches in Section 2.3 discussed the usage of different communication channels and the levels of autonomy as the robot works as an assistant to the human. Only one approach [75] considered the intention of the interacting person that is also time dependent.

2.4 Tactile HRI

Tactile interaction is also an important aspect of HRI. The physical contact between the human and the robot is considered from different angles. In case of HRI safety the contact between the human and the robot is avoided. It is specifically important for an industrial robot interacting with the human [43]. In case of a human interaction with a humanoid, the human touches the robot to guide the robot [4]. The exiting research work in the area of tactile HRI is described in two categories [4]. The first category corresponds to the sensors that are used in tactile HRI. The second category corresponds to the tactile HRI. The sub categories in the second category correspond to different objectives that are achieved by physically touching the robot.

2.4.1 Skin sensors

There exist many approaches for interpreting the tactile response from the sensor. The data analysis approaches differ from each other based on the sensor and the data analysis method. The data analysis approaches for tactile response not only correspond to the binary detection of contact but also the location of contact, magnitude of force of concerning contact. The sensor data may also correspond to orientation, moment, vibration and temperature. The tactile sensor used in HRI involve force / torque sensors, force sensing registers (FSR), electric field sensor, capacitive sensing arrays, resistive sensing arrays, temperature sensors, potentiometers, photoreflectors, etc. The sub categories concerning the tactile sensors correspond to the mechanisms that use the combination of tactile sensors to infer the touch response in HRI. The combination mechanism corresponds to hard skin, soft skin, and alternative to skin-based approaches.

A) Hard Skins

The hard skins correspond to the installation of tactile sensor under the hard and bumper-based cover in the shape of robot body. The tactile sensors that can be installed under the hard skins involve force / torque sensors, FSRs, accelerometers, and the deformations sensors. More than one sensor is installed under the hard skins and the collective response of sensor can be obtained by interpolation. One draw back of hard skin cover is the restriction of obtained measurement types and resolution. The hard skins are commonly used to detect the unexpected collisions. The arms of the 52 degree of freedom humanoid WENDY are covered by a hard plastic having force / torque and FSR sensors underneath [76]. An industrial robotic arm uses the deformation sensors in rubber that is placed under a metal sheet of the robot [56].

B) Soft Skins

The soft skins correspond to the installation of tactile sensors under the flexible cover. The sensors that can be used for soft skins involve potentiometers, FSRs, capacitance sensors, temperature sensors, electric field sensors, and photoreflectors. Multiple different sensors can be installed under the soft skins. The soft skins provide the soft contact while HRI and the contact with soft skin are near to the human skin in similarity. The tactile sensors are arranged in the form of arrays in soft skins. The soft skins enable to detect the tactile sensation performed on an area that is not directly covered by the installed sensors. The tactile operation performed on those areas causes the deformation in the soft skin. The deformation propagates the tactile signal to a tactile sensor. The spatial resolution of array-based soft skins is in millimeter. The soft skin used in the humanoids involve [74][160][97]. The soft skin in the humanoid in [74] corresponds to patches of pressure-sensitive conductivity rubber. The seal robot in [160] contains the soft skin of tactile sensors under its synthetic fur. The child sized android in [97] has the skin of silicone that covers its whole body.

C) Alternative to skin approaches

The tactile sensors are either placed inside the robot body or the sensors are placed on the body of the robot. There exist no explicit covering for the sensors. The skinless tactile sensor-based approaches place the sensors on the surface or within the joints of the robot. The used sensors involve pressure-sensitive conductivity rubber, and commercial tactile sensing pads [6]. The sensors can also be placed in the form of arrays on the robot body. The tactile information that can be obtained from the installed skinless sensors is small, e.g., the spatial resolution with respect to tactile sensation is quite low. The absence of skin can be handled with the installation of arrays of tactile sensors. The robots having the tactile sensors installed inside are mostly the industrial robot arms. In [62] the location and the tactile force of the human are sensed by the torque sensors installed at the joints of the light weight robot arm. There exist many approaches concerning the installation of tactile sensors on the body of the robot, e.g., entertainment robot SDR-4X II (QRIO) [86], dog robot [133], cat robot [134], the robotic creature [168]. In [86] the tactile sensors are used to detect the pinch operation at all the joints of the robot. In [133] the balloon pressure sensor is used to interact with the human. In [134] the piezoelectric force sensors are installed on different parts of the robot to detect hitting and touching on the cat robot. There exist 60 FSR sensors under the fur of the rabbit looking robotic creature to detect the human contact [168].

2.4.2 Tactile HRI

The physical HRI with respect to the existing tactile sensing approaches is divided into three categories [6]. In the first category the considered approaches correspond to the unexpected contact between the human and the robot. It means that either the human or the robot interfere with each other while operation. The tactile sensing corresponds to the safety involved in the HRI, in the first category. The tactile HRI in the second category corresponds to the expected contact between the human and the robot. The physical contact between the human and the robot is used as a communication channel to guide the robot to execute behaviour. In this category the human contact works as a trigger of behaviour of the robot. The third category corresponds to the human contact to the robot that is used to refine and build the behaviours in the robot. The human contact can also be used to correct the robot behaviour.

A) Interfering interactions with the robots

It is considered that unexpected human-robot contacts are unavoidable as the presence of robots in the human community increases day by day [6]. The existing approaches provide the reacting solutions in the result of a physical contact that can occur with a human. In [56] reactive control strategies are proposed. The proposed strategies use a bumper-based skin to detect the unexpected human contact. The redundant degrees of freedom present in light weight robotic arm are used for evasive motion of the robot in physical contact. During the evasive motion the orientation of the tool center point is maintained [62]. In [165] a robot arm of 8 degrees of freedom evades the human contact during the motion. The forces from the tactile sensors are measured in motion vectors and the resulting motion vectors are super imposed for the joint velocities. In [76] a predictive approach is described with respect to interfering interaction. The effects of the human-robot contacts are predicted and the concerning response are encoded into the robot behaviour. The collision tolerance in the end-effector control is implemented by modelling the compliance in the viscoelastic trunk of the robot [90]. In [90] no explicit tactile sensing is performed.

B) Deliberated tactile interaction with the robot

In this tactile HRI the robot expects the touch from the human. The human touch contributes to the robot behaviour. The contact is used as a medium of communication between the human and the robot. There can be two kinds of deliberate tactile HRI. In first case the human contact correspond to guide the robot. In this case the human contact is linked to the robot state. In the other case the human contact is used to convey the information about the human.

The case is linked to the human state. The context of the HRI is important in deliberated interaction with the robot concerning the robot state.

There exist approaches that consider the tap sequence to select the robot behaviour. In [160] a tactile HRI is proposed that focus the industry robot and non-robot expert human user. The tactile interaction corresponds to the human contact at the end-effector of the robot. The human contacts are mapped to the known trajectory. Different human touches correspond to different trajectories. In [165] the tap sequence corresponds to different alphabets that are used to select the behaviour of robot. In [145] multi-finger touch is used to infer the alphabets for teleoperation and robot behaviour.

The deliberate human contact is also used by the robot to interpret the human state. These human touches correspond to the contact that one human uses while interacting with the other humans. The other human estimates the state of first human from the contact. In [109] the robot classifies the five different human touches. The touch corresponds to slap, stroke, pat, scratch, and tickle. The approach proposed in [83] considers the contact-time, repetition, force, and contact area in order to interpret the human touch corresponding to hit, beat, and push. In [82] the humanoid interprets the human touch in different HRI scenarios, e.g., while executing a behaviour, co-execution, and reactive behaviour. In [100], the pose and position of human is estimated by the human touch. The estimated pose is used in reactive behaviour. A robotic bear [140] touches the human in response to the human touch. The robot orientates itself to the direction of human touch. The types of human touches are classified to estimate the human state.

In [151] the tactile HRI corresponds to the interaction between the human and ballroom partner robot. In this HRI the human touches guide the robot behaviour and the robot also estimates the human state from the human contact in order to follow the human while dancing task. The contact with the human is used by the robot to predict the next dance step of the human. The force of the human contact is used to detect the human stride.

C) Robot behaviour development by tactile HRI

In this HRI the robot expect the human touch for the correction and development of robot behaviour. The human contact is used to communicate the intended human correction to the robot. The behaviour development is to produce the adaptive and compliant robots. The human contacts are expected while behaviour development but not at the time execution of the developed behaviour.

The robot behaviour development by tactile HRI relates to the paradigm of “teaching by touching”. There exist different approaches for this paradigm. In [40] the behaviour of the robot is developed by human touch. The robot behaviour corresponds to the pose change of the robot according to the human touch. If the pose change is not according to the human then direct manipulation of robot pose is performed. A mapping is learned between the human touch and the directly manipulated robot pose. In [4] the translating finger touch is used to change the pose of the robot. The pose change is performed while the robot manipulates the objects. The tactile feedback is used to move an industrial robot arm for the demonstration of task. The task corresponds to the insertion of piston [62]. In [97] the idea of “motor development with physical help” is introduced. The experiments are performed with a child sized android CB2. In experiments the human provide physical help to the robot for going from prostrate state to the standing state. The robot minimizes the supporting force provided from the human and also learns the resulting motion.

2.5 Conclusion

HRI is a vast field covering many aspects from the robot side and the human side. It is a multidisciplinary field involving human-computer interaction, artificial intelligence, robotics, natural language understanding, and social sciences. In the literature of HRI multiple aspect of the research are quite heavily explored. For example social human robot interaction, robot as an assistant, autonomy-based issues in HRI, tactile HRI, vision based safe HRI, HRI for teaching the robot, i.e., Programming by Demonstration (PbD), etc. The area of intuitive HRI specifically by intention recognition is not explored considerably.

For intuitive HRI the robot needs to know the human intention. The human intention can be estimated by multiple ways, e.g., language understanding, monitoring, by guessing using the prior knowledge about the human, by combining the described aspects, etc. There exist different approaches for intention recognition in the literature. The existing approaches [75][101][50] focus on specialized solutions based on the problem at hand. There exist a couple of generalized approaches [139][149] for intention recognition but the inference in the proposed architecture requires a large numbers of prior and conditional probabilities [98]. The corresponding modelling required for the general intention recognition approach is quite large that there exist approaches to reduce the modelling [84]. There exists another concerning approach that corresponds to the intention recognition as an observer without letting the robot to actively take part in HRI [125]. The modelling structure used for the approach in [125] requires a relatively large state space [98]. A theoretical approach also exists that deals with intention recognition without taking into account the intuitive HRI [169]. There exist also another approach concerning intention recognition but the approach does not consider the existence of robot in the discussed idea. The described approach relates to the existing literature of plan recognition [98].

Similarly for proactive nature of HRI there exists multiple approaches but they do not strictly correspond to the direct HRI. Either they correspond to teleoperation or involve the mobile-robot navigating in an environment. A couple of approaches concerning direct proactive HRI exist that require that the specific number of intention estimates that should be given already [131][77]. In [77] the experiments do not involve any human rather a simulation is used and proactivity is achieved by the application of entropy.

Furthermore, they are not extensible in the sense that they can be used online to add new intentions understanding to increase the interaction capability of the robot. Similarly the generalization of the human intention is also not available in these approaches. Moreover in the existing literature of HRI the intuitive HRI in an unknown human intention scenario is not explored considerably.

In this research work we introduce a simple approach for intention recognition. The approach is also applied in the areas pointed out, i.e., online intention learning and generalization where the existing approaches do not provide an explicit solution. Additionally the research work also discusses an approach for HRI in a scenario if the human intention is not known to the robot.

Chapter 3

Intention recognition

With the era of modern technologies, machines are becoming necessary part of the human life. More specifically, the presence of robots among the humans is increasing day by day [6]. The goal is to provide the services to the humans. The robots that are intuitive in providing the required services will be preferred to the machines that require considerable input for providing the required service. Intuitiveness is necessary for a robot to exist as a service provider, amongst the humans. Therefore, a robot needs to recognize the intention of an interacting human. Recognizing the human intention, the robot can smoothly cooperate with the human. There are many working scenarios, described in Chapter 1, where the intelligence of a human and the efficiency of a robot can be combined to provide a better output. Intention recognition of the interacting human is the key to intuitive HRI. It guides the robot by answering him the questions about what to do in a HRI workspace. For recognizing the human intention, different methods can be employed, e.g., the human may be directly asked about his intention, the intention can be presumed from the daily strict routines of the interacting human, the human actions along with HRI workspace can be monitored to estimate the human intention, etc.

In this chapter we describe a novel approach [12] for intention recognition based on the human action and / or changes in the HRI workspace. This chapter is organized as follows: In Section 3.1, intention recognition is motivated with the examples of HRI and the problem discussed in Chapter 3 is defined. In Section 3.2, the literature review of the existing intention recognition approaches is provided. The description of the human intention modelling is given in Section 3.3. Each human intention is modelled using a Finite State Machine (FSM). The formal description of a FSM is given in Section 3.3. The approach for intention recognition is discussed in Section 3.4. The approach described in Section 3.4 uses the intention hypotheses to recognize the actual human intention. The experiments performed using the proposed approach, are described in Section 3.5. Section 3.6 summarizes the chapter.

3.1 Problem definition and Motivation

The discussed problem corresponds to the recognition of a human intention. The robot is required to recognize the human intention by the information from the HRI workspace and the human actions $A = \{a_1, a_2, a_3, \ldots, a_m\}$, $m \in \mathbb{N}$. The robot already knows the human intentions $I = \{i_1, i_2, i_3, \ldots, i_n\}$, $n \in \mathbb{N}$. The robot can recognize the human intention by the commanding actions (gestures) performed by the human. The robot can also recognize the human intention by the human actions performed on the objects present in HRI workspace. The human is allowed to switch between his intentions without completing the actions concerning an intention. The human is also allowed to perform unrelated actions while performing the actions concerning an intention. The input to the problem involves the human actions, scene information, the scene change information, and the human intentions. The output corresponds to the recognition of a human intention out of the already known human intentions.

The effectiveness of intention recognition in HRI is motivated with the help of Figure 3.1. The interaction of a humanoid and a human is shown in Figure 3.1 left. The humanoid offers a tray of coffee cups to the human. An accident can occur if the human and robot do not understand each others intention. If the human does not intend to take the tray and the robot does not recognize the human intention. Then the tray may fall down. The interaction of an industrial robot and a human is shown in Figure 3.1 middle. The human piles up the objects. In order to interact intuitively the robot needs to recognize the human intention of *pileup* of objects. The interaction of an industrial robot and a human is shown in Figure 3.1 right. The human holds the object grasped by the robot. The robot needs to recognize if the human wants to take the object from the robot or wants to orientate it in a direction. If the human intends to orientate it and the robot releases the object. Then object will fall down as the robot does not interact intuitively. The robot can only assist the human if it can understand the human intention. Thus recognition of human intention is inevitable for effective HRI. Moreover, in industrial HRI, safety of the interacting human is an important issue. The human intention can be used to predict the future position of the human to improve the safety in HRI. The robot can use the human intention to plan his collision free trajectory.

Figure 3.1: Left: Humanoid HRI [1], Middle: Laboratory HRI, Right: Industrial HRI [127]

3.2 Related work

Youn and Oh presented an approach in [169] for intention recognition, using a graph representation. They used three layered approach for intention recognition. The three layers include action layer, proposition layer, and the goal & intention layer. The action layer has action nodes, the proposition layer has state nodes, and goal & intention layer has goal and intention nodes. The presented approach makes relationships amongst the action, state, and goal & intention nodes. The connected nodes represent an intention graph. Each state node represents a ground literal. A ground literal is an atomic formula. It is assumed that any condition not mentioned in the state is false. An action is represented by a set of preconditions and a set of effects. The preconditions correspond to the conjunction of literals that must be true for the concerning action to be executed. The set of effects correspond to the conjunction of literals concerning the state changes. The effects are generated in result of the executed action. A goal consists of the desired states and termed as goal descriptors. An intention corresponds to goal conditions and related user profile. The nodes in action, states, goals, and intention are connected to each other with six different kinds of edges in an intention graph. The intention recognition process consists of two phase, i.e. goal recognition and intention recognition. It is a theoretical approach that deals with intention recognition without taking into account the intuitive HRI. There exist no experiments that are performed with this approach.

In [149] Tahboub proposed cycle elimination in Dynamic Bayesian Networks (DBN) for intention recognition. The approach in [149] describes that the cycles are generated due to the feedback from the sensed states to the intention states and the actions states. The proposed solution for cycle elimination considers the feedback of sensed states from the previous time slice instead of the current time slice [149]. The inference in the proposed architecture requires a large number of prior and conditional probabilities [98]. The corresponding modelling required for the intention recognition is so large that there exist approaches to reduce the modelling [84].

Mao and Gratch [98] have proposed an intention recognition method based on expected utility [48]. The intentions of the agent are represented by the plans that an agent may have. The expected utilities of the plans are calculated and a plan with maximal expected utility represents the estimated intention of the agent. A plan is represented probabilistically. The actions concerning the plan may have conditional as well as non-deterministic effects. The utility values represent the desirability of action effects. The actions have success or failure probabilities. The actions may be primitive or abstract. A primitive action corresponds to an action that can be directly executed. An abstract action can be decomposed into further abstract actions or primitive actions. The presented approach emphasizes on the desirability of the outcome of the intended task. The outcome of a task corresponds to the utility value of that task. According to this approach the agent whose intention is to be recognized, tries to maximize the expected utility. Thus the results of the plan / intention recognition are influenced by the already defined utility values of the plan / intentions as the agent will try to maximize the utility. The approach concerns intention recognition but the approach does not consider the existence of a robot in the discussed idea. The described approach relates to the existing literature of plan recognition [98].

Richard proposed an approach in [125] for understanding the human intention. They used Hidden Markov Models (HMMs) to recognize the human intention. The experiments are performed with a mobile robot equipped with laser sensor and a camera. The performed experiments involved the human intentions including Follow, Meet, Pass by, Drop off, and Pick up. These intentions correspond to the intentions between two humans that may follow each other, meet each other, cross without meeting and dropping or picking some thing. For each intention a HMM is designed. These models are trained by the Baum-Welch algorithm. The described novelty in [125] corresponds to the models that focus on dynamic interacting properties of an agent, i.e., Meeting, Passing by, Dropping, and Picking up. The selected visible variable for HMM corresponds to the change in the position and angle of the interacting agents. The introduced approach has two parts, i.e., activity modelling and intent recognition. In activity modelling, the already designed HMMs are trained. To train the models concerning Following, Meeting, Passing by, Picking up an object, and Dropping off an object, the robot executes these activities with an interacting human. The transition probabilities concerning HMM are estimated using Baum-Welch algorithm while activity execution. In the intent recognition part, the robot acts as an observer and evaluates the intent of different interacting humans using the already trained HMMs. In recognition part the variables corresponding to the observed states are calculated differently as compared to the activity modelling. The Forward algorithm is used for the calculation of most likely sequence of observation. The Viterbi algorithm is used to detect the most probable sequence of hidden states. The approach corresponds to the intention recognition as an observer without letting the robot to actively take part in HRI. The modelling structure used for the approach in [125] requires relatively large state space [98].

In [139] Schrempf and Hanebeck introduce a generic model based on Hybrid Dynamic Bayesian Network (HDBN) for the estimation of human intention in a HRI scenario. They have emphasized the importance of hybridity for the robots operating in the real world. The hybridity corresponds to the continuous-valued and discrete-valued states. The continuous states are described for the sensor measurements. The sensor measurements and the probabilities concerning the measurements are directly related to the continuous scales. The human aspect, e.g., human intentions is mostly described by discrete values. The proposed HDBN contains the intention variables that are represented by the discrete values and the sensor measurements that are represented by the continuous values. Once again the inference in the proposed architecture requires a large number of prior and conditional probabilities [98]. The corresponding modelling required for the intention recognition is so large that there exist approaches to reduce the modelling [84].

Our approach provides a novel frame work for intention recognition [12]. It considers the possible intentions as particle and provides a particle filter based intention recognition. The particles representing the intentions are modelled using FSMs. The presented approach is discussed in detail in Chapter 3.3. The presented approach [12] models the human intentions as discussed in [84].

3.3 Finite State Machines (FSMs)

It is fairly difficult to come up with a straight forward mathematical state prediction model that can predict the next human action or next state of human, i.e., next posture of the human body or part of the human body concerning the human intention while performing a task. For example if the human has a glass in his hand and he approaches toward the beverages then it can not be mathematically predicted that he will select cola, water, wine, juice, etc from the beverages. These are all hypotheses. If we consider these hypotheses as complete action sequences for performing different possible tasks then these sequences can be represented by different models that will represent different intentions of the human.

The action sequences considered as strings will not be robust due to intolerant string matching, e.g., if *ABCD* is the target string and the experienced string is *ABCDE* then the result of comparison will be negative. The *E* may be due to false recognition or unintentionally performed action.

If all the action sequences are considered as a FSM then the state transition will become very complex. The FSM may require multiple start and end states due to distinct starting and ending action sequences. A state transition problem may occur if the human changes its action sequence (intention) without completing it, e.g., if the human performs actions *A* and *B* corresponding to an intention but switches its intention and performs an action *E*. If there is no state transition at the state (reached after action *B*) corresponding to action *E* then no transition will occur. Thus the changed human action sequence will not be recognized. If there is an action sequence that is completely irrelevant from other action sequences then this situation may result in unconnected states in the FSM. Therefore each action sequence corresponding to a human intention is modelled by a distinct FSM. Different FSMs are designed regarding different human intentions. Each FSM represents the flow of different human actions one after another concerning the human intention.

The FSM models the human intention by considering the concerned action sequence. The performed actions concerning an action sequence give the estimate of current human intention. During the execution of actions of an action sequence concerning an intention, if the human reverses the last performed action. Then there may be different reasons. For example, he can take the same action again with possible correction, he can start performing the actions of a totally different action sequence concerning another intention, he can stop performing further actions, he can keep on reversing the actions, etc. The term reverse means that if the human performs an action A then he can reverse that action A by performing the action $\neg A$. If the human reverses an action then it is not taken care by the FSM model. The reason is that it is assumed that an action sequence corresponds to the concerning *human intention*. The action sequence must be performed in a sequence for the concerning intention to be recognized. Therefore if the human reverses an action but does not change his intention then that action will be taken again by the human. If one intention corresponds to different action sequences then different FSMs can be used to model the same human intention.

It is assumed that an action sequence is attached to the concerning intention. Thus an intention is defined by an action sequence concerning the intention. A FSM modelling a human intention has a single start state. The start state corresponds to the start of the action sequence. The discussed probabilistic FSM model does not consider multiple start states. There are different disadvantages of having multiple start states. The disadvantages exist with respect to the human intention recognition and intuitive HRI. If we consider more than one FSMs having multiple start states then it may be the case that an action A existing as one of the initial actions of a FSM also belongs to the final action of another FSM. If the human intends a task that has the action A as one of initial action but as it exist as the final action in another FSM the false human intention will be recognized due to the multiple start states. Similarly if the human starts performing the actions beginning at the start state S_1 and in-between switches to another action sequence beginning at the start state S_2 of the same FSM then the concerned human intention will not be recognized if the state transition does not exist between the concerning states.

During work the human workers may perform the actions that are not directly related to their working intention. For example a human worker can scratch somewhere on his body, drink, divert his intention from work, talk to some other human, perform some unintentional task due to anxiety, etc. A human working on a task can perform arbitrary actions that are not related to the current task. The arbitrary actions do not emphasize that the human intends to change his intention concerning the current task. The change of intention means that he is not interested to perform that task any more. There may be the case that the human wants to suspend the task for some time. Afterwards, the human worker may start performing the actions concerning the intention. Similarly a human can switch between two tasks corresponding to two different intentions. He may come back to the previous task and starts performing the actions corresponding to that intention. He may also continue with the switched task concerning another intention. There may be multiple reasons that a human can perform arbitrary actions while having the intention of performing a specific task. Thus it is significant to take care of the arbitrary actions of the human while recognizing the human intention. This is taken care automatically by the presented FSM model.

A FSM is shown in Figure 3.2. Each unique human intention is represented by a distinct FSM. A FSM models the action sequence corresponding to a unique human intention. Each FSM carries a probabilistic weight. The weight represents how closely the FSM represents the human intention. If the weight is high then the FSM closely relates to the currently estimated human intention and vice versa. Each action a_{ji} has a probability value $P(a_{ji} \mid S_i)$ at a state S_i, $i=1,\ldots,n$ and $j = \{1,\ldots,m\} \setminus k$ with $k \in \{1,\ldots,m\} \wedge k \neq j$. The $n \in \mathbb{N}$ represents the number of states in a FSM and $m \in \mathbb{N}$ represents the number of transition conditions. For a state S_i the j can have all the values from 1 to m except one value k, $k \in \{1,\ldots,m\} \wedge k \neq j$. The k is variable and it is not required to be the same for n states of a FSM.

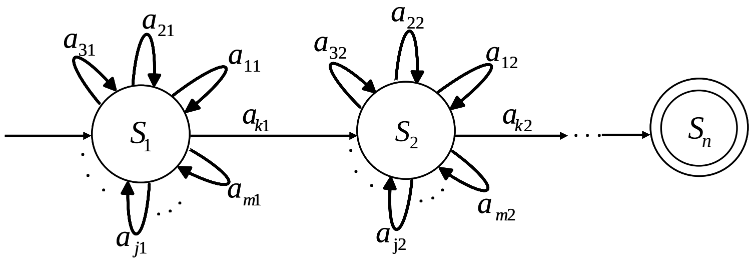


Figure 3.2: A FSM with n states, i.e., $S_1,\ldots,S_n$. Each state S_i $i=1,\ldots,n$ ($n \in \mathbb{N}$) has m transition conditions (actions / scene changes), i.e., $a_{1i},\ldots,a_{mi}$, $m \in \mathbb{N}$. For each state S_i $i=1,\ldots,n$, it is defined that $j = \{1,\ldots,m\} \setminus k$ with $k \in \{1,\ldots,m\} \wedge k \neq j$. If a_{ji} is observed at state S_i then no state transition occurs. The transition only occurs if a_{ki} is observed at state S_i. The k is variable and it is not required to be the same for n states of a FSM

The probability value $P(a_{xi} \mid S_i)$ describes how likely an action a_{xi} is for the state S_i of a FSM and $x = \{1,\ldots,m\}$. The action a_{ki} represents an action that has highest probability $P(a_{ki} \mid S_i)$ for the state S_i and the state transition only occurs if a_{ki} is observed as shown in Figure 3.2. The action a_{ki} is not required to be the same for the n states of a FSM. The formal description of a FSM is given below in Figure 3.3.

$$
\begin{aligned}
&FSM = \langle Q, \Sigma, q_0, F, \delta \rangle \\
&Q = \{S_1, S_2, S_3, \ldots, S_n\} \\
&\Sigma = \{a_1, a_2, a_3, \ldots, a_m\} \\
&\forall\, S_i \in Q \ \ \textit{it holds that} \sum_{x=1,\, a_x \in \Sigma}^{m} P(a_{xi} \mid S_i) = 1 \\
&\forall\, S_i : \exists\, a_{ki} \in \Sigma : \mathop{\forall}_{i=1,\, j \neq k}^{m} a_{ji} \ \ \textit{it holds that} \left[P(a_{ki} \mid S_i) > P(a_{ji} \mid S_i) \right] \\
&\delta : Q \times \Sigma \rightarrow Q \\
&\delta(S_i, a_{ji}) = S_i \ \ \textit{and} \ \ \delta(S_i, a_{ki}) = S_{i+1} \quad i = 1,\ldots,n \\
&q_0 = S_1 \\
&F = \{S_n\}
\end{aligned}
$$

Figure 3.3: A formal description of a FSM. It describes that a FSM is a tuple of five elements

Each $FSM = <Q, \Sigma, q, F, \delta>$ is a tuple that contains set $Q = \{S_1, S_2, S_3, \ldots, S_n\}$ that represents the number of n states in a FSM. The set $\Sigma = \{a_1, a_2, a_3, \ldots, a_m\}$ represents the possible actions for a state $S_i \in Q$. The sum of probabilities of all the actions $\sum_{x=1, a_x \in \Sigma}^{m} P(a_{xi} \mid S_i)$ for a state $S_i \in Q$ adds up to 1, i.e.

$$\forall S_i \in Q \ \ it\ holds\ that \quad \sum_{x=1, a_x \in \Sigma}^{m} P(a_{xi} \mid S_i) = 1$$

For each state $S_i \in Q$ there exists an action a_{ki} such that the probability of the action $P(a_{ki} \mid S_i)$ is greater than all the other actions, $\underset{j=1,\ j\neq k}{\overset{m}{\forall}} P(a_{ji} \mid S_i)$ i.e.

$$\forall S_i : \exists\, a_{ki} \in \Sigma : \underset{j=1,\ j\neq k}{\overset{m}{\forall}} a_{ji}\ it\ holds\ that \left[P(a_{ki} \mid S_i) > P(a_{ji} \mid S_i)\right]^1$$

If the action a_{ji} occurs at a state $S_i \in Q$ then the transition occurs to the same state, i.e., $\delta(S_i, a_{ji}) = S_i$. If the action a_{ki} occurs at a state $S_i \in Q$ then the transition occurs to the next state, i.e., $\delta(S_i, a_{ki}) = S_{i+1}$. The action a_{ki} is not required to be the same for the n states of FSM. The start state and the final state of a FSM are represented by $q_0 = S_1$ and $F = S_n$ respectively. The general flow of the algorithm for probabilistic intention recognition using FSMs is shown in Figure 3.4.

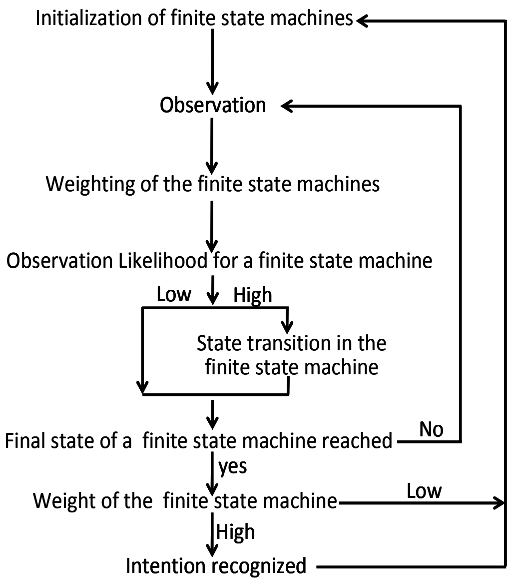


Figure 3.4: The flow diagram describes that initially all the FSMs are in their start state. On each new observation the weights of the FSMs are updated. A currently active state of a FSM is a state whose previous states are travesred and the next states are not traversed. If the observation corresponds to the action that has the highest probability value for the currently active state of a FSM. Then a state transition occurs in that FSM. The state transiton can occur in more than one FSMs if the obseraction corresponds to the highest probability value actions at the currently active states of the concerning FSMs. The intention of the human is considered recognized if the concerning FSM has the highest weight and that FSM reaches its end state

[1] The model is well defined that an action that causes the transition from a state S_i to the next state S_{i+1} has the highest probability as compared to the other actions at the state S_i.

The HRI can be of two types, in the first type the human can command the robot to perform a task and the human communicates his intention explicity. In the second type the human does not command the robot but communicates his intention by performing a task. In the second type the human communicates his intention implicity by intiating a task.

3.3.1 Recognition of explicitly communicated intentions

In real life the humans can communicate with each other using different gestures, e.g., pointing, stopping, etc. The humans also use the speech along with other communication channels to convey their message to other humans. A gesture corresponds to a human action that is used by the human to convey his message. In Section 3.3.1 the gestures are considered for human-robot communication.

Explicitly communicated intentions correspond to the tasks in which the human performs only gestures without performing an operation on the concerning objects, existing in the HRI. The robot performs the intended operation on the concerning objects in the HRI workspace. The explicitly communicated intentions are represented by the FSMs. The state transition for a state in the FSMs corresponds to the different human gestures. The different FSMs representing different explicitly communicated human intentions are shown in Figure 3.5.

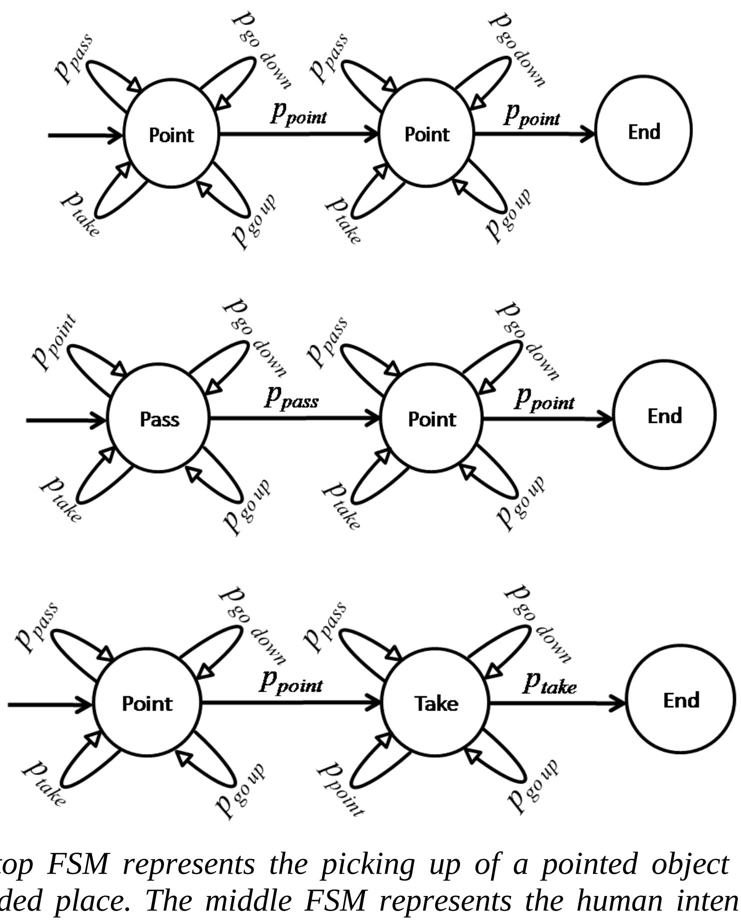


Figure 3.5: The top FSM represents the picking up of a pointed object and placing that object at the intended place. The middle FSM represents the human intention of placing a passed object at the intended place. The bottom FSM represents the human intention of taking an intended object

The sequence of the states in the FSM represents a unique human intention. Different state transitions concerning different human gestures have different values in a state of a FSM. The state transition that has high likelihood / not high likelihood / low likelihood for a state will have high / not high / low value for that state, e.g., the start state of FSM shown in Figure 3.5 (top) represents the *pickandplace* intention. The pointing action p_{point} has high value as compared to the open hand action p_{take} for taking an object, object in hand action p_{pass} for giving an object.

