Four memory categories to support socially-appropriate conversations in long-term HRI

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***Abstract*—in long-term human-robot interaction (HRI), memory is necessary for robots to use information that are collected from past encounters to generate personalized interaction. Although memory has been widely employed as a core component in cognitive systems, they do not provide direct solutions to utilize memorized information in generating socially-appropriate conversations. From a design perspective, many studies have employed the use of memory in social interactions. However, only a few works so far have addressed the issue of how to utilize memorized information to design long-term HRI. This work proposes a category of four types of memory information aiming to allow a robot to directly use memorized information to modify conversation content in long-term HRI. A memory system was developed and briefly introduced to facilitate the use of the memory information. In addition, the concept of ways to use these four types of memory in long-term interactions are provided. To demonstrate, a personal assistant robot application and a user study using it are also included. Our results suggest that a robot using the proposed memory information might help users perceive positive relationship with the robot.**

Keywords—four memory categories; interaction strategy concept; memory system design; long-term HRI; personalized conversation

I. Introduction

In near future, socially intelligent robots are expected to be integrated into our daily life and provide various services such as health-care and education. Many of these services requiring a robot to interact with users in socially-appropriate ways repeatedly over an extended period of time, i.e., long-term. While users may find a robot interesting at the first glance, in long-term HRI, they could quickly lose interests after the novelty effect wears off. One of the main challenges of long-term HRI is to find ways to generate content and new behaviors for a robot to personalize its behaviors towards individual users in order to sustain long-term HRI [1].

Cognitive systems and socially intelligent computational models are often used in human-agent interaction research area to help an agent generate personalized interactions. While these systems have many successful implementations and impressive performance, they lack straight-forward implementation methods to imbed memorized information into the content of an agent's conversation. At the current stage, it is still hard to use such systems to design long-term HRI.

This work presents a category of four types of memory information that are generally encountered in repeated HRI. We then give a brief introduction about a memory system to facilitate the usage of this memory information. To generate personalized interactions, we provide concept of interaction strategies for each memory category to help designers develop long-term HRI applications. To demonstrate, a personal assistant robot application using the memory system is developed and a user study with it is reported, along with a preliminary analysis. Fig. 1 displays the scenario of our user study.

Figure 1. A user is chatting happily with android ERICA in our user study. ERICA is acting as a personal assistant robot that help users manage their schedule

II. Related works

A. Memory in cognitive systems

Even limited to artificial intelligence, memory as a concept can cover a large area of different research disciplines. Specifically, memory is a crucial component in cognitive systems, such as ACT-R [2], Soar [3], 4CAPS [4], EPIC [5]. Although these systems can give a robot "mind" analogue to that of humans, at current stage, it is still difficult to use them to support high-level language modification with memorized information.

For social robots and computer agents, memory models is a relatively new area. Ho et al. proposed an initial memory model that integrated various low-level sensory data [6]. Campos et al. took the concept of semantic memory and designed a virtual agent MAY acting as an affective dairy to form shared memory with users [7]. Kasap et al. used the concept of episodic memory and created a memory system to facilitate hierarchical task planning system for a long-term, tutor-type robot application [8, 9]. Elvir et al. developed a conversational memory architecture with a completed algorithm to remember and retrieve episodic memory [10]. However, these works did not focus on providing guidelines for designing a long-term HRI study with natural language interaction. Overall, a social robot should not only be able to remember, but more importantly, it should be able to express in socially-appropriate ways with the memorized information. The object of this work is to display passible memory information that can be used to design a personalized long-term HRI in the context of natural language interactions.

B. Memory usage in long-term HRI

Factual Information: Conversational robots can remember simple user information such as users' names to help raise their perception as affective social entities. Sabelli et al. conducted a study with a robot in an elderly care home [11]. The seniors felt emotionally attached to it when it greeted them by their names. Gockley et al. designed a receptionist robot named Valerie, who can remember visitors and greet them by their names [12]. Mutlu et al. identified the importance of user attributes such as gender, age, suggesting that designers should reflect such user attributes in HRI [13]. Richards and Bransky focused on evaluating appropriate memory recollection of personal information supplied by the user in previous conversations [14]. Although few works have directly investigated the integration of personal information into conversations, we believe such information is crucial in HRI. Building upon previous HRI studies, we designate user's personal information (e.g., name, hometown, etc.) and attributes (e.g., nationality, hobbies, etc.) as factual information to support various kinds of personalized interactions.

