

Design of an Autobiographical Memory for a Social Robot Supporting Human-Robot Interactions

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Thesis submitted in partial fulfillment of the requirements for the degree Master
of Science in Electrical Engineering

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DECLARATION

I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Dr.A.G.B.P.Jayasekara

Abstract

Artificial companions harnessed with long-term interaction capabilities are useful for a variety of applications. The ability of recalling past memories during ongoing interactions and adapting behavior according to the interaction partner are the reinforcements of a successful long-term interaction. Memory has been figured out as the underlying mechanism which governs these behaviors. Even though a number of efforts have been taken, the capabilities of existing artificial companions have not reached to human level. Modeling the memory is still remains as one of the challenges for achieving long-term human robot interaction (HRI). Memory based system have been designed for remembering users, their preferences and past emotionally salient events with them. However, these systems face difficulties when interacting with a group of users. They have certain limitations including remembering user groups, relationships between users to mention a few. The requirement of memory model that has human-like capabilities has not been fulfilled yet.

This work presents an Autobiographical Memory (AM) based intelligent system which can be applied for HRI. The AM comprises of three layers namely self layer, people layer and episode layer. Methods have been developed for extracting, storing, updating and recalling user information during HRI. A system has been designed for learning user preferences through human friendly interactions and providing user adaptive services for each user in a multi-user domestic environment. Furthermore, the system is capable of adapting according to users hidden preference and changes of preferences. The robots memory has been structured in such a way that it can easily remember the user groups and the relationship between users.

The proposed AM is also capable of remembering spatial information and sequence of past actions. A novel method has been proposed for arranging a set of objects in a surface while interpreting uncertain spatial and qualitative distance information in user commands. Performance of the system has been validated by using a set of experiments. The proposed AM based intelligent system is capable of supporting long-term human-robot interactions.

***Keywords-* Social robotics, Autobiographical memory, Human-robot interactions, Social interactions, Long-term human-robot interactions**

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TABLE OF CONTENTS

Declaration	i
Abstract	ii
Acknowledgments	iii
Table of Contents	vii
List of Figures	x
List of Tables	xii
1 Introduction	1
1.1 Background	1
1.2 Problem Statement	2
1.3 Thesis Overview	3
2 Literature Review	5
2.1 Assistive Social Robot	5
2.2 Long-Term Human-Robot Interactions	7

2.3	Importance of Robot Memory in Long-Term Human-Robot Interactions	8
2.4	Robot Memory Models	8
2.4.1	User Preference Learning and Interaction Adaptation	10
2.5	Human Autobiographical Memory (AM)	12
2.6	Spatial Consideration of Robot Memory	13
2.7	Current State of Memory Based Interactive Systems	14
2.8	Summary	15
3	Design of Robot Autobiographical Memory	17
3.1	System Overview	17
3.2	Robot Memory	19
3.2.1	Robot Autobiographical Memory (AM)	20
3.3	Interaction Manager	24
3.3.1	Finite State Machine	25
3.4	Summary	27
4	Updating Autobiographical Memory During HRI	29
4.1	Information Extraction Mechanism	29
4.2	Management of Autobiographical Memory	32
4.2.1	Storing Information in Autobiographical Memory	32

4.2.2	Recalling the Information in Autobiographical Memory . . .	32
4.3	Experimental Results	33
4.4	Summary	38
5	Learning User Preferences and Adaptation of Robot's Behavior	40
5.1	User Preference Learning from User Utterances	41
5.1.1	Learning from the User's Own Utterances	41
5.1.2	Learning from Another Person's Utterances	42
5.2	Inferring and Decision Making Module	42
5.2.1	Inferring Based on Users Statements	43
5.3	Experiments and Results	44
5.3.1	Ability of Learning User Preferences from Users Statements	45
5.3.2	Ability of Learning User Preferences Based on Robot's Ex- periences	46
5.4	Summary	48
6	Spatial Consideration in Autobiographical Memory	50
6.1	Understanding Uncertain Spatial and Qualitative Distance Infor- mation in Overall Object Placement Related User Commands . . .	51
6.1.1	System Overview	53
6.1.2	Structure of the User Commands Related to Overall Ar- rangement of Objects	55

6.1.3	Uncertain Information Understanding Module	57
6.1.4	Experimental Results and Discussion	64
6.2	Encoding Spatial Information in Autobiographical Memory	69
6.2.1	Experiments	69
6.3	Summary	73
7	Conclusions	74
7.0.1	Evaluation of the System	74
7.0.2	Limitations of the System	75
7.0.3	Recommendation for Future Developments	76
	List of Publications	77
	Bibliography	86
A	Experimental Data of Chapter 5	87
A.1	Ability of Learning User Preferences Based on Robot's Experiences	87

LIST OF FIGURES

1.1	Problem space of the research	3
2.1	Sophia robot developed by Hanson Robotics	5
2.2	Estimated unit sales of social and entertainment robots worldwide from 2015 to 2025 (in millions)	6
2.3	Pepper robot	7
2.4	Eva conversational agent	12
2.5	Knowledge structures in autobiographical memory.	13
3.1	System overview.	18
3.2	knowledge structures of the proposed autobiographical memory .	21
3.3	Knowledge representation in the people layer.	22
3.4	Design of the people and episodic layers of AM	24
3.5	Finite state machine diagram	26
3.6	Dialogue flow for user learning state. Note: only the important part of dialogue flow has been shown.	27
3.7	Dialogue flow for action selection state	28

4.1	Information extraction process	30
4.2	Part of tagging of user statement	31
4.3	MIROb robot platform and a subject during the experiment	33
4.4	Variation of the robot's states and the dialogues with the users during the experiments. Note that the time axis is not drawn to a scale and only the important parts of the dialogue flows are shown.	35
5.1	The classification of user statements.	41
5.2	Contexts and the available service options of beverage and snack suggestion scenario.	45
6.1	Functional overview of the modified system	54
6.2	Spatial area categorization. The probability of relation for each category is indicated by color contours.	56
6.3	Structure of user commands	57
6.4	(a) and (b) show output membership function of X axis and Y axis respectively. Here, T_W and T_L are the width and the length of the table. Fuzzy labels: L, M, R, F, B, are defined as Left, Middle, Right, Front and Back respectively	59
6.5	The MIROb and the user during the experiment.	64

6.6 The arrangements done by the human: (a) “Place all the objects on the right side of the table” (b) “Place all the objects in the middle of the table” (c) “Keep the middle of the table free” (d) “Keep the right side of the table free”; The arrangements done by the robot: (e) “Place all the objects on the right side of the table” (f) “Place all the objects in the middle of the table” (g) “Keep the middle of the table free” (h) “Keep the right side of the table free” 66

6.7 The arrangements done by the human: (a) “ Place all objects compactly on the front side of the table” (b) “Place all objects little separately on the front side of the table” (c) “ Place all objects medium separately on the front side of the table” (d) “ Place all objects fully separately on the front side of the table” ; The arrangements done by the robot: (e) “ Place all objects compactly on the front side of the table” (f) “Place all objects little separately on the front side of the table” (g) “ Place all objects medium separately on the front side of the table” (h) “ Place all objects fully separately on the front side of the table”. In this case, 3 objects were considered for the arrangement 67

6.8 The arrangements done by the human: (a) “ Place all objects compactly on the front side of the table” (b) “Place all objects little separately on the front side of the table” (c) “ Place all objects medium separately on the front side of the table” (d) “ Place all objects fully separately on the front side of the table” ; The arrangements done by the robot: (e) “ Place all objects compactly on the front side of the table” (f) “Place all objects little separately on the front side of the table” (g) “ Place all objects medium separately on the front side of the table” (h) “ Place all objects fully separately on the front side of the table”. For this case, number of objects were increased to 7 68

LIST OF TABLES

2.1	Summary of the literature review	16
3.1	Defined dialogues of the robot	27
4.1	Chunking rules	31
4.2	Initial content of the User Table	33
4.3	Initial content of the Family Member Table	34
4.4	Initial content of the Event Table	34
4.5	Content of the User Table after the interaction with user A	37
4.6	Updated Family Member Table after the interaction with user A	37
4.7	Updated Event Table	38
4.8	Updated Action table	39
4.9	Updated Conversation Outcome Table in the episodic layer	39
5.1	Adverbs of frequency and their probabilities	42
5.2	Responses for the Likert questionnaire	46
5.3	Experiment results for user 1	47
5.4	Experiment results for user 4	48

6.1	Relationship of i and j with spatial areas	59
A.1	Content of the Preference Rule table	90
A.2	Experiment results for user 1	91
A.3	Experiment results for user 2	91
A.4	Experiment results for user 3	91
A.5	Experiment results for user 4	92

INTRODUCTION

1.1 Background

The portion of the population aged 60 years or over is growing at a rate of 3.26 per cent per year. By 2050, all major areas of the world except Africa will have nearly a quarter or more of their populations aged 60 or above [1]. The aging population face difficulties in performing daily activities on their own. At the same time, the proportion of people with disabilities is also increasing. However, the world is facing a growing shortage of caretakers due to the decrease in supply and the increase in demand [2]. As a solution for that, assistive social robots are being developed for assisting elderly or disabled population in order for them to achieve an independent living [3–5]. Generally, the natural domestic environment is multi-user. Therefore, requirement of assistive social robots that are aware of the needs of all of the users including the needs of aged persons has increased.

These robots are expected to engage in humans daily life and maintain long-term relationships with them. Hence, they must possess human-like long-term interaction capabilities for instance, recalling past memories, learning others' preferences and adapting behaviors according to the interaction partner. Thus, prior knowledge about each user is essential for a social robot to maintain a successful interaction with each user in multi-user environment. As the service requirement and level of satisfaction differ from person to person, the knowledge related to each user is helpful for the robot to shape the service according to the user

preferences.

Memory is the fundamental mechanism of long-term interactions, as it involves in all the aspects ranging from identifying a person to adapting own behaviors. Memory has been identified as one of most complex element to model. Therefore, most of exiting memory models have been limited to address a specific domain. Yet, a robot memory that can contribute to all aspects of human like long-term interactions has not been developed. As a result, performance of existing social robots has limited.

1.2 Problem Statement

Ever since the day that social robots start to involve humans everyday lives, the idea of term ‘social robot’ was deviated from a machine to a companion. These robots are expected to initiate social relationships with humans and maintain them over an extended period of time. The social robots that have been designed for long-term HRI must fulfill basic needs such as memory and adaptation, appearance, affective interactions, empathy, continuity, and incremental novel behaviors.

In order to fulfill most of above needs a memory about each interaction partner is essential. Thus, Robot memory plays the central role in long-term interactions. The robot must be able to remembering users, their biographical information and significant past experiences with them. Moreover, robot must be capable of adapting the interaction based on previously acquired information about each user. As the social robots are expected to engage in non-expert users who have different educational and social backgrounds, the interaction between robot and the user must be human friendly. The problem space of this research can be depicted in Figure 1.1.

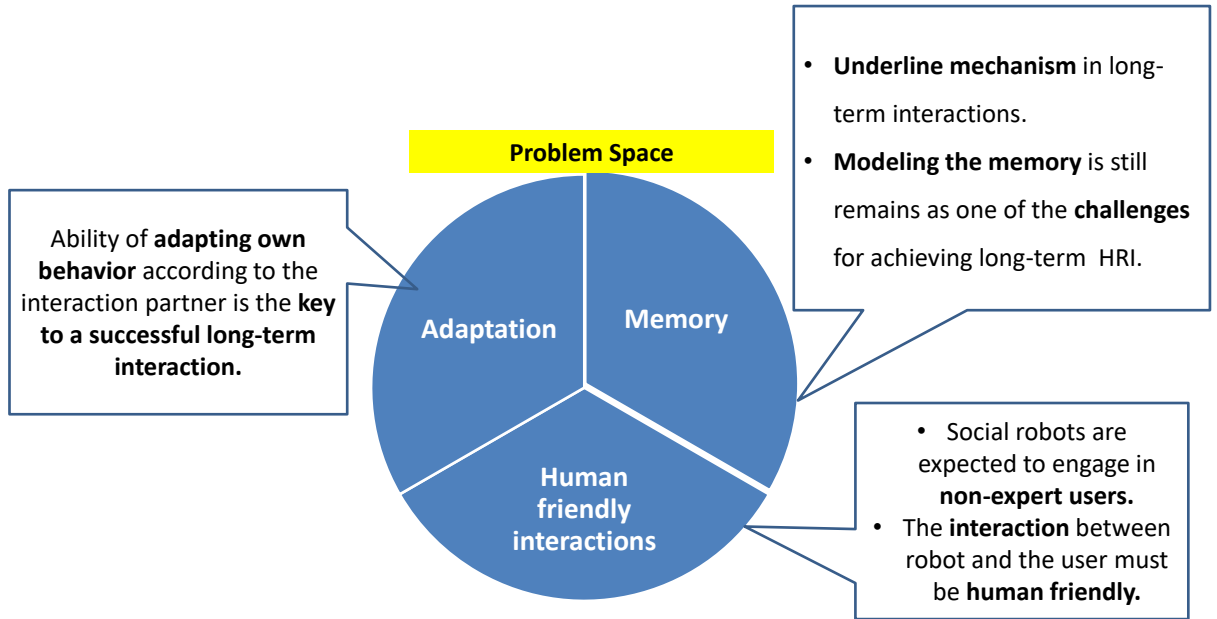


Figure 1.1: Problem space of the research

1.3 Thesis Overview

This thesis consists of seven chapters. A brief introduction about each chapter is given below.

Chapter 1 : Presents an introduction about the thesis including background and research questions that are addressed by this work.

Chapter 2: Presents a literature review on past research studies and related concepts.

Chapter 3: Explains the design and functionalities of robot AM and the overall system. Furthermore, it explains each and every main modules. This chapter provides a detailed description of proposed robot AM, specially its layered architecture and knowledge representation in each layers. It also explains the interaction manager module and its finite state machine that governs the communication between user and the robot.

Chapter 4: Explains how the AM is updated during HRI. This chapter presents

information extraction and memory management mechanisms of the system. Furthermore, it presents a set of experiments that has been conducted to examine the behaviors and performance of memory and entire system during HRI.

Chapter 5: Presents a study on application of the robot AM for user preference learning and adaptation in long-term HRI. The study was conducted based on a snack and beverage suggesting scenario. This chapter introduces a novel method of preference learning. In addition to that, methods of inferring and decision making has been discussed.

Chapter 6: Presents a study on usage of robot AM during spatial arrangement related tasks. This study investigates how AM can be used to remember spatial information of objects together with a sequence of past actions related to object arrangement tasks. Moreover, this chapter proposed a novel method to understand uncertain spatial and qualitative distance information in user commands related to overall object arrangement.

Chapter 7: Presents the conclusion of this research, including capabilities and limitations of the system together with possible future developments.

LITERATURE REVIEW

2.1 Assistive Social Robot

Social robot is defined as an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact [6]. A considerable amount of literature is available on social robotics. Most of them agrees that a social robot should possess certain characteristics such as conversational abilities, cognitive abilities, emotional competence, social-cultural competence, natural language understanding, adaptivity, usefulness and long-term interaction capabilities [7].

Usage of social robots has increased during past few years. In year 2016 estimated unit sale of social and entertainment robots was 2.13 millions. It is around 25% growth when compares to the year 2015. It is estimated that more than

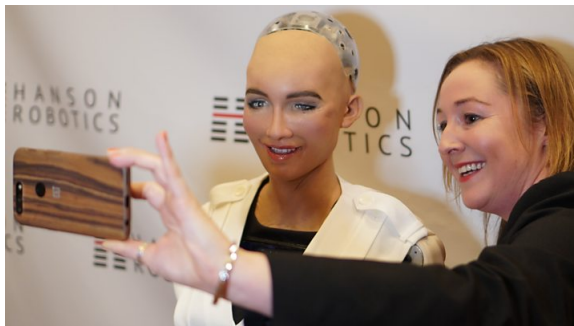


Figure 2.1: Sophia robot developed by Hanson Robotics

13 million sales units of social and entertainment robots will be sold out in the period between year 2015 to 2019. By year 2020 the sales of service and entertainment robots are predicted to be reached 4.22 million units. Social robots are used both in public and domestic environment. They can be used for variety of purposes as research platforms, as toys, as therapeutic aids, or as educational tools [8]. In public environments, they are commonly employed as receptionist and as guides in public places such as museum and shopping malls [9] [10]. Authors in [11] has pointed out three potential application categories for domestic robots: 1) Entertainment, 2) Everyday tasks and 3) Assistance to elderly and handicapped people. The requirements for each applications have been specified in performance matrices.