3.3.2 Recognition of implicitly communicated intentions

The sequence of the states in a FSM represents specific changes in the scene along with the specific human actions concerning a unique implicit human intention. Different human actions and the related scene change information have different probability values for a state in the FSM. Human actions and the related scene change information correspond to the state transitions in a FSM.

The FSMs for implicitly communicated human intention use the scene change information and / or the human actions as the transition conditions. For example, there exist multiple known objects scattered in HRI workspace. The human picks an object (that is already placed on another object) and places that object in the HRI workspace. The robot observes that the number of unpiled objects changes along with the human action of picking and placing of the object. The FSM that models the unpile intention of the human will consider the pick and place actions of the human as the transition conditions. The place action corresponds to the placement of the unpiled object. The related scene change information is the increment in the unpiled objects. The FSMs shown in Figure 3.6 use both the scene information and the human actions to model an implicit human intention.

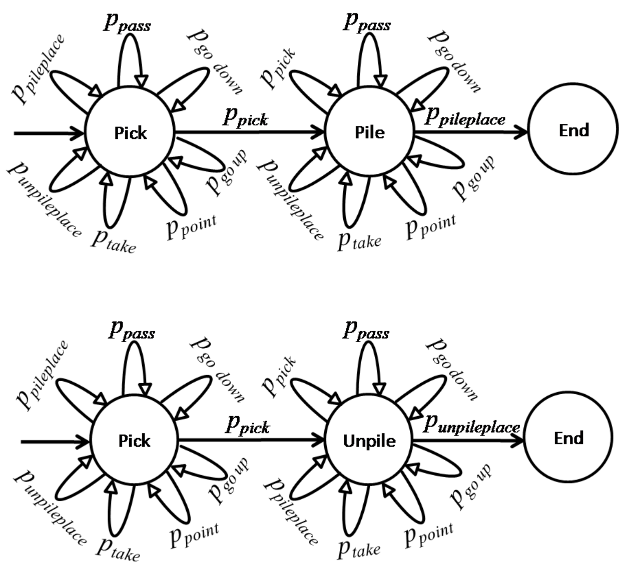


Figure 3.6: Two FSMs are used to demonstrate the recognition of the implicitly communicated intentions of pileup (top) and unpile (bottom). The likelihood of pick action is the same for both of the FSMs, i.e., pileup FSM and unpile FSM. The unpileplace action has high likelihood at the unpile state of unpile FSM. Similarly the pileplace action has high likelihood for the pile state of pileup FSM

The p_{pick} corresponds to the human pick action and the related scene change information. The $p_{pileplace}$ corresponds to the human place action and the related scene change information. This scene change information corresponds to the decrease in the number of objects in (2D) the scene as the objects are piled. Similarly the $p_{unpileplace}$ corresponds to the place human action with the increase in the objects in (2D) the scene.

3.4 Intention recognition algorithm

At the beginning, each FSM representing a unique explicitly / implicitly communicated human intention has the same weight, i.e., the probabilities of human intentions represented by the FSMs are equal. An observation is made and the human actions along with the concerning scene information are extracted. The weights of the FSMs are updated based on the observation (Line 5, Figure 3.8) and normalized so that they add up to 1 (Line 14, Figure 3.8). The weight of a FSM is directly related to the observation. The FSM for which the observation is most probable gets high weight as compared to the other FSMs. If an observation is equally probable for more than one FSM then those FSMs get the same normalized weight. After each observation, along with weight update the important data values necessary for HRI can also be determined, e.g., calculating the pointed object to be picked or to calculate the pointed place to place the object.

After an observation, state transition occurs in none, one or more FSMs (Lines 6-9, Figure 3.8). If an irrelevant human action is observed then no state transition occurs in any FSM. If a relevant human action is observed then it is checked for the currently active states of all the FSMs. If the observation has the highest probability for the currently active state then the state transition will occur in that FSM.

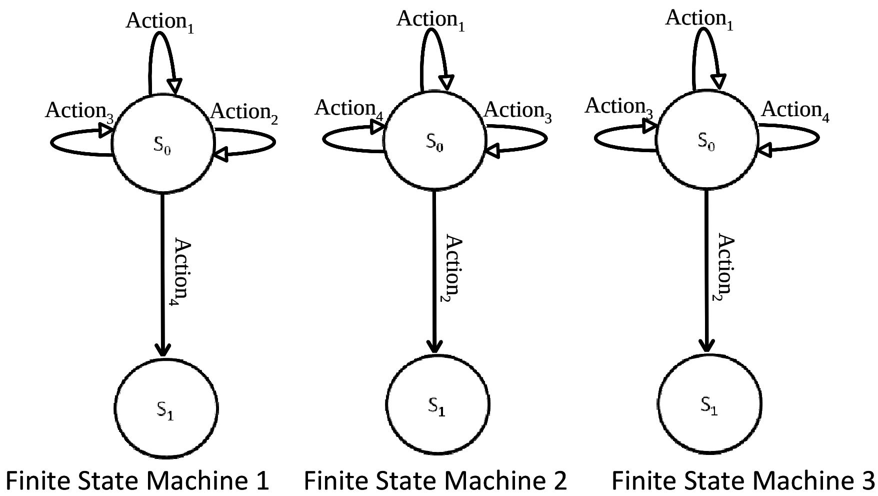


Figure 3.7 : If the $Action_4$ is observed than the state transtion will only occur in FSM 1. If the $Action_2$ is observed than the state transtion will occur in FSM 2 & 3

If the observation is highly probable for more than one FSM (currently active state) then the state transition will occur in more than one FSM. In other FSMs no state transition will occur, i.e., it will loop back to the same state. It is shown in Figure 3.7.

The advantage of making transition in only the most probable FSMs is that if the human changes his intention in-between then this situation can be easily handled, e.g., if the human has an intention and performs an action then the concerned FSM (intention) gets a high weight and only in that FSM a state transition occurs. If the human changes his intention then the new action sequence can be evaluated with the related FSM and the changed intention can be easily recognized.

A non sequential FSM that represents a human intention can be split into multiple sequential FSMs that represent the same human intention. These sequential FSMs describe that a human can represent his single intention using different action sequences. The human performs a task following one of the action sequences concerning a single intention. If the human switches to another action sequence that relates to the same intention then the recognition process will be handled by the concerning sequential FSM.

Now we consider a non sequential FSM that represents a human intention having multiple concerning action sequences. If the human performs a task following one action sequence but switches to another action sequence then it may be difficult to recognize the switch if a state transition is not defined for that in the non sequential FSM. This case can be easily handled by the split sequential FSMs as discussed above.

The disadvantage may be if the sequence of actions performed concerns an intention I_1 and before completing the sequence the human changes his intention to I_2. The human performs an action $\boldsymbol{A}$ concerning the intention I_2. That action $\boldsymbol{A}$ also exists in the FSM_1 modelling I_1 and leads the FSM_1 to the end state. If the currently active state of FSM_1 requires action $\boldsymbol{A}$ to reach the end state and the human performs the action $\boldsymbol{A}$ concerning the intention I_2 then false intention will only be recognized if FSM_1 has the highest weight.

If the end state of a FSM is reached and the FSM has highest weight then that intention is recognized and FSMs are reinitialized (Lines 17-21, Figure 3.8). If the end state is reached but the weight is not the highest then all the FSMs are reinitialized without intention recognition (Line 17, 21, Figure 3.8). The defined intention recognition algorithm is given in Figure 3.8. As described earlier that the FSMs work as the human intention hypotheses. This algorithm updates the intention hypotheses using the current observation. At Line 1 and 2 the FSMs are initialized once with the equal weights, i.e.,

$$w_i = \frac{1}{N} \mid i = 1,...,N$$

The term w_i represents the weight of the i^{th} FSM. The term N represents the total number of FSMs. S^t represents this set at time t, i.e.,

$$S^{t=0} = \{(s_i^0, w_i^0) \mid i = 1,...,N\}$$

It contains the pairs of FSM and the concerning weight, i.e., (s_i^t, w_i^t). The weight w_i^t of the FSM s_i^t represents how closely the hypothesis represents the actual human intention. Line 5 describes how the weights of FSMs are updated according to observation probabilities, i.e.,

$$w_i^{t+1} = w_i^t \bullet \mathrm{p}(z^t | s_{i,\,state_t}^t)$$

The observation probabilities $\mathrm{p}(z^t | s_{i,\,state_t}^t)$ correspond to the likelihood of different human actions for the current state $state_t$ of a FSM s_i^t. The Step 6 checks if the current observation is equal to the transition condition of a FSM s_i^t at the currently active state $state_t$, i.e.,

$$\left(\mathrm{p}(z^t | s_{i,\,state_t}^t) == \operatorname*{argmax}_z \left\langle \mathrm{p}(z \mid s_{i,\,state_t}) \right\rangle \right)$$

If yes then a state transition occurs, i.e., $s_{i,\,state_{t+1}}^{t+1} = s_{i,\,state_t+1}^t$ otherwise no state transition occurs, i.e., $s_{i,\,state_{t+1}}^{t+1} = s_{i,\,state_t}^t$. At Line 11 the set S is updated, i.e.,

$$S^{t+1} \cup \{(s_i^{t+1}, w_i^{t+1})\}$$

The symbol $\cup$ means that the i^{th} FSM at time t is updated with respect to the weight and currently active state at time t+1. The weights of the machines are normalized at Line 14, i.e.,

$$w_i^{t+1} = \frac{w_i^t}{\sum_{i=1}^{N} w_i^t}$$

1- $S^{t=0} = \{(s_i^0, w_i^0) \mid i = 1,\dots,N\}$

2- $w_i = \frac{1}{N} \mid i = 1,\dots,N$

3- **while** $(Running)$ **do**

4-   **for** $(i = 1 \text{ to } N)$ **do**

5- $w_i^{t+1} = w_i^t \bullet \mathrm{p}(z^t | s_{i,\,state_t}^t)$

6-   **if** $\left\langle \mathrm{p}(z^t | s_{i,\,state_t}^t) == \underset{z}{\mathrm{argmax}} \left\langle \mathrm{p}(z \mid s_{i,\,state_t}^t) \right\rangle \right\rangle$ **then**

7- $s_{i,\,state_{t+1}}^{t+1} = s_{i,\,state_t+1}^t$

8-   **else**

9- $s_{i,\,state_{t+1}}^{t+1} = s_{i,\,state_t}^t$

10-   **endif**

11- $S^{t+1} = S^{t+1} \cup \{(s_i^{t+1}, w_i^{t+1})\}$

12-   **end for**

13-   **for** $(i = 1 \text{ to } N)$ **do**

14- $w_i^{t+1} = \frac{w_i^t}{\sum_{i=1}^{N} w_i^t}$

15-   **end for**

16-   **for** $(i = 1 \text{ to } N)$ **do**

17-   **if** ($s_{i,\,state_{t+1}}^{t+1} == s_{i,\,final}$) **then**

18-   **if** $(w_i^{t+1} == \underset{w}{\mathrm{argmax}} \langle w_i^{t+1} \rangle)$ **then**

19-   output Intention($s_{i,\,state_{t+1}}^{t+1}$)

20-   **endif**

21-   reintialize

22-   **endif**

23-   **end for**

24- **end while**

Figure 3.8: Intention recognition using the FSMs. Each FSM carries a weight. The weight of a FSM represents how closely the current human intention corresponds to the intention modelled by the FSM

From Lines 16 to 22 it is checked if any FSM has reached its final state then it is checked that if the state machine has the highest weight then the concerned intention is output and the FSMs are reinitialized. Otherwise the FSMs are simply reinitialized.

3.5 Experiments

The experiments have been performed with a robotic arm. The human and the robot interact in a HRI workspace shown in Figure 3.9.

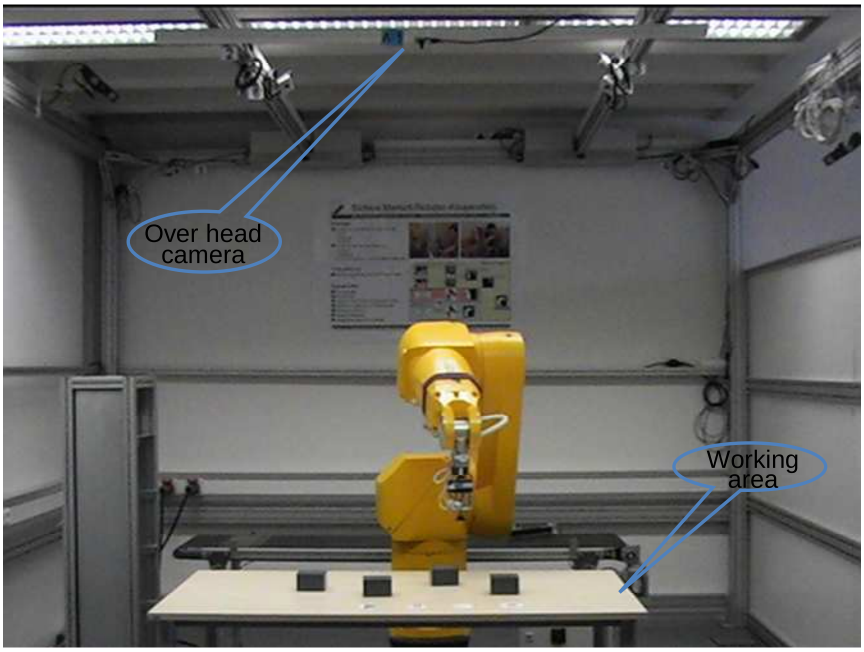


Figure 3.9: The HRI workspace. It consists of a table with known objects on the table. The robot interacts with the human by performing the human intended task. The HRI workspace is monitered with an over head camera

The video data is captured with a FireWire digital camera with the standard frame size of 640 x 480 pixels. Human-robot collaboration and image analysis is implemented using Programming language C++. The robot reactions are realized using the robot Programming language V++ for the robotic arm. The robot is sent the cooperative instructions using the TCP/IP connection for assigning different operation, e.g., pick, place and move to a certain location, etc. Skin detection [161] and Fourier descriptors [171] are used for the image analysis. In order to evaluate the human-robot cooperation by recognizing the explicitly and implicitly communicated human intentions, different scenarios are considered. The interaction activities corresponding to the five explicitly and two implicitly communicated intentions are discussed.

The explicitly communicated intentions are

1. *Picking and placing intention of an object*: The human intends to move an object from one place to another place in the human-robot collaboration workspace. The human explicitly communicates his intention by performing the corresponding actions. The human first points to the object that is to be picked by the robot and then points to the desired location where the object is to be placed by the robot.

2. *Passing intention of the human*: The human has the intention of passing an object to the robot and performs the concerning action. The human gives an object to the robot by offering an object on his hand.

3. *Placing intention of the human*: The robot places the already picked up object at a specific place according to the human intention. The human points with his pointing finger to the desired location. The robot places the already picked object at that location.
4. *Picking and holding intention of an object*: The human intends that the robot picks up a specific object in the human-robot collaboration workspace. The human points to the specific object in the HRI workspace and performs the pick up gesture.
5. *Taking a pointed object intention*: The robot provides the human the intended object that exists in the human-robot collaboration workspace. The human points to an object in HRI workspace and performs the taking gesture.

The above described intentions from 1 to 5 were tested with 3 persons. The results of the number of tested intentions and the number of successfully recognized intention for the explicitly communicated intentions are given in the Table 1.

Tested Intentions	Recognized intention					
	Int1	Int2	Int3	Int4	Int5	Experiments
Int1	19	0	0	0	0	20
Int2	0	20	0	0	0	20
Int3	0	0	18	0	0	20
Int4	0	0	0	20	0	20
Int5	0	0	0	0	20	20

Table 1 : The result of explicitly communicated intention

The implicitly communicated intentions are described as under

1. *Pile up of the objects*:
   Human comes into the scene and starts working without engaging the robot actively. The human starts to pile up the objects. The robot estimates the human intention by observing the human actions and the changes occurring in the HRI workspace. After understanding the human intention of pile up, the robot collaborates with the human by performing the operation of pile up of the objects.
2. *Unpile of the objects*:
   Human comes in the human-robot collaboration workspace and starts the operation of unpile of the objects without engaging actively the robot. The robot understands the human intention and unpiles the objects.

The results of the number of tested intentions and the number of successfully recognized intention for the implicitly communicated intentions are given in the Table 2.
The false results shown in the Tables 1 and 2 are due to the unrecognized human hand gesture, e.g., the pointing hand gesture shown in Fig 3.10 (left) is recognized as pointing hand

while the hand gesture in Figure 3.10 (right) is not recognized as the pointing hand. In case if no expected action sequence is observed then no intention is recognized.

Tested Intention	Recognized Intentions		
	Int1	Int2	Experiments
Int1	7	0	10
Int2	0	9	10

Table 2 : The result of implicitly communicated intentions

Figure 3.10: Extracted outlines of pointing hand posture

The presented approach recognizes the exact human intention using the probabilistic representation of action sequence, e.g., if the human performs a non-related action during explicit intention communication then the FSM concerning the non-related action gets low weight and the FSM concerning the actual human intention gets high weight due to the completely performed action sequence.

The Figures 3.11, 3.12, 3.13, and 3.14 represent how the weights of the intentions represented by different FSMs change during the intention recognition process. In the start all the intentions have normalized equal weight as shown in the intention graphs in Figures 3.11, 3.12, 3.13, and 3.14. At Step 1 an action of human is observed. The FSMs for which currently active state has high probability for the current human action get high weight and the others get low weight. If the end state of a FSM is reached and the weight of that FSM is also high then the concerned intention is recognized as the human intention.

The graph in Figure 3.11 describes the intention recognition of picking an object from one place and placing that object at another place. At the start all the intentions have equal probabilities as shown at Observation 0 in Figure 3.11. An observation can be an action performed by the human and / or scene change information. The first observation made is not directly related to any particular intention of the human. Therefore all the intentions get almost the same weight at Observation 1. The human makes a pointing action to an object that he wants to be operated by the robot. The performed human action has high observation probability for *pickup*, *pickandplace* and *take* intentions. Therefore the weights of these intentions go up and the weights of others go down at the Observation 2 as shown in Figure 3.11. The state transitions occur in the FSMs for which the observed human action is highly probable. Therefore state transitions occur in *pickup*, *pickandplace* and *take* FSMs. At the Observation 3 the perceived human action was unintentionally performed human action. It was due to the fact that the human unintentionally opened his hand while moving it to another location. The unintentional action stance may occur if a human changes his actions stance from one action to another. At Observation 3 the perceived human action has high probability for *place* intention. Therefore the intention weight for *place* goes up and weights for others goes down. The state transition only occurs in the *place* FSM. The human now points to a place where he wants the object to be placed by the robot. The performed human action has high probability for *pickandplace* and low probability for others at the Observation 4. Thus the state transition only occurs in the *pickandplace* FSM and the weight of the intention also increases. The final state of the *pickandplace* FSM is reached and it has also has the high weight as compared to others. Thus the intention of *pickandplace* is recognized.

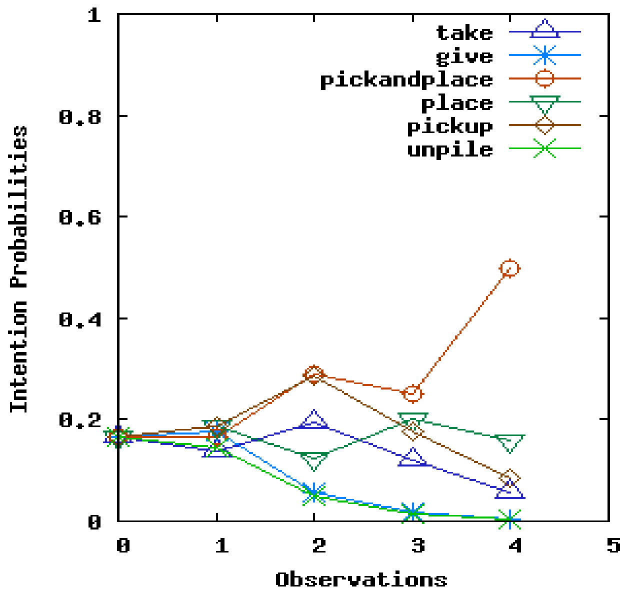


Figure 3.11: The graph represents the change in the weights of FSMs concerning take, give, pickandplace, place pickup, and unpile intention. The graph shows the recognition of pickandplace intention

The graph in Figure 3.12 describes the recognition of pickup intention. The intention weights are equal at Observation 0. At Observation 1 once again the human action stance does not corresponds mainly to any intention. Therefore the intention weights of all the intentions remain almost the same. The human once again makes the pointing action to an object. At Observation 2 the performed human action has high probability for *take*, *pickup* and *pickandplace* intentions and low for others. At Observation 3 the perceived human action does not corresponds mainly to any intention. Therefore there is no significant change in the intention weights. The human makes a makes an upward motion of his open hand for picking up of the pointed object. At Observation 4 the performed human action corresponds mainly to the *pickup* intention. Therefore the intention weight increases for this intention as shown in Figure 3.12. The state transition occurs in the FSM relating to the *pickup* intention and the end state of the FSM is reached. The weight of *pickup* is the highest and the end state is reached. Thus the *pickup* intention is recognized.

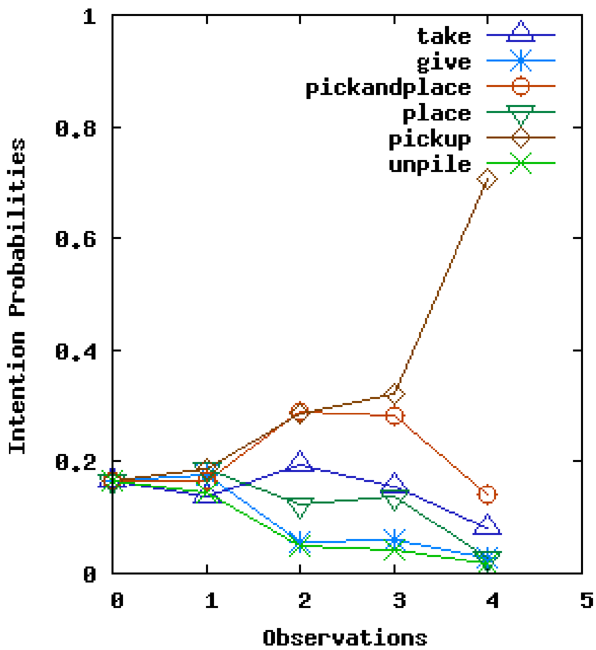


Figure 3.12 : The graph represents the change in the weights of FSMs concerning take, give, pickandplace, place pickup, and unpile intention. The graph shows the recognition of pickup intention

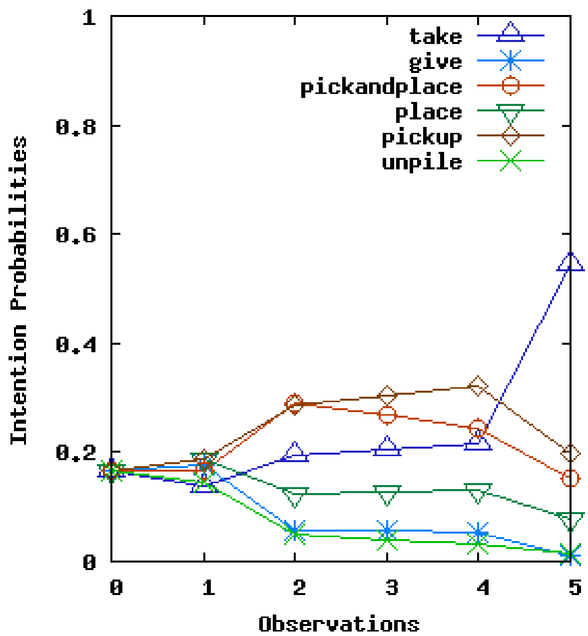


Figure 3.13 : The graph represents the change in the weights of FSMs concerning take, give, pickandplace, place pickup, and unpile intention. The graph shows the recognition of take intention

The graph in Figure 3.13 describes the recognition of *take* intention. The human points to an object that he wants to be provided by the robot. At Observation 2 the intention weights of *take*, *pickandplace* and *pickup* increase and others decrease. The state transitions occur in the corresponding FSMs. At Observation 3 and 4 the perceived human actions do not correspond mainly to any intention. Therefore there is no significant change in the intention weights is observed. The human opens his hand and keeps it in this position. At Observation 5 the performed human action mainly corresponds to the *take* intention. Therefore the weight of intention increases significantly and the state transition only occurs in the FSM relating to *take* intention. The end state of the FSM is reached and the weight is the highest. Thus the *take* intention is recognized.

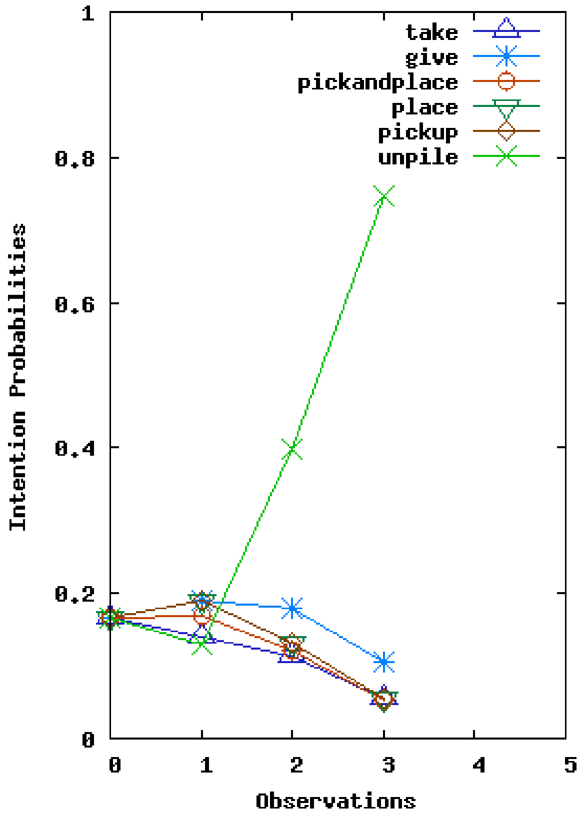


Figure 3.14 : The graph represents the change in the weights of FSMs concerning take, give, pickandplace, place pickup, and unpile intention. The graph shows the recognition of unpile intention

The intention graph shown in Figure 3.14 describes the recognition of implicitly communicated intention of unpile of the objects. The human grabs an object that is placed on the pile of objects. At Observation 2 the recognized human action mainly corresponds to the *unpile* intention. Thus the weight of *unpile* intention increases and the weights of other intentions decrease. While considering an observation the scene information is also taken into account as the human actions correspond to an implicitly communicated intention. The human picks the object from the pile and places it on the surface of the table. At Observation 3 along with the human action, the scene information is also inspected to check the increase or decrease in the unpiled objects. The human action and the scene information relates significantly to the *unpile* intention. Therefore the state transition occurs in the concerning FSM and the intention weight increases significantly. The state transition at Observation 3 brings *unpile* FSM in the end state and the weight of the *unpile* intention is also the highest. Thus *unpile* intention is recognized.

3.6 Summary

In this chapter we presented a probabilistic FSMs based intention recognition algorithm. A human intention is modelled by a FSM. A FSM corresponds to a human action sequence and / or the concerning changes in the HRI workspace. A specific human action sequence and / or the concerning changes in HRI workspace directly relates to a human intention. Each FSM carries a probabilistic value that is called the weight of the FSM. The weight of the FSM describes how closely the FSM represents the human intention. The FSM with highest weight corresponds to the best estimated human intention and vice versa. The weights of the FSMs are updated at each new observation in HRI workspace. The FSM that carries the highest weight and reaches its end state represents the recognized human intention. The suggested solution is applicable for both explicitly and implicitly communicated intention recognition. Explicit intention communication addresses to all the situations where the human commands the robot and implicit intention communication addresses to all the situations where human does not engage the robot but robot actively starts the cooperation by recognizing the intention through scene information and human actions. Addressing both explicitly and implicitly communicated intentions recognition make the human-robot collaboration intuitive. The approach presented in Chapter 3 has differences from Particle Filter and HMM. Particle Filter is mostly used in the problems in which the dynamics of problem can be mathematically modelled, e.g., in robot localization the motion model of the robot is used for prediction of next potential position of the robot. In the current problem the FSMs are used to model the human intention that is totally different from a motion model of the robot. In the normal Particle Filter the resampling is performed to generate new particles and eliminate old particles with less weight. In the presented approach no resampling is required. The normal particle filter applications hypothesize the possible solution that is similar to the approach discussed in Chapter 3. In the HMM each hidden state is considered to have different observation probabilities and the different sequences of observations correspond to different sequences of the hidden states. In the discussed approach in Chapter 3 the sequence of observations corresponds to a human intention.

Chapter 4

Intention Learning

A human has his intentions depending on the scenario, the goal, and the tasks that he is to perform in the current situation and in the near future. A human has different intentions at different places. It is difficult to model all the possible human intentions as the total number of human intentions can be huge. In advance the robot can not anticipate all the services that may be required and should be provided by the robot. That is why Programming by Demonstration (PbD) is introduced and extensively explored. The approach of PbD is different from online intention learning. In PbD the human commands the robot based on the demonstration. In online intention learning the robot learns the new human intention that is used afterwards by the robot to interact with the human. Learning the new human intentions from the human actions and the scene information can help the robots to collaborate with the humans more intuitively.

In this chapter an approach [14] concerning online intention learning is discussed. The chapter is organized as follows: In Section 4.1 the problem of online intention learning is motivated and defined. In Section 4.2 the approaches concerning learning are discussed. In Section 4.3 three intention learning cases are introduced and discussed in detail. In Section 4.4 experimental results of the three intention learning cases are presented. In Section 4.5 the conclusions of chapter on online intention learning are given.

4.1 Problem definition and Motivation

The intention learning corresponds to the modelling of a new human intention that can be used by the robot for HRI. It is assumed that the human only performs the actions concerning a human intention during the intention learning. The human performs the concerning actions in a sequence. The human completes an action sequence concerning a human intention without switching to another action or action sequence. The robot knows the human actions and the information of HRI workspace. The modelling mechanism is provided the human actions and scene information from HRI workspace to model the human intention. The input to the problem is the human actions, scene information, scene change information, and the human intentions in terms of the scene information. The output corresponds to a FSM concerning the new human intention.

For intuitive HRI all the concerning human intentions can not be known to the robot in advance. Thus the robot is required to possess the ability to learn the human intention online to increase its intuitive interaction capability. We discuss three example scenarios of HRI to motivate the intention learning problem. The examples are

1. (House hold example) Consider a robot collaborating with the human for washing the utensils in a house. The robot is provided with the common human intentions specific for the purpose. For example the robot knows what to do with the dirty and clean utensils according to the human intention but he does not know what to do if a utensil is broken, old, useless, etc. Therefore in order to increase the intuitive interaction capabilities of a robot the robot needs to learn the new human intentions online.
2. (Laboratory example) The scenario for HRI is shown in Figure 4.1. The human intentions correspond to the arrangements of the objects in a specific pattern.

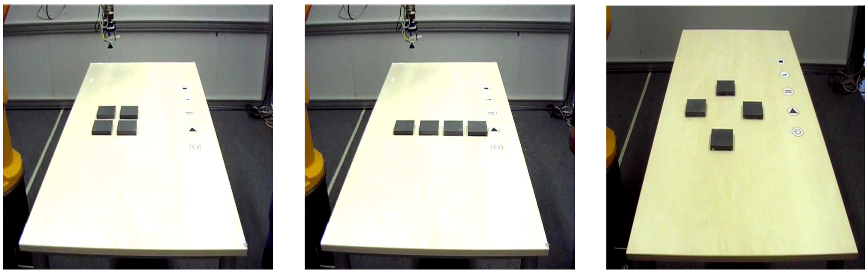


Figure 4.1: Organization of the objects in a specific pattern according to human intention. Left: Organization of objects in a square pattern. Middle: Organization of objects in a longitudinal pattern Right: Organization of objects in a diamond pattern

The human intention of arranging the objects in Figure 4.1 left and middle are known to the robot. The robot can recognize the human intention and interact intuitively regarding the arrangements of the objects. If the human has the intention of arranging the objects shown in Figure 4.1 right. Then the robot can not respond intuitively. The robot is required to learn the new human intention for intuitive interaction in case of Figure 4.1 right.

3. (Industry example) For HRI in industrial workspace the robot is provided with the information of standard human intentions concerning the specific HRI workspace. If any unknown event occurs in the HRI workspace then the robot can not intuitively interact with the human according to his intention. In order to improve the robot's intuitive interaction capability the robot is required to learn the new human intention online. We consider an HRI scenario in Figure 4.2.