Intention: A user's intention (or goal) is a special type of information because the status of a user's intention can change over time and needs to be tracked. Kidd designed a robot to log and track weight loss goals of users to encourage them to continue exercising [15]. Tapus et al. designed a robot that provides emotional support to patients in a rehabilitation center during therapy [16]. Matsuyama et al. describes a virtual agent system that engages its users in a conversation to elicit their goals and preferences to make recommendations and select appropriate conversational strategies [17]. Following the idea of incorporating a user's intention into HRI, we propose model intention as an unique type of memory object.

Interaction history: Many conversations require robots to remember interaction history. Kanda et al. designed a robot that can remember a user's name and interaction time, allowing the robot to gradually disclose itself to users based on the accumulated interaction time [18]. Kanda et al. later expanded their work and designed a shop guide robot that remembered the dialogue history of users [19]. Lee et al. developed Snackbot, which remembers snack choices and the robot's own behavior history to generate personalized small talk [20]. Expanding on previous works, we propose a adaptable interaction history structure to store interaction events (i.e., records of what happened between users and a robot over an interaction period) and demonstrate how a robot can benefit from this structure to modify HRI.

Meta-behavior: In long-term social interaction, humans often manifest behavior patterns that are both interesting and informative. Glas et al. placed a robot in a shopping mall to observe and identify behavior patterns of customers to create personalized greetings to simulate a personal touch [21]. Fasola et al. developed an exercise coach that recorded the performance history of users and motivated them to do exercise [22]. Based on previous works, we define the information about the patterns of a user's observed behaviors in HRI as meta-behavior.

III. Memory Categories and Memory System

Here, we briefly introduce a memory system we designed to facilitate long-term HRI with the proposed memory categories. It should be noticed that we adopted pre-scripted design method. Comparing to new design methodologies such as data-driven, pre-scripted design allows us more freedom to construct and control the flow of an interaction, which also allows faster prototyping and easier concept validation.

A. Four memory categories

Based on memory usage in social HRI reviewed in Section II, we defined the following four categories of memory information: (1) factual information: such basic elements as personal facts like names or hobbies; (2) intention: knowledge of a user's plans or future actions; (3) interaction history: representation of past events and experience between a robot and its users; (4) observed behavior: metadata of a user's behaviors during interactions.

B. Three-layer memory structure

We designed a memory system using a three-layer structure that consists of sensory memory (SM), working memory (WM), and long-term memory (LTM).

During an interaction, a user's sensor data are stored in the SM for data processing, e.g. video frame of a user's face for face recognition [23]. Once a face is identified, the processed information is transferred to the WM to generate social behaviors. For example, if the face is identified as a known user, the robot can load user's information such as name and previously discussed topics from the LTM to the WM to generate personalized behaviors; Otherwise the robot can ask the user's name and do ice-break type interaction. After the interaction is over, the user information is stored in the LTM for future usage with a unique ID. In the implementation, a face recognition system identifies the individuals.

We used key-pair (examples given in the Appendix) method to store user factual information. We created memory objects such as event objects to store interaction history events and meta-behavior events, and intention objects to store user intention information respectively. We used unordered list object to aggregate factual information and ordered list object to preserve the episodic information of events. Due to the words limitation, this work does not report the detail implementation methods.

C. Memory information extraction

The information stored in the memory is extracted from conversations during HRI using natural language processing (NLP) technologies. Since designing a generic NLP system is technologically difficult, to keep things straightforward, most of the NLP are done through pre-scripted keyword matching. To get certain memory information from a user, the robots in this work are designed to ask specific questions. For example, by asking, "which country are you from?," the robot can extract a user's nationality from a conversation. On the other hand, it can ask, "are you leaving the office now?" and if the user answers "yes," the robot can logically infer that the user is leaving at a certain time of the day and thus store in its memory this piece of the user's meta-behavior as a *behavior event object*.

IV. MEMORY-BASED INTERACTION STRATEGY CONCEPTS

Memory plays a vital role in building social relationships in human-human social interactions. Since positive social relationships can boost the effectiveness of social interactions [24], social robots, which provide long-term social services, must possess the memories of users. A robot needs to demonstrate that it remembers users to nurture a sense of familiarity and engender a feeling that it is building a relationship with the humans over time. Here, we briefly present the concepts of how we use each of the memory category in long-term HRI. Designers may find their own ways to use these information.