Social robots are expected to serve a broad user community comprised of humans belong to different age groups, genders and social and cultural environments. According to the Kaplan [12] social robot has to find his value in human life by meeting human needs in both long-term and short-term usage. In most of applications they have to engage in short-term interaction which can tolerate to treat all users in same manner. But when its come to long-term interactions where the robot become a part of person’s life, robot must be able to treat the him in distinct manner [13].

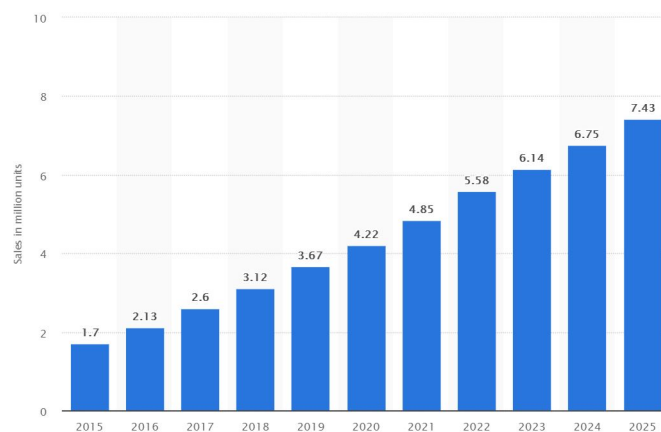


Figure 2.2: Estimated unit sales of social and entertainment robots worldwide from 2015 to 2025 (in millions)

2.2 Long-Term Human-Robot Interactions

The idea of having social robots that can have long-term social relationships with their users emerged in 1990s [8]. In present, social robots involve humans' everyday lives more than ever. Particularly, robots have become a part of the domestic environment. The role of social robot in humans life varies from assistant to trainer [14–17]. Since these robots have to engage with user over a extended period of time, the ability of building long-term rapports with humans is essential for them [18].

Humans have the potential to maintain relationships over a extended period of time and adapt their behaviors according to the partner. Number of previous research studies has tried to develop social companions that can have human-like interaction capabilities [19]. However, the long-term interaction capability of the robot has not developed up to humans' level. Specially, existing robots are lack of competence in non-continuous, temporally extended social interactions [20].

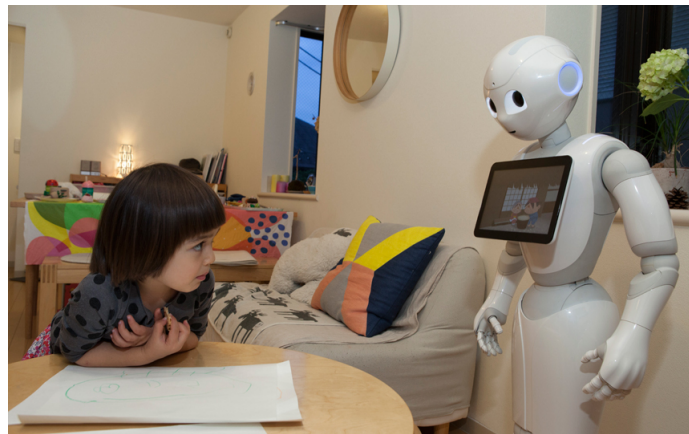


Figure 2.3: Pepper robot

2.3 Importance of Robot Memory in Long-Term Human-Robot Interactions

The goal of developing social robot capable of interacting over long period of time has not still been achieved due to a variety of technical and theoretical issues. The development of a robot memory that can support long-term HRI has been figured out as one of the challenges. The memory has been defined as an active process that serves current and future adaptive behavior, based on previously acquired information [21].

In establishing and maintaining long-term and more natural social interactions with humans, robots must possess with the ability of memorizing information significant to human partner. In a multi-user environment, the situation is much more complex as the robot has to store and recall information related to different users without messing up. In order to maintain a successful long term interaction, robot requires to remember some user biographical information, their preferences, and significant events during previous interactions. Therefore, special care must be given to the design of robot memory.

The ability of natural communication is a key requirement of a social companion. Humans generally use conversations to initiate social relationships with new people and maintain existing relationships. Humans have the ability to extract significant information from conversations and memorise them for future use [20]. The same behavior is expected from social robots.

2.4 Robot Memory Models

The memory is required in a HRI for perception, decision-making and action. According to pervasive memory perspective that is proposed in [22], the memory is an underlying mechanism that involves all the aspects of social interactions,

rather than a passive storage of semantic knowledge. Thus, the memory performs a central role in HRI. The research interest for developing different memory models for storing and processing past memories has been increased during recent past years. According to their characteristics, the existing memory models can be categorized into three distinct categories.

Episodic Memory Systems

Episodic memory is a collection of past events and experiences. Formalization of the episodic memory was first presented by Tulving in [23]. The episodic memory gained the researchers attention during past decades and it has been tested for many social robots and virtual companions. Work in [24] has proposed an episodic long-term memory with mechanisms for acquiring, storing, updating, managing and using episodic information during interactions. The researchers in [25] and [26] have attempted to encode emotional events in episodic memory to facilitate robot for supporting emotion based long-term interactions. Each episode has been represented as memory elements with three dimensions namely context, content and outcome. Figure 2.4 shows the Eva conversational agent who can remember past emotional interactions.

Semantic Memory Systems

Semantic memory is a storage of knowledge about the world. Alternatively, it can be defined as a generalized representation of episodic knowledge. Because of the complexity of converting the facts and events in to semantic knowledge, semantic memory models have been considered in a limited number of studies. This type memory models have been mainly used in mobile robot applications to store semantic knowledge about robot's working environment. [27].

Aggregated Memory Systems

These memory model were developed as combinations of both semantic and episodic memories. Researchers have attempted to model the human long-term memory in a robot companion that intended to use for long-term HRI [28]. They have tried to mimic the important capabilities of human memory including the personalization and long-term adaptation.

Several researchers have attempted to model the human AM. Work in [29] have tested the AM for cognitive robot that can learn about its environment through HRI. This memory model was intended to encode robot's experiences, user inputs ,the action performed by the robot and user world's state before and after performing the actions. The work in [30] has proposed a generic memory model consists of a long-term memory, a short-term memory and a forgetting mechanism. The model was aimed to support learning new behaviors as well as remembering emotional events.

2.4.1 User Preference Learning and Interaction Adaptation

The social robots have to interact with a wide range of users. They are expected to provide user adaptive services while maintaining natural and human-friendly interactions [31]. Therefore, robots need to learn and remember the preferences and characteristics of users. The robot's memory has to play a significant role in adapting their behaviors towards the users. It must facilitates the robot to remember past interactions and to make decisions based on them to adapt future interactions. Sometimes, robots may have to face completely new situations. Therefore, Robot must be able to cope with this type of situations by making appropriate decisions based on stored knowledge. Many research studies are trying to develop models for learning user characteristics and preferences over time and adapting interactions based on them [32–34]. Researchers have tried different methods to learn user preferences.

1. Learning from user feedback

The work in [35] has emphasised the usage of user's feedbacks including facial and voice expressions and gestures for preference learning. They have developed a system which can adapt robot's future behaviors by analysing user's feedbacks during past interactions. They have only used the discrete positive and negative signals as feedbacks from users. The work in [36] has proposed an approach for learning user's preferences for task execution by asking question expressed in natural language. However, users were expected to provide yes/no answers or predefined set of answers.

2. Learning user preferences from symbolic information

Authors of [37] have attempted to encode symbolic information in a robot episodic memory. They have used a probabilistic inference mechanisms for facilitating decision-making by exploiting the stored knowledge. However, this learning method can be applicable in a limited range of situations.

3. Using users personality and gender to predict user preference

These systems use the users personality to create user models. Then, those models were used to generate adaptive behaviors for previously interacted or new users. Authors of [38] have used the user's personality type (introversion/extroversion) to create user models for predicting user preferences.

4. Analyzing user personal history

This method is mostly used in web-based recommendation systems. They analyse users past behaviors such as searching patterns and ratings for products to predict user preferences. [39] These data is used to generate recommendations.

Authors of [40] have introduced a dual-layer user preference model to generate descriptive service recommendations for user-adaptive service robots. It generates recommendations based on rules or probabilistic method depending on the

availability of the rules. Although, above research studies proposed different approaches for preference learning, they have not given their attention regarding the use of user utterances and third person's description for user preference learning.

2.5 Human Autobiographical Memory (AM)

The definition of AM is differ from literature to literature. One common definition of AM is that it is a declarative, explicit memory for specific points in the past which is recalled from the unique perspective of the self in relation to others [41]. Human AM serves three main functions.

1. **Self function:** The self function of AM supports the continuity of the self.
2. **Social function:** AM supports to develop, maintain and cherish social bonds. Humans mainly use conversations in social interactions. The preliminary social function of AM is providing materials for conversations [43]. AM enables the humans to sharing personal memories in conversations. Thus, it facilitates to social interactions.
3. **Directive function:** The directive function of AM supports the humans to use the past knowledge to guide the present and future behaviors and the thoughts. Furthermore, it helps the humans to construct models of inner

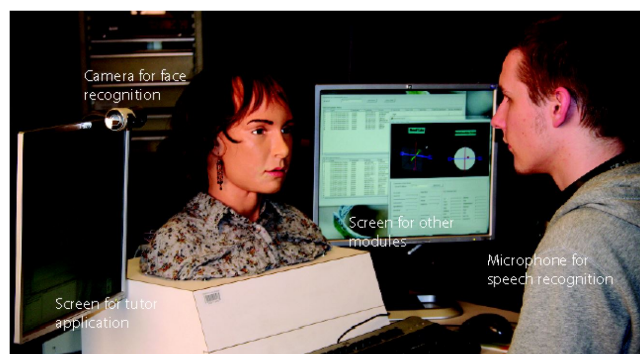


Figure 2.4: Eva conversational agent

life of others based on ones own experiences [42]. Thus it enables humans to predict future behaviors of other people.

Human AM stores the memories of past personal experiences. It is a combination of both semantic and episodic memories. The semantic memory stores the knowledge of world and general facts while episodic memory store the memories of people and events experienced in a specific point in time and space in the form of episodes [41]. Figure 2.5 depicts the knowledge structure of the human AM [44].

2.6 Spatial Consideration of Robot Memory

A rich representation of its surrounding, including the objects location, their spatial relationship is essential for a robot to plan and execute actions. Particularly, a spatial memory is required for a robot to navigate safely in his working environment. Because of the knowledge about robot’s working environment can not be preprogrammed for every situation, Robot must be able to learn and con-

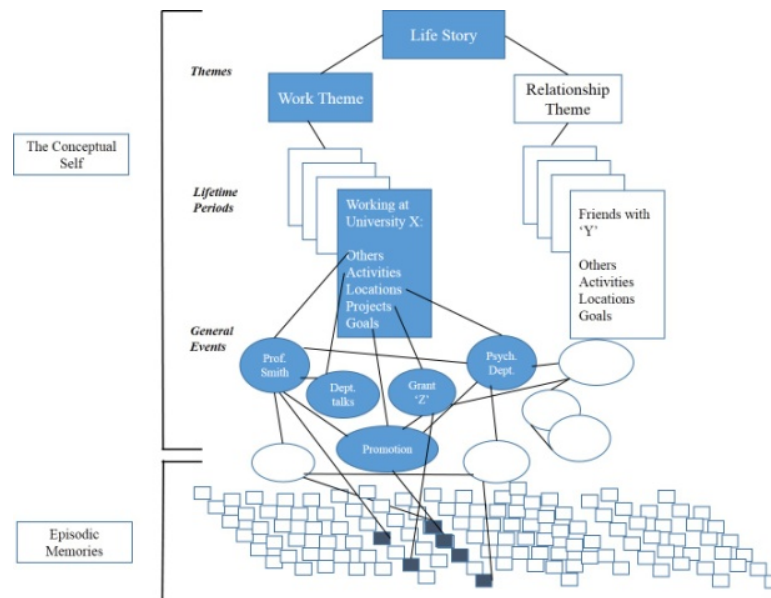


Figure 2.5: Knowledge structures in autobiographical memory.

struct this knowledge from the accumulated experiences while interacting with humans.

Only a few research studies has used robot's experiences in his memory to learn spatial relations. Authors of [29] have attempted to use the robot autobiographical memory based system for constructing a hierarchy of spatial and temporal relations. Then it has been used for learning and executing shared plans with user. That system can learn spatial arrangement such as 'east', 'north', 'near' and temporal relations such as 'before' and 'after' from human demonstrations.

2.7 Current State of Memory Based Interactive Systems

Although a number of effort has been taken to develop robots with long-term interaction capabilities the abilities of these robots are not enough for maintaining human-like long term relationships, which demand advanced cognitive and communication capabilities [45]. The limitations with the existing robot memory models have directly affect this.

Researches have successfully developed memory models that can remember past emotional event and recall them in ongoing interaction [25], [26]. Several studies have been aimed to develop socially aware memory models capable of protecting user privacy by not disclosing sensitive data during interactions [46]. Social robots with a memory have been employed as receptionists, tour guides, domestic service robots and even teacher. However, these robots can remember a limited amount of information about interacted partner which is not enough for maintaining successful long-term interactions [47] [48].

2.8 Summary

Social robots are increasingly involved in human lives in a variety of forms. Specially, they are engaging in domestic environments as assistance and care-givers. They are intended to closely interact with humans and build relationships with them. The memory is a critical component for any social creature. It is true for the social robots as well. The memory enables the robot to remember the users, their likes and dislikes and to adapt his behaviors. Since these robots have to serve non expert users, they should be harnessed with human-like interaction capabilities. Despite, The large number of previous research studies related to the memory based social robots, still there are several unanswered questions. A summary of the literature review is given in Table 2.1 .

Table 2.1: Summary of the literature review

Area	Limitations in exiting systems	Possible improvements	Proposed Methods
Memory structure	Less focus on developing a memory model for facilitating long-term social interactions with multiple users	Design the robot memory structure to facilitate the storage of information related to multiple users	Autobiographical memory with 3 layered architecture
Memory recalling during interactions	Limitation in identifying and recalling relationships between users and similarities user profiles	Developing the memory as a hierarchical semantic network rather than a collection of distinct entities	Developing autobiographical memory as a relational database using SQL
Predicting missing information	Limitations in predicting missing information during interaction adaptation	Exploiting the stored knowledge in the memory to predict missing information	Inference system

DESIGN OF ROBOT AUTOBIOGRAPHICAL MEMORY

3.1 System Overview

The proposed memory model has been integrated to an interactive robotic system. The functional overview of the overall system is given in Fig. 3.1. The main purpose of the system is to facilitate robot for surviving in long-term human-robot interactions. The main components of the robotic system are explained below.

1. **Voice Recognition and Understanding Module (VRUM)**

VRUM acquires and interprets the user utterances. Firstly, it converts the speech into text using speech to text converter. Then the text is tokenized and analysed with the help of language memory. This module also employs a natural language processing based information extraction mechanism to extract relevant information from user utterances. A detailed description of information extraction mechanism is given in next chapter.

2. **Voice Generation Module (VGM)**

This module synthesizes the voice responses and generates the voice outputs using text to speech converter.

3. **Facial Feature Extraction Module (FFEM)**

This module extract the important facial data from user facial images.