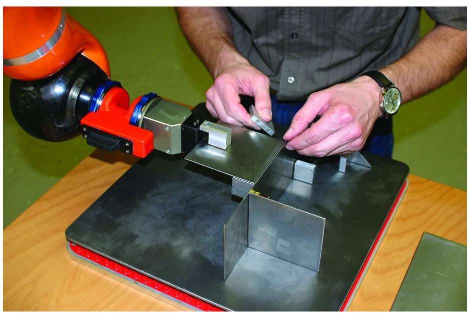


Figure 4.2: Exemplary industrial HRI [88]

The robot knows the human intention about holding and releasing the object but if the human intends to orientate the object then the robot will not interact and release the object. Thus the robot needs to have the capability to learn the new human intention online.

4.2 Related work

In literature, there exist multiple solutions for gesture and action recognition. There exist HMM based gesture understanding solutions [89] [9] that require the Baum-Welch algorithm to train the Markov models. They deal with the recognition of actions and gestures but not with the intention of a human. The available approaches for action recognition consider the image-processing as a core issue. There exist many human action recognition methods based on feature tracking [49] [79], intensity or gradient, and silhouette [163]. The human actions can be recognized based on the pose primitives [153]. The approach [96] uses 2D poses for 3D human pose recovery to recognize the human actions. Similarly the approach in [106] uses local motion appearance features to recognize the human action. The action recognition using HMM corresponds to different phases or key poses of the human while performing an action. These key poses are considered as the hidden states of HMM [118]. The main focus of the above described approaches is the recognition of activity / action / gestures. The recognition of intention is not considered and it can be estimated from the activity / actions. Other related information can also be used, e.g., different characteristics of entities present in the concerning environment. The intention may correspond to more than one activity or an action sequence. There is another significant difference between intention recognition and action / gesture / activity recognition. The difference corresponds to the fact that activity / gesture / action can only be recognized if the concerning action / gesture / activity is completely performed [125]. On the other hand, the intention recognition can only be helpful if the intention is recognized before the concerning action sequence is completely performed [125].

A multitude of research work already exists in the field of PbD in the direction of intention recognition. But the research work does not directly relate to the human-robot collaboration; because it commands the robot an action based on the demonstrated program [5]. The solutions present in the area of PbD use reinforcement learning [126] [139] [80], neural networks [91] [17] and also HMM [166].

In the literature, there exist multiple approaches for intention recognition. The approach proposed in [150] uses DBN, in [139] uses HDBN. The approach proposed in [77] [169] [98] use Ontology, Graph and Utility based intention recognition. The approach [125] uses a novel formulation of HMM to recognize the human intention. The intention recognition approach introduced in [12] uses probabilistic state machines. The described approaches recognize the human intention if the human intentions are already known and modelled. In case if the new intention is to be recognized then that has to be modelled explicitly by the human. The proposed approach [14] describes how a new human intention can be added without the explicit modelling by the human.

To the best of our knowledge, there exists no solution for online intention learning in the area of human-robot collaboration by intention recognition. The presented approach [14] has vital differences to gesture and action recognition. The approach does not focus on single action rather an action sequence concerning the human intention. Further the core issue is not image-processing concerning modelling of different human poses. It models the action sequence concerning the human intention. The sequence concerning an intention may also involve the environment information along with the actions.

In the presented approach, a mapping is performed between the observations (action and / or scene sequences) and the human intentions. Once the mapping is performed then it can be used to understand the human intention for intuitive collaboration. There exists a hidden state concerning an observation in HMM. In the presented approach, the whole action sequence is modelled to represent the human intention, i.e., hidden state.

4.3 Intention learning

In this section different intention learning methods are described. The input to these methods varies but the output of all the methods is the FSM concerning the human intention. The input to the methods involves the scene information, i.e., the objects present in the scene, the human actions, and / or the learning parameters. The *learning parameters* are the features which are specific to the given scene, and enable the robotic system to infer the scene changes. The *scene change* at a human-robot workplace corresponds to the modifications that can occur in the scene by the human actions. For example, if we consider the scene containing different number of objects then the shape of the objects, the distance among the objects, the number of objects, the types of objects, and the arrangements of the objects, etc can be used as learning parameters. Learning parameters are different for different applications depending on the nature of the scene. For example a mechanic working in a garage has different tools and objects around him along with the different intentions as compared to the craftsman working at his workplace. Therefore it is necessary to know the learning parameters, prior to learn the new intention.

The three different intention learning methods correspond to the mappings between the human intention and the observations (action and / or scene sequences). The mappings differ from each other based on the given information: objects in the scene, human actions, scene changes occurred due to the human actions, and the human intentions in terms of the scene information. This given information is used as input for the learning and recognition system. Generally, the input can not be specified as the input depends on the problem at hand. The mapping performed between the human intention and the observation sequence is formally described in the following text.

The intention $i_j \in I, I = \{i_1, i_2, i_3, \ldots, i_p\}, j = 1,\ldots,p$ and $p \in \mathbb{N}$, corresponds to the scene information concerning the human intention. The *observation sequence* $o_k \in O, O = \{o_1, o_2, o_3, \ldots, o_n\}, k = 1,\ldots,q$ and $q \in \mathbb{N}$, consists of the human actions and / or the scene changes occurred due to the human action. M is the mapping from the observed sequence $o_k \in O$ to the concerning intention $i_j \in I$, *i.e.*, $M : O \rightarrow I$. In the Case 1, the human actions, scene changes, objects in the scene, and different possible human intentions $i_j, j = 1,\ldots,p$ in terms of the scene information relating to the human-robot workspace are given. The human intention is learned by mapping the observed sequence o_k and the given intention i_j, i.e., $M(o_k) = i_j$. The observed sequence o_k corresponds to the human actions and / or scene changes. The intention is recognized from the scene information. The recognition is performed by the analysis of the already known information concerning the intention $i_j \in I$ and the information obtained from the current observation. In the Case 2, the given information consists of the human actions, the objects in the scene and the learning parameters without the prior information of the human intention. The output of the method is the mapping between the observed sequence o_k and the newly learned scene information (intention) $i_j \in I$. The scene information is produced by the changes occurred in the scene due to the performed human action sequence. The new intention $i_j \in I$ (scene information) is understood using the learning parameters. In the Case 3, the given information includes the objects present in the scene and the learning parameters and the output is the mapping between the observed sequence o_k and new intention $i_j \in I$ in terms of the scene information. The prior information of the human intention and the human actions are not given. The observed sequence o_k only consists of the scene changes occurred due to the human actions. In the Case 3, the mapping is performed between the sequence o_k (scene changes) and the last scene change that is considered as the human intention, i.e., $i_j \in I$. The scene changes except the last change are considered as the steps that may lead to a specific human intention described by the last scene change. The input and output concerning the three cases are given concisely in the Table 4.1.

	Input	**Output**
Case 1	Human action, human intention, scene information	FSM
Case 2	Human action, scene information, learning parameters	FSM
Case 3	Scene change information, learning parameters	FSM

Table 4.1: The inputs and the outputs concerning Case 1, 2 and 3

4.3.1 Finite State Machine Construction

A FSM is constructed from the intention $i_j \in I,\ j = 1,\ldots,p$ and observed sequence $o_k \in O,\ k = 1,\ldots,q$ that may comprise either the performed human actions or the observed scene changes or both of them (Figure 3.2). At each scene change, occurred due to the human action a state S_i of a FSM is created. The scene change does not strictly correspond to a single event but can represent a single event. Therefore a state corresponds to an observation that may comprise one or more than one event occurring at the same time, e.g., a state may represent pileup operation of boxes that represents human action of placing the box and reduction of boxes in number, observable in 2D. The number of states in a constructed FSM is equal to the number of scene changes occurred due to the human actions.

4.3.2 Mapping actions to the intention

The human teaches the robot his intention online. He does this by performing different actions in a sequence. Each action sequence corresponds to one specific human intention. The action sequence and the corresponding scene information are received from the camera input to construct a FSM out of it. The human actions and the human intentions in terms of the scene information are known to the system beforehand.

This is the simplest case of online intention learning. A mapping is performed between the human actions and the human intention modelled by the FSM as shown in Figure 4.3. It is assumed that the human performs only those actions that are related to the intention.

The function $\psi_{create\text{-}start\text{-}state}$ generates the start state of the FSM. The function $\psi_{observation}$ returns true if a known human action with the concerning scene change information is observed. The function $\psi_{\neg current\text{-}action}$ returns a known human action that is not currently observed. The function $\psi_{create\text{-}transition}$ creates a new transition by the action A from the current state of FSM to the state S, i.e., $\psi_{create\text{-}transition}$: A, current-state $\rightarrow S$. The current state corresponds to the state for which the transition conditions are created. The state S may correspond to the current state or the newly created state (next to the current state). The function $\psi_{create\text{-}new\text{-}state}$ creates a new state of the FSM. The function $\psi_{intention}$ maps the scene information to the known human intentions. The function $\psi_{end\text{-}state}$ assigns the newly created state (in the end) as the end state of the FSM. The function $\psi_{current\text{-}state}$ returns current state and the function $\psi_{new\text{-}state}$ returns the newly constructed state.

Input : Human action, Human intention, Scene information

Output : FSM corresponding to the human intention

Procedure :

1 – $\psi_{create\text{-}start\text{-}state}$
2 – **Loop**
3 – **if** ($\psi_{observation}$) **then**
4 – **for** *all* $\psi_{\neg current-action}$ **do**
5 – $\psi_{create-transition}(\neg current - action, \psi_{current-state})$
6 – **end for**
7 – $\psi_{create-new-state}$
8 – $\psi_{create-transition}(current - action, \psi_{new-state})$
9 – **end if**
10 – **Until** $\psi_{intention}$
11 – $\psi_{end-state}$

Figure 4.3: Mapping the human actions to the human intention

The HRI workspace is observed in which the human performs the concerned actions (Line 3, Figure 4.3). The observation corresponds to the human actions and the scene change information. If $\psi_{observation}$ returns true then a new state is constructed (Line 7, Figure 4.3). The performed human action and the scene change information are considered as the transition condition to the new state (Line 8, Figure 4.3). The not observed actions ($\forall\neg$*current-action*) are considered as transitions to the current state (Lines 4-6, Figure 4.3). The process continues until a known human intention (in terms of scene information) is diagnosed.

The human intentions are extracted from the scene, e.g., at the start, objects of similar type are placed randomly apart from each other. If the human picks one object and places the object on other similar object then the system observes the pick and place action. As the pile operation is performed, the number of objects decreases (observed in 2D). The extracted action sequence along with the scene information will be pick, pile and decrease in the number of objects.

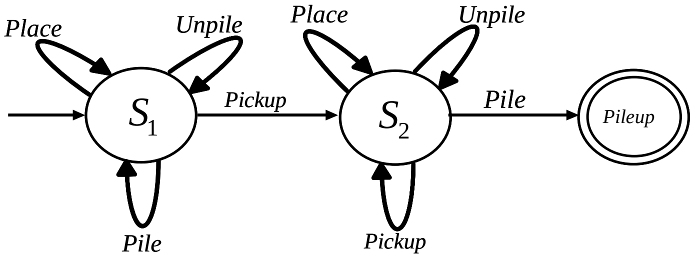


Figure 4.4: FSM built from action sequence of pickup and pile

The already known scene information of decrease in objects corresponds to the pileup intention. The end state of the FSM shown in Figure 4.4 is already known since the different human intentions in terms of the scene information are given. The restriction in this type of intention learning is that the image processing system should be powerful to recognize the human actions performed by the different humans. The different persons can perform the same action with some variation. It is difficult for most of the image processing systems to recognize an action that is performed differently, i.e., variation in the posture while performing the action.

4.3.3 Mapping actions to the scene information

In this type of intention learning, the input to the learning system includes the human actions along with the learning parameters. The learning parameters are specific to a specific application, e.g., in industry scenario the learning parameters may correspond to the assembly of two specific objects, in household scenario the learning parameters may correspond to the specific place of the specific objects, etc.

The scene information changed due to the human actions is understood through the learning parameters. The learning parameters represent the human intention concerning the observed human actions. The mapping of the human action sequence and the intention is performed as described in Section 4.3.2. The only difference is that the human intention is inferred from the learning parameters. The process of action sequence extraction stops if for a specific period of time the human does not perform an action.

In order to explain we consider an example, i.e., if there exist four objects of different types placed randomly in the working area and the learning parameters correspond to the distance and orientation of the objects with respect to each other. The human picks and places the objects near each other in a group. Thus the online-extracted scene information will be concerning the distance and orientation between the objects. The scene change will represent the change in the distance and orientation of the objects. The scene change, i.e., the distances and orientations between the objects is stored as the human intention. The system does not know exactly that the human intention is of grouping the objects but the system only observes the distance and orientation change and stores it. The final state corresponds to the final change in the distance and orientation of the present objects. The robot uses that final state information to react. The FSM built from the action sequence (extracted out of observed human action sequence) and the final scene change is shown in Figure 4.5.

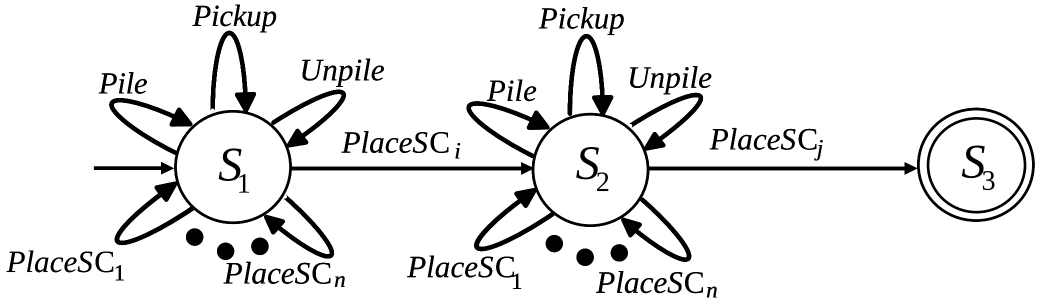


Figure 4.5: FSM built from the action sequence of placeSC$_x$ and the scene change

The action *placeSC*$_x$ x =1,…,n corresponds to the specific placement of the object with respect to the already placed objects. The specific placement of the objects corresponds to specific distance and orientation between the placed objects.

4.3.4 Mapping using the scene changes

It is very difficult to understand the human actions or human activity depending on the shape, size, orientation, etc of the human body parts. It is very difficult to model a complete set of a specific human action (perceived from any possible perspective) with the help of visual descriptors. It gets more complex if the human performs the same action but the related human has completely unexpected shape, orientation, size, etc. It is comparatively easy to recognize the objects using their features. Therefore, it is easy to recognize changes occurred in the scene, related to the objects, due to the human actions. The human actions can be indirectly recognized from the scene changes. In this method, the learning parameters are used to infer the human actions as well as the human intentions. If the human performs a sequence of actions and each action causes a change in the scene that can be uniquely recognized by the system. Then the complete change sequence represents the human action sequence and the scene change at the end represents what the human intends to achieve. All the scene changes are used to infer the human actions and human intention using the learning parameters.

The difference between the mapping in Section 4.3.4 and 4.3.3 is the information required to construct the FSM and to recognize the human intention using the FSM. The transition conditions of the FSMs discussed in Section 4.3.3 mainly correspond to the human actions. The transition conditions of the FSMs in Section 4.3.4 correspond to the scene change information produced due to the human action.

It is considered that human performs actions in a sequence. Each action performed in the sequence corresponds to a scene change $s \in S$ that can be understood by learning parameters. The set $S = \{A, B, C, D, ... \psi\}$ consists of all the scene changes that can occur due to the human action and the set S is already known to the system. Then the sequence of scene changes is observed and a FSM is built online from the observed sequence as described in Section 4.3.2.

If ABCD is the online-observed sequence of scene changes then the constructed FSM is shown in Figure 4.6. The last scene change D represents what the human intends to do. The scene change D is used by the robot to react in response to the recognized intention by the scene change sequence ABC. The scene changes A, B, and C are given maximum observation probabilities as compared to other scene changes at S1, S2 and S3 respectively. The state transitions occur at S1, S2 and S3 due to highest probable observations (scene changes), i.e., A, B and C respectively.

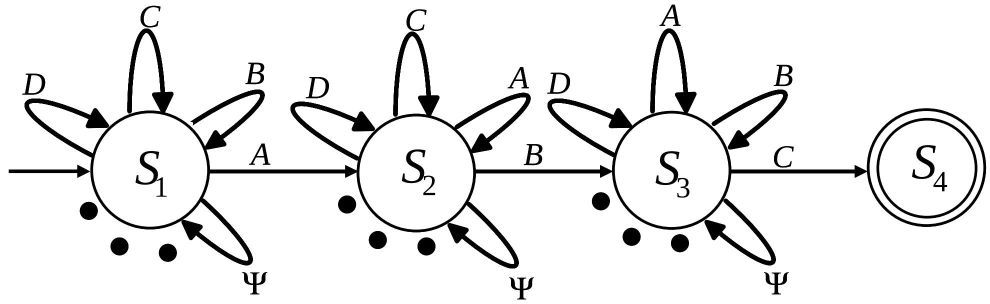


Figure 4.6: FSM built from sequence ABCD

4.4 Experimental results

The experiments are performed with a robotic arm of six degrees of freedom. The HRI workspace is shown in Figure 3.9. The workspace consists of a table with objects. The buttons for Learn, Play, Pause, Stop and Reset are used to interact with the robot, shown in Figure 4.7 right. An overhead FireWire camera is used to observe the scene. In order to evaluate the intention learning, different experiments were performed with three different persons (fifteen times for each phase) with respect to the three discussed cases in Section 4.3.

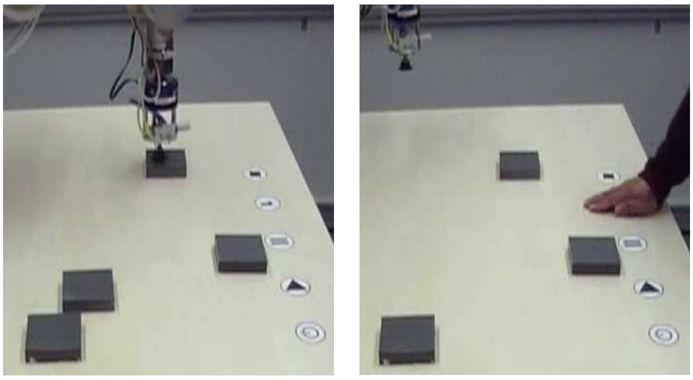


Figure 4.7: Workspace for HRI. Left: The robot reacts intuitively after recognizing the human intention. Right: The human places the hand on the Learn button to start the learning phase

All the experiments have two phases, i.e., the learning phase and testing phase. In the learning phase, the human teaches the robot his intention by performing different actions in a sequence and completing the task. In the testing phase, the robot reacts by recognizing the learned intention and completes the intended task. For the first case, the performed experiments involved pile up of the objects, scattering of the piled objects, and placing the objects in a tray. In the first experiment, for pile up of the objects the human starts the robot's learning phase by placing the hand on the Learn button as shown in Figure 4.7 right. The human performs the actions of pile up of the boxes one by one. In the testing phase, the human starts the testing by pressing the Play button.

The human piles up and the robot recognizes the intention of pile up and reacts by performing the pile up operation for the rest of the boxes. Similarly for the scattering the piled objects and placing the objects into the tray, the human first teaches the robot his intention and afterwards he tests the learned intentions. The human initiates the interaction by taking an action with respect to the intention and the robot reacts by recognizing the intention and completes the human intended task. The robot reacts by completing the last action concerning the recognized human intention. The robot reacts after recognizing the human intention (Section 3.4). In Case 1 the robot is given how to react after recognizing the human intention. In Case 2 and 3 the human intention is inferred using the learning parameters. The robot uses these learning parameters in order to react after recognizing the human intention. The robot utilizes the learning parameters in order to complete the last human action (in the action sequence) according to the recognized human intention.

In the following Figures 4.8, 4.9, 4.10, 4.12, 4.13, and 4.14, the red line represents the average result of the performed experiments. The red line represents the success or failure rate of the performed experiments. The more the line is near to the value 1 at a point the more successful and vice versa.

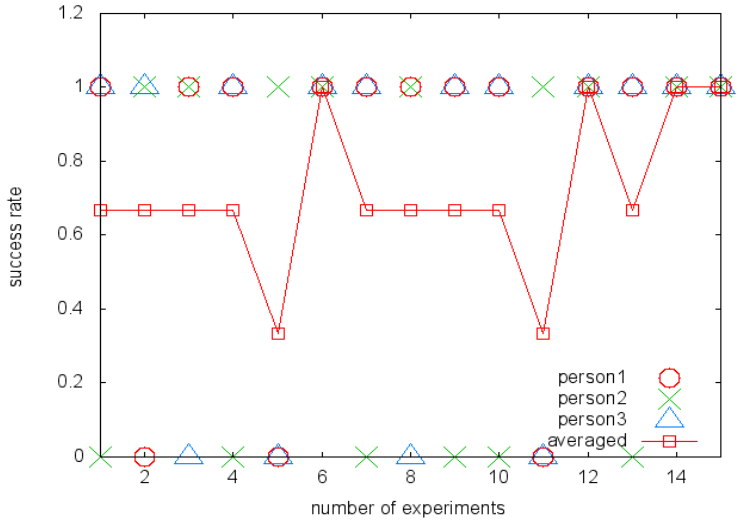


Figure 4.8: Learning phase for Case 1

The successful experiments are represented by a point at the value of 1 and 0 otherwise in the following graphs. A successful experiment means that the expected results are obtained. The expected result in case of teaching the system a human intention means the construction of the corresponding FSM. The expected result in case of testing a human intention means the recognition of the concerning human intention by the system.
In case of testing, the robot is required to react according to the human intention. If the robot reacts according to the human intention then the experiment is considered successful and vice versa. Each point represents one result of experiments of a person. Fluctuations in the average line represent the success and the failure due to the variance of the action postures by different humans with respect to the same action task. The success rate is the ratio between the successful experiments with respect to the total numbers of experiments in one phase of a case.

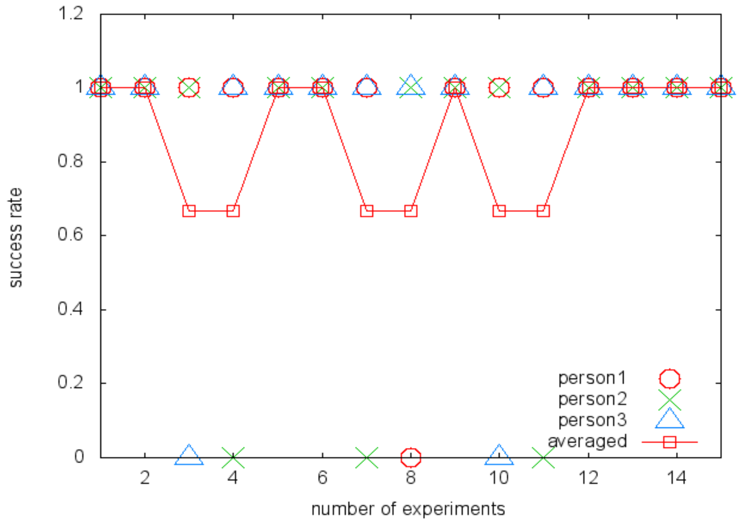


Figure 4.9: Testing phase for Case 1

The success rate is high as the average line remains at the value 1 and vice versa. The average success rate in the learning phases is 73 % and in the testing phase the average success rate is 87 % for the Case 1. The fluctuation of the average line describes that mostly for each point of experiment, two persons performed successfully, as shown in Figure 4.8.
The graph in Figure 4.9 describes the experiment results in the testing phase of Case 1. The fluctuation in the average line of Figure 4.9 is less with respect to Figure 4.8. It is due to the fact that few actions are required to recognize the human intention and the robot reacts afterwards.

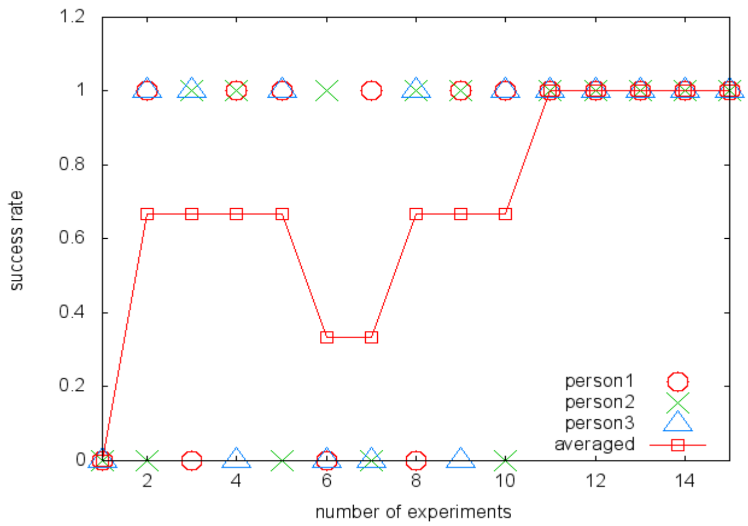


Figure 4.10: Learning phase for Case 2

The reason for the difference in success rate in the testing and learning phases is due to the fact that the system has to perform more image processing in learning phase as compared to the testing phases. In the learning phase all the actions and the human intention are processed and in testing phase only the initial action sequence is processed. Using very simple image-processing (Fourier descriptor for contour recognition and skin detection), an action performed with unexpected human body part posture is less likely to be detected.
For Case 2 and 3 the performed experiments involve the placing of objects in a human intended pattern as shown in Figure 4.11.

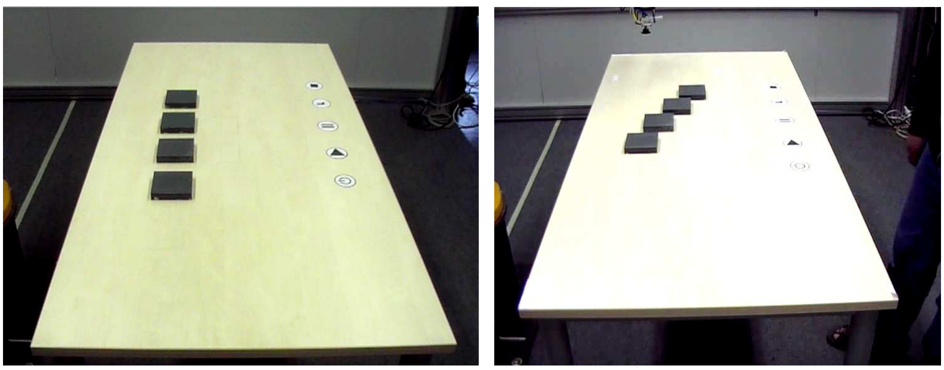


Figure 4.11: Different human intentions regarding placement of objects in a specific pattern

The average line in Figure 4.10 represents that the success rate is almost equal to the success rate shown in Figure 4.8. The success rate of experiments is 69 % shown by the average line in Figure 4.10. The success rate of experiments shown by the average line in Figure 4.12 is 80 %. The difference between the success rates of experiments shown in Figure 4.10 and in Figure 4.12 is almost the same as in experiments shown in Figure 4.8 and in Figure 4.9, due to the same reasons discussed for Case 1.

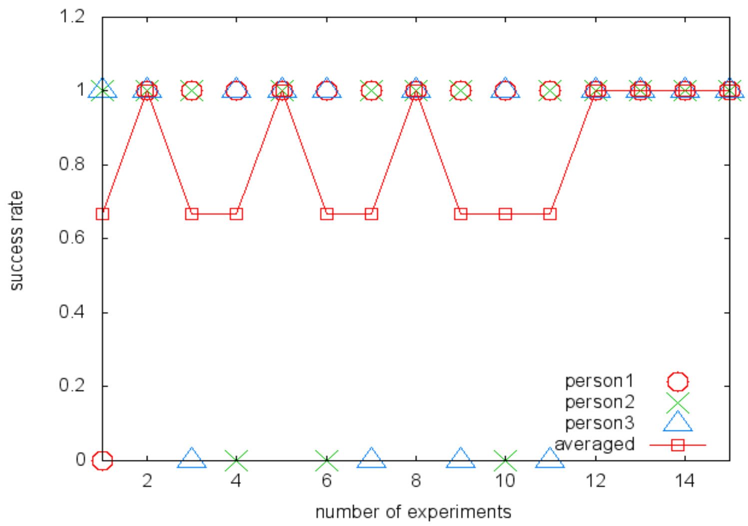


Figure 4.12: Testing phase for Case 2

The success rates of experiments shown by the average lines in Figure 4.13 and 4.14 are 100 % and 95 %. The reason of 100 % success rate is due to the fact that the action sequence was considered in terms of the scene changes performed by the human, i.e., it is observed the result of what the human has performed rather than how the human has performed the action.

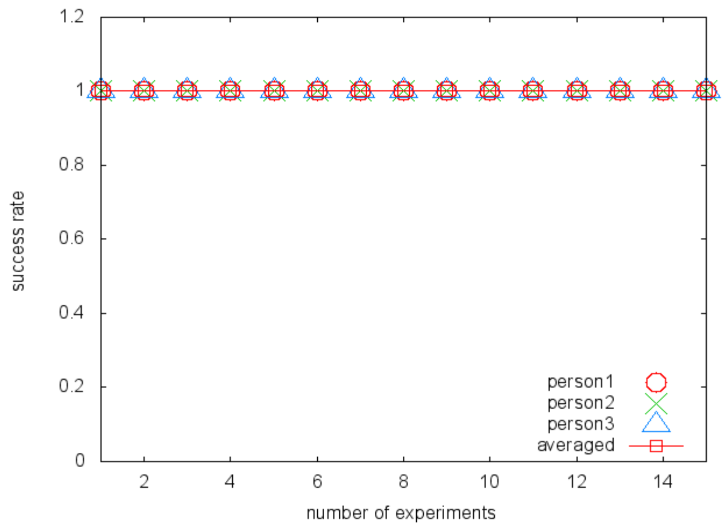


Figure 4.13: Learning phase for Case 3

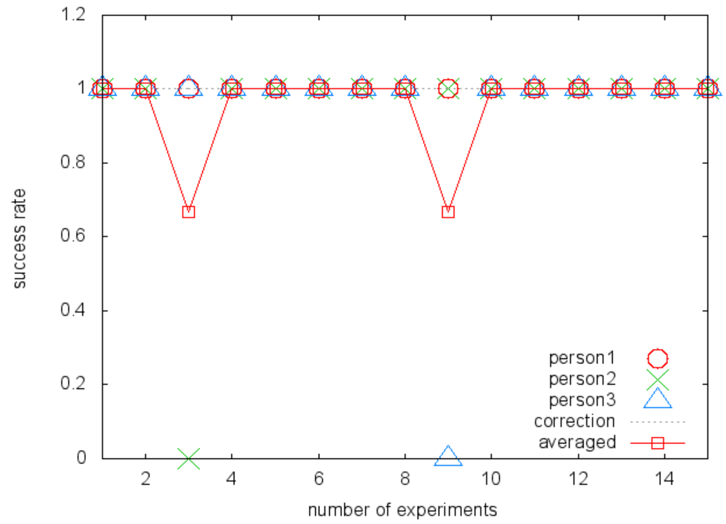


Figure 4.14: Testing phase for Case 3

The ditches in the average line in Figure 4.14 describe the fact that the human has performed an action and in response to that scene change information the human intention was not recognized. Then the human made an appropriate amendment to his action and due to that correction the intention was recognized. This fact is represented by the dotted line part in Figure 4.14.

4.5 Summary

In this chapter we have discussed three cases of intention learning. The cases discussed the mapping of human intention to the corresponding observation sequence. The mechanism used for intention recognition consists of the probabilistic FSMs, described in Section 3.4. For online intention recognition a FSM regarding to a specific intention is constructed online. The online intention learning contributes to the intuitive HRI capability of the robot. The experiments were performed for all the three cases of online intention learning. During the learning phase the intention is conveyed once by performing the concerned action sequence. It was observed that the Case 3 is more flexible for capturing the human actions and human intention and robust in results. The reason of comparative success for capturing human actions is the simple image processing, in the Case 3. The results in Case 1 and Case 2 are also acceptable. In Case 1 and Case 2 the recognition of the action sequences are performed by recognizing the human actions. For this purpose the image analysis corresponds to the processing of the different human gestures. The recognition of gestures focuses on different body parts of the human. The specific orientations of the human body parts are used to recognize the human gestures. For this purpose Skin detection [161] and Fourier descriptors [171] are used. A human can perform a same gesture with different orientation of the same body part. Moreover the structure of the body parts of the humans also varies, e.g., a person may have long hands and others may have wide hands etc. Therefore the recognition of the human actions based on the image processing of the body parts is difficult. In Case 3 the recognition of the human actions is performed based on the scene changes occurred due to the human actions. It is comparatively easy to recognize the human actions based on scene change information as compared to the analysis of the body parts. For example if the human picks an object and places that object at some other place then it is easy to recognize the pick and place action by the scene change information occurred in the presence of the human as compared to the image processing of the concerned body parts.

Chapter 5

Proactive interaction

Proactivity is an important aspect for effective cooperation. The proactivity is defined as the quick response of the robot during HRI. It means that the robot can recognize the human intention as early as possible to quickly start the interaction with the human. The humans working on a common task are required to intuitively collaborate with each other. They are required to be proactive towards each other for intuitive collaboration.

Intuitive HRI requires the robot to attain a high level of understanding of the collaborating human. Therefore it is equally important in the HRI that the robot should be proactive according to the collaborating human, depending on the current situation. For being proactive, the robot needs to recognize the intention of collaborating human as early as possible. The collaborating robot is also required to adapt to the human in the ambiguous situations to be proactive.

Being proactive is not an easy job even for the humans. The humans take into account multiple aspects for a proactive interaction. These aspects may correspond to the interaction situation, social indications, personal profile, etc. Using all these they may be wrong in their decision about the selection of proactive initiative. Thus they are also required to adapt in their proactive behaviours.