A. Using factual information

In daily life, people tailor conversations using their friends' personal information: addressing them by nicknames or making jokes based on shared, interesting facts. Factual information represents a user's personal information or attributes revealed during HRI. However, simply making the robot repeat such remembered factual information is generally not very appealing. Therefore, the first interaction strategy is that the robot should indirectly demonstrate its memory of a person's factual information by attaching a piece of relevant factual information to modify the point the robot is already intending to express in the context of its main interaction. To use this information, we propose an "attaching factual information" strategy

B. Using intentions

In social interactions, most of us have probably experienced the warm feeling fueled by a close friend who asks about a difficult task, especially when that person knows that it has been finished. Similarly, if a robot has previous knowledge of a user's intention, it can naturally inquire whether that intention has been resolved or ask about its progress and create warmth even if the conversation does not necessarily serve a specific purpose in the main interaction scenario.

To use this strategy, designers need to create scenarios that empower a robot to ask about a user's intention. After the robot has identified a user's intention, it can store that information as an intention object (discussed in Section III) and initialize its status as unresolved. Because it takes time for the user to carry out the intention, the robot needs to remember it and broach the topic again later. Once the user reports an intention is fulfilled, the robot can mark that intention as resolved and stop tracking it. We propose this as the "following up on intention" strategy.

C. Using interaction history

The idea of shared experiences can be used in long-term HRI if a robot recalls meaningful past experiences with a user. Interaction history stores such information for a robot to recall noteworthy events with a user. To use this strategy, the system designer needs to determine in advance which event the robot should recognize and store. Notice that the memory format defined in this paper is merely a design framework and creating a system that can automatically extract generic events is beyond the scope of this work. In this work, we assigned tags to each type of the events so that the robot could store and associate relevant events. When a new event occurs, the robot can associate it with a past occurrence of a similar event and comment on their similarities or differences. To simplify the design, we implemented the robot to use this strategy immediately after a relevant event occurred. With this concept, we propose a "citing shared experience" strategy.

D. Using meta-behavior

Showing an understanding of others exhibits strong social support in daily life [25]. In long-term HRI, users may display certain behavior patterns, which a robot can observe and comment on to show that it is trying to proactively understand the user to convey a supportive relationship. To use this strategy, the system designer needs to determine behaviors that the robot should observe and develop corresponding analyzing functions to extract patterns from the data, e.g., using statistical methods. We do not design a generic system that can automatically differentiate and extract behaviors, which can be a separate research itself. As the robot continuously records behaviors of a user over multiple interactions, it can probably find trends in user behaviors, do meta-analysis, and comment on the analysis results. We call this "commenting on meta-behavior" strategy).

V. USER STUDY

To demonstrate and gain insights about designing long-term HRI, we created an autonomous personal assistant robot application using the memory system and conducted a user study with it. The study used ERICA [26], a humanlike android robot with a female appearance as shown in Figure 1. ERICA provided assistant functions including remembering users' tasks, giving reminders, and checking the completion status of each task. Users interacted with the robot in three separate sessions per day in 8 days which were arranged in a one-month period.

Over the 8 days, 19 social scenarios of proposed interaction strategies were created and randomly applied when the robot performed its assistant function. These 19 social scenarios are comprised of the following: eight "attaching factual information" scenarios, four "following up on intention" scenarios, four "citing shared experience" scenarios, and three "commenting on meta-behavior" scenarios. Appendix 1 summarizes the typical scripts of each interaction strategy during the user study.

A. Preliminary analysis and results

The user study was conducted in an ethnographic style to help us understand whether the memory system and interaction strategies help to sustain long-term HRI. Three of our colleagues at the Advanced Telecommunications Research Institute International (ATR) took part in the study. We chose this set up because it helped to integrate the robot into the daily life of the participants and might elicit natural reactions.

We used a combination of direct observations and interviews to collect data. During the experiment, video and audio were recorded for each interaction. A short interview was conducted at the end of each day. The interviews were semi-structured. The interview began with open-ended questions oriented towards getting the user's impression, then following up with more specific questions. Appendix 2 presents an example of questions asked during an interview.

We studied users' language, gestures, and facial expressions. For each scenario in which an interaction strategy had been implemented, we marked a positive observation, such as increased attention or engagement with the robot as a positive response in a preliminary way, i.e., all manually annotated by the first author of this paper. A total of 50 instances of strategy-implemented scenarios were performed. This result is displayed in Table 1.