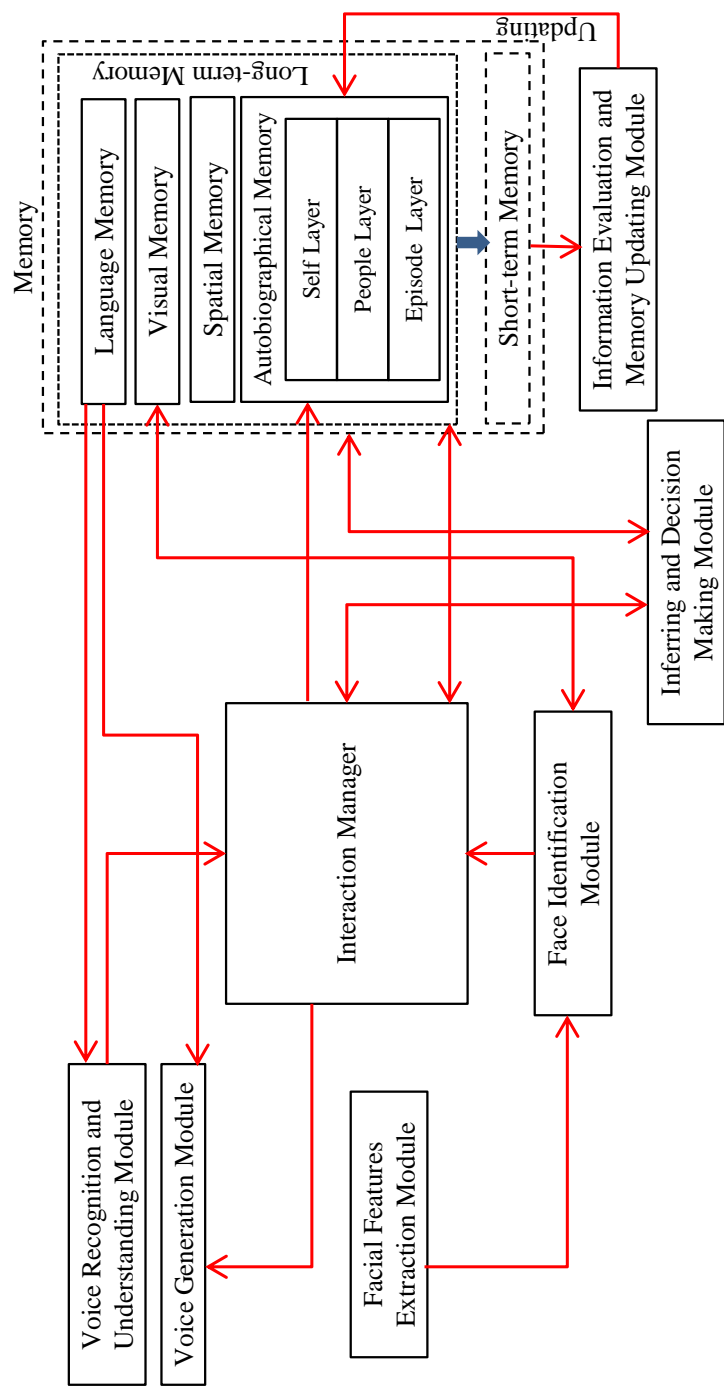


Figure 3.1: System overview.

4. **Facial Identification Module (FIM)**

The FIM identifies users by comparing the facial data extracted by FFEM with the stored data in Visual Memory (VM). Whenever a new user is acquainted, it stores the facial images of user in VM with an identification number.

5. **Information Evaluation and Memory Updating Module (IEMUM)**

The memory module has been integrated with an Information Evaluation and Memory Updating Module (IEMUM). The updating of people and episode layers are managed by this module. It compares the newly acquired knowledge with the existing knowledge of the AM. If an addition or a modification should be made, it updates the relevant entry.

6. **Inferring and Decision Making Module (IDMM)**

An Inferring and Decision Making Module (IDMM) has been introduced in order to facilitate robot for inferring user preferences and making appropriate decisions during interactions. A detailed description about this module is given in chapter 5.

3.2 **Robot Memory**

Designing a memory for a robot is a very complex task as we have to pay attention to many aspects. Therefore, when designing the robot memory, the structure of human memory is considered. Proposed memory module consists of two sub modules namely Short-Term Memory (STM) and Long-Term Memory (LTM). The STM is employed for storing information related to the ongoing interactions while the LTM acts as a vast storage of previously acquired knowledge. The content of the STM is erased after completing the interaction. The development of the forgetting mechanisms for both the STM and LTM is proposed as a future work.

The long-term memory has been designed as a combination of four sub-modules namely Autobiographical Memory, Visual Memory, Spatial Memory (SM) and Language Memory (LM).

Language Memory (LM)

The LM is a database of grammar patterns and keywords. It acts as the resource provider for both VRUM and VGM modules.

Visual Memory (VM)

The VM stores visual features and face images of known users and it provides necessary resources for face identification module.

Spatial Memory (SM)

A map of the robot's working environment is stored in the spatial memory. Important information like table location and orientation is given in this map.

3.2.1 Robot Autobiographical Memory (AM)

The development of the AM is one of the main contributions of this research and it is the critical component of this intelligent system. It stores significant information related to the each interaction partner along with the knowledge of previous interactions. As the robot expected to serve multiple users, the knowledge structure of AM must be facilitate the storage of information of different users. Furthermore, it must support higher accuracy, and efficiency in order to maintain smooth interactions. Moreover, it should support the growing number of users. Thus, the memory must be scalable. All of these factors have to be considered during the design of the AM.

Knowledge structure of the proposed robot autobiographical memory has been designed by considering the basic aspects of humans' AM. It has been developed as a three layer (i.e Self layer, People layer and Episode layer) model for facilitating the multiuser interactions. The knowledge structure of proposed robot AM is depicted in Fig.3.2. The knowledge representation and functionality of each layer can be explained as follows.

1. Self layer

In order to maintain more natural interactions with users, robot is designed with a personality. The top most layer of AM is named as Self layer and it stores basic information related to the robot himself (E.g.: name, date of production, duty etc). These information help robot to introduce himself to others. The content in self layer is per-installed and do not update after interactions.

2. People layer

The middle layer is named as People layer. It stores the knowledge related to users including their preferences. The knowledge of this layer is structured as a semantic network which is quite similar to the way that humans

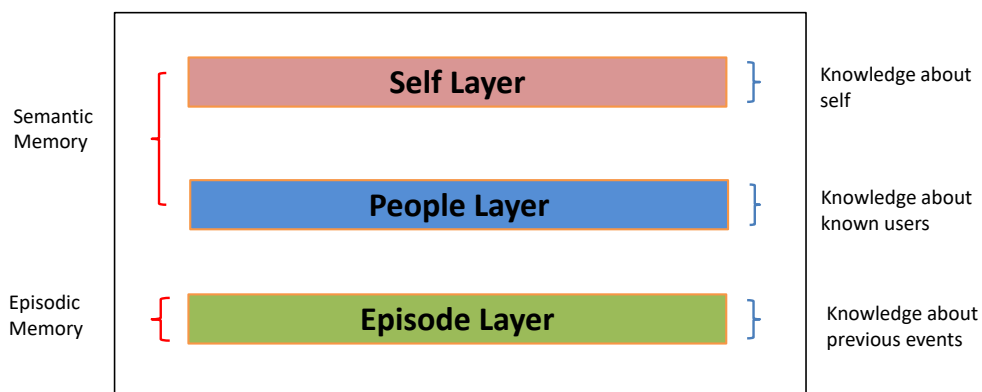


Figure 3.2: knowledge structures of the proposed autobiographical memory

structure the knowledge. Humans construct the knowledge by building mental links between entities [49]. In order to mimic this aspect, a semantic network was used to represent the knowledge. Each node of the network represents a entity and arcs represent the relationship between them. The knowledge structure of the people layer is depicted in Fig.3.3. This knowledge representation facilitates the robot to identify and remember the relationship between users and user groups. It gives the users freedom to refer to other users by their relationship (E.g. Father, Mother, Sister etc) while interacting with the robot. Furthermore, it facilitates the users to instruct the robot easily regarding common preferences of a group of users.

3. Episode layer

The bottom layer of the AM is named as episodic layer. The episodic layer stores knowledge of previous events (i.e. interactions) that robot experienced with different users. Each episode consists of following entities.

- (a) **Event:** Semantic representation of an ongoing interaction. An event is a collection of one to many actions.
- (b) **Date and Time:** The date and time of the interaction which oc-

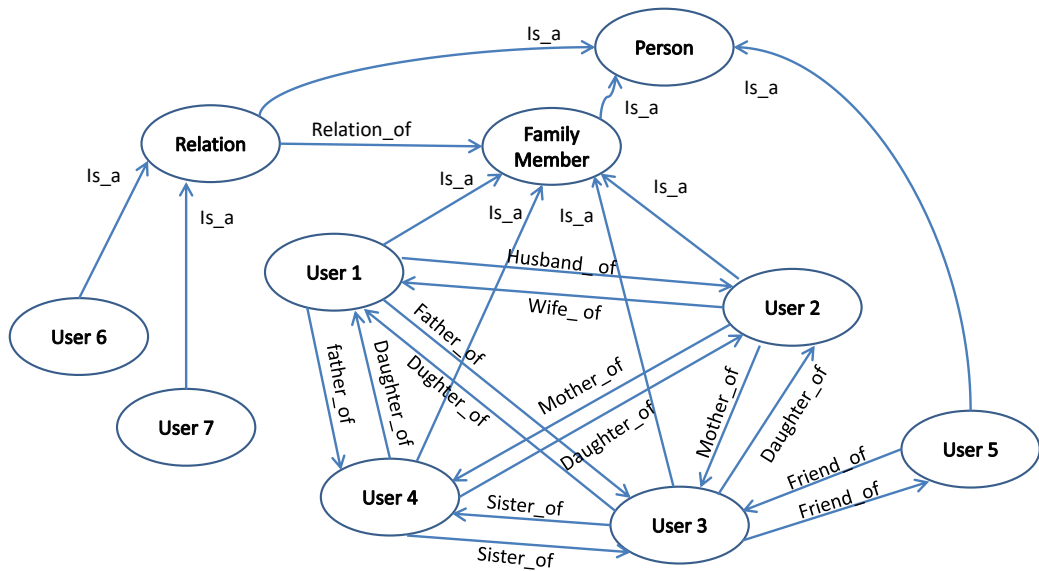


Figure 3.3: Knowledge representation in the people layer.

curred.

- (c) **Participant:** The person who participated in the interaction.
- (d) **Action:** The actions that are performed by the robot during the interaction. An action can result one to many outcomes.
- (e) **Context attributes:** Information about the context including weather condition, users' health and hunger. These data relate with beverage and snack suggesting task described in chapter 5.
- (f) **Conversation outcomes:** In this scenario outcomes can be new information about the user or another user which mentioned during the interaction.
- (g) **Related person:** The person who is related with the new information.
- (h) **Object:** Description of objects that are manipulated by the robot.

Only the people and episodic layers of the AM are updated with the new information.

MySQL Design

Entire AM was developed as a SQL relational database. This enables the memory to easily storing records related to any number of users. Furthermore, this facilitates the robot to easily remembering relationship between users and events. It also ensures the fast retrieval of user information without loss of accuracy. AM is consists of 11 tables and it can be expanded according to the requirement. Both visual memory and the AM use the same identification number to identify a user.

The people layer consists of six SQL tables. User table is the main table of the AM and it stores basic biographical information related to all users. User table is connected to a preference rule table in a one to many relationship. It stores the rules related snack and beverage preferences of users. Family member table

stores the informations specific to family members while relation table stores the details of relations of the family. Family member table is again related to another two tables namely friend table and relationship table. Episodic layer is designed as a combination of five table. The user table and the event table is related with one to many relationship as a user can experience many events with the robot. The MySQL design of the AM is depicted in Figure 3.4

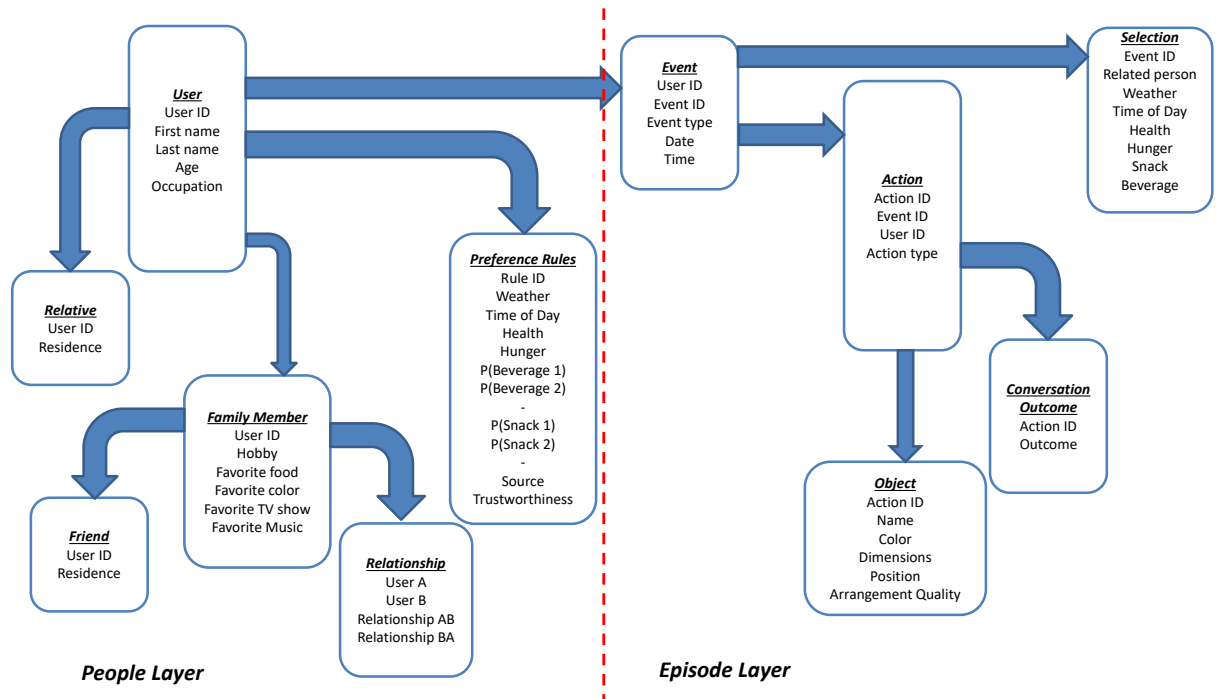


Figure 3.4: Design of the people and episodic layers of AM .

3.3 Interaction Manager

The Interaction Manager (IM) facilitates the communication between the user and the robot by coordinating the internal modules of the robot. Furthermore, IM decides the sequence of internal processes which is needed to execute a particular user command and it coordinates the internal modules of intelligent robot system to meet user requirement. IM has been designed as a finite state machine.

3.3.1 Finite State Machine

As the system has to transit between many states, designing the state machine was a bit challenging task. Functional overview of IM is depicted in Fig. 3.5. The default state of the robot is “waiting” state. In this state robot waits until a user face is detected by its vision system. Once a face is detected, the state is changed to “user identification” state. In this state user’s facial data is extracted and is compared with stored data in visual memory. If the user is identified as an unknown user, the state is changed to “user learning” state. Otherwise, robot greets the user by name and state is changed to “action selection” state. In “user learning” state the extracted user’s facial data is stored in robot’s visual memory with a new user ID and important biographical information of the user is obtained by using a friendly conversation. Depending on the availability of updates, system’s state can be changed from “user learning” to “memory updating”.

Once the “user learning” is completed, the state is changed to “action selection” state. In “action selection” state robot inquire the user requirements. If a user needs a service, robot’s state is changed to “service behavior”. In this state a process sequence is executed to provide the required service to the user. If a user likes to chat with the robot, the state is changed to “conversation behavior”. When new information is detected during performing a service or making a conversation the system’s state is changed from the respective state to “memory updating” state. Once the memory updating is completed the state is changed back to respective state. If user neither requires a service nor needs to converse with the robot then robot’s state is changed to “waiting” state. If a user gives up during any of intermediate states, then the robots state changes to ”waiting” state. The robot uses predefined dialogues for communicate with user during intermediate states. The dialogue flows for “user learning” and “action selection” are given in Fig. 3.6 and Fig. 3.7 respectively. The defined dialogues corresponding to the letter codes are given in Table 3.1.