The approach [13] introduced in this chapter describes the FSM based method for proactive interaction. The FSM based intention recognition [12] is discussed in Chapter 3. The proactiveness corresponds to the recognition of the intention as early as possible. The remainder of the chapter is organized as follows: In Section 5.1, the problem of proactive interaction is defined and motivated. The existing approaches concerning the proactivity of the robot are discussed in Section 5.2. The proactive intention recognition is discussed in Section 5.3. Section 5.4 describes the adaption capability of robot according to human intention for proactive HRI in almost similar scenarios. The experiments performed using the current approach, are discussed in Section 5.5. Section 5.6 summarizes the chapter.

5.1 Problem definition and Motivation

The problem of proactive HRI corresponds to the fact that the robot can quickly start the interaction with the human. The robot can also decide in an ambiguous situation $\mathbf{A}$ that may lead to two or more different human intentions, i.e., $\mathbf{A} \rightarrow \{i_1,\ldots,i_m\}$, $m \geq 2$, $m \in \mathbb{N}$. In case of quick HRI, the robot knows the human intentions $\mathbf{I} = \{i_1,\ldots,i_n\}$, $n \in \mathbb{N}$ and the robot is required to recognize the current human intention $i_{current} \in \mathbf{I}$ quickly without confusing with the other known human intentions. In case of decision making, the robot is provided with an ambiguous situation in which the robot is required to choose a human intention for HRI. In

both the cases the robot is given the actions performed by the human, the scene information, the scene change information, and the human intentions. The output in both the cases corresponds to the selection of a human intention.
Proactivity is an important aspect of intuitive interaction. Along with many other characteristics for intuitive interaction, the humans possess the capability of proactiveness. The capability of proactiveness helps the human to ease the interaction and causes the reduction of explicit commands for communication. The humans practice the capability of proactiveness by the different kinds of indications from each other [22]. The capability of proactiveness in the humans concerns the early recognition of the intention of the cooperating person with the help of available indications.
We consider an example of interaction between the mother and the young children. Before the children start playing at a place, the mother cleans that place and removes all the harmful objects proactively. The removal of harmful objects will keep the children unharmed and safe. Similarly the example of a waiter serving drinks at a party. The waiter observes the guests in the party and proactively offers the drinks to the guests. The waiter takes proactive decisions depending on the social cues from the guests. The waiter adapts its proactive behaviour with respect to the responses from the guests.
The significance of proactiveness in HRI is discussed in the following two examples, i.e.

A. Safety in HRI
B. Improvement of intuitiveness in HRI

5.1.1 Safety in HRI

We consider the HRI in an industrial scenario shown in Figure 5.1. The robotic arm and the human interact to complete a common task. The robotic arm interacts intuitively with the human according to his intention. The robot plans his motion path to interact and perform the tasks according to the human intention. There may be a collision between the human and the robot. The chance of collision can be reduced if the robot can proactively anticipate the human intention and plan its motion path accordingly.

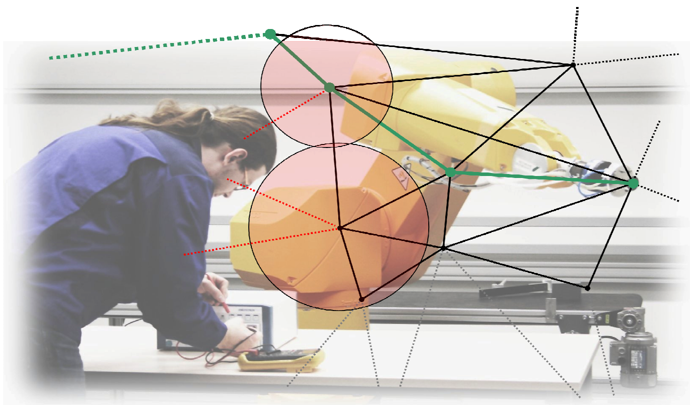


Figure 5.1: [148] Human and robot working on a common task in a workspace. The robot can avoid any potential collision by anticipating the future human intentions proactively. The robot then plans its collision free trajectory based on the estimated future locations of the human

For example the human is performing an operation concerning a task. The robot is given the information about the complete task, i.e., what is the sequence of different operations concerning the task. The robot can also learn the interaction profile of the interacting human or it can be given to the robot. With this information, the robot can predict the future locations of the human taking into account the left over operations and the interaction profile. More parameters influencing the human location can be considered to predict the human locations for more accurate results.

5.1.2 Importance of proactiveness in intuitive HRI

Proactivity is an important aspect for intuitive HRI. In intuitive HRI the proactivity of the robot can correspond to the recognition of human intention as early as possible even if the intention of the human is not obvious.

In a motor mechanic's workshop, the robot can proactively recognize the intention for repairing the specific problem and can operate on the concerning areas of the vehicle performing the necessary initial tasks. In the big kitchens, the robot can proactively perform the necessary operations concerning the tasks in the kitchen, e.g., if the cook intends to prepare a specific dish then the robot can proactively perform actions in order to ready the necessary ingredients. The robot interacting intuitively with the craftsman can prove to be the third hand of the craftsman. The proactivity of the robot may correspond to different robot operation concerning different tasks during HRI. For example the robot can grasp and orientate the surface of the object on which the craftsman intends to perform. Proactivity in the rescue robots may correspond to the necessary first aid actions that should be taken by the rescue robots depending on the situation and the condition of the victim.

A man-machine interaction in a close contact to each other on the vehicle assembly line is shown in Figure 5.2. The humans have the task of installing different accessories into the vehicle. The accessories may include the doors, dash board, seats, steering wheel, wind screen, etc. The robot can help by the bringing the next objects that are to be assembled after the object that is currently being assembled.

In an industrial HRI the proactivity of robot can increase the output of the assembly line workers, e.g., by providing the necessary articles by the early recognition of the human intention and the HRI workspace. Proactiveness eases the HRI and increases the intuitiveness in HRI. In case of correction from the human the robot can rectify its proactive behaviour according to the human intention.

Figure 5.2: The assembly line workers are fixing the wind screen on a vehicle. The wind screen is carried by a device and guided to its exact location by the human workers [72]. In case of intuitive HRI the robot can create ease of navigation by slowly moving in the guided direction and proactively cooperating in the next tasks

5.2 Related work

Proactiveness corresponds to the early anticipation of the future actions of the interacting person and their application. It is mostly applied in the business to anticipate the business trends and take the anticipated actions that are beneficial. In robotics, there exist also the approaches that apply the proactiveness in robotic tasks. The application mostly exists in mobile robots. In robot navigation the term of proactivity is used in the context of planning, e.g., in [105] the term proactivity is used for parallel planning and execution of navigation operations. In [103] proactivity is used for planning a safe trajectory for a mobile robot. The safety corresponds to the selection of the robot speed to avoid collisions.

Armano, Cherchi, and Vargin proposed an agent planning in a dynamic environment [3]. The agent is created to act in the virtual world designed for a computer game. They described a layered approach for agent actions in the dynamic environment. Each layer consists of deliberative, proactive, and reactive modules. The theoretical description is not given in detail and no related experiments or simulation is performed.

Finzi and Orlandini have proposed a control architecture for rescue robots using HRI. It shows the combination of decision processes with the functional process of the robot. HRI introduced in the approach [51] corresponds to the mixed initiative planning. The term mixed initiative means that along with the human the robot can also proactively react. The mixed initiative based approach described in [51] does not correspond to a HRI in which robot responds proactively understanding the human intention of the victims to be rescued.

Dee proposed the use of internal states in order to design the proactive embodied agents [44]. The difference between the reactive and proactive embodied agents is the application of internal state. The proactive agents develop the internal states by integrating the sensory-motor information with respect to time. Afterwards the agent can use the internal state to apply the stored motor modulation information. The motor reaction is the function of sensory information of the internal state and the current environment state. The internal states are modelled using different variations of neural networks. The authors described that the understanding of internal states can help to develop better proactive agents.

The simulating robot “Embodied Proactive Human Interface” named “PICO-2” described in [85] is an interactive interface. The idea corresponds to the two humans communicating over a telephone line. Instead of using the telephone, the robots communicate the information between the two persons. The robot communicates the message by performing the gestures demonstrating the intention of the remote person. The robot works as an Avatar of the remote person. To our understanding “PICO-2” is the demonstration of the recognized intention of the remote person. The proactiveness of the robot in the current scenario may correspond to the capability of the robot if the robot can anticipate the future response of the remote person and indicate the anticipation in current message. The message is conveyed by the corresponding robot gestures.

Cesta proposed the proactive behavior of the robot by activity monitoring [28]. The proposed approach focuses on the elder care by the robot assistant. Two ways of interactions are described namely, On-Demand interaction and Proactive interaction. Proactive interaction corresponds to the activity monitoring and constraint-based proactive and warning giving response. An abstract algorithm is described for adding and removing the constraints while monitoring the activities. The elder care project is at its beginning as described by the authors.

The described behavior appears warning or reminding of some operation forgotten by the humans.
Jeon, Kim, and Choi have presented Ontology based user intention recognition in [77]. Their focus is on the planning given the user intention. The user intention is recognized using the rule-based RuleML approach. The experiments are performed with a simulated robot. The system is implemented using DBN. To our understanding, the DBN is used to model the plan concerning the actions to be performed given a recognized intention using RuleML. The experiments in [77] do not involve any human rather a simulation is used and proactivity is achieved by the application of entropy. All the previously discussed approaches do not relate exactly to direct HRI.
The proactive action selection proposed in [131] describes the proactive robot response concerning HRI. The robot selects actions concerning the known human intention. The proactive action selection is performed given the estimate of the human intention. The number of given intention estimates are represented by $|\Gamma|$. An action tendency value is assigned to each action selected for proactive reaction. If $|\Gamma| = 0$ then all the action get zero action tendency value. If the number of estimated intentions is greater than threshold $\boldsymbol{\omega}$ then once again the action tendency is zero. The value of threshold $\boldsymbol{\omega}$ is used 3. If $|\Gamma| = 1$ then the actions related to the intention get the concerned action tendency values. These values are assigned by the human experts. Then an action is selected using Lorenz's psycho-hydraulic model [95]. In case if $1 < |\Gamma| < \boldsymbol{\omega}$ then action selection is performed using conditional entropy, expected success rate, valence value, safety requirement and most likely action sequence.
The proactive reaction in [131] given the intention estimate is related in its concept to the research presented here [13]. However, there are vital differences between both approaches. The approach presented in [131] assumes that the intention estimates are given, uses a threshold number of intention for proactive reaction, focuses on the actions rather on the proactive action selection and considers all the intentions without considering them any relevance with respect to the current situation. The presented approach [131] also does not provide a confusion resolution if the intention estimates consists of conflicting intentions.
All in all, the proactive reaction of robot is still novel when the human and robot are in strict cooperation with each other. The proactive response of the robot means that the robot can quickly recognize the human intention and react accordingly. The robot recognizes the intention implicitly by the human actions and the surrounding environment. Although the safety is an issue for autonomous HRI; that is why the proactiveness of robot is still in its beginning with respect to strict HRI especially in industrial robotics where big and power full robotic arms work at considerably high speed.

5.3 Trigger state determination

Proactive and in-time reactions from the robot are important for intuitive HRI. The procedure given in Figure 5.3 describes the method to enable the robot to respond as quickly as possible by selecting the earliest possible trigger states of the FSM_i, $i = 1,...,n$. The *trigger state* is the end state which corresponds to the state that finishes the intention recognition process. The intention recognition process [12] is discussed in detail in Chapter 3. The FSM_i, $i = 1,...,n$ represent the human intentions. The input to the procedure in Figure 5.3 consists of all the previous FSM_i and FSM_{n+1} that may be added to a group of Finite State Machines (FSMs).

1 – $\psi_{trigger-state}(FSM_{n+1}.startState)$ // *Trigger state assignment*
2 – **for** $FSM_i \quad i = 1,...,n$ **do**
3 – **for** *all the j states of* FSM_{n+1} **do**
4 – **if** $(j < \psi_{size}(FSM_i))$ **then**
5 – **if** $(Match\ (\psi_{state}(FSM_{n+1}, j), \psi_{state}(FSM_i, j)))$ **then**
6 – *incr j*
7 – **else**
8 – $\psi_{trigger-state}(\psi_{state}(FSM_{n+1}, j))$ // *Trigger state assignment*
9 – **end if**
10 – **if** $(j > \psi_{index}(\psi_{return-trigger-state}(FSM_i))$ **then**
11 – $\psi_{\neg trigger-state}(\psi_{return-trigger-state}(FSM_i))$ // *Convert trigger to normal state*
12 – $\psi_{trigger-state}(\psi_{state}(FSM_i, j))$ // *Trigger state assignment*
13 – **break** // *exit loop at step* 3
14 – **end if**
15 – **else**
16 – $\psi_{trigger-state}(\psi_{state}(FSM_i, (\psi_{size}(FSM_i) - 1)))$ // *Trigger state assignment*
17 – $\psi_{trigger-state}(\psi_{state}(FSM_{n+1}, (\psi_{size}(FSM_i) - 1)))$ // *Trigger state assignment*
18 – **break** // *exit loop at step* 3
19 – **end if**
20 – **end for** // *Go back to step* 3
21 – **if** $(j == \psi_{size}(FSM_{n+1}) \ \| \ j == \psi_{size}(FSM_i))$ **then**
22 – **if** $(j == \psi_{size}(FSM_{n+1}) \ \&\& \ j == \psi_{size}(FSM_i))$ **then**
23 – **delete** FSM_{n+1}
24 – **break** // *exit loop at step* 2
25 – **end if**
26 – **for** *all the k Groups* **do**
27 – **if** $(FSM_i \in G_k)$ **then**
28 – *assign* FSM_{n+1} *to Group* G_k
29 – *update priors of* G_k
30 – **break** // *exit loop at step* 2
31 – **end if**
32 – **end for** // *Go back to step* 26.
33 – **if** $(FSM_i \notin G_k)$ **then**
34 – *assign* FSM_i *and* FSM_{n+1} *to* G_{k+1}
35 – *assign priors to the* G_{k+1}
36 – **break** // *exit loop at step* 2
37 – **end if**
38 – **end if**
39 – **end for** // *Go back to step* 2

Figure 5.3: Trigger state determination algorithm

The trigger state of FSM$_{n+1}$ is selected with respect to all the already existing FSM$_i$. The output of the procedure corresponds to the possible new groups of FSMs, discussed later in this section and the update of the trigger state of the FSM$_i$ within the exiting groups and / or without the groups. The trigger state is represented by $S_{trigger}$. In Figure 5.3, the function ψ_{index} maps the state S to its index I in a FSM, i.e., $\psi_{index} : S \rightarrow$ I .The index I corresponds to the position of the state S in a FSM. Similarly the function ψ_{size} maps a FSM to the number of states, i.e., N, present in the FSM, i.e., ψ_{size} : FSM $\rightarrow N$. The function ψ_{state} maps a FSM to its state S at the position j, i.e., ψ_{state} : FSM, $j \rightarrow S_j$. The function $\psi_{trigger\text{-}state}$ assigns a state S of a FSM as the trigger state $S_{trigger}$ of the FSM, i.e., $\psi_{trigger\text{-}state} : S \rightarrow S_{trigger}$. The function $\psi_{\neg trigger\text{-}state}$ does the reverse of $\psi_{trigger\text{-}state}$,i.e., it converts the trigger state $S_{trigger}$ into a normal state S. The function $\psi_{return\text{-}trigger\text{-}state}$ returns the trigger state $S_{trigger}$ of a FSM.

In this procedure, the FSM$_{n+1}$ is added by comparing with all the already existing FSM$_i$. Initially the start state of FSM$_{n+1}$ is considered as the trigger state (Line 1). The comparison between FSM$_{n+1}$ and FSM$_i$ is performed by comparing the transition conditions of the states of both the FSMs, i.e., FSM$_{n+1}$ and FSM$_i$, in a sequence (Lines 2-20). If during the comparison of FSM$_{n+1}$ and FSM$_i$ (Line 4) the state index j of FSM$_{n+1}$ increases than the size of FSM$_i$ then update of trigger state is performed for FSM$_{n+1}$ and FSM$_i$ (Lines 16-17). If FSM$_i$ belongs to a group G_k, discussed later in Section 5.3, i.e., FSM$_i$ $\in G_k$ then FSM$_{n+1}$ is added to that group (Lines 27-30). The intention prior values of the FSMs belonging to the group G_k are updated. The *intention priors* correspond to the prior probabilities of concerning FSMs $\in G_k$. If FSM$_i$ does not belong to a group then a new group is created (Lines 33-37). If a mismatch occurs (Line 5) then the trigger state assignment is performed for the FSM$_{n+1}$ (Line 8). The trigger state of the FSM$_i$ is also updated if necessary (Lines 10-14). If the state index j corresponding to the last successful comparison between FSM$_i$ and FSM$_{n+1}$ is greater than the current trigger state index of FSM$_i$ (Line 10) then the update is performed for the trigger state for FSM$_i$. Otherwise no update of trigger state is performed for the FSM$_i$. The trigger state always moves toward the actual end state of FSM$_i$ during the process of comparison. The lines 22-25 correspond to the situation if FSM$_{n+1}$ and FSM$_i$ are same and are of same size then FSM$_{n+1}$ is removed and procedure exits (Line 24). The lines 21, 26-37 correspond to the situation if FSM$_{n+1}$ and FSM$_i$ are same and one is of bigger in size form the other. The procedure stops if initial part of FSM$_i$ matches to complete FSM$_{n+1}$ or vice versa and if there exists a group G_k such that FSM$_i$ $\in G_k$ (Line 27) then FSM$_{n+1}$ is assigned to that group G_k. Otherwise a new group G_{k+1} is created and FSM$_{n+1}$ and FSM$_i$ are assigned to that group. The matching of initial part of FSM$_i$ to FSM$_{n+1}$ means that the sequence from the start state of FSM$_i$ to some intermediate state of FSM$_i$ matches to FSM$_{n+1}$ from the start state to the end state with respect to the state transition conditions. The matching can also occur in the reverse manner, i.e., initial part of FSM$_{n+1}$ matches to a complete FSM$_i$.

A group G of FSMs is only created if there is a FSM$_i$ and FSM$_{n+1}$ such that they exactly match with each other and one is bigger than the other and already no group exists (Lines 33-37). In case, if a group already exists then FSM$_{n+1}$ is simply added to that group (Lines 27-31). If a group is constructed then a common trigger state is nominated for the group that is the actual end state of the smallest FSM in the group. If that trigger state is reached then the intention selection in the group is performed depending on the intention priors of the FSMs in the group, i.e., FSMs $\in G_k$. Initially if the intention priors are uniform (Line 35) then the intention selection is performed randomly and the switch between the different intentions (represented by different FSMs $\in G_k$) in the group is performed by the human interruption. After an intention is recognized the intention priors are updated accordingly, e.g., if we suppose there are three FSMs in a group G_k that initially have the uniform priors of 1/|FSMs| then if the intention concerning FSM_1 out of three in the group is recognized then the priors will be updated as given in Figure 5.4. The term |FSMs| corresponds to the number of FSMs. In the update step (Figure 5.4) the prior of the FSM concerning the recognized intention (FSM_1) is increased. The increment is performed by adding the uniform prior. Afterwards the normalization is performed. The time complexity of this algorithm is given below where n is the total number of the existing finite state machines FSMs and m is the number of the states of FSM_{n+1}.

$$T(n) \quad = \quad n.(m-1)$$

The best case occurs if FSM_{n+1} already exist or it belongs to some already existing group. The normal case involves FSM_{n+1} that does not belong to any existing group. The worst case occurs if all the state machines FSM_i have the same initial part as the FSM_{n+1} till the second last state of FSM_{n+1}.

$$\mathrm{FSM}_1 = \frac{1}{|\mathrm{FSMs}|}, \quad \mathrm{FSM}_2 = \frac{1}{|\mathrm{FSMs}|}, \quad \mathrm{FSM}_3 = \frac{1}{|\mathrm{FSMs}|}$$

Updation :

$$\mathrm{FSM}_1 = \frac{1}{|\mathrm{FSMs}|} + \frac{1}{|\mathrm{FSMs}|} \quad = \frac{2}{|\mathrm{FSMs}|}$$

Normalization :

$$\frac{2}{|\mathrm{FSMs}|} + \frac{1}{|\mathrm{FSMs}|} + \frac{1}{|\mathrm{FSMs}|} \quad = \quad \frac{4}{|\mathrm{FSMs}|}$$

$$\mathrm{FSM}_1 = \ \frac{2}{|\mathrm{FSMs}|} \Big/ \frac{4}{|\mathrm{FSMs}|}, \quad \mathrm{FSM}_2 = \frac{1}{|\mathrm{FSMs}|} \Big/ \frac{4}{|\mathrm{FSMs}|}, \quad \mathrm{FSM}_3 = \frac{1}{|\mathrm{FSMs}|} \Big/ \frac{4}{|\mathrm{FSMs}|}$$

$$\mathrm{FSM}_1 = \frac{1}{2}, \quad \mathrm{FSM}_2 = \frac{1}{4}, \quad \mathrm{FSM}_3 = \frac{1}{4}$$

Figure 5.4: Update of the intention priors

The Figure 5.5 shows the recognition of the intention depending upon the priors of the FSMs in case if common end state relating to a group is reached.

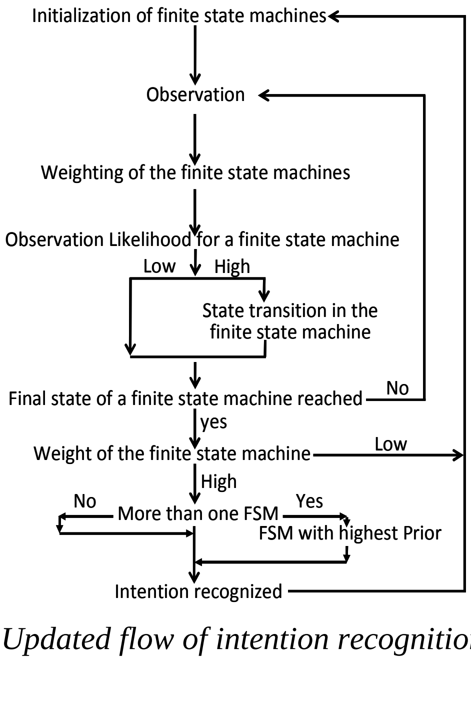


Figure 5.5: Updated flow of intention recognition algorithm

5.4 Online update of transition weight

The *transition weights* correspond to the weights assigned to the transition conditions in a FSM_i, $i = 1,\ldots, n$. The weights are used to control the transition conditions. The transition weights help the robot to take the premature intuitive decision for intention recognition. The robot response becomes quick (proactive) by taking the decision prematurely. The robot can decide in an ambiguous situation that may lead to two or more different human intentions.
In this section different aspects existing in an observation are focused. The observation has the highest probability for the state and causes the state transition. The observation is decomposed into multiple aspects of the observation. Each aspect of the observation corresponds to a transition condition. All the transition conditions (observation aspects) are equally assigned the high transition probability as the transition conditions correspond to the highly likely observation for the state. The observation aspects that are unique to the observation (unique transition conditions) get the maximum transition weight. The observation aspects that are common among the different observations (common transition conditions) get uniform transition weight with respect to the number of observations. It is explained with example concerning Figure 5.6 and 5.7. The transition weights are calculated for the transition conditions that are common among different FSMs. Every unique transition condition is given the maximum transition weight, i.e., 1 that is not common among a group of FSMs. Here the common transition conditions mean the conditions that are common with respect to the observation's specification and the state's place, i.e., the states are equally apart from the start state and previous transition conditions, if exist, are the same. These FSMs are grouped together based on the common transition conditions. The group of FSMs is not the same as described earlier in Figure 5.3 (Lines 26-37), in Section 5.3. In the previous grouping only one transition condition is considered among the states and the grouping is performed on the basis of similar sequence of transition conditions. In this grouping the focus is on the common transition conditions that exist along with other unique transition conditions among the states. The characteristics of common and unique transition conditions are explained through Figure 5.6. In Figure 5.6 a_i, b_i and c_i represent the observation aspects (transition conditions) of observations *a*, *b*, and *c*.

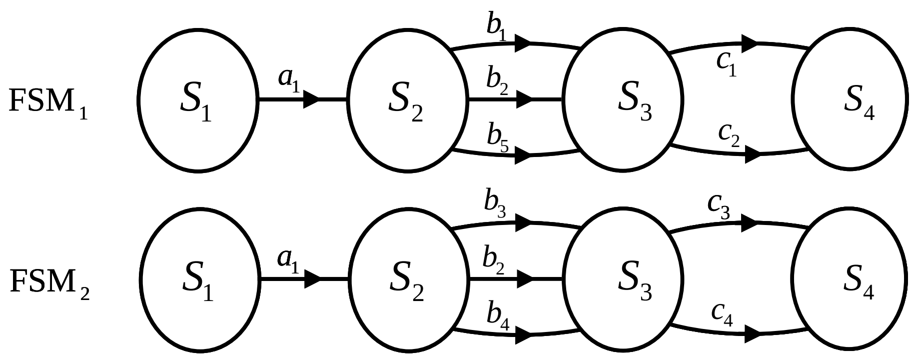


Figure 5.6: FSM_1 and FSM_2 representing the common transition conditions

The unique transition conditions a_1, b_1, b_3, b_4, b_5, c_1, c_2, c_3, c_4 get the transition weight of 1 and the transition condition b_2 get initially the uniformly distributed transition weights among the common transition condition, i.e., 0.5. The weight of b_2 is updated with the recognition of the intention represented by the FSMs relating to b_2.

At the construction time of the FSM different probabilities are assigned to the transition conditions between the states. The transition condition that is highly likely to occur at the state and leads to the next state gets the highest transition probability. This highest probability is used as a threshold for the state transition from the state to the next state [12] [14].
There may be the case as shown for FSM_1 and FSM_2 in Figure 5.6 that some of the highly likely transition conditions are common among different FSMs. These common transition conditions among the FSMs, in a group, are initially assigned the uniform transition weights. The update of the weights is performed by the addition of 1/|FSMs| to the weight of transition condition that belongs to the FSM representing the recognized intention and then doing the normalization as shown in Figure 5.8. The |FSM| represents the number of FSMs having the common transition condition in a group. Since for a transition to occur between the states the observed transition condition should have the transition value greater or equal to the threshold value. The common transition condition that was earlier unique and had the maximum transition weight and had the maximum observation probability could trigger the transition. However, as a common transition condition the transition weight is reduced to 1/| FSMs|. Thus the assigned maximum transition probability of the common observation, multiplied by the transition weight can not trigger the transition to the next state. It will take very long that the weight of the common transition is updated very near to one and the weight of the other related common transition conditions near to zero. Then that common transition condition with updated weight near to 1, multiplied by the transition probability may cause the transition. For the purpose of the faster increment in the update of transition condition's weight an adaption factor θ is introduced. That is also multiplied by the transition weight and transition probability to calculate the transition value. The adaption factor θ may be changed in order to adjust the adaption rate. The adaption factor used for different no of FSMs is given below

$$\text{FSM} = 2 \qquad \theta = 1.3$$

$$\text{FSM} > 3 \qquad \theta = \frac{|\text{FSM}|}{2}, \frac{|\text{FSM}|}{3}, \frac{|\text{FSM}|}{4}, \cdots$$

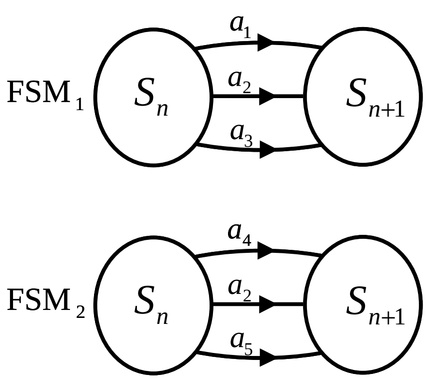


Figure 5.7: FSMs with common transition condition

The transition weights are further explained by an example using two FSMs. These two FSMs have one common transition condition as shown in Figure 5.7. There exist three transition conditions a_1, a_2, and a_3 in FSM_1. FSM_2 has transition conditions a_2, a_4, and a_5 for the states S_n to S_{n+1}. The transition condition a_2 is common among the FSMs. Therefore, initially the transition condition a_2 in both the FSMs get the uniform transition weight, i.e., 0.5

and all the other transition condition get the highest transition weight, i.e., 1. Now, whenever the observation of a_1, a_3, a_4, a_5 occurs then a transition occurs from the state S_n to S_{n+1}. As the observations that are highly likely for a state are given the high observation probability for that state. Therefore the transition conditions a_1, a_2, a_3, a_4, a_5 have the highest transition probability. The adaption factor for all the unique transition conditions is 1. Therefore calculating the transition value for the transition condition a_1, a_3, a_4, a_5 will give the value equal to the transition threshold for the concerned states. The transition threshold is equal to the highest transition probability between the consecutive states. The transition due to a transition condition only occurs if the calculated transition value for that transition condition is greater or equal to the transition threshold for the state. In case of transition condition a_2, no state transition will occur in both the FSMs. Although the transition probability initially assigned to a_2 in both the FSMs is equal to the threshold value. But the transition weight is 0.5 and the adaption factor is 1.3. Thus the calculated transition value will be less than the transition threshold value as shown below

$$\begin{aligned} &= 0.5 \times transition\_value \times 1.3 \\ &= 0.65 \times transition\_value \\ &< threshold\_value \end{aligned}$$

If the human performs an action and the observation relates to one of the unique transition condition of a FSM and the concerned intention is recognized then the transition weights of all the common transition conditions are increased for concerned FSM and for the other FSMs are decreased.

$$s_1 = FSM_{1:a2} \quad s_2 = FSM_{2:a2} \quad \theta = adaption\ \ factor = 1.3$$

$$Transition\_value\ = \pi$$

$$Step\quad 1:$$

$$Updation$$

$$s_1 = 0.5 + 0.5, \qquad s_2 = 0.5$$

$$T = \sum_{i=1}^{2} s_i = 1 + 0.5 = 1.5$$

$$Normalization$$

$$s_1 = \frac{s_1}{T} = 0.66667$$

$$s_2 = \frac{s_2}{T} = 0.33333$$

$$\theta \times \arg\max(s_1, s_2) \quad = \quad 1.3 \times 0.66667 = 0.86667 \times \pi\ <\ \pi$$

$$Step\quad 2:$$

$$Updation$$

$$s_1 = 0.66667 + 0.5, \qquad s_2 = 0.33333$$

$$T = \sum_{i=1}^{2} s_i = 1.667 + 0.33333 = 1.5$$

$$Normalization$$

$$s_1 = \frac{s_1}{T} = 0.77780$$

$$s_2 = \frac{s_2}{T} = 0.22222$$

$$\theta \times \arg\max(s_1, s_2) \quad = \quad 1.3 \times 0.77780 = 1.0111 \times \pi \quad \geq \pi$$

Figure 5.8: Update and Normalization of transition weights for common transition conditions using the adaption factor θ

Now if a unique observation relating FSM_1 (Figure 5.7) at state S_n occurs and intention regarding FSM_1 is recognized then the transition weight of a_2 in FSM_1 (Figure 5.7) is increased and intention weight of a_2 in FSM_2 (Figure 5.7) is decreased. The update is performed by the addition of 1/| FSMs|, i.e., the average value of the numbers of FSMs having the common transition condition.
In the above described example there are two FSMs having one common transition condition. The transition weight is multiplied with the adaption factor to calculate the transition value as shown in Figure 5.8. The intention related to FSM_1 (Figure 5.7) is recognized thus the transition weight of a_2 in FSM_1 (Figure 5.7) is increased by 0.5. The adaption factor θ increases the transition weight to the extent that a common transition condition in a specific FSM is triggered as shown in the calculation, given in Figure 5.8. For that intention to be recognized the human produces the unique transition condition relating to the concerned FSM. The common transition condition causes the transition between the states for a specific FSM that represent the recognized human intention.
If θ is selected as |FSM|/2 then the adaption rate for a common transition condition a_{ij} (at i^{th} state of j^{th} FSM) of FSM_j becomes 2 for |FSM| > 3. The adaption rate of 2 means that if an intention represented by FSM_j is recognized 2 times consecutively with respect to other FSMs in a group having the common transition conditions. It is assumed that the transition weights are uniform. Then the transition weight of a_{ij} of FSM_j is increased and the weights of other related common transition conditions in the group FSMs are decreased. The two times consecutive increments of transition weight of a_{ij} and the scaling performed with |FSMs|/2 causes the state transition due to a_{ij} for |FSMs| > 3. If |FSMs| = 3 then three times consecutive increments in the transition weight of a_{ij} is required to trigger the a_{ij} state transition. Similarly, if θ = |FSMs|/3 then the specific increment in the transition weight requires 3 steps for |FSMs| > 7. In case if 5 ≤ |FSMs| ≤ 7 then 4 steps are required. The Table in 5.1 describes the number of steps required with respect to the |FSMs| and θ.