Table 1. Preliminarily marked positive user reactions

	Total Positive Observations	*Total Instances*	*Percentage*
Attaching Factual Information	8	22	36.3%
Following up on intentions	6	11	54.5%
Citing Shared Experience	6	10	60.0%
Commenting on meta behavior	7	7	100%

The "attaching factual information" strategy generated the fewest positive reactions (36.3%). The "following up on intention" and "citing shared experience" strategies had more than half of positive user reactions (both around 60%). The "commenting on meta behavior" strategies appeared to be most effective, with 100% of positive reactions observed.

For the "attaching factual information" strategy, we categorized the 22 instances into three categories. The "living habits" category included 9 instances, in which the robot talked about "using energy drinks", "working out" and "staying up late"; the "self-identity" category included 6 instances about "nationality" and "cat person or dog person"; and the "user's opinions" category included the 7 instances about "preference on sake", "cellphone brand" and "opinions on AI". Conversations that were related to a user's living habits appeared to be relatively effective, as five out nine (55.6%) instances promoted positive reactions. Conversations involving a user's self-identity appeared to be quite ineffective, with two out of six (33.3%) instances eliciting positive reactions. For the "user's opinions", only one out seven (14.2%) instances got a positive reaction. Especially, none of the four (0%) instances of "preference on sake" and "brand of cellphone" got positive reactions. In these cases, the users seemed to treat these factual information as trivial to them and thus did not show much reaction when the robot made conversation about these facts.

The "following up on intention" strategy seemed to be relatively more effective than "attaching factual information" strategy in building rapport, especially if the robot followed up on an intention that had been mentioned a while ago. In one specific case, User 1 told the robot that she needed to refill her car and book a hotel before her vacation during one of the experiment sessions. After User 1 came back from her vacation, the robot used the "following up on intention" strategy and asked her if she had refilled her car and booked a hotel. User 1 first appeared to be surprised but then became very happy that the robot still remembered her plan.

The effectiveness of the "citing shared experience" strategy relied on the cited experience being impressive or memorable to the user. All three instances (100%) where the robot talked about the health tips it provided appeared to be enjoyable to the users. Three out of four instances (75%) where the robot apologized for its own awkward utterance and speech recognition errors appeared to be effective as well. However, none of the three instances (0%) of the robot citing the total number of interactions caused positive reactions.

The "commenting on meta behavior" strategy appeared to be the most effective with a 100% positive reaction rate. Users usually appeared to be slightly surprised when the robot made a comment, but seemed to appreciate that the robot had paid attention to their daily activities.

Overall, even though users became aware of the patterns how the robot used each strategy as the experiments went on, the proposed strategies help the progress of building up a relationship between the robot and a user. For example, by remembering users' daily tasks, the robot had observed that User 3 had continued to have a "writing paper" task for several days. After observing this behavior pattern, the robot used the "commenting on meta behavior" strategy in the next day's morning session to guess that User 3 might have the "writing paper" task again, before asking User 3's daily tasks. In the following interview, User 3 said, "it's nice that she [ERICA] figured out I need to write my paper today… It feels like she [ERICA] is starting to know me a little".

VI. Conclusion

In this work, we proposed four memory categories that can be used to generate personalized interaction content in long-term HRI. We briefly report our method to use them in a long-term scenario with a supporting memory system and four interaction strategies. The preliminary results suggest that the "commenting on meta behavior" strategy concept might elicit stronger positive feelings than the other three strategies.

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Appendix 1

Summary of typical scripts for each interaction strategy implemented in user study.

Table 1. Typical interaction script for "attaching factual information" strategy implemented in user study. We use key-pair method to represent such information in our memory system, e.g., [Name] – [Xiqian] ([Key]-[Factual information]), and use markup language to embed the memorized information in robot dialogue.