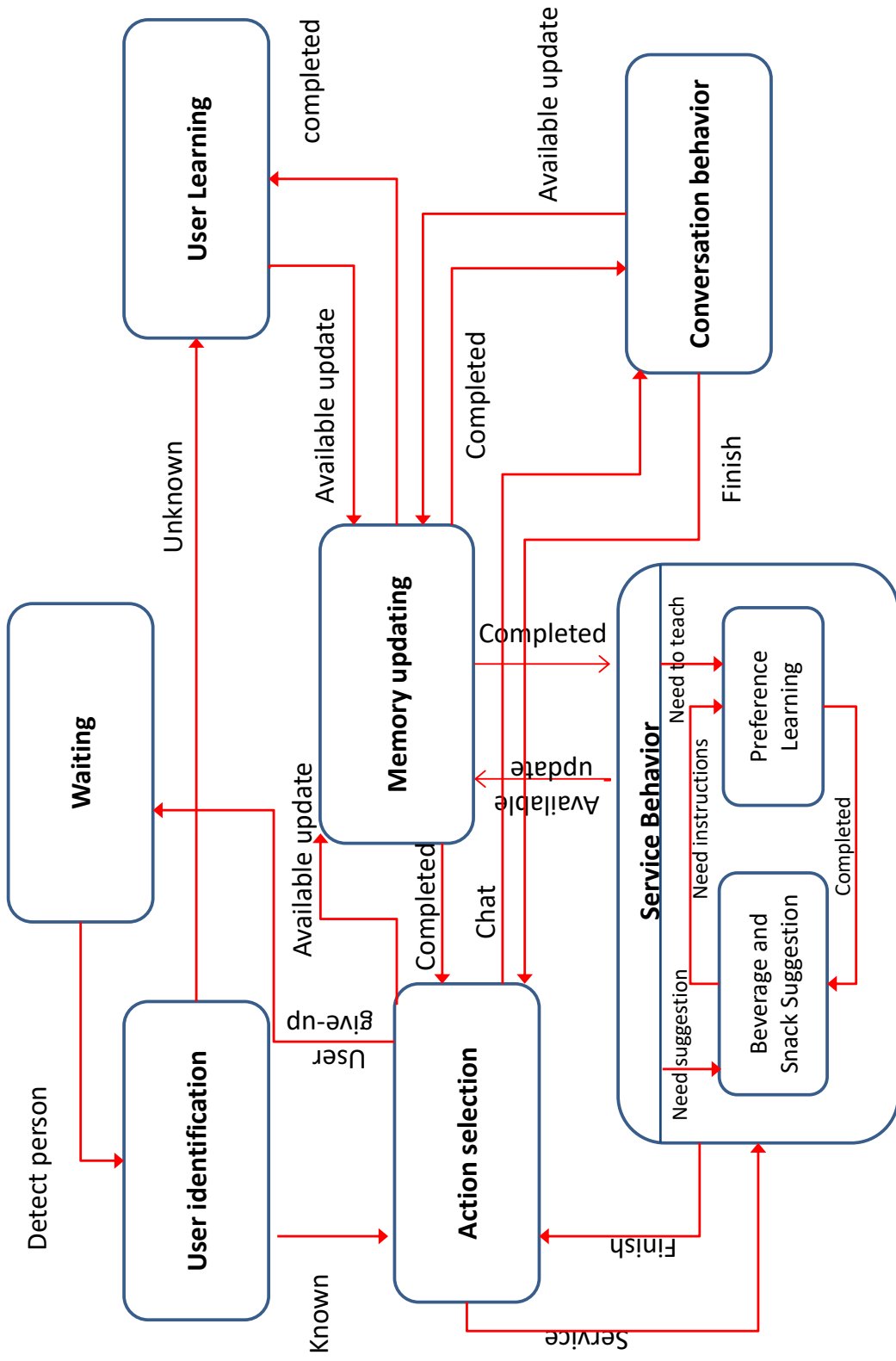


Figure 3.5: Finite state machine diagram

Table 3.1: Defined dialogues of the robot

Code	Speech output
A	Hello.
B	Hello, <Name of the person>
C	I don't think we've met. I am MIRob. Do you mind if I ask your name?
D	Could you tell me what your age is?
E	What do you do?
F	What is your hobby?
G	It is a pleasure to have met you <name of the person>
H	Do you need a service from me?
I	Would you like to chat with me?
J	I'm sorry. I couldn't hear what you said.
K	Ok.
L	Have a nice day.

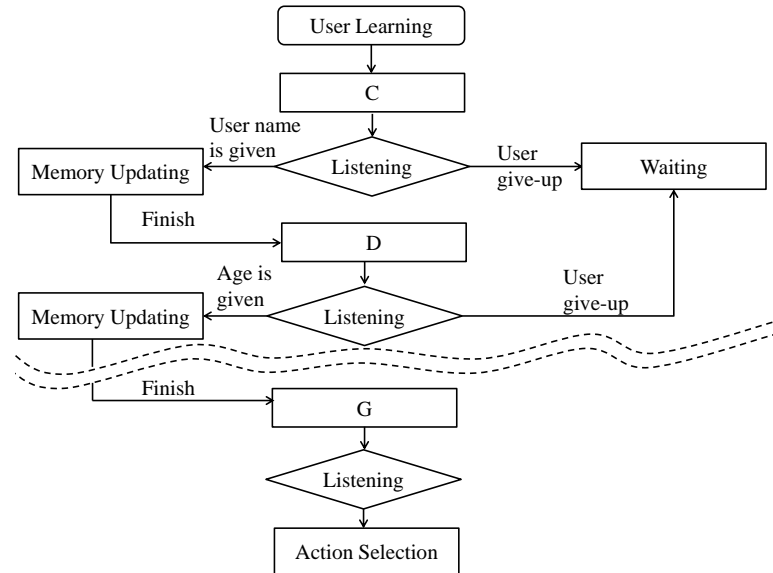


Figure 3.6: Dialogue flow for user learning state. Note: only the important part of dialogue flow has been shown.

3.4 Summary

This chapter presents an overview of the entire system including its modules and functionalities. Some of the modules will be further explained in following chapters according to the necessity. This system is aimed to support long-HRI. An autobiographical memory model, that can facilitate the storage of information

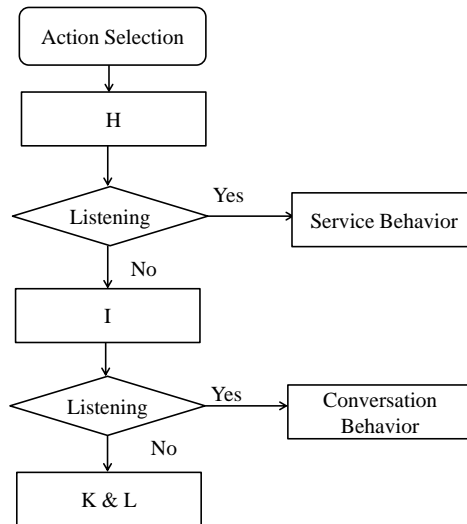


Figure 3.7: Dialogue flow for action selection state

required for long-term HRI has been proposed. The interaction manager acts as an interface between user and the robotic system. It ensures a smoothness of the interaction by coordinating internal modules. The entire system has been designed as a finite state machine. Dialogue flows have been defined for the robot to communicate with users.

UPDATING AUTOBIOGRAPHICAL MEMORY DURING HRI

This chapter discusses the following aspects of the system.

1. Initiating relationships with new users and maintaining them.
2. Extracting significant information of its users through conversations and recalling them during future interactions.
3. A natural language processing based information extraction methodology for improving the flexibility of communication.

4.1 Information Extraction Mechanism

The robot uses a set of questions to acquire key biographical information of users and stores them in user profiles. In order to provide more natural and flexible communication during user learning state, Natural Language Processing (NLP) based information extraction mechanism was developed. It gives users the freedom to use flexible grammar while answering to the robot's questions, rather than sticking into a strict grammar pattern. Python NLTK (Natural Language Tool Kit) [50] was used for analyzing the content of user answers and to extract required information. Fig. 4.1 shows the functional flow diagram of information extraction process. Each step of the information extraction process can be explained below.

1. **Speech to text conversion:** The first step of the information extraction process is capturing user voice from microphone and converting it in to text. In the practical implementation *PyAudio* package and *SpeechRecognition* library were used for serving those purposes respectively.
2. **Tokenising:** Creating a list of words from a text is a prerequisite step of text processing. In this step text is broken up to sentences and then to words.
3. **Removing stop words:** As the next stage, stop words are removed from the text. Stop words are referred to the most common words in language that do not contribute to the meaning of a sentence [51]. For examples “a”, “the”, “at”, “this” etc. Furthermore, they are not necessary in NLP as they retain unnecessary information. Therefore, these words are filtered out from word list.
4. **Inserting part of speech tags:** In this stage, speech tags are inserted to each word using Part of Speech tagging (POS) method. The POS is defined as the process of labeling a word in a text as corresponding to a particular part of speech, based on both its definition as well as its context. In other

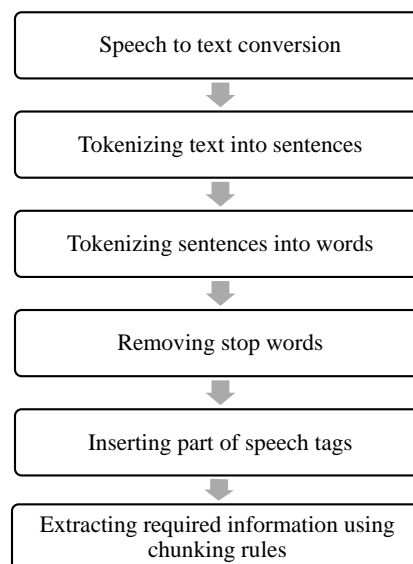


Figure 4.1: Information extraction process

Table 4.1: Chunking rules

Entity	Chunking rule
Name	{<NNP VBP><NNP>?}
Age	{<CD>}
Occupation	{<NN><NN>?} {<VBP>}
Hobby	{<VBG><NNS?><NNS?>?} {<VBG>}

All the part-of-speech (POS) tags and special characters have their usual meanings in NLP given in [50].

words, it is the process of identifying whether a word is act as a noun, or a verb, or a pronoun and so on. Fig.4.2 shows a example sentences for POS tagging.

5. **Extracting required information using chunking rules:** Finally, required information will be extracted using chunking rules [52]. Chunking rules were designed by analyzing grammar patterns of commonly used sentences for answering each question. These rules were implemented using regular expression syntax. Table 4.1 shows entities and the designed chunking rule for identifying them within a user response.

I	am	working	as	a	research	assistant
PRP	VBP	VBG	IN	DT	NN	NN
<i>Personal pronoun</i>	<i>Verb present</i>	<i>verb, gerund</i>	<i>Preposition</i>	<i>Determiner</i>	<i>Noun, singular</i>	<i>Noun, singular</i>

Figure 4.2: Part of tagging of user statement

4.2 Management of Autobiographical Memory

The managing of robot AM is achieved by using SQL queries. As the rest of the system including the interaction manager module was developed using Python, an interface is needed between Python and MySQL. PyMySQL library is employed for fulfilling that requirement. It facilitates to execute SQL queries in Python environment. When a user interacts with the robot for the first time, his facial data is stored with an identification number in the visual memory. The same number is used in AM to uniquely identify the user.

4.2.1 Storing Information in Autobiographical Memory

New records of the users are inserted to the memory using *SQL insert* queries. Sometimes, robot may encounter changes of previously acquired knowledge during interactions. In such situations, existing memory records should be updated. The updating of existing entries is done using *SQL update* queries together with *where* clauses. The *where* clauses are used to select the required record.

4.2.2 Recalling the Information in Autobiographical Memory

The ability of recalling relevant information during an interaction is essential for a robot. Therefore, a recalling mechanism is needed. An effective memory recalling mechanism must be able to accurately retrieve information relevant to the context and interaction partner. Furthermore, it should be efficient enough to eliminate unnecessary delays during HRI. Here, *SQL select* statements are used to serve this purpose. The *where* clauses are used along with the *select* statements to extract the records that satisfy specific conditions. Example select query is given below.

```
Select FirstName From User Where ID=1;
```

This statement retrieves the first name of the user 1.

4.3 Experimental Results

A set of experiments was conducted to analyse the performance of the robotic system during human-robot interactions. The experiments were aimed to examine the robot's ability to extract, store and recall user information during the interactions. The experimental setup is shown in Figure 4.3. All together 18 subjects were participated to the experiment and all of them were non-native English speakers. As the experiments, each subject was asked to interact with the robot more than one occasion and conversation between robot and each subject was recorded. After each interaction, the content of AM was recorded.



Figure 4.3: MIROb robot platform and a subject during the experiment

Table 4.2: Initial content of the User Table

ID	First Name	Last Name	Age	Occupation
1	Narmada	Gunasekara	23	student
2	Chami	Edirisinghe	23	student
3	Sahan	Kodikara	26	Research assistant

Table 4.3: Initial content of the Family Member Table

Family Member ID	Hobby	Favorite Food	Favorite TV show	Favorite Color	Favorite Music	User ID
1	listening to music	ice cream	sherlock	pink	classic	1

Table 4.4: Initial content of the Event Table

Event ID	Event	Date	Time	User ID
1	User learning	2018-09-20	13:31:20.00	1
2	Action selection	2018-09-20	13:31:20.00	1
3	Action selection	2018-09-20	13:33:12.00	1
4	Action selection	2018-09-20	13:33:38.00	1
5	Chat about Favorites	2018-09-20	13:33:48.00	1
6	Action selection	2018-09-20	13:35:00.00	1
7	User learning	2018-09-20	14:19:31.00	2
8	Action selection	2018-09-20	14:19:31.00	2
9	Action selection	2018-09-20	14:32:35.00	2

Consider the situation that user A (user #4) interacted with the robot for the first time. Content of *user table*, *family* and *event* tables at the beginning of the experiment is shown in Table 4.2, Table 4.3 ,Table 4.4 respectively. The variation of robot’s states and speech outputs during the experiments were given in Fig. 4.4. The conversation between user A and the robot during the experiment is given below.

1.1) **Robot:** *Hello*

1.2) **User A:** *Hello*

1.3) **Robot:** *I don't think we've met. I'm MIRob. Do you mind if I ask your first name?*

1.4) **User A:** *Yes. I'm Chapa*

1.5) **Robot:** *Could you tell me your last name?*

1.6) **User A:** *It's Sirithunge.*

1.7) **Robot:** *Chapa. Could you tell me what your age is?*

1.8) **User A:** *I'm 27.*

1.9) **Robot:** *What do you do?*

User	Dialogue No	State
		Waiting
A	1.1 1.2	User Identification
	<i>Memory Updating</i>	
	1.3 1.4	User Learning
	<i>Memory Updating</i>	
	1.13	Action Selection
	<i>Memory Updating</i>	
	1.17	Conversation Behavior
	<i>Memory Updating</i>	
	1.30	Action Selection
	<i>Memory Updating</i>	
		Waiting
B	2.1 2.2	User Identification
	<i>Memory Updating</i>	
	2.3 2.4	Action Selection
	<i>Memory Updating</i>	
	2.5	Service Behavior

Figure 4.4: Variation of the robot's states and the dialogues with the users during the experiments. Note that the time axis is not drawn to a scale and only the important parts of the dialogue flows are shown.

1.10) **User A:** *I work as a researcher.*

1.11) **Robot:** *Nice to meet you Chapa.*

1.12) **User A:** *Nice to meet you.*

- 1.13) **Robot:** *Do you need a service from me?*
- 1.14) **User A:** *No. No thank you*
- 1.15) **Robot:** *Would you like to chat with me?*
- 1.16) **User A:** *Yes*
- 1.17) **Robot:** *Shall we talk about family, friends or favorites?*
- 1.18) **User A:** *Favorites.*
- 1.19) **Robot:** *That is an interesting topic. Could you tell me what your favorite food is?*
- 1.20) **User A:** *Pizza*
- 1.21) **Robot:** *They are delicious. You have a good taste in food. So tell me which color you prefer the most?.*
- 1.22) **User A:** *Green.*
- 1.23) **Robot:** *That is a good choice. What is your favorite TV show?*
- 1.24) **User A:** *Friends.*
- 1.25) **Robot:** *It's a quite famous TV show. Which music do you like to listen?*
- 1.26) **User A:** *Classic*
- 1.27) **Robot:** *Grate ! There are so many beautiful songs in that category. So tell me what is your hobby?*
- 1.28) **User A:** *Reading*
- 1.29) **Robot:** *Interesting!. Thank you for telling me about your favorites.*
- 1.30) **Robot:** *Do you need a service form Me?*
- 1.31) **User A:** *No, Thanks.*
- 1.32) **Robot:** *Would you like to chat with me?*
- 1.33) **User A:** *No.*
- 1.34) **Robot:** *Ok. Have a nice day*
- 1.35) **User A:** *Nice day*

At the beginning, the robot was in “waiting state”. After user A was detected by the vision system, the robot’s state was changed to “user identification” state. Because of the user A had not previously interacted with the robot, people layer

Table 4.5: Content of the User Table after the interaction with user A

ID	First Name	Last Name	Age	Occupation
1	Narmada	Gunasekara	23	student
2	Chami	Edirisinghe	23	student
3	Sahan	Kodikara	26	research assistant
4	Chapa	Sirithunge	27	researcher

Table 4.6: Updated Family Member Table after the interaction with user A

Family Member ID	Hobby	Favorite Food	Favorite TV show	Favorite Color	Favorite Music	User ID
1	listening to music	ice cream	sherlock	pink	classic	1
2	reading	pizza	friends	green	classic	4

did not possess any record related to user A. Therefore, user A was identified as an unknown user and the robot responded with dialogue 1.1. The user replied with dialogue 1.2. Then, robot’s state was changed to “memory updating”. The user A’s facial image was saved in robot’s visual memory with new user identification number i.e. 4. Next, the robot’s state was changed to “user learning state”. The robot asked the user’s name using dialogue 1.3 and user replied with dialogue 1.4. Thus the conversation is continued. After successfully finishing the user learning, robot’s state was changed back to “memory updating” and user biographical information was saved in user table with user ID (number 4).