θ	**No of Steps**	**|FSM|**
| FSMs|/2	2	> 3
| FSMs|/2	3	= 3
| FSMs|/3	3	> 7
| FSMs|/3	4	≥ 5
| FSMs|/3	5	≥ 3
| FSMs|/4	4	> 11
| FSMs|/4	5	≥ 8
| FSMs|/4 ⋮	6 ⋮	≥ 6 ⋮

Table 5.1: Description of θ with respect to |FSM| and no of steps

The transition weights are calculated in terms of 1/|FSMs| as shown in Figure 5.9 and 5.10. The calculation is so performed that the transition weight m_1 is increased at each step by $1/n$ = 1/| FSMs|. At each step m_1 is updated (increased by $1/n$) and then normalized. The six step update and normalization is performed for m_n transition weights in Figure 5.9 and 5.10. Thus m_1 increases and $m_{2...n}$ decrease.

m_i Local transition weight $i = 1, 2, 3, ..., n.$

n Number of FSM_s with common condition

$m_i = \frac{1}{n}$ Initially

Step 1:

Weight updation

$$m_1 = \frac{1}{n} + \frac{1}{n} = \frac{2}{n}$$

Normalization

$$\sum_{i=1}^{n} m_i = \frac{2}{n} + (n-1) \times \frac{1}{n} = \frac{n+1}{n}$$

$$m_1 = \frac{2}{n+1} \ , m_2 = \frac{1}{n+1}, m_3 = \frac{1}{n+1}, ..., m_n = \frac{1}{n+1}$$

Step 2:

Weight updation

$$m_1 = \frac{2}{n+1} + \frac{1}{n} = \frac{3n+1}{n(n+1)}$$

Normalization

$$\sum_{i=1}^{n} m_i = \frac{3n+1}{n(n+1)} + (n-1) \times \frac{1}{n+1} = \frac{n+1}{n}$$

$$m_1 = \frac{3n+1}{(n+1)^2} \ , m_2 = \frac{n}{(n+1)^2}, ..., m_n = \frac{n}{(n+1)^2}$$

Step 3:

Weight updation

$$m_1 = \frac{3n+1}{(n+1)^2} + \frac{1}{n} = \frac{4n^2+3n+1}{n(n+1)^2}$$

Normalization

$$\sum_{i=1}^{n} m_i = \frac{4n^2+3n+1}{n(n+1)^2} + (n-1) \times \frac{n}{(n+1)^2}$$

$$= \frac{n^3+3n^2+3n+1}{n(n+1)^2}$$

$$m_1 = \frac{4n^2+3n+1}{n^3+3n^2+3n+1}$$

$$m_2 = \frac{n^2}{n^3+3n^2+3n+1}, ..., m_n = \frac{n^2}{n^3+3n^2+3n+1}$$

Figure 5.9: Calculated Transition weights

$$\text{Step } 4:$$
$$m_1 = \frac{5n^3 + 6n^2 + 4n + 1}{n^4 + 4n^3 + 6n^2 + 4n + 1}$$
$$m_2 \ldots m_n = \frac{n^3}{n^4 + 4n^3 + 6n^2 + 4n + 1}$$
$$\text{Step } 5:$$
$$m_1 = \frac{6n^4 + 10n^3 + 10n^2 + 5n + 1}{n^5 + 5n^4 + 10n^3 + 10n^2 + 5n + 1}$$
$$m_2 \ldots m_n = \frac{n^4}{n^5 + 5n^4 + 10n^3 + 10n^2 + 5n + 1}$$
$$\text{Step } 6:$$
$$m_1 = \frac{7n^5 + 15n^4 + 20n^3 + 15n^2 + 6n + 1}{n^6 + 6n^5 + 15n^4 + 20n^3 + 15n^2 + 6n + 1}$$
$$m_2, \ldots, m_n = \frac{n^5}{n^6 + 6n^5 + 15n^4 + 20n^3 + 15n^2 + 6n + 1}$$

•

•

•

Figure 5.10: Calculated Transition weights

Therefore it can be easily checked by multiplying the θ with m_1 at different steps that how many consecutive steps (weight increments) are required for increment of m_1 such that m_1 can cause state transition, e.g., if we take θ = |FSM|/2 and |FSM|= 3 m_1 can cause state transition, results are shown in Figure 5.11.

It is also mentioned above in the Table 5.1 row 2 that at Step 3 the transition weight (updated and normalized) multiplied by θ causes the state transition. That value multiplied with the transition probability (a_j) will not decrease the calculated transition value and will cause the state transition.

$$n = |\,\text{FSMs}\,| = 3$$
$$Step\ 1: m_1 = \frac{2}{n+1} \times \frac{n}{2} = \frac{2}{4} \times 1.5 = 0.75 < 1$$
$$Step\ 2: m_1 = \frac{3n+1}{(n+1)^2} \times \frac{n}{2} = \frac{3 \times 3 + 1}{(3+1)^2} \times 1.5 = 0.93750 < 1$$
$$Step\ 3: m_1 = \frac{4n^2 + 3n + 1}{n^3 + 3n^2 + 3n + 1} \times \frac{n}{2} = \frac{36 + 9 + 1}{64} \times 1.5$$
$$= 1.0781 > 1$$

Figure 5.11: Consecutive increment of a transition weight

5.5 Experiments

The experiments have been performed with a robotic arm of six degrees of freedom. The human and the robot interact in a HRI workspace shown in Figure 3.9. The work space consists of a table with objects and buttons on the table along with the robotic arm. The video data is captured with an overhead FireWire digital camera with the frame size of 640 x 480 pixels. The camera provides video data at the speed of 30 frames / sec. HRI and image analysis is implemented using Programming language C++. The robot reactions are realized using the robot Programming language V++ for the robotic arm. The robot is communicated the cooperative instructions using the TCP/IP connection for assigning different operation, e.g., pick, place and move to a certain location, etc. Common Skin detection, Edge detection algorithms and Fourier descriptors are used for the image analysis.

The buttons on the table include Stop, Learn, Pause, Play, and Reset as shown in Figures 5.12, 5.13, and 5.14. These buttons are used by the human for communication with the robot during HRI. If the human wants to teach the robot about his intention then the human puts the hand on the Learn button. Afterwards the human performs the intended task. The Stop button is used by the human if the human wants to stop the robot from performing a task and undo the current robot action. The robot temporarily stops its activity if the Pause button is used. If the Play button is used then the robot starts recognizing the known intentions and after recognizing an intention the robot reacts accordingly. The Reset button is used to remove all the known intentions that are stored as FSMs.

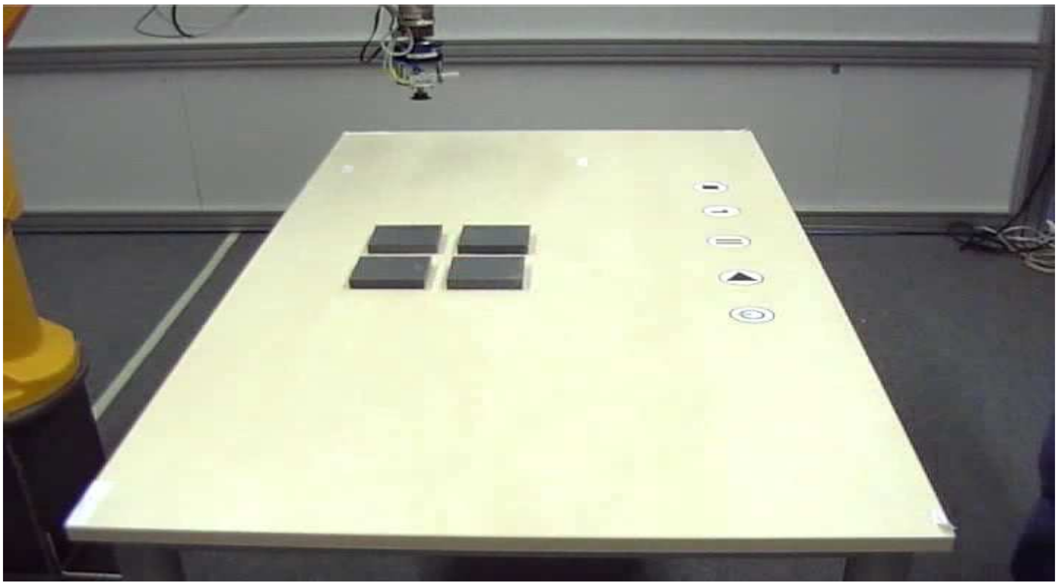


Figure 5.12: Intention for placing the boxes in a square pattern

The perception of human intention is performed based on Case 3 discussed in Chapter 4, i.e., the human actions and intention is recognized from the scene changes occurred due to the human action. For performing the experiment regarding the arrangements of objects on the table, different human intentions are taught to the robot as discussed in Chapter 4. The two taught human intentions are shown in Figure 5.12 and 5.13.

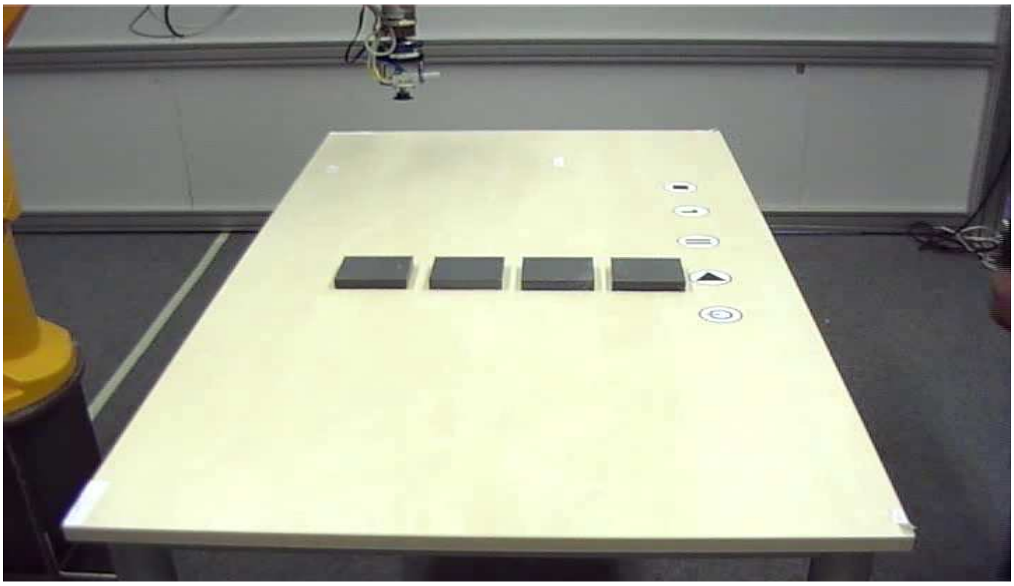


Figure 5.13: Intention for placing the boxes in longitudinal pattern

The Figure 5.14 shows the similarity of the situation (ellipse) for which the robot needs to decide for premature action selection. First the intentions relating to Figure 5.12 and 5.13 are taught to the robot. Then the robot is presented the situation shown in Figure 5.14. The robot can not decide how to react in the situation shown in Figure 5.14. The robot waits for the human to disambiguate the situation.

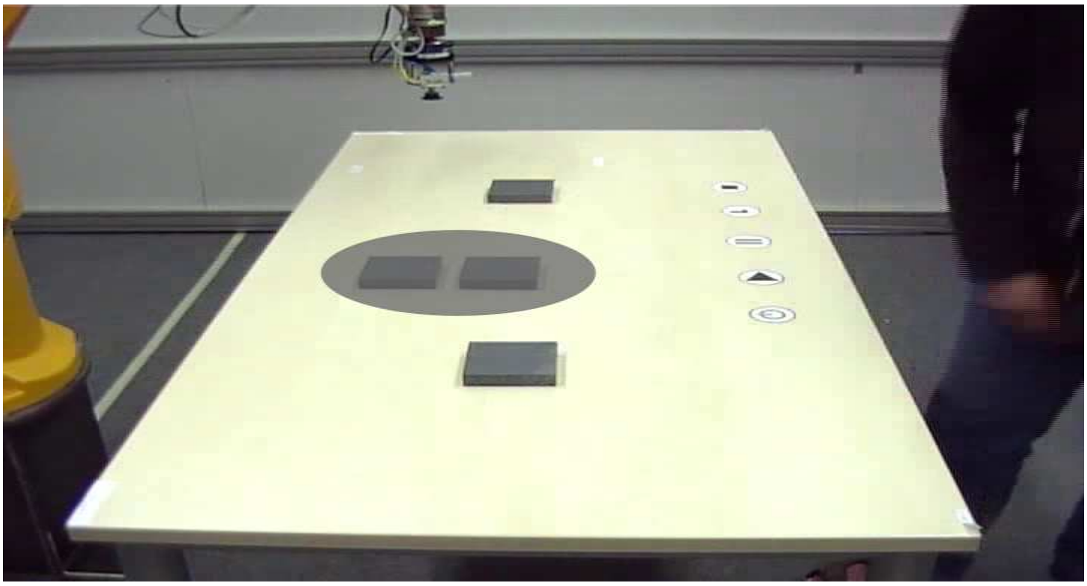


Figure 5.14: Human robot interaction workspace

Now, if the human performs the action regarding to one of the intentions as shown in Figure 5.12 and 5.13 then the transition weight of the common transition condition in concerned FSM is increased and for the other FSM is decreased. Initially, the ambiguous case as shown in Figure 5.14, if a task is disambiguated consecutively two times and third time the robot is faced with the ambiguous situation then the robot reacts accordingly, i.e., the robot performs the most likely human intended task in that situation.

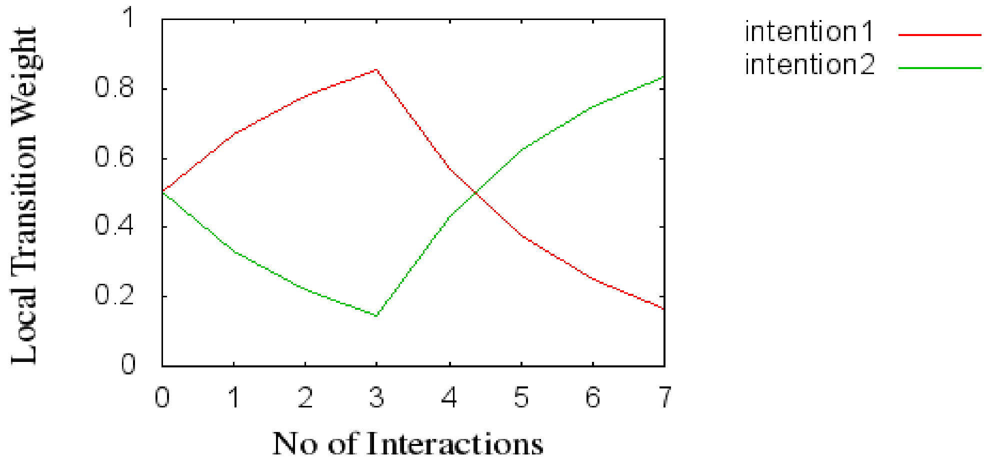


Figure 5.15: Transition weights with out adaption factor

The graph in Figure 5.15 corresponds to the transition weights in two FSMs with one common transition condition as shown in Figure 5.12 and 5.13. Initially, at Step 0 the transition weights are uniform, i.e., 0.5 for both the common transition conditions. The transition weight represented by red line represent the transition condition whose concerning intention is selected consecutively three times. Thus the red line rises and green line falls. In spite of rise in the red line, the transition weight (red line) is less than 1 at the Step 2 and 3 as shown in Figure 5.15.

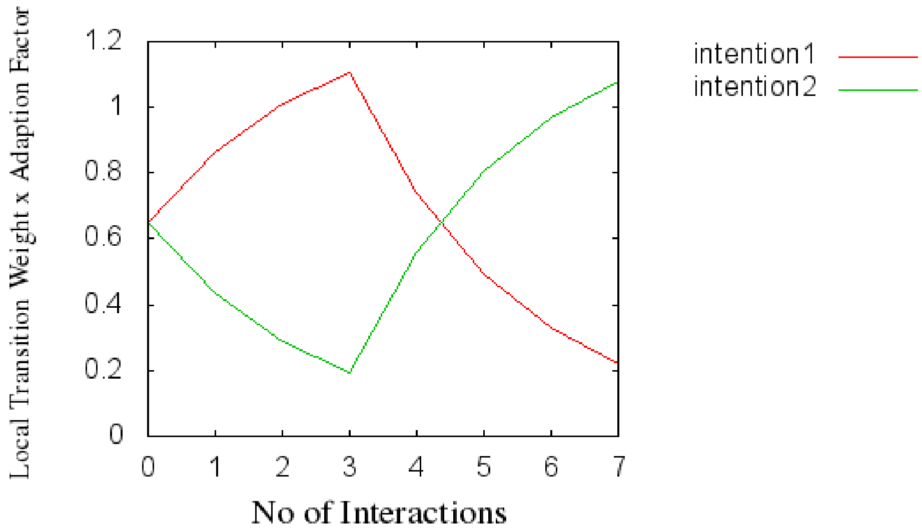


Figure 5.16: Transition weights with adaption factor

The transition weight scaled with adaption factor 1.3 reaches the value 1 at Step 2, as shown in Figure 5.16 and causes the state transition. Form Step 3-7 the transition weight of transition condition (green line) is increased due to the consecutive selection of the concerning intention as shown in Figure 5.15 and 5.16. At Step 7, the transition weight (green line) in combination with adaption factor can cause transition.

Similarly in the case of trigger state determination and update the premature intention recognition is performed with the help of priors. The robot reacts according to the intention of highest prior FSM in the group. If the human intends an FSM with lower prior then the robot switches to the next intention (FSM) with the next highest prior. The priors of FSMs are updated such that the prior of intention (FSM) that is successfully applied is increased and the priors of the others are decreased. The priors of two FSMs in a group are shown in Figure 5.17. The graph in Figure 5.17 represents that for first 11 interactions an intention is selected consecutively and for the rest of 9 interactions the other intention is selected consecutively.

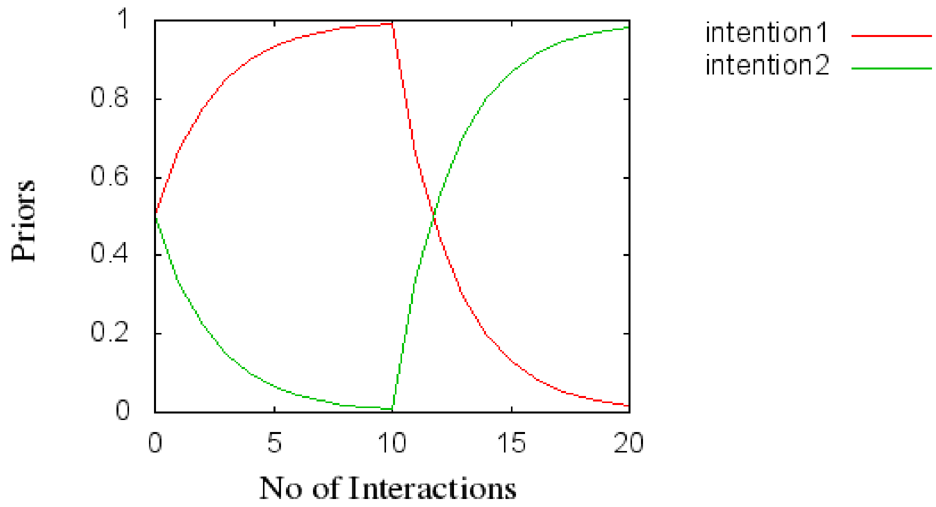


Figure 5.17: Priors alternating due to the intention switch after 10th interaction.

5.6 Summary

In this chapter we presented a probabilistic proactive approach for the intuitive HRI in the ambiguous situation. Two cases were discussed for proactive robot response for intuitive HRI. For making the robot interactions as quick as possible, trigger state selection algorithm is discussed that describes how the trigger states are selected in case of similar state sequence of different FSMs. In this algorithm FSM_{n+1} is compared with all the already existing FSM_i, i = 1,…, n. During the comparison the FSM_{n+1} can be added to the already existing group of FSMs. A new group can also be made concerning the FSM_{n+1} and already existing FSM_i. A group of FSMs is only created if there is an already existing FSM_i and FSM_{n+1} such that they exactly match with each other and one has higher number of states than the other. In case of groups the intention priors concerning the FSMs are created or updated. The increment and decrement of the intention priors is performed if an intention concerning a FSM that belong to a group is recognized. In this case the intention prior of the FSM concerning the recognized intention is increased by 1/ |FSMs|. The term |FSMs| corresponds to the number of FSMs in the group. After increment in the intention prior of the concerned FSM, all the intention priors are normalized. Thus the intention priors of other FSMs concerning other intentions in the group are decreased.

In the second case, the proactive nature of HRI is discussed at lower level, i.e., the ambiguous (leading to two or more different human intentions) human action performed by the interacting human is probabilistically handled for proactive HRI. The ambiguous human intention case is handled by the transition weights. The transition weights correspond to the weights assigned to the transition conditions in the FSMs. The transition conditions that are common in different FSMs are assigned the uniform transition weight. A common transition condition with uniform transition weight can not cause the state transition. Although the transition probability of the common transition condition is high but multiplied with the uniform transition weight the state transition does not occur. If the recognized intention corresponds to a FSM that has common transition condition then the transition weight for that common transition condition is increased and for other concerning common transition conditions the transition weights are decreased. An adaption factor θ is used to quickly increase the transition weight of a common transition condition. The adaption factor is multiplied by the transition weight to increase the value of the transition weight.

If the robot has proactively responded according to the human intention then the human intention does not change. In case if the proactive response is not exactly according to the human intention then the human intention may change, e.g., if the human intended to drink cola but he was offered water then he may change his intention to drink water. If the robot's proactive response is totally different from the human intention then the human intention may not change and the robot's reaction can be rejected by the human. If the human has no specific intention then a proactive action by the robot may induce the intention (concerning the robot's proactive action) in the human.

Chapter 6

Interaction in unknown scenarios

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. For a robot to be intuitive, it should possess the capability to interact with the human even if the intention of the human is not known.
In this chapter an approach is introduced to HRI in a known scenario with unknown human intention. Initially, the robot reacts by copying the human action. Before each reaction, the robot hypothesizes its potential actions and selects one that is found most suitable. The robot may also use the HRI history to hypothesize the potential actions. Along with the history, the robot also considers the action randomness and action predictions to hypothesize the potential actions. As solution, a general Reinforcement Learning (RL) based algorithm is proposed that suggests learning of HRI in an unknown human intention scenario. A Particle Filter (PF) based algorithm is proposed to support the probabilistic action selection for HRI. The experiments for HRI 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 action.
The remainder of this chapter is organized as follows: In Section 6.1 the problem of HRI with unknown human intention is defined and motivated. The approaches related to the discussed problem are described in Section 6.2. In Section 6.3 a general RL based HRI algorithm is proposed. In Section 6.4 the process of probabilistic action selection is explained in detail. Section 6.5 describes the experiments performed using the proposed approach. Finally, Section 6.6 summarizes the chapter.

6.1 Problem definition and Motivation

The problem corresponds to HRI in an unknown human intention scenario. The human can has an intention $i \in \Gamma$, $\Gamma = \{i_1,\ldots,i_n\}$, $n \in \mathbb{N}$ while working in the HRI workspace. The robot does not know Γ. The robot also does not know how to react. The robot knows the HRI workspace and the actions $\Omega = \{a_1,\ldots,a_m\}$, $m \in \mathbb{N}$ that can be performed by the human in HRI workspace. The input to the problem corresponds to the scene information, the scene change information, and the understanding of human actions. The robot is required to select an action a_k, $k \in \{1,\ldots, m\}$ for interaction with the human. It is assumed that during the HRI the human only performs the actions that are related to his current intention.
The humans possess the capability of responding to the problem in an unknown or unseen situation. This is a significant difference between a machine and a man. A machine can only perform the task that it is made to perform. A machine can usually not perform in a new situation. On the contrary the human has built-in capability to interact with another human

without knowing his intention. The interacting human adapts himself as he interacts with the other human whose intention is not known to him. We discuss two cases in which one human interacts with another human in a situation that the intention of the other human is unknown to him. In first case, we consider a human *A* that is working in an industrial workplace with some machines along with another human co-worker *B*. The human *B* picks and places the objects to perform an operation on them with the help of machines. The human *A* can interact with *B* by placing the objects without knowing the operation that *B* wants to perform on the objects (with the help of the machines). The human *A* can also correct himself by the correcting response from *B*. The correcting response may be the type of objects that should be picked and placed. In the second case, two humans interact in a household scenario. The second human does not know the intention of first human. The first human has the intention of tidy up the things. The second human performs as he observes the first human and maintains a record about the actions of the first human and the estimated intention. As the interaction between both the humans proceeds, the second human interacts more intuitively by repeating the previously performed actions.

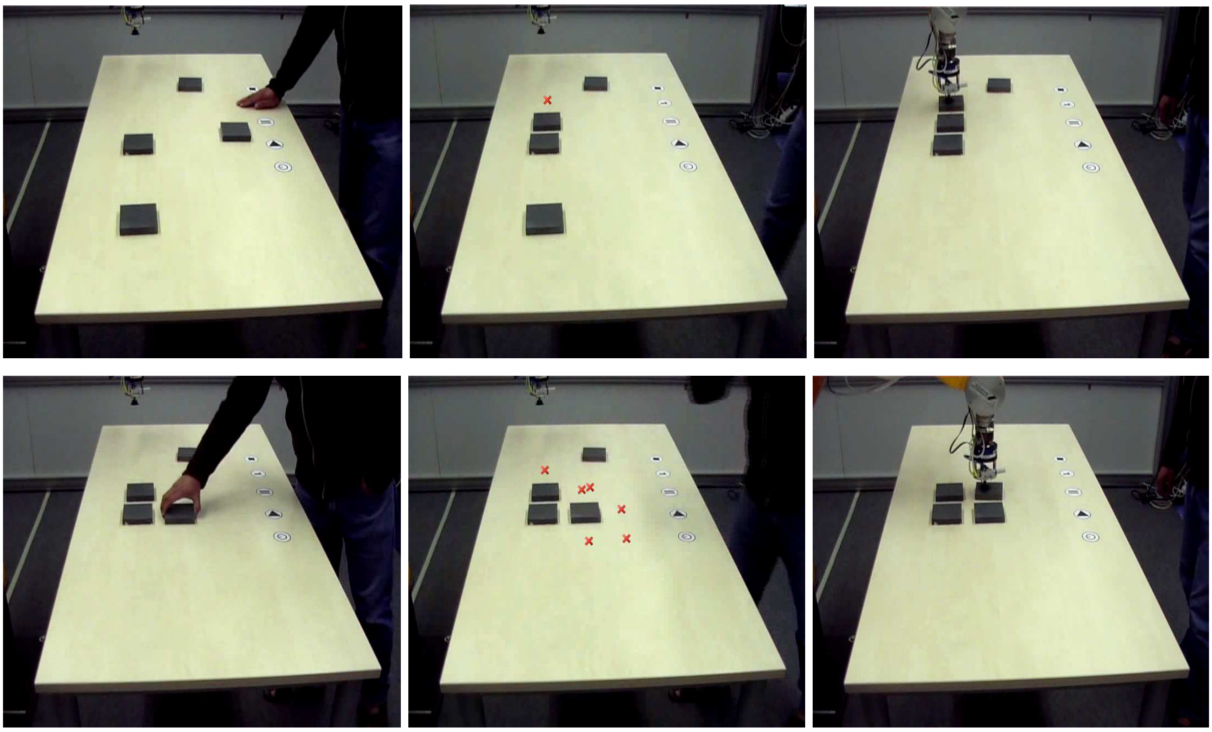


Figure 6.1: Intuitive HRI in a scenario where the human intention is unknown to the robot. In the top left figure the human starts the HRI by pressing (putting the hand on) the interaction button and picks and places an object according to his intention. In the top middle figure the robot makes a hypothesis (red cross) to react intuitively and places the object in the top right figure. The human corrects the robotic reaction in the bottom left figure. The robot once again makes hypotheses (red crosses) in the bottom middle figure. The robot performs the action according to the most suitable action hypothesis in the bottom right figure.

The actions of the second human may also be corrected by the first human. It is very important property of the humans that they can interact in a situation if they are not given the

intention of the cooperating humans. This property is equally important for HRI, i.e., if the robot does not know the intention of the interacting human then he must respond intuitively.
We discuss a simple example for HRI in which the robot does not know the human intention. The HRI workspace consists of objects on the table as shown in Figure 6.1. The human has the intention of arranging the objects in a specific order on the table that is not known to the robot. The human initiates its actions according to his intention. The robot reacts by copying the human actions and changes its action on correction by the cooperating human as shown in Figure 6.1.

6.2 Related work

The section describes the related approaches. In this section the differences between the presented approach and the related approaches is also discussed. A large amount of literature exists for RL. In RL the agent learns the optimal policy for performing a task [78] without focusing the human and its intention. In the literature of RL many solutions exist with no human input. In some of RL-based solutions, human input exist, e.g., [94] and [22]. These are required to be trained. The presented solution is not required to be trained. In [4] RL is used to refine (teach) the robot behaviour.
With a significant deviation from the basic focus of the HRI, there exist a lot of such solutions under the umbrella of Programming by Demonstration (PbD) that is almost a complete field in itself. The approaches [126][139][137][9] apply RL to PbD. Artificial Neural Networks (ANN) are used in [91][17], Hidden Markov Model (HMM) is used in [166] for PbD. The approaches in PbD try to enable the robot to reproduce what has been performed in front of the robot without focusing HRI.
In the area of intention recognition for HRI, there exist a number of approaches [150][139][125] that use HMM, Dynamic Bayesian Network, and Hybrid Dynamic Bayesian Network to recognize the human intention. The approaches described in [77][98][169] perform Ontology, Utility-and Graph-based intention recognition. The HRI based on the probabilistically weighted Finite State Machines (FSM) is described in [12]. Each FSM represents a potential human intention that is already known to the system. The described intention recognition approaches can only recognize the already modelled human intentions for intuitive HRI. In case of a new (not modelled) intention the described intention recognition approaches can not be used by the robot for HRI. The approaches described in [131] [13] deal with the proactive recognition of the premature human intention. The approaches [131] [13] can not be used if the concerning human intention is not modelled. More specifically [14] describes how to handle the totally new situation in intention recognition based HRI. The approach described in [14] does not suggest the robot how to react in the totally unseen situation. Rather it suggests first to learn how to react and then to interact in that situation.
In the literature of intuitive HRI, the topic of intuitive HRI in an unknown human intention scenario is not considerably explored. The proposed approach corresponds to HRI in the known HRI scenario with an unknown human intention. The known scenario means that the objects present in the scene are known to the robotic system. The changes in the scene along with the associated human actions are also known to the robot. The *unknown human intention* describes what the human intends about the scene and that is not known already to the robot.

6.3 Interaction in an unknown intention scenario

The presented approach proposes a probabilistic solution for the HRI 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.

An algorithm is proposed on the basis of RL for intuitive HRI in the unknown intention scenario. In this algorithm, the robot interacts by taking into account the human response while interacting with the human. The robot's reactions become pertinent 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 [78], 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 6.2.

Initially the action set A and state set S are empty. Each action $a_{F1,\ldots,Fn}$ is characterized by n different features $F_1,\ldots, F_n$. 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 $a_{F1,\ldots,Fn}$ such that $F_1,\ldots,F_n$ have specific values for the action $a_{F1,\ldots,Fn}$. 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 as the intention of the human is not known to the robot.

After the human has performed an action, a 3-tuple is added to set S, i.e., state s_i (before the human has performed the action), the performed human action $a_{F1,\ \ldots,\ Fn}$ and the state s_{i+1} (after the human has performed the action) (Line 5). The robot reacts after making an educated guess. The educated guess corresponds to the selection of the appropriate action. The process of selecting an appropriate reaction is discussed in Section 6.4. 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 asks to change the action then the robot acts 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 $a_{F1,\ldots,Fn}$ is added to the set A if the action is newly performed by the human (Lines 8-12). The input of the algorithm involves the human feedback concerning the robot action. The output of the algorithm given in Figure 6.2 is the set S. The set S can be used to construct a probabilistic FSM [12]. 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 do not perform any further action. The goal state is also reached if the human stops the robot from further interaction.

Input : human actions, human feedback

Output : Set S of 3 - tuple elements

1 - Set $A = \{\}$ // contain the human action

2 - Set $S = \{\}$, $i = 1$ // contain the 3 - tuple elements

3 - Wait for human action $a_{F_1,\dots,F_n}$

4 - Add the taken action to A, i.e., $A = A \cup \{a_{F_1,\dots,F_n}\}$

5 - Add s_0 , s_1 and $a_{F_1,\dots,F_n}$ to S,
i.e., $S = S \cup \{(s_0, a_{F_1,\dots,F_n}, s_1)\}$

6 - **repeat**

7 - React with highly likely action

8 - **if** "the human corrects the action" **then**

9 - **if** $(a_{F_1,\dots,F_n} \notin A)$ **then** // new human action

10 - Add the human action to A,
i.e., $A = A \cup \{a_{F_1,\dots,F_n}\}$

11 - **end if**

12 - Add s_i, $a_{F_1,\dots,F_n}$ and s_{i+1} to S , i.e.,
$S = S \cup \{(s_i, a_{F_1,\dots,F_n}, s_{i+1})\}$
$i = i + 1$

13 - **else if** "human asks to change the action" **then**

14 - React with the next highly likely action

15 - **esle**

16 - Add s_i, $a_{F_1,\dots,F_n}$, s_{i+1} to S , i.e.,
$S = S \cup \{ (s_i, a_{F_1,\dots,F_n}, s_{i+1})\}$
$i = i + 1$

17 - **end if**

18 - **until** the goal state is reached.

Figure 6.2: Reinforcement-based HRI algorithm

6.4 Probabilistic action selection

We motivate the problem of probabilistic action selection for intuitive HRI 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 actions by the correction performed by the person *B*. Afterwards the person *A* may analyze the similarities in the action sequence performed in the new task and the action sequences performed previously. The similarity corresponds to the fact that how many times after an action *a* the action *b* was performed.

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. 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 the features. The scene information is also known to the robot, i.e., the objects that exist in the scene. In order to collaborate intuitively with the human, the robot needs to follow the pattern of human activities simulating him. 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 following aspects are considered in order to interact with the human in the unknown human intention case:

A. Action probability
B. Action prediction
C. Weighting of the predicted actions
D. History-based action prediction
E. Combination of action aspects

6.4.1 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 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 and 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.

6.4.2 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. $F_1,\ldots,F_n$. The future actions are predicted based on the human actions and accepted robot actions, observed during the HRI. 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 6.3 (left). 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 Figure 6.3 (right). The Figure 6.3 (left & right) is further explained in next subsection with respect to weighting of actions.