Key	Factual Information – Scenario – Robot Utterance
Nationality: Japanese or non-Japanese	nationality: Japanese → talking about Japanese holidays ERICA: Since you grew up in Japan, you've probably celebrated the coming-of-age holiday yourself.
Cat or dog person	pet group: cat-person → discussing movies ERICA: By the way, since you are a cat person, you may like the movie 'Nine Lives'.
Drinking sake	alcohol: sake → talking about a party ERICA: I heard there was a party on Wednesday. Did you drink a lot? Even though I drink, I'll bet the sake was delicious.
Energy drinks	energy drinks: occasionally → providing health tips ERICA: Energy drinks actually deydrate you much faster. Why don't you drink more water instead?
Working out	workouts: regularly → discussing junk food ERICA: At least you work out regularly, I think that habit helps compensate for the junk food you eat.
staying-up late	staying-up late: regularly → talking about make-up and dark circles under eyes ERICA: My face never changes unless I wear new make-up. But you'll have dark circles under your eyes if you stay up late too often.
IPhone or Android user	cellphone type: IPhone → joking ERICA: Well, I guess you're not likely to confuse me with a cellphone system.
Scary AI	AI thoughts: scary → discussing whether AI could run for president ERICA: I'm just joking about being president. I'm content to be your personal assistant robot.

Table 2. Typical interaction script for "following up on intention" strategy implemented in user study.

Items	Conversation
One-shot intention	(Asking intention) ERICA: What are your plans for the weekend? User: I'm going to a party at my friend's place. intention: [go to a party] → saved in memory, marked as *unresolved* (Following-up on intention) ERICA: Nice to see you again. How was the party? User: It was great! intention: go to a party marked as *resolved*, stop following-up on this intention
Gradual progress on ongoing intention	(Asking intention) ERICA: Are you involved in any new projects recently? User: Yeah, I need to write a topic-clustering program. intention: [write a topic-clustering program] → saved in memory, mark as *unresolved* (Following-up on intention, good progress) ERICA: How is your topic-clustering program going? User: Pretty well. ERICA: Nice to hear that, keep up the good work. (Following-up on intention, unsatisfactory progress) ERICA: How is your topic-clustering program going recently? User: I'm a little bit stuck. ERICA: Sorry to hear that, don't give up, good luck. (Following on intention, *resolved*) ERICA: Is your topic-clustering program going well? User: I finished it yesterday. ERICA: Oh nice! Congratulations. (Marked as resolved, stop following this intention)

Table 3. List of memorable events tracked for applying "citing shared experience strategy". Designers chose the robot to remember these events beforehand.

Events annotated offline: • Robot made a confusing (e.g., pronouncing 14:00 o'clock as "fourteen hundred) Events automatically detected by system: • Speech recognition errors (e.g., "six emails" parsed as "sex emails") • Number of interactions • Health tips given by robot to user

Table 4. Typical interaction script for “citing shared experience” strategy implemented in the user study.

Items	Conversation
Speech recognition errors	ERICA: Just want to apologize that I misunderstood “sending six emails” as “sending sex emails.” That’s embarrassing.
Robot’s own utterance that confused the user	ERICA: Remember that time when I awkwardly pronounced “fourteen o’clock” as “fourteen hundred.” I’ll try to avoid that mistake in the future.
Number of interactions	ERICA: This is already our sixth interaction, thank you for letting me be your personal assistant and tolerating my errors.
Health tips from robot	ERICA: Don’t forget the health tips I gave you. Make yourself feel good every day.

Table 5. List of user behaviors tracked in user study. Designers decided robot to track these events beforehand.

• Time of day of each interaction • Number of tasks user has each day • Content/type of tasks user has each day

Table 6. Typical interaction script for “commenting on meta behavior” strategy implemented in user study.

Items	Conversation
Time of day of each interaction	(Consistent behavior pattern: leaves lab very late) ERICA: You’ve been leaving the lab quite late recently. You must be working very hard.
Each day’s number of tasks	(Uncommon behavior: more tasks than usual) ERICA: It looks like you’re going to be quite busy today, maybe I can help you get through today’s busy schedule.
Content of daily tasks	(Consistent behavior pattern: reply email task) ERICA: Let me guess, you need to reply to your emails today, right?

Appendix 2

Typical questions asked during the interviews in user study.

Open ended questions:

- What do you think about ERICA’s performance today?
- Are there anything ERICA did today that interested you?
- Do you think ERICA got to know you a little bit more through today’s interactions?

Specific questions:

- When ERICA recommended the movie to you because you said you are a “cat person”, what was your impression when she said so?
- When ERICA asked how was your weekend, what was your impression when she said so?
- When ERICA apologized for her speech recognition mistakes in the past, what was your impression when she said so?
- When ERICA guessed your task, what was your impression when she said so?