Next, the state was changed to “action selection”. The robot used the dialogue 1.13 and 1.14 to inquire the user’s requirement. As the user was willing to chat with the robot, his state was changed to “conversation behavior”, where robot used dialogue 1.17 to ask a conversation topic. After finishing the conversation, the robot’s state was changed to “memory updating”. Then the family member table was updated with user A’s information (Table 4.6). After that robot’s state was changed to “action selection” where robot asked the user’s requirement. Since user A did not need any further interaction at that moment, robot concluded the interaction by greeting the user. Then system’s state was changed to memory “updating” and the episodic memory was updated. Finally, the robot’s state was changed to “waiting”.

As the second experiment user B (user #3) was asked to interact with the robot. Selected segment of the conversation between user B and robot is given below.

2.1) **Robot:** *Hello, Sahan, Nice to see you again !*

2.2) **User B:** *Hello*

2.3) **Robot:** *Do you need a service from me?.*

2.4) **User B:** *Yeah.*

2.5) **Robot:** *How can I help you?.*

Table 4.7: Updated Event Table

Event ID	Event	Date	Time	User ID
9	Action selection	2018-09-20	14:32:35.00	2
10	User learning	2018-09-20	15:41:52.00	3
11	Action selection	2018-09-20	15:41:52.00	3
12	User learning	2018-09-20	15:51:29.00	4
13	Action selection	2018-09-20	15:51:29.00	4
14	Chat about Favorites	2018-09-20	15:51:39.00	4
15	Action selection	2018-09-20	15:53:10.00	4
16	Action selection	2018-09-20	16:04:09.00	3

Initially, robot was in “waiting” state. After detecting the user B by the vision system, the robot’s state was changed to “ user identification”. Since the robot had a memory about user B, user B was identified as a known user and greeted with his name. Next, the state was changed to “memory updating” to updated the episodic memory. Then the robot’s state was changed to ”action selection” state and the interaction was continued.

4.4 Summary

This chapter presents functionality of the robot AM during the HRI. The AM is managed by using SQL quires. A natural language based information extraction mechanism has been proposed for extracting user biographical information.

Table 4.8: Updated Action table

Action ID	Action	Event ID	User ID	
38	Greet	12	4	
39	Ask first name			
40	Ask last name			
41	Ask age	13		
42	Ask occupation			
43	Ask user requirement			
44	Ask conversation topic			
45	Ask favorite food			
46	Ask favorite color	14		
47	Ask favorite TV show			
48	Ask favorite music			
49	Ask hobby	15		
50	Ask user requirement			
51	Greet	16		3
52	Greet			
53	Ask user requirement			

Table 4.9: Updated Conversation Outcome Table in the episodic layer

Conversation Outcome ID	Conversation Outcome	Action ID
31	User greet	38
32	User first name : Chapa	39
33	User last name : Sirithunge	40
34	User age : 27	41
35	User occupation : researcher	42
36	Requirement : chat	43
37	Topic : favorites	44
38	Food : pizza	45
39	Color : green	46
40	TV show : friends	47
41	Music : classic	48
42	Hobby : reading	49
43	Requirement : no	50
44	User greet	52
45	Requirement : service	53

The performance of the system has been analysed by a set of experiments. The experiments verify the data acquisition, storing and recalling capabilities of the people and episodic layers of the robot autobiographical memory.

LEARNING USER PREFERENCES AND ADAPTATION OF ROBOT'S BEHAVIOR

Humans are capable of learning preferences of their companions over the time. Social robots must possess the similar capabilities to make more natural interactions with the humans. They must be intelligent enough to infer user preferences based on information acquired from previous interactions. In general, humans come into initial assumptions about others by the knowledge gathered about them from their friends or family members. Then these assumptions are modified according to the experiences which are obtained while actually interacting with them. This method can be applicable to social robots for guessing the missing information of users when creating user models.

This chapter presents the application of robot's autobiographical for adapting towards each user in a multi-user environment. This chapter explains and validates the following capabilities of the system.

1. Use the user's statement and/or third person's descriptions about him/her to infer user preferences
2. Ability of learning users' hidden preferences or changes of preferences over time.

In order to analyse the above abilities, a beverage and snack suggesting scenario was used. A detailed description of tested scenario is given in experiments and results section.

5.1 User Preference Learning from User Utterances

The ability of learning users' preferences through more natural and human-friendly interactions is essential for a social robot. This system enables the user to inform the robot about their preferences in a way similar to informing a human companion. Simple grammar models were created to facilitate the users to instruct the robot. Users can use either simple present sentences with frequency adverbs (Type I statements) or condition conclusion pairs (Type II statements) to state their preferences. The classification of user statements is given in Fig.5.1. Each frequency adverbs in type I statements is associated with a probability. The frequency adverbs and associated probabilities are given in Table 5.1.2. Robot can learn user preferences from following two types of utterances.

5.1.1 Learning from the User's Own Utterances

Users can directly state their own preferences to the robot by using statements like " I usually prefer to have coffee with cake", and " If I am sick, then I don't drink fruit juice".

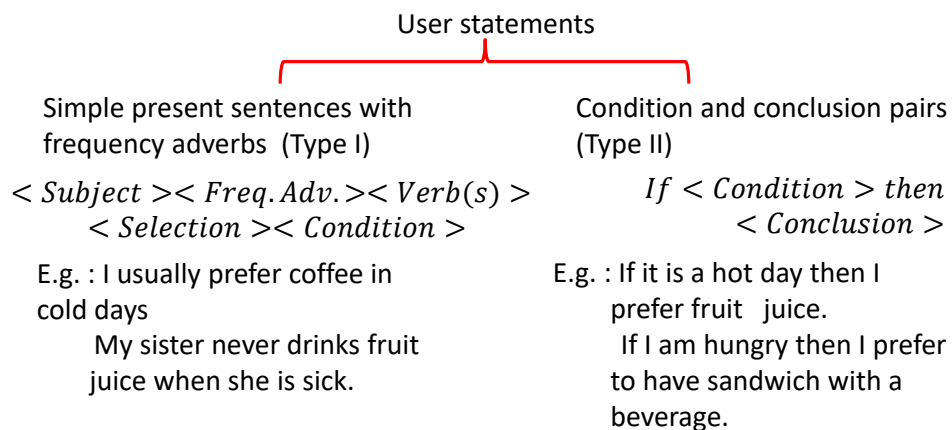


Figure 5.1: The classification of user statements.

Frequency adverb	Associated probability (%)
Always	100
Usually	80
Sometimes	50
Never	0

Table 5.1: Adverbs of frequency and their probabilities

5.1.2 Learning from Another Person’s Utterances

Robot is capable of learning the user’s preferences based on utterances of a third person. This is quite similar to the way how humans initially learn the facts about others which they have not experienced. Users can use the utterances such as “ My father usually prefers to drink coffee in cold days” and “ My sister never eats cake” to inform the robot about others’ preferences. Furthermore, users have the freedom to use statements regarding preferences that are common to a group of users. For examples, “All family members usually prefer tea in the morning” can be considered.

5.2 Inferring and Decision Making Module

Robot uses a conditional probability and joint probability based method to infer the user’s selection according to a given context. If X,Y and Z are three sets of context attributes, and C is a set of contexts, then the probability of occurring i^{th} context can be given as follows.

$$X = \{x_1, x_2, \dots, x_p\}, Y = \{y_1, y_2, \dots, y_q\}, Z = \{z_1, z_2, \dots, z_r\} \quad (1)$$

$$C = \{c_1, c_2, \dots, c_v\} \quad (2)$$

$$c_i = x_k \cap y_l \cap z_m \quad (3)$$

$$P(c_i) = P(x_k \cap y_l \cap z_m) \quad (4)$$

Here, $1 \leq k \leq p, 1 \leq l \leq q, 1 \leq m \leq r$ and $1 \leq i \leq v$

If S is a set of services then the probability of choosing a particular service for a given context can be obtained as (6)

$$S = \{s_1, s_2, \dots, s_w\} \quad (5)$$

$$P(s_j/c_i) = P(s_j/x_k) \times P(s_j/y_l) \times P(s_j/z_m) \quad (6)$$

Here, $1 \leq j \leq w$

Robot is capable of inferencing user's choices based on user statements and his past experience with the user.

5.2.1 Inferring Based on Users Statements

When robot has less or no prior experiences with a user, it predict user's choice based on user statements. The probabilities associated with user statements are used to infer the user's choices according to different contexts. Type II statements are assumed to have 100% probability to occur while that of type I statement varies with frequency adverb.

Robot uses the facts learned from users to create rules about user preferences related to different contexts. Each rule is associated with a trustworthiness value (0.5 or 1) depending on the way which the fact is learned. The facts which are learned about the user from his/her utterances have highest trustworthiness value (i.e. 1). The facts that learned based on another person's utterances are assumed to have equal probability to be true or false. Hence they are given the trustworthiness value of 0.5. This facilitates the robot to replace the erroneous rules which are learned from another user with rules learned from the user.

Inferring Based on Robot’s Experiences

The rules learned from user’s utterances can be modified according to the experiences which robot gathers over the time. Robot uses the calculated probabilities to support or oppose a previously learned rule. It enables the robot to adapt according to user preference changes. If a user preference which taught by a user is different from what robot experiences over time while interacting with the user, then robot will replace the previous rule with a new rule. Once a user makes a selection, the *Selection table* of AM is updated. Then these data is used to learn the user’s preferences over time.

5.3 Experiments and Results

Performance of the proposed system was tested and validated by using a beverage and snack suggestion scenario. The experiments were conducted in a private apartment. Subjects with varying beverage and snack preferences participated in the experiment. Their ages vary from 22 to 56 years. The experiment was conducted by assuming that both the user’s preferences and context will affect the user’s selection.

The beverage selection is assumed to be affected by the weather condition, user’s health condition and the time, while snack selection is affected by user’s health condition and hunger. The contexts and the available service options are shown in Fig. 5.2. During the experiment, the conditions were given as input to the system. Once user requests a suggestion, robot verbally suggests the beverage and the snack. During the experiments, users were asked to wear a wireless headset with a microphone to increase the voice recognition accuracy.

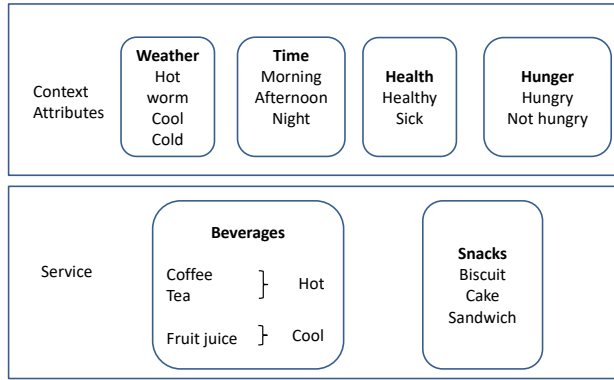


Figure 5.2: Contexts and the available service options of beverage and snack suggestion scenario.

5.3.1 Ability of Learning User Preferences from Users Statements

The aim of first experiment was evaluating the robot’s ability of learning user preferences from user’s statements. The experiment was conducted with 12 subjects and four of them were family members. As the first part of the experiment, users were asked to instruct the robot regarding their own preferences related to different contexts using type I and II statements. In the next day users were asked to request suggestion from the robot. Each user was given 5 opportunities to request suggestions by varying input conditions. The suggestion made by the robot and user’s preference were compared. As the second part of the experiment, each users of the same family were asked to instruct the robot regarding another family member’s preferences related to 5 different contexts. After that, each relevant member was asked to request suggestion from the robot under the learned contexts.

As the next part of the experiment a user was asked to instruct robot about the preferences that are common to specific group of users (i.e. family and relations). Then the users who belong to those groups were asked to request suggestions from the robot for the given context. Then results were recorded. In the final step of the experiment, users were paired and 6 groups were formed. Then one user of each pair was asked to provide erroneous instructions to the robot regarding other user’s preferences related to 3 randomly selected contexts. Then other

Table 5.2: Responses for the Likert questionnaire

Statement	Frequency of Likert Responses					Median
	1	2	3	4	5	
The interactions were natural and human friendly	0	0	2	6	4	4.17
It is easy to teach the robot	0	0	1	6	5	4.33
Robot can easily adapt to my beverage and snack preferences	0	0	0	8	4	4.25
Robot’s speech was clear and understandable	0	0	0	3	9	4.83

Here; 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree.

users were asked to teach robot their own preferences related to those contexts. After that they were asked to request for beverage and snack suggestions.

At the end of the first experiment, subjects were requested to fill a Likert questionnaire [53] based on their experience with the robot. This questionnaire is designed to analyse the robot’s interaction capability, preference learning and adaptation capabilities. The responses of the users are given in Table 5.2. According to the user’s responses, a majority of users have high level of satisfaction about robot’s performances.

5.3.2 Ability of Learning User Preferences Based on Robot’s Experiences

The second experiment evaluates the adaptability of robot’s behavior according to users’ hidden preferences or changes of preferences based on experiences. This experiment was conducted with 8 users over a period of one week. Initially, each user was asked to teach robot about their beverage and snack preference related to randomly selected contexts. Then, they were asked to interact with the robot over a period of one week and to make selections different from the stated preferences. Then robot’s ability of learning user’s preference change is analysed. Note that the experiment results of only two randomly selected users

(#1 and #4) are show in Table 5.3 and 5.4.

Table 5.3: Experiment results for user 1

<i>Day</i>	<i>Health</i>	<i>T</i>	<i>W</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No.of Iteration</i>
<i>1</i>	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	<i>1</i>
<i>2</i>	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	<i>1</i>
<i>3</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	<i>3</i>
<i>4</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	<i>2</i>
<i>5</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	<i>1</i>
<i>6</i>	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	<i>1</i>
<i>7</i>	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	<i>1</i>

Here; T:Time, W:Weather, H:Healthy, and M:Morning.

At the beginning of the experiment, user #1 stated the robot that he always preferred tea in the morning and he did not prefer to have snack when he is not hungry. However, the user did not state about his preference of coffee over tea for cold days. First two morning were declared as hot days and user was healthy. As the robot has learned that the user always prefer tea in the morning, robot neglected other two context attributes (weather and user’s health) and suggested the user, tea as the beverage. The user accepted it. As the next day was declared as a cold day, user selected coffee instead of tea. Since robot did not know user’s intention in advance, it took three interaction to infer the user selection. As the 4th day was again declared as a cold day and user selected coffee. However, robot took 2 interactions to guess the user selection correctly. By the 5th day robot was able to perceive that the user prefer coffee over tea for cold days and to guess the user’s reference from the 1st iteration.

The experiment with user #4 was conducted by increasing the complexity of the scenario. At the beginning of the experiment, the user stated the robot that he usually preferred fruit juice in every context and preferred sandwich if he is hungry. Also, He declared that he did not prefer to have a snack if he is not hungry. However, during suggesting interactions, user was asked to select tea instead of fruit juice when he is sick and to change his snack preference by selecting cake over sandwich. The variation of contexts, user’s selection, and

the number of iterations to correctly guess the user’s selection during the week are shown in Table 5.4. The 1st day was declared as a hot day and user was hungry and sick. Robot initially suggested fruit juice and sandwich according to user’s statement. But, user rejected robot’s suggestion due to his bad health condition and new preference of snack. Robot kept on suggesting new snack and beverage combinations until user accept it. It took four iterations to correctly infer the user’s preference. Similarly, for the rest of days robot inferred the user’s preferences. According to results of the experiment, it can be seen that the number of iterations reduces with increase of the number of interactions. It verifies the robot’s ability of learning users’ hidden preferences and changes of preferences from the experiences. The experimental data is shown in Appendix A.

Table 5.4: Experiment results for user 4

<i>Day</i>	<i>Health</i>	<i>T.</i>	<i>W.</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No.of Iteration</i>
<i>1</i>	<i>S</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>4</i>
<i>2</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>4</i>
<i>3</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>yes</i>	<i>cake</i>	<i>fruit juice</i>	<i>1</i>
<i>4</i>	<i>S</i>	<i>N</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>tea</i>	<i>2</i>
<i>5</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>fruit juice</i>	<i>1</i>
<i>6</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>2</i>
<i>7</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>1</i>

Here; T:Time, W:Weather, H:Healthy, S:Sick, M:Morning, A:Afternoon, and N:Night.