The prediction of actions is the performed after each HRI 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.

6.4.3 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 Figure 6.3 (left & right), the predicted hypotheses are represented by the encircled dots. The simple dots represent the acted upon hypotheses that were accepted.

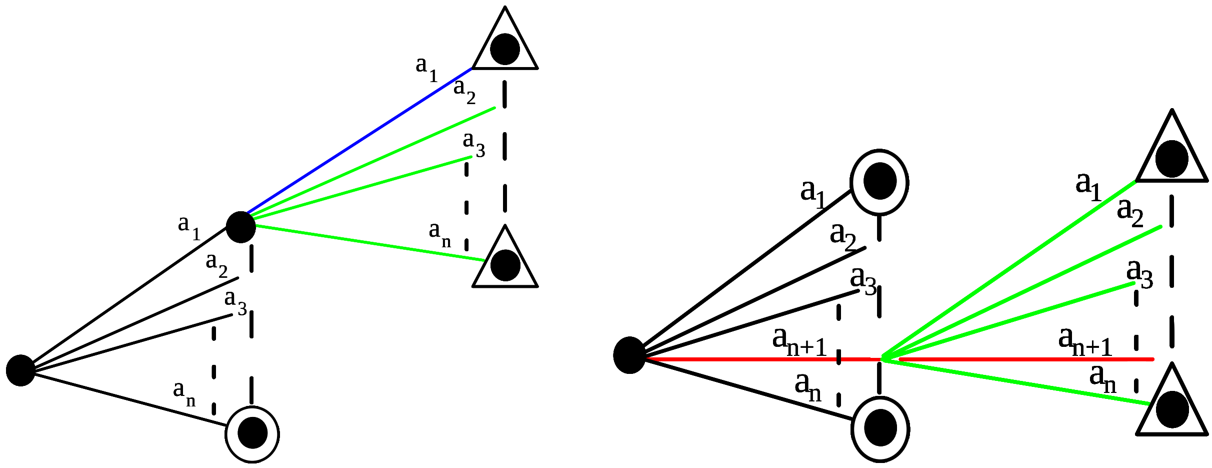


Figure 6.3: Generation and weighting of potential action hypotheses, a dot represents a performed action hypothesis, an encircled dot represents the result of a previously created action hypothesis, a triangulated dot represents the result of a currently created action hypothesis and the lines represent the action that lead to result of that action, i.e., encircled dot and triangulated dot. Left: Generation of hypotheses if robot action is accepted Right: Generation of hypotheses if robot action is corrected

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 6.3 (left). 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 6.3 (left) gets higher weight with respect to the newly generated (green) hypotheses. It is assumed that an action can be repeated while performing a task, e.g., there may be multiple objects and the same action is required to be performed on them.

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 6.3 (right). The new action (shown red in Figure 6.3 (right)) 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 6.3 (right)). In new hypotheses the newly added action (shown red) gets higher weight with respect to newly generated hypotheses. The higher weight is due to the assumption that an action can be repeated while performing a task.

6.4.4 History-based actions prediction

As descried earlier that a human intention consists of a sequence of actions. Each action can be characterized by a set of *n* features. It means that each action can be represented as a point in the *n* dimensional space. Thus each intention consisting of a sequence of action (represented as point in the *n* dimensional space) is represented as an ordered set of points.
A complete action sequence concerning an intention represents an *intention trajectory*. Graphically an intention can be represented as a trajectory in the *n* dimensional space as shown in Figure 6.4.

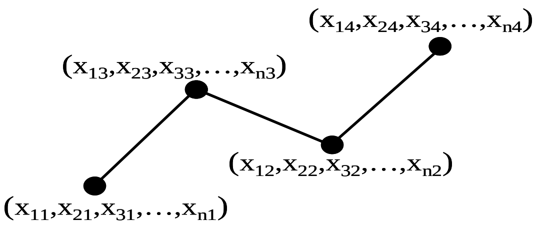


Figure 6.4: Action sequence trajectory concerning a human intention, each dot represents an action and a complete trajectory represents a task concerning a human intention

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 following Figure 6.5.
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.

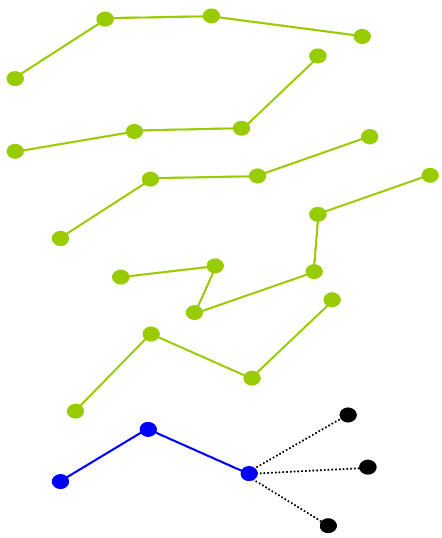


Figure 6.5: Hypothesis evaluation using previous intention trajectories

6.4.5 Combination of action aspects

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 $w^i_t \cdot p(\mathrm{A}^i_t|\mathrm{H})$ and weighted action randomness $w^i_t \cdot p(\mathrm{A}^i_t|\mathrm{A}_{t-1})$, i.e., $w^i_t \cdot p(\mathrm{A}^i_t|\mathrm{A}_{t-1}) + w^i_t \cdot p(\mathrm{A}^i_t|\mathrm{H})$. 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. The combination of the history support, randomness and the hypotheses weight is shown in Figure 6.6.

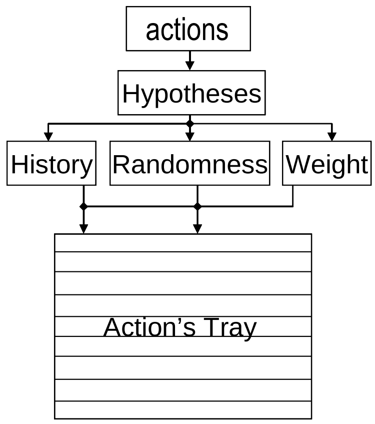


Figure 6.6: Final action selection for HRI by the combination of history support and randomness of each action hypothesis with the weight of the hypothesis, resulting in a value, the action hypotheses are arranged in descending order with respect to the resulting value

6.5 Particle Filter based action selection

The mechanism used in Particle Filter (PF) considers all the possible solutions as particles. PF is an iterative 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 [45]. Using the particles the distribution of 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 or the previous accepted action of the robot to predict the action for HRI. The update is performed on the basis of human response. If the human accepts the reaction then the accepted action is predicted with more likelihood (Figure 6.3 left). In case if the human responds by simply correcting the robot’s reaction. Then the corrected human action (new human action) is predicted with more likelihood (Figure 6.3 right).
The difference between the application of PF algorithm for the current problem and problems where PF is usually applied is spatial. As PF is mostly applied in the robot localization and

usually 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 space. Then the future actions can not be predicted based on the location of the current action. 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.

Initialization()

Input : human actions

Output : Set S_t of action particles

1 - $S_t = \phi$

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

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

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

5 - **end for**

Figure 6.7: Initialization of the action particles

The algorithm is described in Figures 6.7, 6.8, 6.9, and 6.10. In the initialization phase, all the action particles are created with equal weights as shown in Figure 6.7. The elements of set S_t (Line 4) correspond to a tuple of action particle, its weight and action value (discussed later in this section). In the probabilistic action selection described in Figure 6.8 the action values of all the existing action particles are calculated as shown in Line 3. The value of each action particle is calculated by multiplying the conditional probability of the action and historical support with the weight and adding them. 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 Line 5 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 Line 6 to 20 until a suitable action is selected or all the actions are tried or the human performs a correction. 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 10-11), Figure 6.3 left (green lines). The particle corresponding to the accepted action gets higher weight than the newly generated particles. It is shown in Figure 6.3 left (blue).

If the robotic reaction is not accepted then the human may ask the robot to change its reaction. The robot selects the next highest value action for reaction (Lines 12-13).

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 15-16), Figure 6.3 left (green lines). The particle corresponding to the human correction gets higher weight than the newly generated particles, Figure 6.3 left (blue).

$S_t = \{\langle A_1, w_1, v_1 \rangle, \langle A_2, w_2, v_2 \rangle, ..., \langle A_n, w_n, v_n \rangle\}$
Input : S_t, human actions, human feedback
Output : Selection of an action for the robot to react
Algorithm Particle_filter(S_t)
1- $\eta = 0 \quad index = 0$
2- **for** int $i = 1,...,n$ **do**
3- $v_i = w_t \cdot p(A_t \mid A_{t-1}) + w_t \cdot p(A_t \mid H)$ // action value calculation
4- **end for**
5- $\Lambda = Descending\ Order(S_t.v)$ // storing the actions with respect to action value
6- **do**{
7- $\hat{A} = \Lambda.at(index^{++}).A$ //selecting the action with highest action value
8- $Execute\ \hat{A}$ // robotic reaction
9- **if** $(Accepted(\hat{A}))$ **then** // performed robot action is accepted
10- Sample A_{t+1}^k from $p(A_{t+1}|\hat{A})$
11- $S_t = S_t \cup \{< A_{t+1}^k, w_{\text{high}} >\}$
12- **else if** $(Change(\hat{A}))$ **then** // robot is asked to change the reaction
13- $\hat{A} = \Lambda.at(index^{++}).A$
14- **else if** $(A_{human\_correction} \in \Lambda)$ **then** // human correction is already known to robot
15- Sample A_{t+1}^k from $p(A_{t+1}|A_{human\_correction})$
16- $S_t = S_t \cup \{< A_{t+1}^k, w_{\text{high}} >\}$
17- **else if** $(A_{human\_correction} \notin \Lambda)$ **then** // human correction is not known to robot
18- Re_Initialization($A_{human\_correction}, S_t$)
19- **end if**
20- }**while**$(\hat{A} != A_{optimal} \parallel \hat{A} == \phi \parallel A_{human\_correction})$;

Figure 6.8: Probabilistic action selection for HRI

In case if the human corrected action does not belong to the set of predicted actions (Line 17-18, Figure 6.8) then re-initialization of the particles is performed, described in Figure 6.9. The human correction is represented by A_t in Figure 6.9. 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 2-5, Figure 6.9), Figure 6.3 (right) (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 6-7, Figure 6.9).
The weight of these new action particles is higher than the previously created (Lines 2-5, Figure 6.9) new action particles. The newly created particles (Lines 6-7, Figure 6.9) correspond to the green lines in Figure 6.3 (right). The new action particle representing the repetition of newly added action Figure 6.3 (right) (red line among green lines) is given the highest weight with respect to the all newly created particles.

Re_Initialization(A_t, S_t)

Input : S_t (Set of action particles), A_t (new human action (correction))

Ouput : S_t updated with respect to the A_t

1- $\eta = 0$

2- **for** $i = 1...m$ **do** //m corresponds to the previously existing action particles

3- Sample A_{t+1}^k from $p(A_t|A_{t-1})$

4- $S_t = S_t \cup \{< A_{t+1}^k, w_1, 0 >\}$ // $w_1 > w_{previous\_particles}$

5- **end for**

6- Sample A_{t+1}^k from $p(A_{t+1} \mid A_t)$

7- $S_t = S_t \cup \{< A_{t+1}^k, w_2, 0 >\}$ // $w_2 > w_1$

8- **for** $i = 1...n$ **do** // $n > m$ n is the total number of action particles

9- $\eta = w_i + \eta$

10- **end for**

11- **for** $i = 1...n$ **do** // $n > m$

12- $w_i = w_i / \eta$

13- **end for**

Figure 6.9: Creation and weighting of the new action particles

Afterwards the particles weight is normalized (Lines 8-13, Figure 6.9). 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 6.10. A threshold value τ is selected between 0 and 1 / (total number of the particles), including 1 / (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.

Input : S

Output : $\bar{S}, \bar{S} \subseteq S$

$\bar{S} = \phi, \eta = 0$

for $i = 1,...,n$ **do**

if $(w_i > \tau)$ **then** $\tau \in]0, 1/n]$

$\bar{S} \cup \{< A_i, w_i, v_i >\}$

end if

end for

for $i = 1,...,m$ **do** $m \le n$

$\eta = \eta + w_i$

end for

for $i = 1,...,m$ **do**

$w_i = w_i / \eta$

end for

Figure 6.10: Re-sampling of the action particles

6.6 Experiments

The experiments are performed with a robotic arm with six degrees of freedom. The human and the robot interact in a HRI workspace shown in Figure 3.9. The HRI workspace consists of a table with the objects on the table. The video data is captured by an overhead FireWire digital camera with the standard frame size of 640 x 480 pixels at a frame rate of 30 frames / sec. HRI and image analysis are implemented using programming language C++. The robot reactions are realized using the robot programming language V++ for the robotic arm. The human actions are inferred from the scene changes occurred due to the human actions. The performed experiments involve actions that are characterized by two features, i.e., the distance between the objects and the orientation of the objects with respect to each other. The objects in the experiments involve the boxes on the table as shown in Figures 6.11 and 6.12. The performed experiments concern different arrangements of the objects according to the human intention.

Each task representing a human intention is described by a trajectory (Section 6.4.4). In 2D case the trajectory is drawn in a plane having distance between the objects and orientation as axes. Each action is represented as a point in the plane. For a trajectory the angle concerning the slope of the line passing through the two immediate connected-points (Figure 6.4) is calculated.

Thus for each trajectory, there exists a set of angles between the consecutive action points. For trajectory comparison the difference is calculated between the related sets of two concerning trajectories. The difference corresponds to different angle values in the two sets. The difference between the current (incomplete) HRI trajectory and the previous (complete task representing a human intention) trajectory is calculated. The trajectory, for which the difference is least, is used to evaluate the predicted action hypotheses.

For spaces more than two dimensions, the direction vector between the two n-dimensional (n > 2) points of the intention trajectory can be calculated by subtracting second point from the first point, i.e., if ($x_{11}, x_{12}, ..., x_{1n}$) and ($x_{21}, x_{22}, ..., x_{2n}$) are two points then the direction vector will be calculated as $v = [x_{21} - x_{11}, x_{22} - x_{12}, ..., x_{2n} - x_{1n}]$. Now the comparison between the two direction vectors can simply be performed by calculating the angle between the two direction vector using the dot product of the vectors, i.e.,

$$\theta = \cos^{-1}\left\langle \frac{v_1 \bullet v_2}{\|v_1\| \, \|v_2\|} \right\rangle$$

First the anatomy and reasons for selecting a reaction in the experiments is explained. Afterwards the results of the performed experiments are discussed. The following experiments are considered for explaining the reaction selection mechanism. The unknown human intentions correspond to the arrangement of the objects. The considered unknown human intentions involve the arrangement of the objects in vertical and horizontal pattern, arrangements of the objects in a square pattern, and the arrangement of the objects in a diamond pattern. The arrangements of the objects according to the above described unknown human intentions are shown below in Figures 6.11 and 6.12.

At the start the boxes are placed randomly on the table. The human picks and places the box at a point on the table as shown in Figure 6.13 by the box at (235, 150). Afterwards the human places another box vertically near the previously placed box as shown in Figure 6.13 by the box at (235, 208). The system infers the human action as the distance and angle between the two vertically placed boxes, i.e., θ_1 and d_1. A hypothesis is created based on the observed action, i.e., the place to put the next box, shown in Figure 6.13 by the green circle. The hypotheses weights (Figure 6.9), action probabilities (Section 6.4.1), and the history support (Section 6.4.4) are considered for the estimation of the action.

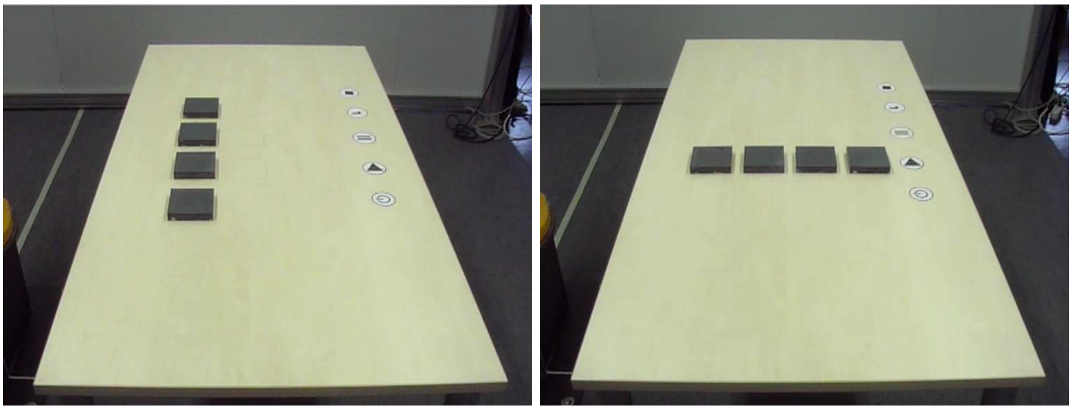


Figure 6.11: Unknown human intentions for arranging the boxes

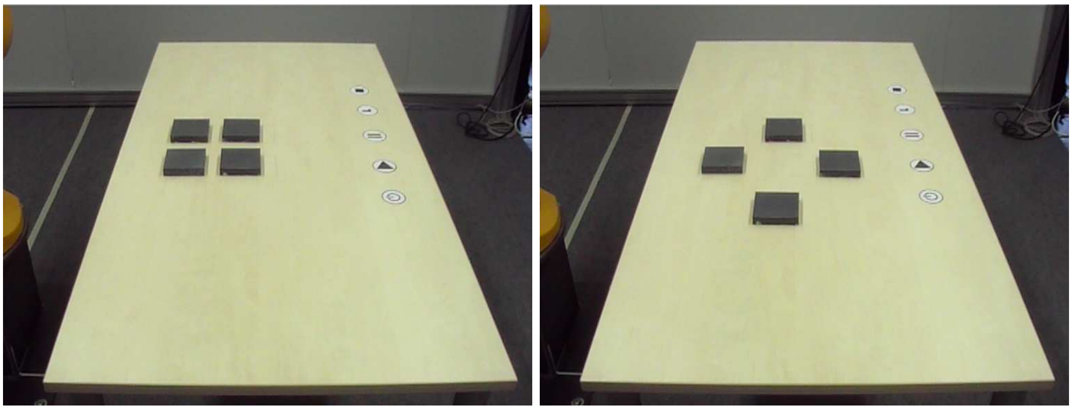


Figure 6.12: Unknown human intentions for arranging the boxes

For the very first reaction there exist no conditional probability value and historical support value. In such case the prior probability of that action is used. In case of absence of historical support of action sequence all the predicted actions for the current HRI are given uniform weight. Therefore the system has the only highest value available reaction, i.e., placement of the box in the vertical pattern at the next location at an angle θ_1 and distance d_1. The weight of the hypothesis is represented by red cross at first interaction step in Figure 6.14.

Now if the human intercepts and corrects the robot reaction then the system updates its possible actions by adding the corrected action if it is new and updates the conditional probability tables and the prior probability tables. The system also appends the corrected action in the current human robot interaction action sequence.

The human accepts the robot reaction and the system updates its table without adding any new actions in its action table. Now the robot once again creates the hypothesis as shown in Figure 6.13 by the blue circle. Till now the robot has observed one action thus it only creates one hypothesis which is the next place in the vertical pattern.

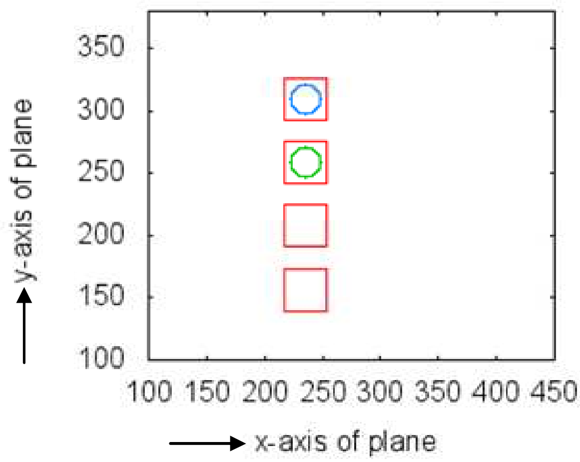


Figure 6.13: Hypotheses graph for intention shown in Figure 6.11 left

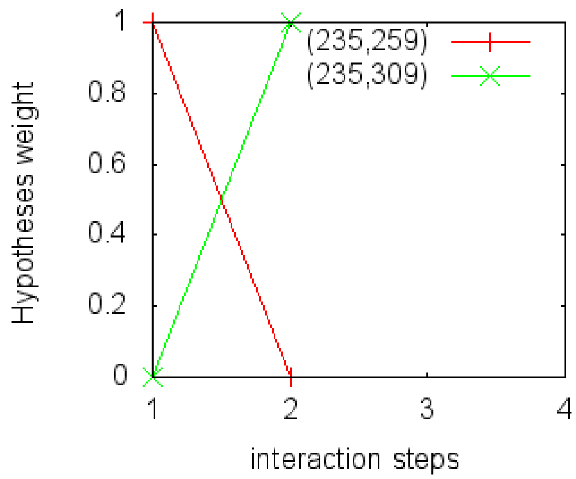


Figure 6.14: Weight graph for intention shown in Figure 6.11 left

That robotic reaction is also accepted by the human as he has the similar intention of arranging the boxes in vertical pattern. After each complete interaction the system stores the action sequence separately. The sequence consists of the human action, human correction and accepted robot reactions.

In the hypotheses weight graph if a hypothesis is accepted as a reaction then that hypothesis is removed by making its value zero as shown in Figure 6.14 at interaction Step 2, i.e., the red line goes to zero.

In the next HRI experiment the human intends to arrange the boxes in a horizontal order. The boxes are once again placed randomly on the table. The human picks a box and places it at a point on the table as shown in Figure 6.15 by the box at (156, 193). Now the system creates a hypothesis based on the known action, i.e., θ_1 and d_1 represented as green circle in Figure 6.15 and the robot reacts by picking and placing another box at the angle θ_1 and distance d_1. This time the human has the intention of placing the boxes horizontally.

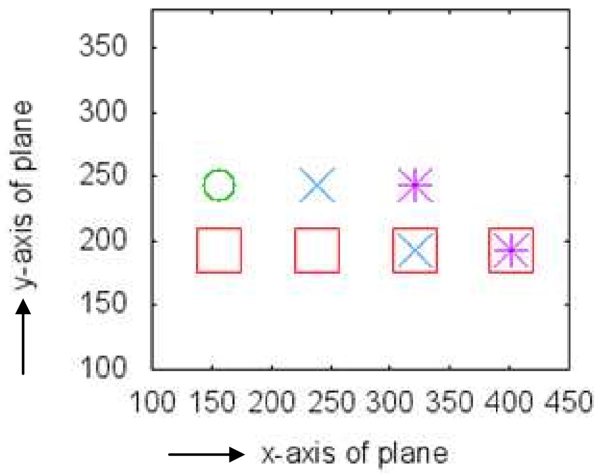


Figure 6.15: Hypotheses graph for intention shown in Figure 6.11 right

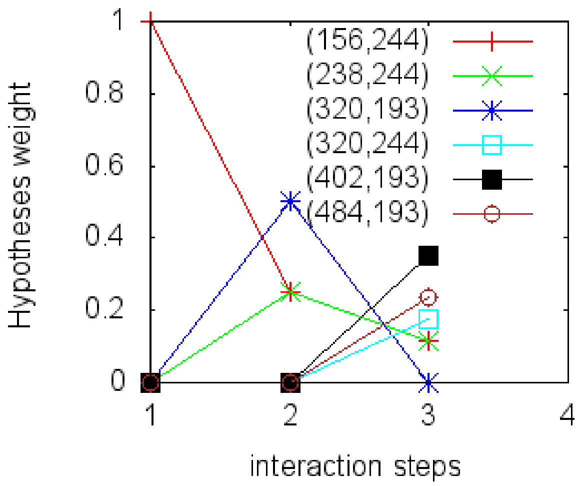


Figure 6.16: Weight graph for intention shown in Figure 6.11 right

Therefore the human corrects the robotic reaction and picks and place the box (placed by the robot) at an angle θ_2 and distance d_2 as shown in Figure 6.15 by the box (238, 193). Now the system adds the new action to its action table and updates the conditional probability as well as prior probability tables.

For the next reaction, the robot has three hypotheses based on the two actions (green circle and blue crosses Figure 6.15). The hypothesis instructing the robot to place the next box horizontally with respect to the previously placed box (238,193) gets highest weight according to the hypothesis weighting mechanism described earlier with respect to the other two hypotheses. The hypothesis (320, 193) has the highest weight at interaction Step 2, represented by blue star in Figure 6.16. The reaction value is calculated using the conditional probability or prior probability, historical support and the hypotheses weight. As there is no historical support for the currently predicted actions thus all the hypotheses based on the predicted actions get equal weight. There exists no conditional probability value for the currently predicted actions. Thus the prior probability is used instead of conditional probability.

As the prior probability of vertical box placing action is high therefore the hypotheses value for placing the box vertically gets higher values as compared to the horizontal placement of the box.
Thus the robot reacts by placing the box vertically that is rejected by the human as the human intends to place the boxes horizontally. Now due to the rejection of the human the robot resorts to next highest value action that is once again placing the box vertically at another location which is once again rejected by the human. The robot resorts to next available action that is placing the box horizontally with respect to the lastly placed box at (320, 193). The reaction is accepted by the human. It is not selected for reaction for the first time due to the low prior of the concerning action (horizontal action). The robot creates the new hypotheses (represented as purple stars in Figure 6.15) for the next reaction for placing the fourth box. This time the robot reacts by placing the box horizontally with respect to the lastly placed box. This time placing the box horizontally has highest conditional probability of 1 and highest weight as compared to the priors for vertically located hypotheses with low weight. It is shown by the black box in Figure 6.16 at intersection Step 3.
In the next HRI experiment the human intends to place the boxes in a squared pattern, Figure 6.12 left. Once again the human places the box and the robot generates the reaction hypotheses based on the previously observed actions, represented as green circles in Figure 6.17. The hypotheses get the same action value due to the same hypothesis weight, same history weight and same prior probability. The robot places the box (318, 156) in horizontal pattern and that is accepted by the human due to the similar intention. Next time the robot once again places the box on the horizontal pattern as the action has highest value due to the high hypothesis weight and history support for the action as the current pattern matches to more to the horizontal placement than vertical placement.

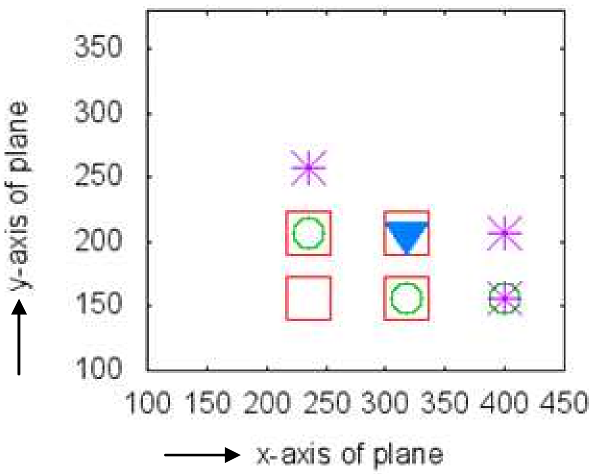


Figure 6.17: Hypotheses graph for intention shown in Figure 6.12 left

The reaction is rejected and the robot resorts to next highest value reaction, i.e., place the box orthogonal to previously placed box (236, 156) (according to the squared pattern intention, Figure 6.12 left) at (236, 207) which is accepted. Afterwards the robot reacts by placing the box on the fourth corner of the square (Figure 6.12 left) due to the high value for that action (blue triangle in Figure 6.17). That high action value is due to highest hypothesis weight and highest prior probability as compared to other hypotheses, represented as cyan colour box in Figure 6.18.

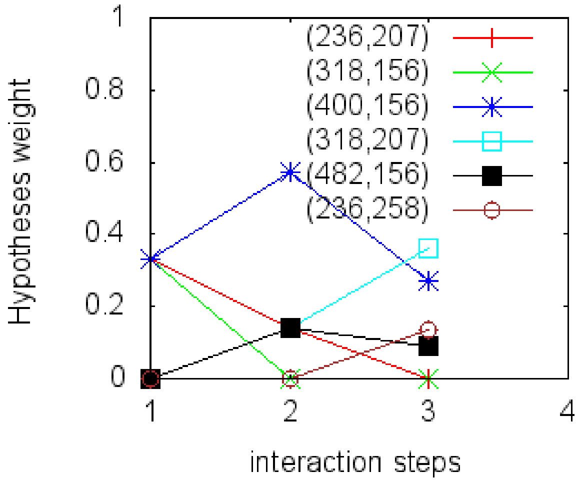


Figure 6.18: Weight graphs for intention shown in Figure 6.12 left

The next interaction corresponds to the placement of the boxes in a shape of diamond as shown in Figure 6.12 right. In this case, the human places the first box. The reaction hypotheses (green circles in Figure 6.19) are created based on the known actions. The robot reacts by placing the box at (402, 155) which is rejected. The selection of this action is performed due to the high prior probability value as all the other factors have the same value.

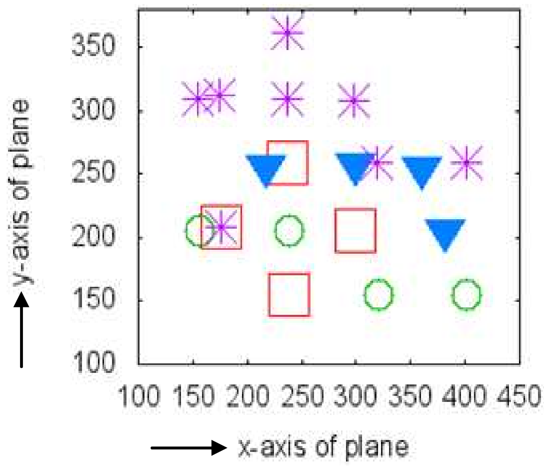


Figure 6.19: Hypotheses graph for intention shown in Figure 6.12 right

The human intercepts and corrects the robot reaction by placing the box at (299, 206) as shown in Figure 6.19. The system creates new reaction hypotheses. That comprises the green circles and blue triangles as shown in Figure 6.19. The robot once again reacts by placing the box in horizontal pattern and rejected. The highest weighted reaction is represented by brown triangle (360, 255) in Figure 6.20 at interaction Step 2 and blue triangle in Figure 6.19 at (360, 255). The selection of horizontal box placement action is mainly contributed due to the high prior value.

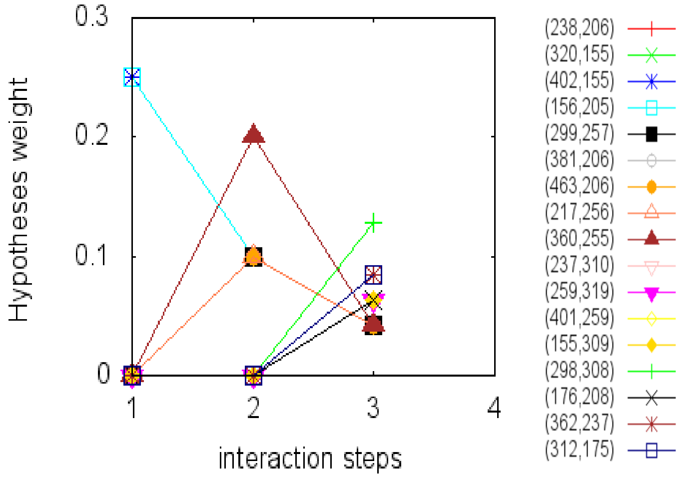


Figure 6.20: Weight graph for intention shown in Figure 6.12 right

The human corrects the robotic reaction by placing the box at (237, 259) that is near to comparatively low weighted hypothesis, i.e., (217,256), represented as blue triangle in Figure 6.19. The robot recreates the hypotheses including the newly created purple star hypotheses shown in Figure 6.19.

The very first reaction is selected due to the history supported value of the hypothesis (308, 298) as the current action sequence closely match to the action trajectory of squared pattern as compared to other action trajectories. That reaction is rejected. After 3 rejections the hypothesis that closely relates to the human intended action, i.e., (176, 208) is accepted.

The hypothesis (176, 208) is represented by black cross in Figure 6.20 at intersection Step 3.

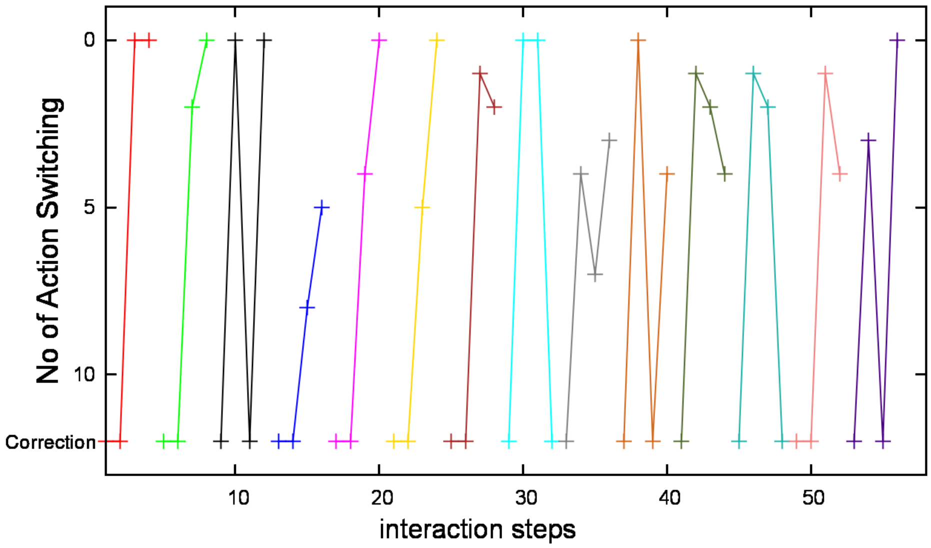


Figure 6.21: Robot reaction in unknown human intention scenario

The graph shown in Figure 6.21 describes the 14 different interaction tasks, independent from each other. The horizontal axis of the graph represents the numbers of interaction steps and vertical axis represents the number of action switching (Lines 13-14, Figure 6.2) requested by the human during the HRI. The graph in Figure 6.21 describes the fact that 73% of the robotic reactions were accepted by the human and 27% of the robotic reactions were corrected. Out of 27% corrections almost half of the corrections were performed at the second step of interaction. Out of 73% accepted reactions, 45% reactions involved maximum switching of three actions, 21% reactions involved maximum switching of five actions and 7 % involved maximum switching of seven actions.

6.7 Summary

In this chapter, we presented a probabilistic approach for the robotic reaction in the HRI scenario with unknown human intention. The approach corresponds to a RL based interaction algorithm. In which the robot performs the estimated action in order to cooperate with the human without knowing the human intention. If the action performed by the robot corresponds to the human intention then the robot action is accepted by the human. Otherwise the human rejects the robot action and expect from the robot to act differently. The human can either wait for the expected action from the robot or he can simply correct the robot according to his expected action. The most suitable action selection is performed probabilistically. The robot considers the human actions and the accepted robot actions for action prediction (Section 6.4.2), weighting of the predicted actions (Section 6.4.3), action probability (Section 6.4.1), and the history support of the action (Section 6.4.4). The value of all the action hypotheses is calculated using the described aspects (Section 6.4.5). The actions are sorted with respect to their calculated value. The action with highest value is selected for robotic reaction.

The performed experiments can be applied to other cooperation scenarios where the action may involve other than picking and placing of objects, e.g., washing, opening, closing, pouring, etc. 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 on each other. The order of the objects is used to hypothesize the new human 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. In this case the length can be used to hypothesize different human actions. In the discussed experiments the distance and orientation was used to hypothesize the human actions. More complex tasks can be modelled using one or more complex features (given) concerning the human actions.

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 during HRI 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.

Chapter 7

Intention generalization

Generalization of a concept corresponds to the reduction of the number of conditions present in the selection criterion of the concept [15]. The lesser the conditions in the selection criterion of a concept the more general is the concept and vice versa. Generalization of the concept is one of the basic capabilities of the humans and it is the fundamental element of the logical reasoning. With the help of generalization a human can extend his knowledge with respect to various aspects. For example, if a human is asked to place the object *A* at the place *B* then he will make a rule for placing the objects matching to the object *A* at the place like *B*. This rule can be further purified for that human if he is corrected while applying that rule. The generalization capabilities of the human enable him to extend his knowledge very fast. The extended knowledge corresponds to the actions in the specific situations. This extension is made by logical inference of the human. The generalization capability enables the human to perform in the unknown situations.

Robots are becoming more and more part of the human activities, specifically in the industry [47]. The presented approach [15] is confined to the generalization relating to the reduction of the concept criterion as described earlier. The application of these generalized rules in the intuitive HRI aims to improve the interaction capabilities of the robot as the robot can interact more intelligently by performing the actions that are not explicitly taught to the robot.

The remainder of this chapter is organized as follows: The generalization capability is motivated and defined in Section 7.1. In Section 7.2, the existing approaches are discussed. The approaches concerning generalization in the field of robotics are also discussed. Section 7.3 describes the online rule induction and generalization approach. Section 7.4 discusses the rule conflict resolution. Section 7.5 describes the experiments performed using the proposed approach. At the end of Chapter 7, Section 7.6 summarizes the chapter.

7.1 Problem definition and Motivation

The discussed problem corresponds to the generalization of the human intention. The term generalization means to infer the important criterions of the human intention and discard the non important criterions, concerning the performed human action. The important criterions mean that due to these criterions the human intends to perform the action. The human performs an action a concerning the intention Γ with the complete set of criterions $\psi = \{c_1, c_2, c_3, \ldots, c_n\}, n \in \mathbb{N}$. After the process of intention generalization the set ψ becomes $\overline{\psi}$ such that $\overline{\psi} \subseteq \psi$. In case if the criterion ψ concerning the perceived action is already generalized then there will be no generalization, i.e., $\overline{\psi} = \psi$. The input to this problem is the human action, scene information, scene change information, and the human feedback. The output is the generalized human intention concerning the human action.

The capability of generalization possessed by the human can enable him to take appropriate decisions in almost all fields of life. The humans practice this capability without noticing. Many examples concerning the application of generalization capability of human can be described, e.g.,

1. Household tasks
2. Office tasks
3. Common workplace tasks

The generalization helps the human to take decision in an unknown situation. The unknown situation corresponds to the situation that the human has not experienced before. The household tasks concerning generalization can involve the following

1. Tidying up of things
2. Washing tasks
3. Gardening tasks
4. Repairing tasks
5. Cooking tasks, etc

The application of generalization in household tasks is explained using two humans. In case of tidying up of the things, first human picks the objects and places at the specific places. The second human observes the actions of the first human and generalizes the information for placing specific objects at specific places. The generalization helps the second human to place the objects that the first human did not place in front of the second human. Similarly in case of washing, gardening, repairing, cooking, etc the second human can generalize the information to act in the situations for which he has not observed from the first human. The Office tasks concerning generalization can be the following

1. Solving specific tasks
2. Interacting with the colleagues, etc

The human takes into account the necessary characteristics of the tasks that are solved with the known solutions. Then he observes the characteristics of the new task. If the problem has the necessary characteristics that are same to the necessary conditions of the previously known solution then he applies the previous solution to the new task. He generalizes the information of one specific solved task and tries to solve similar tasks. Similarly the humans generalize the successful interaction experience attained from one colleague to the other colleague for generally similar interaction scenarios.

The generalization involved in the common workspace tasks concerns the following

1. Assembly, making, and fabrication of different entities (vehicles, machines, electrical appliances, etc)
2. Building and construction tasks
3. Repairing and dismantling tasks, etc

There exists general information concerning specific workspaces tasks. The humans generalize the information concerning the workspace tasks and apply the information from one solved / observed task to a new task to be accomplished.

Similarly generalizing capability present in a robot can improve the intuitiveness in HRI. For making the robot intuitive with respect to generalization, the robot must be able to generalize the intention of the interacting person. With the ability of generalization, the robot can perform such operations that are not explicitly instructed to the robot. In HRI, with the

generalization ability the robot can generalize the human intention and interact with the human intuitively. The term intuitive means that the robot performs the known operation during HRI that was not explicitly instructed him to perform. The ability of intention generalization instructs the robot to perform such operation.
The intention generalization is discussed in a simple HRI scenario as shown in Figure 7.1. The human picks and places a speckled object into a tray. The robot generalizes the human intention and picks and places all the speckled objects into the tray.

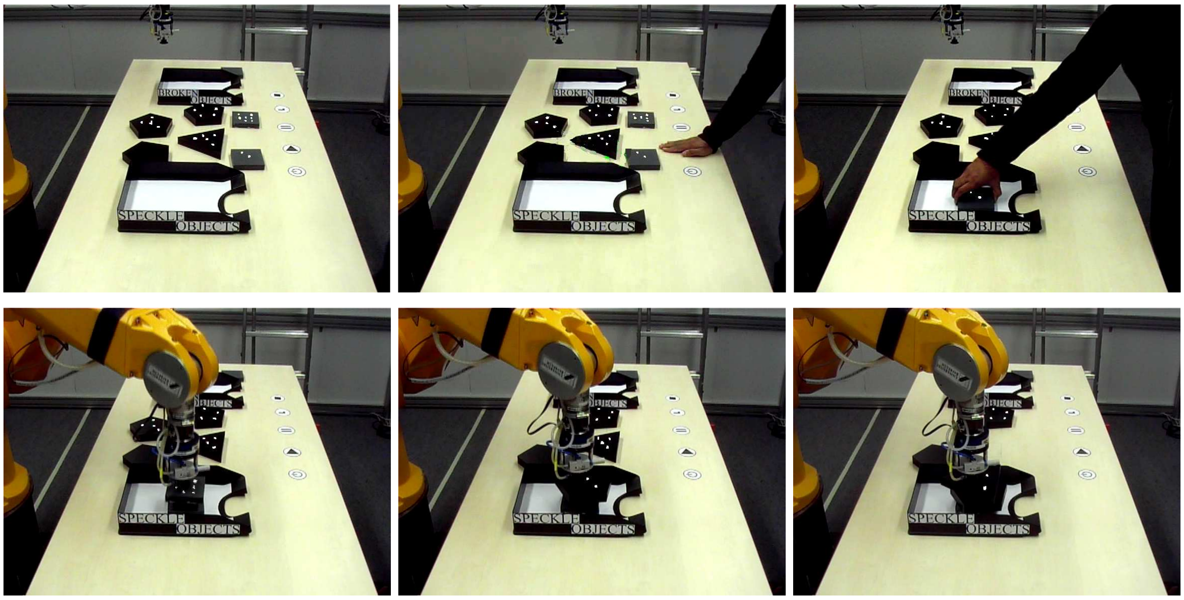


Figure 7.1: The HRI workspace concerning intention generalization consists of triangles, pentagons, and square objects. Some of the objects have speckle on them, some objects are without speckles, and some objects have hole and speckles on them. In top left figure the objects and two racks can be seen. The human starts the intention generalization based HRI by pressing the hand on Play as shown in top middle figure. In the top right figure, the human picks and places a speckled object (square) into the rack. The robot generalizes the human intention and picks and places the speckled objects into the tray as shown in the bottom left, middle, and right figures.

7.2 Related work

There exist concepts related to generalization, e.g., applying the knowledge obtained from one case to another case and transferring the knowledge obtained from one scenario to another. This relates to Case Based Reasoning (CBR) [21] and Knowledge Transfer (KT) [57], [64] which are the examples of Lazy Learning algorithms. Each case in CBR consists of at least two parts, i.e., the problem description part and the solution part. Each case is marked by a number of characteristics. These characteristics may include the case numbers, justification, and evaluation. The characteristic of justification defines steps from the problem to the solution. The evaluation characteristic corresponds to the quality and reusability of the case. The steps discussed in the CBR cycle mainly consists of case retrieval, case adaption and case retaining. The case retrieval corresponds to search a related case with respect to the target case that is to be solved. The adaption of the retrieved solution may be performed by tuning a few parameters or by the application of knowledge based problem solution. The retaining of a learned case is performed by storing successfully the adapted case to the target problem [21].

The CBR may use different feature representations, e.g., Rough Sets [138]. The Lazy Learning algorithms use different kinds of distance functions to calculate the similarity between cases [164]. Traditionally nearest neighbour approaches are used that compute similarity between the stored cases and the new cases, based on the features and the weights of cases [38]. The distance function in CBR is used for case comparison. The distance function does not consider the concept generalization and HRI.

Lutz Formberger describes the learning of KT for generalizing the navigational capabilities of a mobile robot [57]. An agent-centered qualitative spatial representation is used for generalization and KT. The author claims that the learned strategies become robust using the described representation. The robustness corresponds to the ability of the robot to cope up with the environment noise and imprecise world knowledge. A simulated indoor robot is used for experimentation. The task of the robot is to learn a goal directed path finding strategy. The generalization is described by the abstract state space selection mechanism [57].

Association based rule learning in Data Mining [59], [136], [36] requires a data set of huge amount to generate rules with certain probabilistic measures. An association rule can be represented by the expression $X \Rightarrow Y$. The symbols X and Y represent sets of items. The rule describes that if the transaction of X occurs then the transaction of Y will also occur [66]. There exist several generalizations of the rule problem in Data Mining [66], e.g., [59] proposed generalized rule induction using probabilistic rules. The data mining approaches require huge amount of data and no HRI is involved.

Learning from Demonstration (LfD) [19], [110] use the term generalization for the robot to learn comprehensively from many times performed demonstration in different conditions for a certain task. An approach proposed in [58] describes that correction based HRI gives better results in LfD. HRI is used to correct the task performed by the robot [4], for behaviour adaption [104], and to learn the environment dynamics [118].

The approach in [4] introduces a tactile policy correction algorithm. Initially, a policy is derived from LfD technique. Afterwards through the tactile interface, the human teacher indicates the relative refinement in the robot pose. The robot adjusts its poses according to the human tactile input. The corrected robot pose corresponds to the new training data for the policy generated by the tactile input. The tactile input from human helps the robot to refine its demonstrations. The experiments are performed with a humanoid. The HRI concerns the touching of human at the tactile interfaces of the robot to adjust the robot pose. The learning performed by robot during HRI corresponds to the robot’s pose. The focus of the HRI-based approach is correction and not generalization.

Mitsunaga, Smith, and Kanda introduce the behaviour adaption based on policy gradient reinforcement learning [104]. They use HRI to adapt towards the human behaviour. The focus of the approach is the interaction-distance between the human and the robot. The robot monitors the repositioning count of the human in order to estimate the human discomfort during HRI. The robot also considers the gaze averting of the human. Both of the values are used as rewards that are minimized in the policy gradient reinforcement learning algorithm. The robot adapts towards the human behaviour during HRI.

There exist generalization approaches for mobile robot, e.g., [20] describes navigational generalization based on evolutionary algorithms. The focus of the approach is general behaviour of mobile robot for navigation, concerning obstacle avoidance. The approach [20] corresponds to a feed-forward neural network in combination with evolution strategies.

The presented work focuses on Piagetian schemes [118]. The dynamics of environment are estimated. The model anticipates the step forward values of the chosen variables. The variables relates to the dynamics of environment. The anticipation is performed by the current state of sensors and taken actions. The model assumes that the world is deterministic. The HRI occurs in a simulated experiment. The human interacts by clicking on the cart target location on the interface. The interface displays the 2D physical system. The approach in [115] discussed Differential Equations based motor skill generalization. All the above described approaches do not consider generalization as concept generalization.

The most related approach to concept generalization is described in [99]. It is also known as Version Space strategy. This approach can be successfully applied in classification. A version space can be represented by two sets. One set contains most specific consistent hypotheses and the other set contains the most general consistent hypotheses. The most specific consistent hypotheses correspond to the hypotheses that contain the smallest number of conditions that are necessary to select a positive training example. The most general consistent hypotheses contain the conditions such that no negative training example can be selected. The approach in [99] considers generalization as a search problem. The HRI based concept generalization can not be performed using [99]. Since [99] does not suggest what to do if a correction is performed by the human during HRI. Similarly, [99] also does not explicitly describe the rule conflict resolution.

In the concept generalization, the generated generalized rules may face conflict with each other. There exist approaches for conflict resolution, e.g., [32] uses the classification frequencies of the rules (that cover the example to be classified) with respect to the classes to classify a conflicting example. For example, consider a class A and class B with two conflicting rules R_1 and R_2. The samples X that belong to both the classes A and B are needed to be classified. For this purpose, the number of classified examples of a class with respect to all the conflicting rules are summed. This is performed for both the classes. The class that has higher number of examples is assigned to the samples X.

The approach proposed in [37] uses the product of prior probability of the class with the product of conditional probabilities of the rule with respect to that class. The class with higher value is selected. The Rule Discovery System proposed in [37] applies the naive Bayes classifier to resolve the rule conflict. The posterior probability of a class with respect to all the conflicting rules is determined. Since the joint prior probability of the rules in conflict does not influence thus it is ignored. It is assumed that each conflicting rule is independent from each other. The posterior of each class is determined. The class with higher maximum value is assigned to the sample X that belongs to more than one class. In [130] each conflicting rule votes for its predicted class with a weight. The weights of all the classes are summed up and the class with the highest weight is selected for the samples X that belong to more than one class. The approach in [92] is the same as [37] if there is no training example in the intersection of the conflicting rules. If it exists then it uses the conditional probabilities of the intersecting rules with respect to the class. The double induction approach in [93] proposed the new induction of rules from the examples that are covered by the rules in conflict. The idea introduced in [93] suggested that there is higher chance to find rules that can classify the classes by concentrating on a small subspace of the example space in conflict.

The above described approaches discuss the resolution of conflict using probability and the frequency of the class and by inducing new rules. No approach tries to focus on the antecedents of the rule that influence classification. Along with concept based generalization, the conflict resolution of rules is also suggested based on the importance of individual antecedents of the rule.
The presented approach [15] is the generalization concerning the reduction of a concept criterion by HRI. A conflict resolution is also proposed that is based on the importance of the antecedents of the generalized rule. The application of the generalized rules in the intuitive HRI improves the interaction capabilities of the robot.

7.3 Rule generalization

We introduce an approach to human intention generalization based on the rule generalization. The rule generalization corresponds to the generalization of the transition conditions of FSMs discussed in detail in Chapters 3 and 4. The transition conditions correspond to the actions a_{ki} for the FSMs, discussed in Section 3.2 of Chapter 3. Each transition condition corresponds to a rule that is generalized using HRI. After recognizing the human intention the robot also reacts according to the generalized rules.
The rules are induced online during HRI. The rule generalization is performed by HRI, based on the idea of concept generalization. The robot generalizes the human intention by applying the known action on a group of related objects. The group of objects corresponds to those objects that are similar to the object in some respect on which the human has performed the operation. The process of intention generalization is performed according to the following steps

A. Grouping of the objects
B. Online rule induction
C. Rule application
D. Rule generalization
E. Transition pool

7.3.1 Grouping of the objects

The procedure describes the construction of the classes from the available objects such that the characteristics of all the objects are similar. For example, if we have a group of the following objects, i.e., jug, plate, bowl, book, notebook, shirt and trousers. Then the jug, plate and bowl will fall into one class, book and notebook will fall into second class and shirt and trousers will fall into third class. The reason is that the jug, plate and bowl have similar characteristics of being broken along with other characteristics. The book, note book, shirt and trousers do not have the characteristics of being broken. Similarly shirt and trousers can be dirty and book and note book can not be dirty. There may be more than one different characteristics present in the different classes. The procedure of classifying the objects based on their characteristics is described in Figure 7.2. Initially the set S of classes is empty. Each class C contains the elements having similar type of characteristics.

Input : *n known objects O with known characteristics*
Output : *Set S of all classes* $C_i \quad i = 1,\ldots,m$

1 – $S = \{\ \} \quad C_i = \{\ \}$
2 – $C_1 = C_1 \cup O_1$ *Adding object* O_1 *to set* C_1
3 – $S = S \cup C_1$
4 – **for** *all the objects* $O_j \ \ j > 1$ **do**
5 –   **if** $(COMPARE(O_1, O_j))$ **then**
6 – $C_1 = C_1 \cup O_j$
7 –   **else**
8 – $CLASSIFY(O_j)$
9 –   **end if**
10 – **end for**

Figure 7.2: Objects classification based on their characteristics

At start (Lines 2-3, Figure 7.2), an object is classified into a class C_1. Other objects O are compared with the characteristics of the object in the existing class (Line 5, Figure 7.2).

1 – $COMPARE\ (O_x, O_y)$
2 – **for** *all characteristics* Ch_p *of* O_x **do**
3 –   **for** *all characteristics* Ch_q *of* O_y **do**
4 –   **if** *notSimilar* (Ch_p, Ch_q) **then**
5 –   **return false**
6 –   **end if**
7 –   **end for**
8 – **end for**
9 – **return true**

Figure 7.3: Comparison of objects based on their characteristics

If the object O_j is similar to an object of class C_i then it is added to the class C_i (Line 6, Figure 7.2). The objects are compared with respect to their characteristics (feature) that are already known, shown in Figure 7.3.

The types of characteristics of the objects O are compared with each other (Line 4, Figure 7.3), e.g., if an object O_j has the characteristics of a class C_i, i =1,…,m then for the other object O_k it is checked if O_k also has the same characteristic of class C_i. If O_k does not has the characteristics then it is classified into another class (Line 8, Figure 7.2). The object O_k is checked against an object of all the exiting classes, (Lines 4-5, Figure 7.4). If it matches to an object of exiting class then it is added to that class (Line 6, Figure 7.4). The object O_k is classified into a new class if it does not match with the objects of the existing classes (Line 11, Figure 7.4). The newly created class is added to the set S (Line 12, Figure 7.4). In case of the object classification, if the set S has only one element (Line 3, Figure 7.4) then a new class C_{N+1} for O_k is created and added to the set S (Lines 14-16, Figure 7.4).

$CLASSIFY$ (O)
$\mathrm{N} = |S|$ *number of classes* C_i $i = 1,...,m$
if $(\mathrm{N} > 1)$ **then**
    for $i = 1,...,\mathrm{N}$ **do**
        if $(COMPARE\,(\mathrm{O}, O \in C_i))$ **then**
            $C_i = \mathrm{O} \cup C_i$
            exit
        end if
    end for
    $C_{N+1} =$ **new** $(Class)$
    $C_{N+1} = C_{N+1} \cup \mathrm{O}$
    $S = S \cup C_{N+1}$
else
    $C_{N+1} =$ **new** $(Class)$
    $C_{N+1} = C_{N+1} \cup \mathrm{O}$
    $S = S \cup C_{N+1}$
end if

Figure 7.4: Classification of objects into concerning classes

7.3.2 Online rule induction

The procedure of online induction is given in Figure 7.5. The *n* objects present in the scene are known to robot. The objects may belong to *m* classes which are already known. The robot also understands the human actions and the changes in the scene occurred due to the human action. The characteristics of *n* objects present in the scene are known to the robot.

If an action comprehensible by the robot is performed by the human on an object O_j with characteristics Ch_k then the robot induces a rule considering the characteristics Ch_k of object O_j as the antecedents and the performed action as the consequent of the rule (Lines 1-8, Figure 7.5).

Input : *n known objects O in the scene belonging to m Classes*
Changes in scene due to human action are known
Characteristics Ch_k *of the objects* O_j *in the scene are known*
A performed human action
Output : *Rule describing an action on Object* O_j *with characteristics* Ch_k

1 – **while** (**true**) **do**
2 –   **if** $(actionPerformed\,(O_j))$ **then**
3 – $Rule.Consequent = Action\,(O_j)$
4 –   **for** *all characteristics* Ch_k *of* O_j **do**
5 – $Rule.Antecedent = Ch_{kj}$
6 –   **end for**
7 –   **end if**
8 – **end while**

Figure 7.5: Online rule induction

7.3.3 Rule application

For generalization based on HRI, the robot initiates by applying the induced rules on the suitable objects present in the scene. The suitable objects are determined using the procedure given in Figure 7.6. The input of the procedure includes the n objects along with their characteristics present in the scene. The number r of induced rules are also available from the previously performed step. The output of the procedure given in Figure 7.6 is a set $S = \{\langle L, R, O\rangle_1, \ldots, \langle L, R, O\rangle_h\}$. The set S consists of h hypotheses. Each hypothesis $\langle L, R, O\rangle_i$ consists of a list L_i, a rule R_i, and object an O_i. The List L_i corresponds to a set of characteristics that are similar in the object O_i present in the scene and the antecedents of rule R_i, in the hypothesis i. The List L_i is obtained by the intersection of the set of characteristics of the object O_i and the set of antecedents of the rule R_i (Figure 7.9). The hypotheses are constructed by comparing all the given rules and the known objects present in the scene. The object O_o and the rule R_r are matched and if found similar then a hypothesis is constructed (Lines 3-4, Figure 7.6).

Input : *n known objects O in the scene belonging to m Classes*
Number r of Rules
Output : *Set of hypotheses* $S = \{\langle L, R, O\rangle_1, \ldots, \langle L, R, O\rangle_h\}$
L_i *contains the common characteristics Ch of Object* O_i
and Rule R_i *in a hypothesis* i, $i = 1, \ldots, h$

1 – **for** *all r Rule* R_r **do**
2 –   **for** *all o Object* O_o **do**
3 –   **if** $(MATCH(O_O, R_r, L))$ **then**
4 – $S = S \cup \langle L, R, O\rangle_{i+1}$
5 –   **end if**
6 –   **end for**
7 – **end for**

Figure 7.6: Selection of object for rule application

The similarity is checked by comparing each antecedent A_a of the Rule R with each characteristic Ch_k. If a characteristic Ch_k found similar with antecedent A_a then it is added to the list L (Lines 2-8, Figure 7.7).

INTERSECT (L, R)
1 – **for** *all i antecedents of* R **do**
2 –   **for** *all j characteristics of* L **do**
3 –   **if** $(equal(\mathrm{R}_i, \mathrm{L}_j))$ **then**
4 – $\Omega = \Omega \cup \mathrm{R}_i$
5 –   **break**
6 –   **end if**
7 –   **end for**
8 – **end for**
9 – **return** Ω

Figure 7.9: Intersection between the antecedents R and list L of characteristics

If the List L contains one or more than one element then **True** is returned (Lines 9-10, Figure 7.7) to construct a hypothesis (Line 4, Figure 7.6). If no similarity is found between the antecedents A_a of rule R and the characteristics Ch_k of object O then **False** is returned (Line 12, Figure 7.7) and no hypothesis is constructed.

1 – *MATCH* (O, R, L)
2 – **for** *all k Characteristics* Ch_k *of Object O* **do**
3 –   **for** *all a Antecedents* A_a *of Rule R* **do**
4 –   **if** *match* (A_a, Ch_k) **then**
5 –   *add* (Ch_k, L)
6 –   **end if**
7 –   **end for**
8 – **end for**
9 – **if** *notEmpty* (L) **then**
10 –   **return True**
11 – **else**
12 –   **return False**

Figure 7.7: Matching the objects with respect to the rules

7.3.4 Rule generalization

In the process of generalization the robot applies the rule R_h to the object O_h of the h hypothesis in set $S = \{\langle L,R,O\rangle_1,...,\langle L,R,O\rangle_h\}$. The robot expects the human's feedback on the application of rule R_h to the object O_h. Generalization is performed based on the human action in response to robot's rule application. The robot expects three kinds of responses from the human. The human can accept, reject or correct. The generalization algorithm is given in Figure 7.8. The input of the algorithm includes set S of hypotheses that is generated in the rule application step (Figure 7.6). The robot can recognize the n objects present in the scene and their related characteristics. The human feedback and the changes occurred in the scene due to the human actions are also known to the robot. The output of the algorithm is the possible generalization of the rules in the hypotheses set S. The algorithm in Figure 7.8 proceeds by applying the consequent part of rule R_h on the object O_h for each hypothesis $\langle L, R, O\rangle_h$ in the set S (Lines 1-2, Figure 7.8). If the human accepts the robot's action the rule R_h is updated (Line 4, Figure 7.8) by replacing the antecedents of rule R_h with the list L_h (Lines 1-2, Figure 7.10). The list L_h is produced by the intersection of set of characteristics of O_h and the set of antecedents of R_h (Figure 7.9). All the necessary antecedents concerning the consequent of R_h exist in the list L_h. Since the application of rule R_h on the object O_h is accepted thus the necessary antecedents are also present in the set of characteristics of object O_h. If the robot's action is rejected by the human (Line 6, Figure 7.8) then the difference between the rule R_h and the L_h is performed (Line 7, Figure 7.8). The rejection means that the necessary antecedent / antecedents for the application of the rule R_h do not exist in set of characteristics of the object O_h.

1 – $RULE\_UPDATE(L, R)$
2 – $R.Antecedent = L$

Figure 7.10: Update of the antecedents of rule R by list L

Input : *Human feedback*

n known objects O in the scene

Changes in scene due to human action are known

Characteristics of the objects in the scene

$S = \left\{ \langle L, R, O \rangle_1, \ldots, \langle L, R, O \rangle_h \right\}$

Hypotheses generated in rule application section

Output : *Possible Generalization of rules*

for *all h Hypotheses* **do**
    $Exectue(Consequent\,(R_h), O_h)$
    if $Reward\,(Accepted)$ **then**
        $RULE\_UPDATE\,(L_h, R_h)$
    end if
    if $Reward\,(Rejected)$ **then**
        $\mathbf{L} = R\_DIFFERECE(R_h, L_h)$
        $RULE\_UPDATE(\mathbf{L}, R_h)$
    end if
    if $Reward\,(Rejected + Corrected)$ **then**
        $\mathbf{L} = RC\_DIFFERECE(R_h, O_h)$
        $RC\_RULE\_UPDATE(\mathbf{L}, R_h, A_{Correction}, O_h)$
    end if
end for

Figure 7.8: HRI based rule generalization

The necessary antecedents exist in the rule R_h. Thus a difference is performed between R_h and L_h in order to find out the necessary antecedents. The difference between R_h and L_h results in a list **L** that contains the elements that belong to R_h but do not belong to L_h (Lines 1-13, Figure 7.11).

$R\_DIFFERENCE(\mathrm{R}, \mathrm{L})$

1 – **for** *all i antecedents of* R **do**
2 –   ADD = True
3 –   **for** *all j characteristics of* L **do**
4 –   **if** $(equal(\mathrm{R}_i, \mathrm{L}_j))$ **then**
5 –   ADD = False
6 –   **break**
7 –   **end if**
8 –   **end for**
9 –   **if** (ADD) **then**
10 – $\Omega = \Omega \cup \mathrm{R}_i$
11 –   **end if**
12 – **end for**
13 – **return** Ω

Figure 7.11: Relative complement of L with respect to R

The rule R_h is updated (Line 8, Figure 7.8) by replacing the antecedents of rule R_h with the list **L** (Lines 1-2, Figure 7.10). The list **L** is produced at Line 7, Figure 7.8. In case if the human not only rejects the robot action but also corrects the robot reaction (Line 10, Figure 7.8). Then once again the difference between the rule R_h and the list O_h is performed (Line 11, Figure 7.8). The rejection and correction corresponds to the fact that the antecedents in rule R_h are not exactly related to the characteristics of the object O_h. Therefore only those characteristics are considered as antecedents of the rule that exist in O_h but do not exist in R_h. The consequent of the rule is changed with the correction performed by the human. The difference between the R_h and O_h results in a list **L** containing the elements that belong to O_h but do not belong to R_h (Lines 1-13, Figure 7.12).

```
RC_DIFFERENCE(R, O)
1–  for all i characteristics of O do
2–     ADD = True
3–     for all j antecedents of R do
4–        if (equal(R_j, O_i)) then
5–           ADD = False
6–           break
7–        end if
8–     end for
9–     if (ADD) then
10–       Ω = Ω ∪ O_i
11–    end if
12– end for
13– return Ω
```

Figure 7.12: Relative complement of R with respect to L

The rule R_h is updated (Line 12, Figure 7.8) by replacing the antecedents of rule R_h with the list **L** (Lines 1-4, Figure 7.13). The list **L** is produced at Line 11, Figure 7.8.

$$
\begin{aligned}
&1-RC\_RULE\_UPDATE(L,R,A,C)\\
&2-\ R.Antecedent \quad = L\\
&3-\ R.Concequent \quad = A\\
&4-\ R.IR.Antecedent = C\ ,\quad R.IR.Consequent = A
\end{aligned}
$$

Figure 7.13: Update of the antecedents and consequent of rule R and the Induced rule IR

The consequent of rule R_h is replaced by the human correction (Line 3, Figure 7.13). The Induced Rule (IR) for the newly constructed rule is also updated (Line 4, Figure 7.13). The IR corresponds to the rule induced from the human action or by the human correction.

The rules that are generalized by the process of REJECT and REJECT plus CORRECT are tested before they are moved into the transition pool (Section 7.3.5).

The *intermediate generalized rules* (IGRs) are the rules that are produced by the result of ACCEPT, REJECT or REJECT plus CORRECT, performed by the human during the process of generalization in Figure 7.8. Each IGR has its corresponding IR.

The IGRs generalized by REJECT may lead to false generalized rule. There can be two cases of false generalizations. In Case 1, if the IR is applied on an object of another class then the intermediate generalized rule (IGR) will be false generalization. For example, if IR and the characteristics of the object are as under

IR : IF {*Plate*, *Dirty*, *Intact*} THEN *W.B* (*Wash Basin*)
Object : {*Shirt*, *Dirty*, *Good*}

Then the IGR due to REJECT (Lines 6-9, Figure 7.8) will be as under
IGR : IF {*Plate*, *Intact*} THEN *W.B*
The objects *Plate* and *Shirt* belong to two different classes. The IGR is a false generalization as the robot will put a *Plate* that is *Intact* into the *W.B* without taking into account if it is *Dirty* or not. In Case 2, if IR is applied on the object of the same class and if the IGR does not contain all the necessary antecedents then IGR will be a false generalization. For example, if IR and the characteristics of the object are as under

IR : IF {*A*, *B*, *C*, *D*} THEN $\mathcal{A}$
Object : {*A*, *B*, *D*}

Then the IGR due to REJECT (Lines 6-9, Figure 7.8) will be as under

IGR : IF {*C*} THEN $\mathcal{A}$

If *B* and *C* are the necessary antecedents with respect to the action $\mathcal{A}$ then IGR is a false generalization.
Similarly in case of REJECT plus CORRECT, there exist two cases. In Case 1, if IR is applied on an object of another class then the IGR will be a false generalization. For example, if IR and the characteristics of the applied object are as under

IR : IF {*Plate*, *Dirty*, *Intact*} THEN *W.B*
Object : {*Shirt*, *Dirty*, *Good*}

Then the IGR due to REJECT plus CORRECT (Lines 10-13, Figure 7.8) will be as under

IGR : IF {*Shirt*, *Good*} THEN *W.M* (*Wash Machine*)
IR : IF {*Shirt*, *Dirty*, *Good*} THEN *W.M*

The IGR is a false generalization as the robot will put a *Shirt* that is *Good* into the *W.M* without taking into account if it is *Dirty* or not.
In Case 2, if the necessary antecedents are not considered then the IGR will be a false generalization. For example, if IR and the characteristics of the object are as under

IR : IF {*A*, *B*, *C*, *D*} THEN A
Object : {*A*, *B*, *D*, *E*}

Then the IGR due to REJECT plus CORRECT (Lines 10-13, Figure 7.8) will be as under

IGR : IF {*E*} THEN **A**
IR : IF {*A*, *B*, *D*, *E*} THEN **A**
If *B* and *E* are the necessary antecedents with respect to the action **A** then IGR is a false generalization. Therefore the IGRs are first tested with the procedure given in Figure 7.14 and then moved into the transition pool (Section 7.3.5). The input to the procedure given in Figure 7.14 is the set **IGR**. Each IGR_i $i=1,\ldots, M$ has its corresponding IR. The output of the procedure in Figure 7.14 is the set of IGRs with corrected generalization problems. All the IGRs are tested for all the related objects (Line 1, 2 Figure 7.14) present in the scene. The

related object with respect to an IGR$_i$ corresponds to the object that has all the characteristics concerned to the IGR$_i$.