5.4 Summary

The experimental results verify the potential of the system in providing adaptive services while learning user’s preferences through natural interactions. The users are enabled to instruct the robot regarding their preferences in a way similar to instructing a human peer. The system is capable of modifying initially learned facts about users by considering the experiences which robot gathers over time.

Thus robot can learn and adapt to user's preference changes. The structure of people layer enables the robot to remember the relationship between users and identify user groups which is a very useful feature for a domestic social robot. Although the system has been only tested and validated using a beverage and snack suggestion scenario, it can be applicable for a vast range of human robot interactions in a multi-user domestic environment.

SPATIAL CONSIDERATION IN AUTOBIOGRAPHICAL MEMORY

Humans are capable of remembering the previous events along with the places where they happened. Furthermore, they can recall the spatial arrangement of significant objects in that spatial locations. For example, when you are describing a party you have attended last night, you can recall the place where it was held including the table you sat and the nice decorations on it. Incorporating this aspect to social robot may beneficial for maintaining human-like interactions.

A large portion of daily tasks includes pick and placement or rearrangement of objects on surfaces. Sometimes, assistive social robots are expected to perform these tasks. This chapter presents a study on how the robot autobiographical memory is used to remember the spatial arrangement related previous events. This chapter attempts to address following questions.

1. How does the robot interpret uncertain spatial and qualitative distance information in object placement related user commands?
2. How does the robot remember and recall the spatial information related to previous events?

6.1 Understanding Uncertain Spatial and Qualitative Distance Information in Overall Object Placement Related User Commands

Human friendly robots are expected to communicate with their non-expert users in a natural and intuitive manner [54]. They are expected to have the capability to maintain a natural interaction with humans in identifying voice and gesture commands as well. Many researches have been carried out to equip service robots with human friendly features [55, 56]. Humans prefer to use voice commands upon any other actions or gestures, to guide their companions in assistive tasks. Most of these voice instructions contain uncertain terms which express qualitative information rather than quantitative information [57]. Therefore, service robots must possess the ability to understand uncertain information in voice instructions precisely.

Most of the voice commands related to object arrangement tasks contain uncertain terms. For an example, terminologies which are used to describe the spatial areas on a tabletop often include uncertain terms related to spatial categorization such as “right side of the table” and “middle of the table” [58]. These spatial categories do not include definite boundaries. Hence the boundaries are often fuzzy. Therefore, service robots must be intelligent enough to understand adequately the user referred spatial area.

A learning approach for placing multiple objects has been proposed in [59]. That system can stack objects while considering the stability and placing constraints. However, it does not deal with uncertain qualitative terms. A computational method for rearranging multiple objects in a cluttered surface has been introduced in [60]. However, this system is not capable of handling uncertain information in user commands. Schiffer et al. [61] have proposed a method for reasoning the spatial relationships between objects on a table given by the uncertain position information such as “Cup is near the dish”. However, this system was not capable of effectively understanding the meaning of spatial categories.

As an example, system was not able to understand commands such as “place the cup in the left corner of the table”. A method for manipulating objects on a table by using natural language instructions including uncertain information such as “move the bottle a little right” has been proposed [62]. However, the system is only capable of interpreting quantitative values for the distance related uncertain information and it is not capable of identifying the information related to spatial categorization. Therefore, the system is not capable of understanding commands similar to “place the bottle on the left side of the table”. The method proposed in [63] is capable of grounding the spatial relations about objects on top of table using natural language instructions such as “the apple is on the left of the table”. However, it cannot be adopted for object placement tasks using language instructions that include uncertain spatial categories.

A fuzzy logic based multimodal system has been proposed in [64] for interpreting uncertain information in object placement using hand gesture positioning information and voice information. However, this concept has been proposed for placing of a single object and does not address the arrangement of a set of objects. For an example, the system was capable of obeying the commands such as “place the bottle on the front left corner of the table”. However, it was not capable of dealing with the commands similar to “place all the things in the left corner of the table”. Furthermore, it was not capable of identifying the qualitative information related to the arrangement of the objects to be placed such as “place them together”.

Most of the day-to-day object handling tasks deal with arranging multiple objects. When people need to arrange a set of objects in a particular spatial area or according to a particular arrangement quality, they prefer to use single voice command related to the overall arrangement of objects rather than repeating the same command over and over for each and every object. For instance, the commands similar to “Keep all the objects on the left side of the table” and “Keep the center of the table free” can be considered. The commands re-

lated to overall arrangement of objects contain uncertain qualitative terms like “Free”, “Occupy”, “Together” and “Separate”. Hence, the service robot should be capable of understanding these uncertain qualitative spatial categories.

This work proposes a novel approach to arrange multiple objects in a table top while interpreting the uncertain spatial terms and qualitative terms in voice instructions related to the overall arrangement of the objects. This system facilitates the user to instruct robot in a way similar to guiding a human companion. For example, the user may issue a single command related to the overall spatial arrangement such as “Keep all the objects on the middle of the table” in order to guide the robot, rather than giving a set of commands to arrange each object. In addition to that, system enables the user to deliver qualitative information to modify spatial arrangement of a set of objects (e.g. “Together”, “Separate”).

6.1.1 System Overview

For this research, initial robotic system was modified by adding few new modules. Overview of modified system is depicted in Fig. 6.1. The system is aimed at providing an effective method of arranging a set of objects on a table surface by understanding the uncertain spatial area qualitative distance information in user commands. Visual inputs are acquired through the RGB-D camera of Kinect sensor and the Visual Information Extraction Module (VIEM) processes these visual inputs in order to determine table width, length and area covered by each object. VIEM is supported by a visual feature database in VM. This visual feature database contains information such as RGB values and feature descriptors of objects. Voice inputs are acquired through the microphone array of the Kinect sensor. The user commands are analyzed through VRUM by using the information available in LM.

LM has been enriched with grammar patterns, frequently used action keywords, spatial terms and qualitative terms related to overall placement of objects.

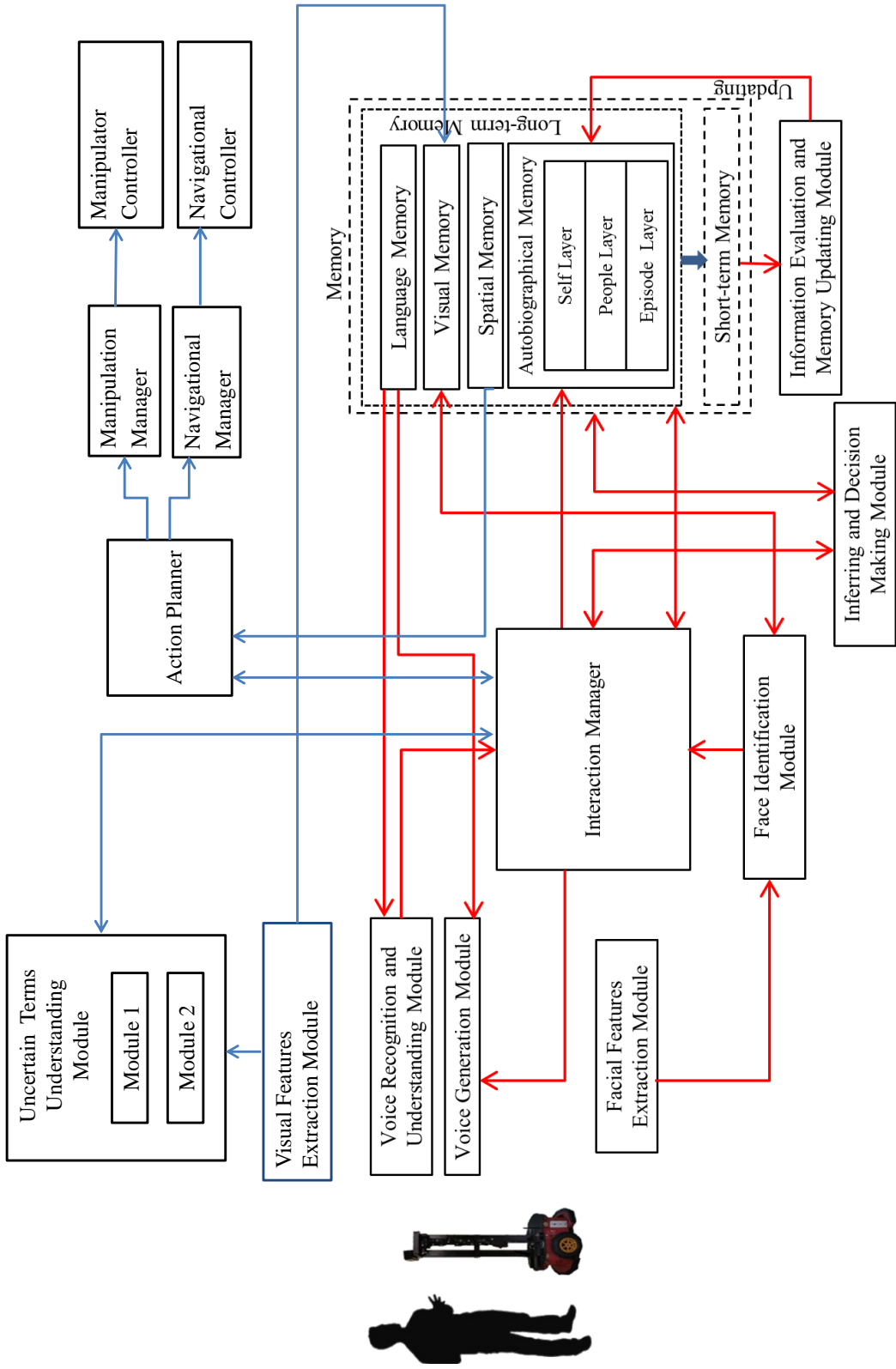


Figure 6.1: Functional overview of the modified system

The action keywords include frequently used verbs related to object placement task. As an example terms such as “Place”, “Keep” and “Move” can be cited. The spatial terms are used to describe the areas of table. Words like “Left”, “Right”, “Front”, “Back”, “Center” and “Front left corner” are included in this category. The spatial areas on a table top are depicted in Fig. 6.2. The qualitative keywords are the terms which are used to describe way of object placement/arrangement. “Together” and “Apart” are some of them. LM also contains the synonyms for frequently used spatial and qualitative keywords. For examples, “Center” and “Middle” can be considered. Uncertain information understanding module is used to interpret the uncertain spatial terms and qualitative terms in user commands.

There are two modules called Navigational Manager (NM) and Manipulation Manager (MM) to manage the navigation of the robot and manipulator motion respectively. The Action Planner (AP) is responsible for managing the coordination between the NM and the MM. The NM is used when robot needs to move towards the table location from its initial position or around the table during object placement task. The NM issues navigational commands to the navigational controller. Navigational controller performs all the low-level navigation controlling functions of the robot such as robot localizing and path planning from an initial position to a target position. The MM submodule handles the high-level function related to object handling. It issues commands to the manipulator controller. Manipulator controller performs low-level control functions such as planning collision free path for the end effector and velocity controlling.

6.1.2 Structure of the User Commands Related to Overall Arrangement of Objects

The flexibility of user commands is essential for maintaining a more natural interaction between the robot and the user. Therefore, the command structure is carefully designed in order to facilitate the user to issue flexible commands.

Here, the user commands are classified into three types namely command type I, II and III. These command types are identified by considering the commands which are used frequently during tasks related to overall object placement on a table top. This command classification is demonstrated in Fig. 6.3.

User commands related to the overall placement of objects can be classified into two main categories. They are direct placement commands and indirect placement commands. The direct placement commands can further be categorized into two groups. They are commands that include only spatial terms (Command type I) and commands that include both spatial terms and qualitative terms (Command type II) related to the arrangement of objects. The command type I is used to guide robot just to position the objects in a particular spatial area of a table. This type of commands does not reveal information related to the quality of object arrangement. Commands similar to “Place all objects in the right side of the table” or “keep the right side of the table occupy” fall under this category. Command type II provides information related to spatial location of object placement as well as the qualitative information related to the overall arrangement of objects. For an example, “Place all objects together on the left

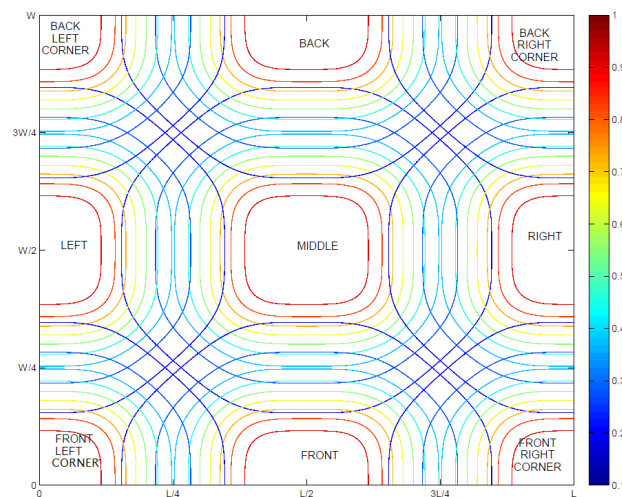


Figure 6.2: Spatial area categorization. The probability of relation for each category is indicated by color contours.

side of the table” can be considered. Indirect placement commands (Command type III) include neither spatial information related to object placement location nor information related to the quality of object arrangement. Instead, it includes the spatial location where objects should not be placed. Consider “Keep the center of the table free” can be considered as an example.

Once the robot receives a user command, the command type and key information are identified through comparison of the command with grammar patterns and keywords in language memory. Then, the key information in the command will be extracted. As the language memory is enriched with several grammar patterns and a broader set of keywords related to object placement, user has a higher choice of commands rather than sticking into a fixed set of commands.

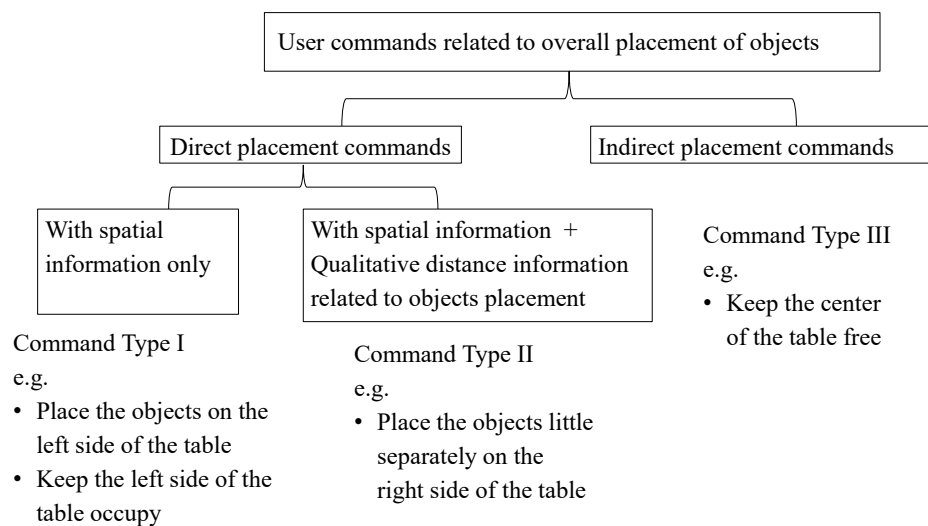


Figure 6.3: Structure of user commands

6.1.3 Uncertain Information Understanding Module

This module is used to evaluate the uncertain information in user commands. This is further categorized into Module I and Module II based upon the functionality. These two are explained below.

Module I: Spatial Area Understanding Module

The role of this module is to interpret areas referred by the uncertain spatial terms such as “Left”, “Right”, “Front”, “Middle” and “Front Left corner” in user commands. A fuzzy inference system has been developed similar to the system described in [64] to obtain the X and Y ranges for each area by analyzing the spatial information in user commands. In this scenario, spatial areas do not have strict boundaries. Thus Gaussian membership functions are chosen to be the output. Membership functions for X and Y axes are shown in Fig. 6.4. If μ_{X_i} and μ_{Y_j} are degrees of membership associated with a particular X axis value and Y axis value, the probability of matching with k^{th} area is P_k is given by following equation. The relationship between i, j and k is given in Table 6.1.

$$P_k = \mu_{X_i} \times \mu_{Y_j} \quad (6.1)$$

Three algorithms have been introduced for executing the object placement commands. Algorithm 1 is used to determine the locations which the objects should be placed while executing type I commands and algorithm 2 is used while executing type III commands. Algorithm 3 is used to adjust the distance between objects while understanding type II commands. Algorithm 3 is discussed under module II.