After IGR$_i$ is applied (Line 3, Figure 7.14), the human responds by accepting, rejecting or rejecting and correcting the robot reaction. If the human accepts the robot reaction then intersection is performed between the IR$_i$ concerned to IGR$_i$ and the characteristics of the object O_j and IGR$_i$ is updated (Figure 7.10) with the results of intersection (Lines 4-6, Figure 7.14). The intersection (Line 5, Figure 7.14) is performed due to the fact that it results in all the necessary antecedents. For example, if we consider the example of Case 2 in REJECT case described earlier, i.e.

IR$_i$: IF $\{A, B, C, D\}$ THEN $\mathcal{A}$

IGR$_i$: IF $\{C\}$ THEN $\mathcal{A}$

O_j : $\{E, B, G, F, C\}$

Input : *Set* IGR *of Intermediate Generalized Rule* (*IGR*)
concerned Induced Rule (*IR*)

Output : *Intermediate Generalized Rule*

```
1– for all Intermediate Generalized Rule IGR_i do
2–   for all applicable Objects O_j for IGR_i do
3–     Apply IGR_i on O_j
4–     if (REWARD == "ACCEPT") then
5–       L = INTERSECT(Characteristics(O_j), IGR_i.IR)
6–       RULE_UPDATE(L, IGR_i)
7–     else if (REWARD == "REJECT") then
8–       L = R_DIFFEENCE (IGR_i.IR, Characteristics(O_j))
9–       RULE_UPDATE(L ∪ IGR_i.Antecedents, IGR_i)
10–    else if (REWARD == "REJECT + CORRECT") then
11–      L = RC_DIFFERENCE(IGR_i.IR, Characteristics(O_j))
12–      RC_RULE_UPDATE(L, IGR_i, A_Correction, Characteristics(O_j))
13–    end if
14–  end for
15– end for
```

Figure 7.14: Evaluation of IGRs for false generalization

The object O_j will contain all the necessary antecedents as the action is accepted for O_j. After acceptance (Lines 4-6, Figure 7.14) the IGR$_i$ will be as under

IGR$_i$: IF $\{B, C\}$ THEN $\mathcal{A}$

The IGR$_i$ updated in the result of ACCEPT (Lines 4-6, Figure 7.14) is added to the transition pool (Section 7.3.5).

In case if the human rejects the robot reaction then the difference given in Figure 7.11 is performed (Lines 7-8, Figure 7.14). The difference results in unconsidered necessary antecedents that are added to IGR$_i$ (Line 9, Figure 7.14). For example, if we once again consider the example of Case 2 with different object O_j in REJECT case discussed earlier, i.e.

IR_i : IF {A, B, C, D} THEN $\mathcal{A}$
IGR_i : IF {C} THEN $\mathcal{A}$
O_j : {A, D, G, F, C}

The difference (Line 8, Figure 7.14) will result in the necessary antecedent and the IGR_i will be updated (Line 9, Figure 7.14). The IGR_i will be as under

IGR_i : IF {B, C} THEN $\mathcal{A}$

If B and C are the necessary antecedents then the generalization is performed but if A is also the necessary antecedent then the IGR_i will be a false generalization. Therefore the updated IGR_i is once again made available to the set **IGR** to be tested if more necessary antecedents do not exist in the IGR_i.

In case if an IGR_i generated due to REJECT plus CORRECT and results in a false generalization. Then that IGR_i is corrected by adding the necessary antecedents. For example, if we consider the Case 1 in REJECT plus CORRECT case described earlier.

IR_i : IF {*Shirt*, *Dirty*, *Good*} THEN *W.M*
IGR_i : IF {*Shirt*, *Good*} THEN *W.M*
O_j : {*Shirt*, *Good*, *Clean*}

After (Lines 7-9, Figure 7.14) the IGR_i will be as under

IGR_i : {*Shirt*, *Dirty*, *Good*} → *W.M*

If the human rejects the robot reaction and corrects the reaction then an IGR_i is updated (Lines 11-12, Figure 7.14). This rule is once again made available to the set **IGR** to be tested. The IGR_i.IR corresponds to the characteristics of O_j and $A_{Correction}$ (Line 12, Figure 7.14).

The advantage of REJECT and REJECT plus CORRECT in Figure 7.14 corresponds to the fact that next time the robot will test the rule on more suitable objects. The suitability means that the chances of rejection or rejection and correction will be less as the IGR is updated due to REJECT or REJECT plus CORRECT. The objects for testing the rule are selected on the basis of IGR as described earlier.

7.3.5 Transition pool

The IGRs are added to the transition pool. Each IGR_i present in the transition pool is matched against another IGR_j. If both the rules match, i.e., the consequent of both the rules IGR_i and IGR_j are similar and at least one antecedent in both the rules is similar. Then intersection of the antecedents of the both the rules is performed, i.e.

```
for all i antecedents of IGR_x do
    for all j antecedents of IGR_y do
        if (equal(IGR_xi, IGR_yj)) then
            IGR_zk = IGR_xi
        end if
    end for
end for
IGR_z.consequent = IGR_x.consequent
```

The process of generalization of IGRs is shown in Figure 7.15. The rules IGR_i and IGR_j are dissolved into another rule IGR_z with the similar consequent and possibly with little number of antecedents as compared to IGR_i and IGR_j.

If the rule is completely generalized then it is moved into pool of generalized rules otherwise it is sent back to the pool of intermediate generalized rules, shown in Figure 7.15. The IGRs are kept in the transition pool until they are completely generalized. There are two cases in which the rules are considered completely generalized. The Case 1 corresponds to the rules that have only one antecedent left. The Case 2 corresponds to the rules that can not be further generalized after **C** cycles of generalization in the transition pool. A generalization cycle corresponds to the fact that an IGR_i in the transition pool once again comes into the transition pool, shown in Figure 7.15. For the generalized rules in Case 2, one copy of the rule is kept in the transition pool for possible generalization. The Case 2 rules are available for use like Case 1. In case if any further generalization occurs for the copy of Case 2 rule kept in transition pool. Then the corresponding generalization is updated in the concerning applied rule.

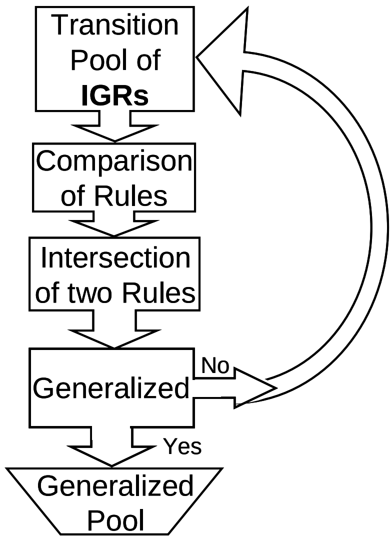


Figure 7.15: Further generalization of IGRs in transition pool

7.4 Rule conflict resolution

The proposed approach generalizes the human intention by generalizing the concept related to the human intention during HRI. The generalization of a concept corresponds to the creation of a generalized rule for a specific human intention. That rule is used to recognize the human intention as well as to interact after the intention recognition. The problem arises if the conflict occurs in the robotic reaction due to the generalized rule. The conflict corresponds to different robotic reactions according to different rules on an object. The robot performs a specified action on the objects according to the generalized rule. The reason of the conflict corresponds to the presence of more than one characteristics of an object. One characteristic relates to one generalized rule and other characteristic relates to another generalized rule. The robot is required to interact intuitively taking into account the generalized rule related to the recognized intention and the characteristics of the objects on which the concerned action is to be applied.

In the rule based classification, all the antecedents of a rule are considered without any distinction. Similarly for conflict resolution, all the approaches discussed earlier (Section 7.2) consider all the antecedents of a rule and decide probabilistically in most of the cases to classify the result for two conflicting rules. The proposed approach for rule conflict resolution takes into account the significance of each antecedent of a rule to resolve the conflict. An antecedent of a rule corresponds to a known characteristics of a known object observed in the scene. The significance of an antecedent is termed as the *importance factor*. The importance factor of an antecedent can have the value in an interval of 1 and 0, i.e., $Importance\ Factor\ (A) \in [1,0]$. The importance factor of an antecedent is calculated as under

$$Importance\ Factor = \frac{\sigma}{\Omega}$$

$$\sigma : Number\ of\ Times\ a\ characteristics\ is\ selected$$

$$\Omega : Number\ of\ Times\ a\ characteristics\ is\ considered$$

Each characteristic known to the robot is assigned an importance factor. The importance factors of the concerning characteristics are embedded along with the antecedents while online rule induction. The importance factors of the characteristics are updated during HRI. For example, an object has characteristics ch_1, ch_2 and ch_3 and the robot has performed an action A on that object according to the IR, i.e.,

$$IR \quad : \text{IF} \quad \{ch_1, ch_2, ch_5\} \quad \text{THEN} \quad A$$

$$\text{Object} \ : \{ch_1, ch_2, ch_3\}$$

If the human has accepted the action A then the rule will be generalized as under

$$IGR : \text{IF} \quad ch_1, ch_2 \quad \text{THEN} \quad A$$

The considered (Ω) characteristics are the antecedents corresponding to the induced rule, i.e., ch_1, ch_2 and ch_5. The selected (σ) characteristics correspond to the antecedents that remain in the rule, i.e., $ch_1$and ch_2.

The conflict resolution using importance factor is explained with an example. The robot knows two generalized rules, i.e.,

$$R1 : \text{IF} \quad Ch_1 \quad \text{THEN} \quad A_1$$

$$R2 : \text{IF} \quad Ch_2 \quad \text{THEN} \quad A_2$$

There exist different objects with one or more than one characteristics, i.e., ch_1, ch_2 and ch_3. Initially all the characteristics will have the same importance factor, i.e., 1. During generalization by HRI, if ch_1 is considered three times and selected two times, ch_2 is considered two times and selected one time, and ch_3 is considered two times and selected two times then the importance factor of ch_1, ch_2 and ch_3 will be 0.66667, 0.5, and 1 respectively.

If the robot has recognized a generalized intention with respect to the rule $R1$, given above, then it will apply the action on the objects where the ch_1 is true. There is an object that has more than one characteristic, i.e., ch_1 and ch_2 then both the rules are applicable on the object. The robot uses the importance factor to resolve the conflict for rule application. The rule A_1 will be applied as the importance factor of ch_1 is greater than the importance factor of ch_2. In case if an object has the characteristics, i.e., ch_1 and ch_3 then rule A_1 will not be applied as the importance factor of ch_3 is greater than the importance factor of ch_1.

In case if the generalized rule has more than one antecedent then the antecedent with highest importance factor is used for conflict resolution. The highest importance factor antecedent is also used to select the objects for the generalized rule application.

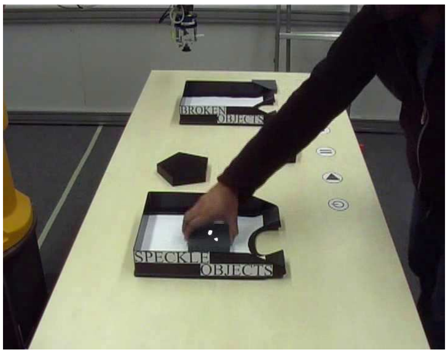
7.5 Experiments

The experiments are performed with a robotic arm of six degrees of freedom. The workspace regarding the experiments consists of a table with different known objects on the table as shown in Figure 3.9. The workspace is observed by an overhead Firewire camera that delivers the video frame of size 640 x 480 pixels at a speed of 30 frames / sec. The robot operations are implemented using robot programming language V++. Image processing is performed using common Edge and Skin detection [161] algorithms and Fourier descriptors [171]. HRI based experiments are performed by performing different known actions and using the buttons shown in Figures 7.16 (a-j). The buttons on the table include Stop, Learn, Pause, Play, and Reset. The Stop button is used to stop a robot reaction. The Learn button is used to start the learning of a human intention and generalization procedure. The learning corresponds to learning a human intention in terms of a Finite State Machine. The Learn button is also used as reject button during the HRI. The Pause button is used to temporarily stop the robot reaction. The Play button is used to test the generalization performed during the HRI. The Reset button is used to remove the learned and generalized human intention in terms of Finite State Machine. The learning and generalization procedure is explained with one of the performed experiments, as shown in Figure 7.16. The Figures from 7.16(a) to 7.16(f) describe the learning and the performed generalization. The Figure 7.16(a) shows different objects present in the scene. The objects belong to one class and one characteristic is significant for the concerning action. Therefore the procedure in Figure 7.14 is not considered. The objects include two squares, two pentagons, and two containers. One container is labelled as SPECKLE OBJECTS and other is labelled as BROKEN OBJECTS. One box and pentagon have speckles on them and additionally that pentagon has a hole (broken) in the centre.

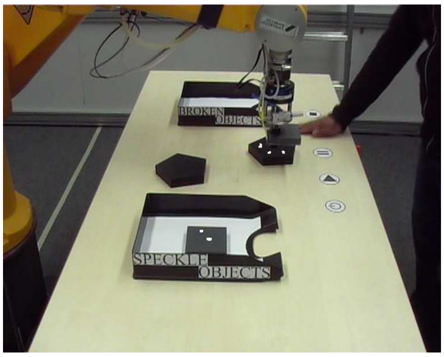
The other box and pentagon are intact and without speckles. The human starts the learning phase by putting the hand on Learn button. The human picks and places the speckled box into the speckle container as shown in Figure 7.16(b). Afterwards the robot induces a rule and starts generalizing that rule. The robot picks and tries to place the intact and without speckle square into the speckle container, as shown in Figure 7.16(c). The human rejects the robot reaction by putting the hand on Learn button as shown in Figure 7.16(c). The robot undoes the reaction and tries to pick and place the intact and without speckle pentagon into the speckle container as shown in Figure 7.16(d). The human once again rejects the robot reaction by putting the hand on Learn button as sown in Figure 7.16(d). The robot once again does the possible generalization. Next the robot picks the speckled pentagon with the hole in the pentagon and tries to place into to speckle container. That is also rejected by the human and robot undoes the reaction. The human performs the correction by placing the speckled and broken pentagon into the broken container as shown in Figure 7.16(f). The robot also updates the importance factors along with the rule generalization. In the testing phase, the human starts by putting the hand on the Play button. The human picks and places the speckled and intact square into the speckle container, as shown in Figure 7.16(g). The robot reacts according to the generalized human intention. The robot picks and places the speckled square, pentagon and triangle into the speckle container as shown in Figures 7.16(h), 7.16(i) and 7.16(j).

The robot does not pick and place the speckled pentagon with hole in the center due to the high importance factor of broken characteristic as compared to the speckle. It is shown in Figure 7.16(j).

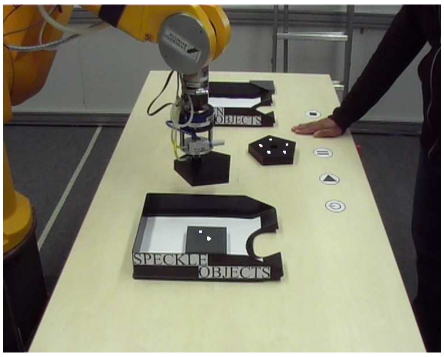
(a): Speckled and non speckled objects



(b): Pick and place of speckled object

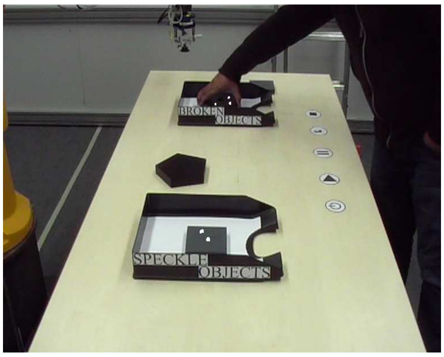


(c): Rejection of the robot reaction

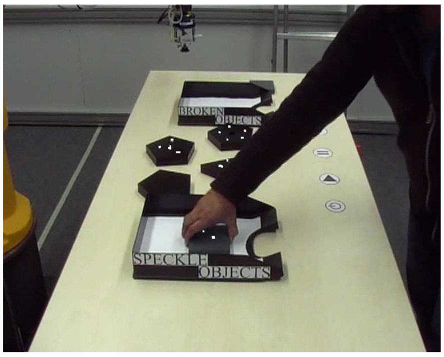


(d): Rejection of the robot reaction

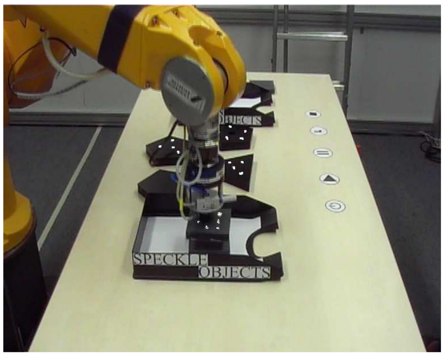
(e): Robot picks a speckled Pentagon



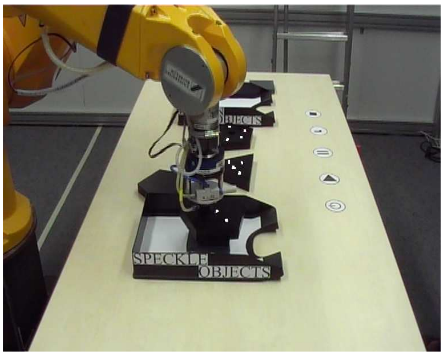
(f): Human correction concerning robot reaction



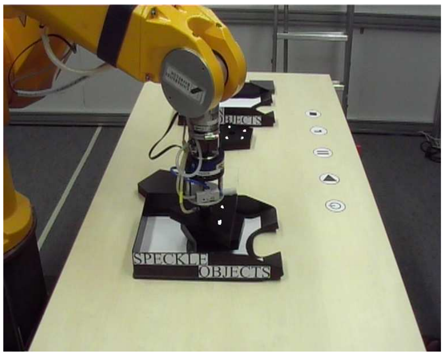
(g): Pick and place of speckled object



(h): Robot places a speckled object in response



(i): Placement of speckled object in response



(j): Placement of speckled object in response

Figure 7.16: Intention generalization by HRI

The graph in Figure 7.17 represents the generalization capability of the robot. The generalization axis represents the number of objects acted upon by the robot while reacting to the recognized human intention. The green bars represent the results with generalization and red bars represent without generalization.

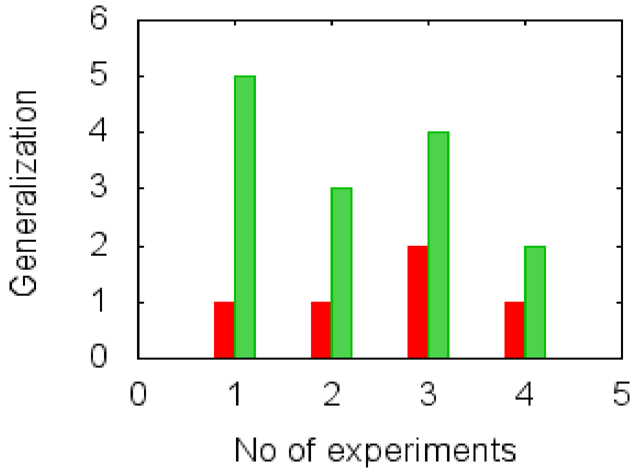


Figure 7.17: Graph for intention generalization by HRI

The experiments were performed on the objects shown in Figures 7.16 (a-f). The experiments number 1 in Figure 7.17 corresponds to the placement of speckled objects into the speckled tray. The human picks and places a speckled square into the speckled tray. In a non generalized HRI, the robot picks and places another square that is speckled into the speckled tray and stops. In the generalized HRI, the robot picks and places all the speckled objects other than the objects that have hole in them. The objects that have hole in them are considered broken. The objects having speckle on them are considered dirty and without speckle are considered clean. The antecedent (characteristic) of broken has high importance factor as compared to the dirty. Therefore a dirty object that is also broken is not operated as the HRI corresponds to picking and placing the dirty objects into the speckled tray. The second experiment corresponds to the placement of intact objects, the third experiment corresponds to the placement of clean objects, and the fourth experiment corresponds to the placement of broken objects.

The graph in Figure 7.18 shows the rule conflict results. The RDS [37] , CN2 [32] and C5.0 [130] produce false results as they resolve using probability and do not consider the individual antecedents as importance factor does.

The success axis in Figure 7.18 represents the binary scale, i.e., either all the expected objects are acted upon or a few are left. If all the expected objects according to the human intention are operated then the result is considered 1 and 0 otherwise. The first experiment shown in Figure 7.18 corresponds to the resolution of the conflict concerning the objects with the hole (broken) and the objects with the speckles (dirty) on them. In the generalized HRI, using the importance factor the robot takes into account the importance factor of individual characteristics of each object while applying the rule of placing the speckled object (dirty) into the container of speckled object (wash basin). The robot does not pick and place a dirty object that is broken. The importance factor of broken is greater than that of dirty. It means that a dirty object can be washed for reuse and is supposed to be placed in the wash basin. A dirty and broken object is not required to be placed in the wash basin because it is broken and thus useless. The RDS, CN2, and C5.0 use the probability without taking into account the significance of individual antecedents and thus produce false results. Similarly the second experiment corresponds to the conflict resolution between the dirty and different shaped objects, i.e., triangles, squares, and pentagons. The robot is supposed to pick and place all the dirty objects no matter of which shape into the wash basin. Using the importance factor, the robot picks and places all the dirty objects into the wash basin. Using the probabilistic conflict resolution approaches RDS, CN2, and C5.0 the robot does not pick and place all the dirty objects. Similarly the third experiment corresponds to the placement of no speckle object (clean) into the concerned container. Using the importance factor the robot picks and places all the clean objects and using the probabilistic approaches specific shaped objects are left. The probabilistic approaches RDS, CN2, and C5.0 do not perform well due to the fact that they decide probabilistically and do not consider individual antecedents of the rule with the concerning significance.

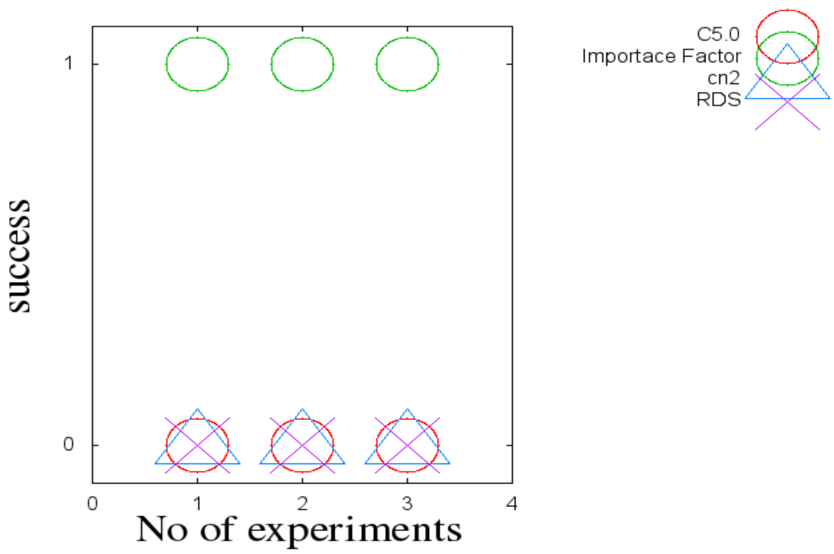


Figure 7.18: Graph for conflict resolution in intention generalization by HRI

7.6 Summary

In this chapter we have introduced a generalization approach for the human intention generalization. The focus of the approach is intuitive HRI by human intention generalization. The intention generalization corresponds to the understanding of the key concept of the human intention and to react accordingly to that concept. The approach describes the rule generalization by HRI. This rule is then embedded into the probabilistic FSM, discussed in detail in Chapter 3. That is used to recognize the general human intention and to react generally. The experiments performed with the robotic arm demonstrated the usefulness of generalization approach, i.e., the robot reacts generally according to the human intention. For example, if the human has intention of putting the speckled objects into the speckled container then the human picks and places a speckled square into the speckle container. The robot recognizes the generalized human intention of picking and placing the speckled objects into the speckled container. The robot places all the speckled objects into the speckle object container. The robot also takes into account the importance factor and does not places an object into speckle object container that is speckled and also broken.

The approach enables the robot to react intuitively in a known scenario that was not explicitly instructed to the robot. The known scenario corresponds to the known objects present in the scenario and the known related actions. The generalization capability of robot increases the range of intuitive reactions.

The false generalization problem is resolved by testing each IGR$_i$. The solution provided for false generalization resolves the problem but it may not produce the optimal generalization. The optimality of the resolution of false generalization depends on the present objects. The objects are used to resolve the generalization problem. The optimality of generalization with respect to the objects is explained using two cases. In Case 1, the false generalization does not consider the necessary antecedents. For example, consider IGR$_i$ with concerned IR$_i$ and the available object O_j that is used to resolve the false generalization.

IR$_i$: IF $\{A, B, C, D\}$ THEN $\mathcal{A}$

IGR$_i$: IF $\{C\}$ THEN $\mathcal{A}$

O_j : $\{A, B, G, F, C\}$

After resolving the generalization problem (Line 6, Figure 7.14) IGR$_i$ becomes as under

IGR$_i$: IF $\{A, B, C\}$ THEN $\mathcal{A}$

If B and C are the necessary antecedents then the generalization is solved. The antecedent A decreases the optimality of generalization as it is unnecessary antecedents for action $\mathcal{A}$. Thus the optimality of the generalization depends on the object used for generalization. The IGR$_i$ may be optimized in the transition pool. If all the objects present in the scene are of diverse characteristics then the generalization can be optimal and vice versa.

In Case 2 the false generalization (IGR$_i$), produced due to the different class object, is discussed. For example, consider the IGR$_i$ with concerned IR$_i$ and available object O_j that is used to resolve the false generalization.

IR$_i$: IF {*Shirt*, *Dirty*, *Good*} THEN *W.M*

IGR$_i$: IF {*Shirt*, *Good*} THEN *W.M*

O_j : {*Pants*, *Dirty*, *Good*}

The generalization problem IGR$_i$ is resolved by ACCEPT, given in Figure 7.14.

IGR$_i$: IF {*Dirty*, *Good*} THEN *W.M*

The resolved IGR$_i$ is generalized differently if the O_j is as under

O_j : {*Shirt*, *Dirty*, *Good*}
Then the IGR_i resolved would be as under
IGR_i : IF {*Shirt*, *Dirty*, *Good*} THEN *W.M*
These resolved IGRs are moved to the transition pool. There the IGRs are further generalized. Moreover, if the objects available for generalization are properly classified and one characteristic is significant for the concerned action then the algorithm in Figure 7.14 is not required.
Furthermore, the robot needs to distinguish between the situations when he needs to react based on the generalization or based on specialization according to the human intention.

Chapter 8

Conclusions

In this chapter, in Section 8.1, 8.2, 8.3, 8.4 and 8.5 the presented work is concluded. Section 8.6 provides an outlook with respect to the presented research work.

In the presented research work, five contributions to the area of intuitive HRI are discussed. The discussed contributions mainly correspond to the intention of the cooperating human, i.e., how the robot can improve its intuitive interaction with the human based on different aspects of the human intention. The following intention aspects of the interacting human are considered to improve the intuitive HRI.

A. Intuitive HRI by intention recognition
B. Intention learning
C. Proactive HRI
D. Interaction in unknown scenarios
E. Intention generalization

8.1 Intuitive HRI by intention recognition

The recognition of the human intention plays a key role in human-human interaction. It is equally significant for HRI. An intention recognition approach based on probabilistic FSMs is proposed. A FSM represents a human intention. The FSM corresponds to a human action sequence and / or the concerning scene changes in the HRI workspace. Each FSM carries a probabilistic value that is called the weight of the FSM. The weight of the FSM describes how closely the FSM represents the human intention. The FSM with highest weight corresponds to the best estimated human intention and vice versa. The weights of the FSMs are updated at each new observation in HRI workspace. The suggested solution is applicable for both explicitly and implicitly communicated intentions. Explicit intention communication addresses to all the situations where the human commands the robot and implicit intention communication addresses to all the situations where the human does not engage the robot but robot actively starts the cooperation by recognizing the intention through scene information and human actions.

8.2 Intention learning

It is quite difficult to anticipate all the real time situations a robot may encounter. Therefore the capability of extension is inevitable for a robot. Three different cases are discussed to learn the new human intentions. The cases discussed the mapping of human intention to the corresponding observation sequence. The discussed Case 1 corresponds to the mapping between the sequence of the known actions and the known human intention. The known human intention corresponds to the scene information. The Case 2 corresponds to the situation in which the actions are known to the robot but the human intention is inferred using the learning parameters. In the Case 3 the human actions and the human intentions are not given. The robot infers the human actions from the scene changes and the human intention is also inferred from the scene information. The mechanism used for intention recognition consists of the probabilistic FSMs. For online intention recognition a FSM regarding to a specific intention is constructed online.

The capability of learning the new intention can be made more intelligent. The intelligence corresponds to the fact that the robot can take a decision about the human intention. The decision corresponds to the fact that the human intention is already known to the robot or not. If not then the robot is supposed to learn the new human intention. The robot should also be intelligent enough to recognize the start and end of the sequence of action and / or scene changes concerning the new human intention. Moreover the robot must also be able to decide if the human actions correspond to an intention or they are just random actions. The random actions correspond to the actions that are performed unintentionally by the human.

8.3 Proactive HRI

Proactivity is also an important aspect in intuitive HRI. For a robot to be proactive in HRI, he needs to quickly recognize the human intention. A probabilistic approach for the intuitive HRI in an ambiguous situation is presented. Two cases are discussed for quick robot response for intuitive HRI. In first case, trigger state selection algorithm is discussed that describes how the trigger states are selected in case of similar state sequence of different FSMs. In the second case the proactive nature of HRI is discussed at lower level, i.e., the robot is required to prematurely decide in an ambiguous situation that may lead to two or more different human intentions. The ambiguous human intentions are handled by the transition weights that correspond to the weights assigned to the transition conditions in the FSMs.

The robot can extend its capability of proactiveness by taking into account the daily routine work and concerning intentions of the interacting human. The robot can consider which tasks are most probable, which tasks are least probable, etc. Similarly the robot can consider the habits of the interacting human and customize itself according to them for being proactive. The domain information about the HRI workplace can also improve the proactive behaviour of the robot. The domain information can help the robot in quick decision making.

8.4 Interaction in unknown scenarios

In reality a human can encounter the situation while interacting with other human that he does not know the intention of the other human. The human can either intuitively interact depending on the previous experiences or he can simply ask about the unknown intention. The presence of this capability in robots is also important for HRI. A probabilistic approach for the robotic reaction in the known scenario with unknown human intention is presented. The approach corresponds to a RL-based interaction algorithm. In which the robot performs the most suitable action in order to cooperate with the human without knowing the human intention. If the action performed by the robot corresponds to the human intention then the robot action is accepted by the human. Otherwise the human rejects the robot action and expect from the robot to act differently. The human can either wait for the expected action from the robot or he can simply correct the robot according to his expected action. The most

suitable action selection is performed probabilistically. The robot considers the predicted action, weight of the predicted action, action probability, and the history support of the action. The value of all the action hypotheses is calculated using the considered aspects.
The capability of the robot for interaction with the human without knowing his intention can be improved by providing the domain knowledge to the robot. The domain knowledge corresponds to the end results of the known tasks concerning the unknown human intention. Similarly the interaction can also be improved by the agreed upon procedures. The agreed upon procedures correspond to the gestures that are known the robot and the human. The human can guide and convey his message to the robot using the agreed upon procedures.

8.5 Intention generalization

A generalization approach for the human intention is introduced. The intention generalization corresponds to the understanding of the key concept of the human intention and to react according to that concept. The approach describes the rule generalization by HRI. A rule is induced online and then that rule is generalized by removing the unnecessary antecedents according to the human intention during HRI. This rule is then embedded into the probabilistic FSM. This rule is used to recognize the general human intention and to react according to the general intention.
The robot can extend the range of its intuitive interaction with the human by the intention generalization. For being intelligent partner of the human in HRI, the robot must distinguish the situations in which he should generalize and the situations in which he should specialize the human intention. The robot should also customize itself according to the interacting human with respect to its intention generalization capability.

8.6 Outlook

The presented research work can be extended in multiple ways as described in Section 8.2, 8.3, 8.4 and 8.5. The extension mainly corresponds to the human intention with applications in the HRI workspace.
The robot possessing the capabilities of intention recognition, proactivity, and intention generalization may interact more safely with the human in a HRI workspace. The safety in HRI can be improved based on the intuitive HRI. The robot can anticipate the current and future human intentions. The robot can predict the future locations of the human. The robot divides the HRI workspace into cells. The current human location along with the future possible locations can be considered as the occupied cells. The robot planes its motion trajectory by taking into account the occupied cells to avoid human robot collision. The robot can differentiate between the virtually occupied locations with respect to the probability of being occupied. The robot can also consider the cells with low occupancy probability for its path planning to be efficient in its motion. The robot can also ignore the cells with more than zero occupancy probability in order to improve the safety in HRI.

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