The number of objects to be placed in a particular area are assumed to be n . If the object has a length of a_{i_0} and a width of b_{i_0} , and a default clearance value between two objects to be c , then algorithm 1 and 2 give the location that the centroid of the object to be placed for command type I and III respectively in the form of x and y coordinates.

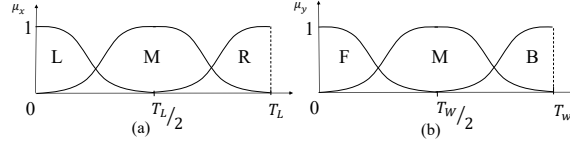


Figure 6.4: (a) and (b) show output membership function of X axis and Y axis respectively. Here, T_W and T_L are the width and the length of the table. Fuzzy labels: L, M, R, F, B, are defined as Left, Middle, Right, Front and Back respectively

Table 6.1: Relationship of i and j with spatial areas

k	i	j
Left	L	M
Right	R	M
Middle	M	M
Front	M	F
Back	M	B
Front Left Corner	L	F
Front Right Corner	R	F
Back Left Corner	L	B
Back Right Corner	R	B

Module II: Spatial Distance Evaluation Module

This module is employed to interpret the quantitative distance related to uncertain qualitative terms when performing command type II. For example, commands such as “keep all objects compactly in left side of the table” and “Keep objects little separately in the left side of the table” can be considered. Spatial distances between objects related to terms like “Compactly”, “Little Separately” and “Fully separately” are assumed to depend on the remaining free area within spatial boundaries after placing all the objects with minimum clearance in a particular area of the table.

The algorithm 1 and 3 are used to execute the type II commands. During this approach, initially it is assumed all the objects are placed with the minimum clearance($c=0$) and then the gap between objects is adjusted according to the user requirement while keeping the all objects within the required spatial boundary.

First, algorithm 1 is executed to calculate locations of each object. Next, algorithm 3 is executed to adjust the spaces between objects. As a result, a maximum value for the distance multiplication factor has been introduced. According to algorithm 1, the first object is always placed at the maximum probability point. Hence, the object which is placed first is kept fixed and the locations of other objects will be adjusted with respect to the first, by multiplying the distance between centroids of particular object and the object which is placed first, with the common multiplication factor.

Assuming the objects will be placed aligning the length with table length and the width with the table width, the common distance multiplication factor can be found for both the X and Y axis in k^{th} spatial area. The maximum values of distance multiplication factor for positive X direction and negative X direction are given by (6.2) and (6.3) respectively.

$$d_{x_+} = \frac{l_{max} - x_1 - (a_{x_{max}}/2)}{x_{max} - x_1} \quad (6.2)$$

$$d_{x_-} = \frac{x_1 - l_{min} - (a_{x_{min}}/2)}{x_1 - x_{min}} \quad (6.3)$$

where

l_{min} - Lower x axis boundary of the spatial area

l_{max} - Upper x axis boundary of the spatial area

$a_{x_{max}}$ - Length of the object located at the maximum x coordinate within the spatial area

$a_{x_{min}}$ - Length of the object located at the minimum x coordinate within the spatial area

x_{max} - Maximum x coordinate which an object centroid is located within the

spatial area

x_{min} - Minimum x coordinate which an object centroid is located within the spatial area

x_1 - x coordinate of the centroid of the object placed at first

Then, maximum values of distance multiplication factor for positive Y direction and negative Y direction are given by (6.4) and (6.5) respectively.

$$d_{y_+} = \frac{w_{max} - y_1 - (b_{y_{max}}/2)}{y_{max} - y_1} \quad (6.4)$$

$$d_{y_-} = \frac{y_1 - w_{min} - (b_{y_{min}}/2)}{y_1 - y_{min}} \quad (6.5)$$

where

w_{min} - Lower y axis boundary of the spatial area

w_{max} - Upper y axis boundary of the spatial area

$b_{y_{max}}$ - Width of the object located at the maximum y coordinate within the spatial area

$b_{y_{min}}$ - Width of the object located at the minimum y coordinate within the spatial area

y_{max} - Maximum y coordinate which an object centroid is located within the spatial area

y_{min} - Minimum y coordinate which an object centroid is located within the spatial area

y_1 - y coordinate of the centroid of the object placed at first

For cases where $x_1 = x_{max}$ or $x_1 = x_{min}$ or $y_1 = y_{max}$ or $y_1 = y_{min}$, the multiplication factor is assumed to be zero.

In order to keep all the objects within the boundary, the minimum distance multiplication factor is chosen as follows.

$$d = \min\{d_{x+}, d_{x-}, d_{y+}, d_{y-}\}$$

A distance modification factor is used to modify the distance depending on the qualitative distance term in user command.

Distance Modification factor = Δ (varies from: $1/d..1$)

$\Delta = 1/d$: compact/ together

$\Delta = 1/d + 0.25 \times (1 - 1/d)$: little

$\Delta = 1/d + 0.5 \times (1 - 1/d)$: medium

$\Delta = 1$: large

Algorithm 1 For direct placement commands

```

for  $i_0 = 1$  to  $n$  do
  while true do
     $\max(P_k) \rightarrow (x,y)$ 
    if Area between  $(x - [c + a_{i_0}/2])$ ,  $(x + [c + a_{i_0}/2])$  and  $(y - [c + b_{i_0}/2])$ ,  $(y + [c + b_{i_0}/2])$  is not occupied and it is within the table boundaries then
      Place the object at  $(x,y)$ 
      Break inner loop
    else
      Go to the next maximum
    end
  end
end

```

If g_x is the distance from centroid of the object placed first, to the centroid of a particular object along X axis and g_y is the distance from centroid of the object placed first, to the centroid of a particular object along Y axis, then g_x and g_y are given by (6.6) and (6.7) respectively.

$$g_x = |x_1 - x_{i_0}| \quad (6.6)$$

$$g_y = |y_1 - y_{i_0}| \quad (6.7)$$

$(x_{i_0,new}, y_{i_0,new})$ is the new location of the centroid of a object.

Algorithm 2 For indirect placement commands

```

for  $i_0 = 1$  to  $n$  do
  while true do
     $\min(P_k) \rightarrow (x,y)$ 
    if Area between  $(x - [c + a_{i_0}/2]), (x + [c + a_{i_0}/2])$  and  $(y - [c + b_{i_0}/2]),$ 
     $(y + [c + b_{i_0}/2])$  is not occupied and it is within the table boundaries then
      Place the object at  $(x,y)$ 
      Break inner loop
    else
      Go to the next minimum
    end
  end
end

```

Algorithm 3 For distance adjustment

```

for  $i_0 = 1$  to  $n$  do
   $g_x = |x_1 - x_{i_0}|$ 
   $g_y = |y_1 - y_{i_0}|$ 
  if  $x_{i_0} < x_1$  then
     $x_{i_0,new} = x_1 - g_x d\Delta$ 
  else
     $x_{i_0,new} = x_1 + g_x d\Delta$ 
  end
  if  $y_{i_0} < y_1$  then
     $y_{i_0,new} = y_1 - g_y d\Delta$ 
  else
     $y_{i_0,new} = y_1 + g_y d\Delta$ 
  end
  Place the object at  $(x_{i_0,new}, y_{i_0,new})$ 
end

```

6.1.4 Experimental Results and Discussion

Experimental Setup

Proposed concept has been implemented on the Moratuwa Intelligent Robot (MIRob) platform in [65]. The experiments have been conducted on a table with a length of (T_L) 875 mm and a width (T_W) of 505 mm. A set of identical cups with the height of 80 mm and the diameter of 75 mm were used. Two sets of experiments have been conducted to evaluate the performance of the system. The experiment setup is shown in Fig. 6.5. Experiment I and II were conducted for examining the uncertain spatial area understanding capability while experiment III was done to analyse the uncertain qualitative distance understanding capability of the robot. In order to increase the accuracy of speech recognition subject was asked to wear a wireless headset with a microphone while issuing the commands. During the experiment the centroid locations of objects in the arrangements done by the robot and the user for each command were recorded.

Uncertain Spatial Area Understanding Capability

In order to analyze the performance of the Uncertain Spatial Area Understanding module, capability of the robot to arrange objects according to type I



Figure 6.5: The MIRob and the user during the experiment.

commands and type III commands was tested by experiment I and II.

Experiment I

Five cups were used for the first experiment. Initially the user was asked to issue commands to the robot to arrange the set of cups on particular spatial area without giving any qualitative information regarding the arrangement (Type I commands). The responses of the robot were recorded. After that, the user was asked to arrange the objects himself, according to same command. The arrangements made by the user for experiment I are shown in Fig. 6.6 (a), (b) and arrangement made by the robot is given in Fig. 6.6 (e) and (f). Then the results in both these situations were compared. According to results of experiment I, it can be seen that the arrangement made by the robot for type I command is quite similar to that of the human. This verifies the robots capability of understanding the spatial area which is mentioned in type I commands.

Experiment II

The second experiment was conducted using nine cups. The user was ask to issue type III commands. Then the arrangements made by the robot and the user were compared. A comparison between the arrangements made by the user and the robot for command type III is given in (c), (d), (g) and (h) in Fig. 6.6. When comparing these arrangements it can be observed that robot can effectively identify the spatial areas which are indirectly referred to in type III commands.

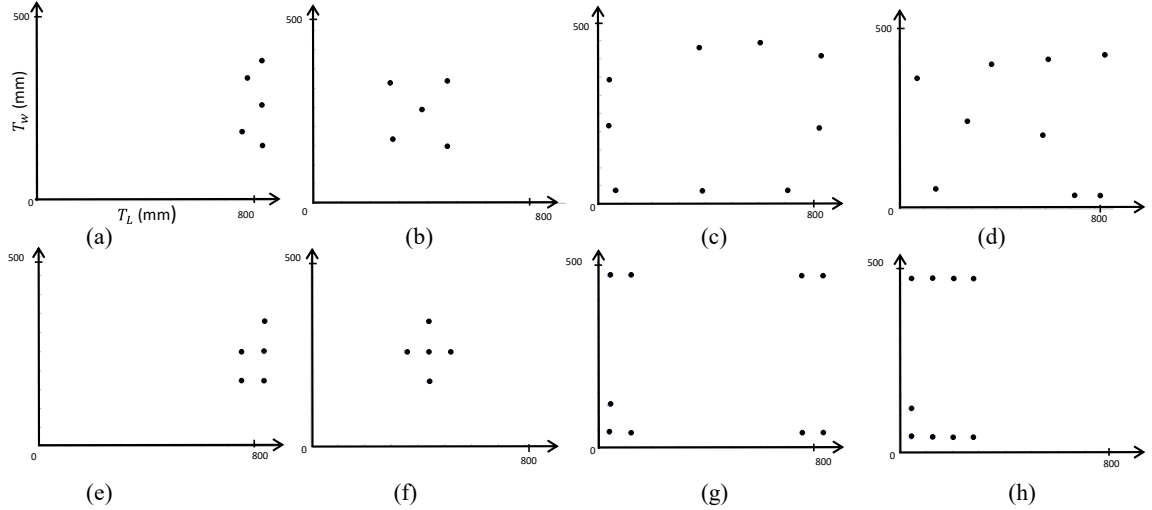


Figure 6.6: The arrangements done by the human: (a) “Place all the objects on the right side of the table” (b) “Place all the objects in the middle of the table” (c) “Keep the middle of the table free” (d) “Keep the right side of the table free”; The arrangements done by the robot: (e) “Place all the objects on the right side of the table” (f) “Place all the objects in the middle of the table” (g) “Keep the middle of the table free” (h) “Keep the right side of the table free”

Uncertain Qualitative Distance Understanding Capability

Experiment III

As the experiment III, capability of the robot to perceive qualitative distances was tested. For this experiment, the user was asked to issue commands related to command type II which include both uncertain spatial area information and the qualitative distance terms. The first case of the experiment was conducted using three cups. In order to analyze how the performance of robot varies with the number of object, experiment was repeated by varying the number of cups. After that, the performance of the robot in the two cases were compared with the arrangement of objects done by the human for the same command. The comparison of these arrangements is given in Fig. 6.7 (for 3 cups) and Fig.6.8 (for 7 cups).

According to the result shown in Fig. 6.7, it can be seen that the distance

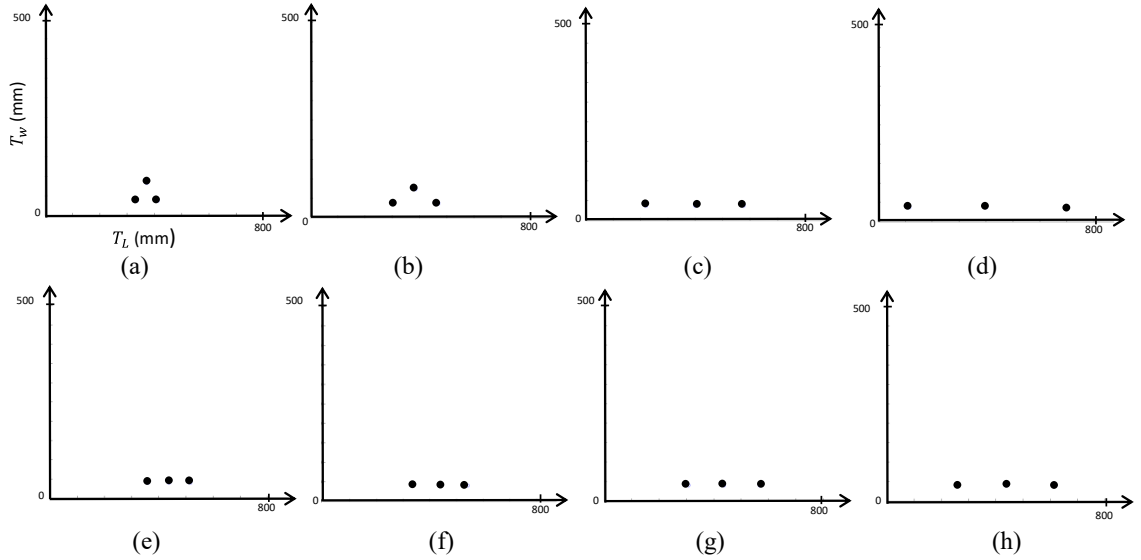


Figure 6.7: The arrangements done by the human: (a) “ Place all objects compactly on the front side of the table” (b) “Place all objects little separately on the front side of the table” (c) “ Place all objects medium separately on the front side of the table” (d) “ Place all objects fully separately on the front side of the table” ; The arrangements done by the robot: (e) “ Place all objects compactly on the front side of the table” (f) “Place all objects little separately on the front side of the table” (g) “ Place all objects medium separately on the front side of the table” (h) “ Place all objects fully separately on the front side of the table”. In this case, 3 objects were considered for the arrangement

between objects in the arrangement made by the robot is quite similar to that of human for “Compactly”, “Little separately” and “Medium separately”. However, for “Fully separately” term the arrangement made by robot was slightly deviated from that of human. This deviation has occurred because humans sometimes do the arrangement without considering the corners of the table as separate spatial areas.

According to the observations it can be seen that when increasing the number of objects, the distances between objects in the arrangements made by the robot for “Medium separately” and “Fully separately” are slightly lower than that of human. In this experiment the distance between objects in “Fully separately” condition is only few mm higher than that of “ Medium separately” condition. This deviation occurs due to several reasons. In arranging large number of objects

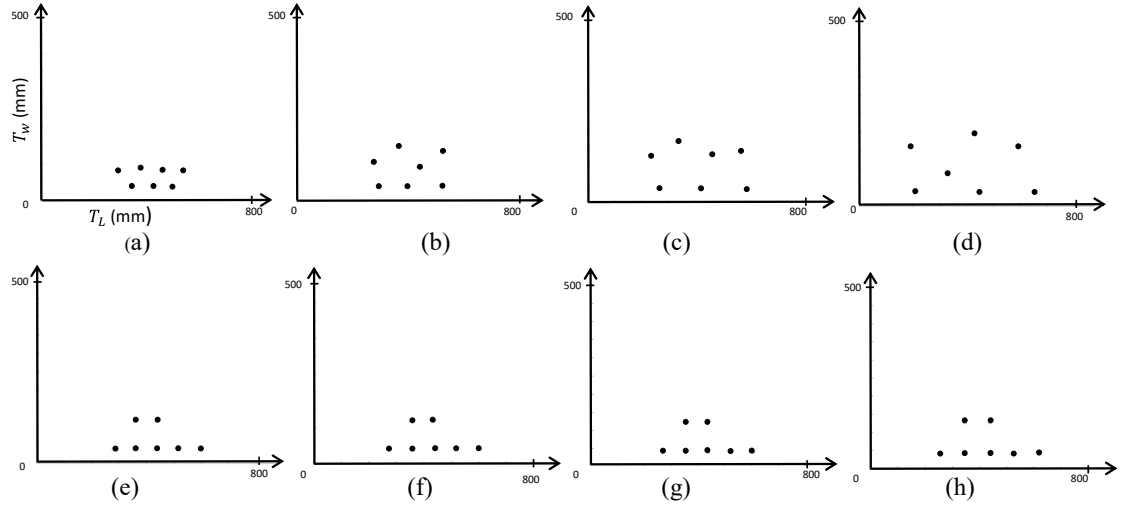


Figure 6.8: The arrangements done by the human: (a) “ Place all objects compactly on the front side of the table” (b) “Place all objects little separately on the front side of the table” (c) “ Place all objects medium separately on the front side of the table” (d) “ Place all objects fully separately on the front side of the table” ; The arrangements done by the robot: (e) “ Place all objects compactly on the front side of the table” (f) “Place all objects little separately on the front side of the table” (g) “ Place all objects medium separately on the front side of the table” (h) “ Place all objects fully separately on the front side of the table”. For this case, number of objects were increased to 7

(i.e :If the total area covered by the objects is a considerable amount compared to the referred spatial area) according to type II commands humans give the first priority for qualitative distance and second priority to the spatial area. Therefore human neglect the spatial area boundaries while increasing the distance between objects. In proposed methodology, robot gives the first priority to the spatial area term and tries to varies the distance between the objects for each keyword while keeping the objects at the maximum probability points with in the boundary. Therefore when increasing the number of objects the distance increment for each qualitative distance will decrease.

6.2 Encoding Spatial Information in Autobiographical Memory

Humans prefer to fuzzy categorizations rather than precise values. The same is applicable for spatial locations as well. For an instance, they prefer to say "Cup is on the left side of the table", rather than "Cup is at (x,y)". Most of the day to day pick and place tasks or table arrangement tasks do not need precise location of objects. Therefore, humans tends to remember an estimated location based on the spatial area categories. This feature can be incorporated to a social robots' AM when precise object locations are not required.

6.2.1 Experiments

In order to examine the performance of the system a set of experiments was conducted. Five participants were used for the experiment and altogether twenty interactions were considered (4 interactions with each participant). A set of red (3), green (3) and blue (4) colour cups that have identical dimensions were used as the objects. The objects were expected to arrange on a table surface with 875mm \times 505mm dimensions. The experimental procedure has been explained below.

Each experiment consists of two parts. As the first part, subjects were asked to instruct the robot to make an arrangement using uncertain spatial and qualitative commands that are described in the previous section. They were asked to use maximum three commands. Then the robot's arrangements were recorded. After completing all the interaction sessions with the subjects, a set of questions was asked from the robot. Then robots answers and the information of previous interaction were compared. It is important to mention that, only a few example dialogues between robot and user has been presented.

Remembering the Spatial Location of Objects and Arrangement Quality

The purpose of these experiments is examining the robot's ability of remembering information related to the object arrangement. For this part of experiment, subjects were allowed to choose any number of cups from the provided set. After the interactions, the robot is expected to answer these questions.

Q1: Can you remember the <1st/2nd /3rd/4th > table arrangement task with <user first name>?

Q2: Where did you place the <colour> cups?

Q3: How many <colour> cups were there?

Q4: Could you please make the same arrangement again?

User A selected 2 blue cups, 3 red cups and a green cup for his first arrangement task. Then she used three commands to guide the robot. The commands given by user A (i.e. Ramya)is shown below.

Place blue cups on the right side of the table

Place green cup on the left side of the table

Place red cups compactly in the middle of the table

Each user command is stored in robot's short term memory. Then, robot extracts keywords from the commands and interprets uncertain spatial and qualitative distance terms. After that, the arrangement is done and the robot episodic memory is updated. After the interactions, several questions are asked form the robot. The conversation between the robot and examiner is given bellow.

Examiner: Can you remember the 1st table arrangement task with Ramya?

First, robot extracts the user ID of *Ramya* form *User table* in people layer. Then these ID is used to retrieve records of user A from the episodic layer. The information of 1st table arrangement task event with user A is selected from *Event table* by filtering based on event type, and event ID.

Robot: Yes. It was yesterday.

Examiner: How many red cups were there?

To answer this question, robot selects the action IDs comes under relevant event ID. Then a *select query* is generated to filter the records from *Object table* based on Action ID, object name and colour. Likewise, the conditions of the select query are varied according to the examiner's question.

Robot: Three

Examiner: Where did you place the red cups?

Robot:In the middle of the table

Examiner: How many blue cups were there?

Robot:Two

Examiner: How many green cups were there?

Robot: One

Examiner: Could you please make the same arrangement again?

Robot: Ok. I will do it.

Remembering an Action Sequence along with Spatial Locations.

This experiment is aimed to verify the robots capability of remembering an action sequence performed in a past arrangement task along with spatial loca-

tions. For this experiment, subjects were asked to use three objects. Then they were asked to issue commands to place one object at a time. The command sequence and the object arrangement were recorded. After the interactions, robot was expected to answer following questions.

Q1: Can you remember the <1st/2nd /3rd/4th > table arrangement task with<user name>?

Q2: What colour cup did you place <firstly/secondly/finally>?

Q3: Where did you place the <first/second/third> object?

User B (i.e. Sadeepa) chose a red cup, a green cup and a blue cup for her 4th arrangement task. She used these three commands to guide the robot.

1. *Place the green cup on the front side of the table*
2. *Place the red cup on the back left corner of the table*
3. *Place the blue cup on the back side of the table*

After the interaction, examiner few questions form the robot.

Examiner: Can you remember the 4th table arrangement task with Sadeepa?

Robot: Yes. It was today.

Examiner: What colour cup did you place firstly?

In order to recall an past action sequence, robot filters the records in the Action table based on the event ID and action type then action IDs are extracted. After that, they are used to access the relevant information in the *Object table*.

Robot: Green colour cup

Examiner: Where did you place the second object?

Robot: On the back left corner of the table

Examiner: What colour cup did you place finally?

Robot: Blue colour cup

6.3 Summary

This chapter has presented a study on how robot autobiographical memory can be used during spatial arrangement related activities. Methods have been developed to understand uncertain spatial and qualitative distance information in user commands. The robot's abilities of recalling object locations, arrangement quality and performed action sequence in previous arrangement tasks were examined. Robot was able to successfully recall those information by using SQL queries. However, this study only considers the spatial informations related to object manipulation tasks on a table surface.

CONCLUSIONS

This research proposes an AM based system that can support long-term human-robot interactions. Design of the robot AM is inspired by the human AM. It has been designed as a three-layered architecture which consists of self, people and episodic layers. Each layer intends to store specific information as their names imply. The AM has been embedded to the robot's long-term memory. An interactive system has been designed and integrated with the memory. Entire system works as a finite state machine.

A NLP based information extraction mechanism has been proposed for extracting user biographical information during interactions. The communication between robot and user is achieved using simple grammar. An inferring and decision making module has been developed for supporting the user adaptability in long-term interactions. Usability of Robot AM has been tested for remembering the spatial location information and past action sequences. A system has been introduced to understand the uncertain spatial and qualitative distance terms related to object arrangement tasks.

7.0.1 Evaluation of the System

The proposed AM based system can be applied for a social robot intends to build and maintain relationships with humans. The novelty of the AM is the human memory inspired design which can support long-term HRI. The structure of AM enables the robot to store informations of multiple users. Thus, robot can

survive in multi-user environments. Because of the semantic network approach robot can remember user groups and relationships which are useful for many aspects. The memory design, memory updating, and recalling mechanisms support the proper operation of AM during HRIs.

The proposed preference learning method can be introduced as a step towards the human-like interactions. According to the literature on previous research studies, this is the first system which uses third person's utterances to learn user preferences. It enables the humans to instruct the robot as another human being. The proposed inferring and decision making module facilitates the robot to adapt according to user's hidden or changes of preferences.

As an extension to the research, a novel method has been introduced to arrange a set of objects in a table surface by understanding uncertain spatial areas and qualitative distance terms that are used to describe the arrangement. Spatial area understanding module has been developed by using fuzzy logic. The proposed methodology facilitates the robot to remember object locations based on spatial areas and distances between objects in situations where precise values are not required. This is quite similar to the way that humans remember spatial information. The AM has been used for encoding these spatial information. The system is capable of recalling spatial location and arrangement quality of objects along with informations related to sequence of past actions.

7.0.2 Limitations of the System

The major problem related to the episodic memory is the managing of information. As the amount of information in the episodic memory grows with the number of interactions, an effective forgetting mechanism is needed. Presently, the long-term memory does not have any forgetting mechanism. However, proposing a forgetting mechanism is beyond the scope of this research.

As the voice recognition is not one of the main concerns of this research we have

employed a simple voice recognition mechanism. Due to the limited capabilities of the used method, it exhibited low performances in noisy environments. As a solution for that, long user utterances have to be taken as keyboard inputs to ensure the accuracy. Another limitation of the system is limited capability of NLP based information extraction mechanism. The rules have been created to extract only users biographical information and it can not be applicable for other complex conversations.

7.0.3 Recommendation for Future Developments

As a future research, one can introduce an effective forgetting mechanism to manage the growing storage of episodic memory. A methodology is needed to evaluate the information based on its significance and time. Then, less significant information should be decayed with the time. In present the conversation between robot and user is direct and simple. Robot can not identify user's requirement without direct communication. If robot can interpret user's intentions from indirect conversations or by analyzing user's behaviors, it would be more human like. This can be partially achieved by enhancing the NLP based information extraction mechanism to interpret more complex user utterances. Further, a multi-model mechanism which is capable of interpreting gestures, emotions and language can be incorporated.

Another interesting research area is application of AM during multi-user interactions where robot needs to interact with more than one user at a time. In such situations robot must be able to update and recall information related to multiple users without any conflict during the same interaction. Finally, the combination of spatial memory and AM can be applied for more complex situations where robot needs to remember additional information such room locations and orientations of objects etc.

LIST OF PUBLICATIONS

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2. M. M. S. N. Edirisinghe, M. A. V. J. Muthugala and A. G. B. P. Jayasekara, “Application of Robot Autobiographical Memory in Long-Term Human-Robot Social Interactions,” in The 2nd International Conference on Electrical Engineering (EECon) , 2018. IEEE, 2018 (*In press*).
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EXPERIMENTAL DATA OF CHAPTER 5

A.1 Ability of Learning User Preferences Based on Robot's Experiences

A detailed description of the experimental procedure is given in subsection 5.3.2. The experimental data for first four subjects are shown here. As described in subsection 5.3.2, subjects used Type I and Type II statements to instruct the robot regarding their snack and beverage preferences. The stated and hidden(unstated) or changed preferences of each subject are shown below.

User 1

Stated preferences:

*I **always** preferred tea in the morning.*

If am not hungry then I do not have snack.

Hidden preferences:

I prefer coffee over tea for cold days.

User 2

Stated preferences:

I usually drink tea in the morning.

I never drink fruit juice when I am sick.

I always eat sandwich when I am hungry.

Hidden preferences:

I prefer fruit juice over tea when it is hot and I am healthy.

User 3

Stated preferences:

I usually drink tea if I am sick.

I always drink fruit juice when I am healthy.

I always eat sandwich when I am hungry.

Hidden preferences:

If I am healthy and not hungry then I do not eat snack.

If I am sick and not hungry then I eat biscuit.

User 4

Stated preferences:

I usually preferred fruit juice in every context.

If I am hungry then I eat sandwich.

If I am not hungry then I do not have snack.

Change of preferences:

I drink tea instead of fruit juice when I am sick.

I prefer cake over sandwich when I am hungry.

Robot uses above statements to create rules in the Preference Rule table. As described in chapter 5, the probabilities associated with each rule have been derived according to the type of statement and adverbs. Each rule is stored with source of learning (user's own or third person statement) and trustworthiness value. The content of the Preference Rule table is shown in Table A.1.

Table A.1: Content of the Preference Rule table

Rule Id	User ID	Weat -her	Time	Health	Hunger	P(Co -fee)	P(Tea)	P(fruit -juice)	P(Bis -cuit)	P(Cake)	P(Sand -wich)	P(No Snack)	Sou -rce	Trust -worthiness
1	1		morning				1						own	1
2	1				no							1	own	1
3	2		morning				0.8						own	1
4	2			sick				0					own	1
5	2				yes						1		own	1
6	3			sick			0.8						own	1
7	3			healthy				1					own	1
8	3				yes						1		own	1
9	4	any	any	any				0.8					own	1
10	4				no							1	own	1
11	4				yes						1		own	1

The experiment was conducted as explained in subsection 5.3.2. The experimental results including the variation of contexts, user beverage and snack selections and number of iterations to correctly infer the user selection for user #1,#2,#3,#4 are shown in Table A.2, Table A.3, Table A.4 and Table A.5 respectively.

Table A.2: Experiment results for user 1

<i>Day</i>	<i>Health</i>	<i>T</i>	<i>W</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No. of Iteration</i>
1	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	1
2	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	1
3	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	3
4	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	2
5	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	1
6	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>tea</i>	1
7	<i>H</i>	<i>M</i>	<i>hot</i>	<i>no</i>	<i>no</i>	<i>coffee</i>	1

Table A.3: Experiment results for user 2

<i>Day</i>	<i>Health</i>	<i>T</i>	<i>W</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No. of Iteration</i>
1	<i>S</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>sandwich</i>	<i>tea</i>	1
2	<i>H</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>sandwich</i>	<i>fruit juice</i>	2
3	<i>H</i>	<i>M</i>	<i>cold</i>	<i>yes</i>	<i>sandwich</i>	<i>tea</i>	1
4	<i>S</i>	<i>M</i>	<i>warm</i>	<i>yes</i>	<i>sandwich</i>	<i>tea</i>	1
5	<i>H</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>sandwich</i>	<i>fruit juice</i>	2
6	<i>H</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>sandwich</i>	<i>fruit juice</i>	1
7	<i>S</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>sandwich</i>	<i>tea</i>	1

Table A.4: Experiment results for user 3

<i>Day</i>	<i>Health</i>	<i>T</i>	<i>W</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No. of Iteration</i>
1	<i>S</i>	<i>M</i>	<i>warm</i>	<i>yes</i>	<i>sandwich</i>	<i>tea</i>	1
2	<i>S</i>	<i>A</i>	<i>warm</i>	<i>no</i>	<i>biscuit</i>	<i>tea</i>	3
3	<i>H</i>	<i>N</i>	<i>warm</i>	<i>no</i>	<i>no</i>	<i>fruit juice</i>	4
4	<i>S</i>	<i>M</i>	<i>warm</i>	<i>no</i>	<i>biscuit</i>	<i>tea</i>	1
5	<i>H</i>	<i>A</i>	<i>warm</i>	<i>no</i>	<i>no</i>	<i>fruit juice</i>	1
6	<i>H</i>	<i>M</i>	<i>warm</i>	<i>yes</i>	<i>sandwich</i>	<i>fruit juice</i>	1
7	<i>H</i>	<i>M</i>	<i>warm</i>	<i>no</i>	<i>no</i>	<i>fruit juice</i>	1

Table A.5: Experiment results for user 4

<i>Day</i>	<i>Health</i>	<i>T.</i>	<i>W.</i>	<i>Hun.</i>	<i>Snack</i>	<i>Bev.</i>	<i>No. of Iteration</i>
<i>1</i>	<i>S</i>	<i>M</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>4</i>
<i>2</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>4</i>
<i>3</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>yes</i>	<i>cake</i>	<i>fruit juice</i>	<i>1</i>
<i>4</i>	<i>S</i>	<i>N</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>tea</i>	<i>2</i>
<i>5</i>	<i>H</i>	<i>M</i>	<i>cold</i>	<i>no</i>	<i>no</i>	<i>fruit juice</i>	<i>1</i>
<i>6</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>2</i>
<i>7</i>	<i>S</i>	<i>A</i>	<i>hot</i>	<i>yes</i>	<i>cake</i>	<i>tea</i>	<i>1</i>