Aupair: A Home Robot for Personal Care

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***Abstract*— To create intelligent systems for use in personal robots, the integration of information from various sensors to conceptualize knowledge and understand complex events are crucial. In this paper, we attempt to build a cognitive model which integrates various modalities of observed people (location, object recognition, reading emotions and activity recognition) to create a plan library which is further used to build a plan recognition model. We present an improved method of plan recognition by developing an automated plan library builder which addresses the limitations of existing predefined plan libraries. This provides a more robust system, more suited to functioning in real-life situations where the infinite number of actions can be managed. Experiments were undertaken in real time, in a real-life home environment setting with a specially built turtlebot and human subjects. Our proposed system consists of two parts, first the human modality collecting module, second the automatic plan library builder and plan recognition module by the Deep Concept Hierarchy (DCH) model. The results from our model show promising performance in the designed plan recognition. This demonstrates the integration of multimodal information and conceptualization of knowledge for an interactive system which efficiently infers and responds to the goals and plans of observed people.**

Keywords—Cognitive Robotics, Machine Learning, Plan Recognition

I. INTRODUCTION

The development of AI is entering a new phase where it has progressed from expert systems to building autonomous robots to assist people. As a result, many are now expecting the agents to be smart enough to support them with more complex tasks, understand emotions and behaviors, learning from their lives and even protecting them from danger. Therefore, in this paper, we propose a new approach for designing a cognitive model for intelligent systems, which connects concept learning with plan recognition.

II. RELATED WORK

For a robot to assist people, it is essential for the robot to have a conceptual knowledge to recognize the current situation and decide the best action to respond. Much of the current research on building knowledgeable concepts has approached through probabilistic inference [1], and applications to visual-linguistics construction [2]. Moreover, for achieving the ability of situation awareness, [3-4] has reported significant results for recognizing other agent's situation or goal from plan recognition. However there exists a strong constraint in plan recognition algorithms which needs a complete set of rules to recognize situation or goal of other agent. Therefore by employing the methodology of probabilistic concept construction and online learning [5] to plan recognition, we present a cognitive architecture that autonomously builds and recognizes plans of human for the robot to provide personal caring services.

III. METHODOLOGY

To build an autonomous personal caring robot, various modules are needed. The basic modules necessary for the system to execute are listed below:

- SLAM
- Human detector
- Human position estimator
- Human follower
- Modality(whom, object, place, activity) recognizer
- Plan library builder and recognizer

In this paper we mainly discuss about the plan library builder and recognizer.

A. Plan Library Building and Recognizing

The proposed DCH model was originally used to learn concepts by automatically constructing knowledge from visual-linguistic information [2]. However, modifications can be made to design a DCH model which captures the characteristics of a plan library to build a plan library with enhanced abilities. The design of our DCH model is elaborated below.

First, the hyperedges in the second layer of the DCH model can be interpreted as the basic actions in the plan library. The observation set($\boldsymbol{o}$) in Fig.1(top) includes the recognized outputs, such as who, place, emotion, activity and the time of occurrence. This set of hyperedges becomes the primitives in the plan library used in the plan recognizer:

$$\boldsymbol{o} \in A \text{ when } V(\boldsymbol{o}) > \mathrm{r}$$

$$\Delta \mathrm{E} = \Delta \mathrm{E} \cup \{\mathrm{e}\} \text{ and } e = \cup_{m=1}^{k} o_m$$

$$\mathrm{P}(\mathrm{e}) = \prod P(\boldsymbol{o})$$

Where V($\boldsymbol{o}$) is the vertex value and r is set to 30, ΔE indicates the new hyperedge set and e is the created hyperedge. P($\boldsymbol{o}$) is the total probability of each component in $\boldsymbol{o}$.

With the created primitive, we learn the relationship between the primitive by the graphical Monte Carlo method.

$$G' = \underset{G_t}{\operatorname{argmax}}\, P(G_t|O) = \underset{G_t}{\operatorname{argmax}}\, P(O|G_t)P(G_{t-1})$$

By estimating the P(G_t |O) to be maximum while observing observations, the library builds up to find the optimal relations of the primitives.

To recognize the plan, the recognizer infers the maximal probability of the relation from the observation.

IV. Experiment

We examined the performance of the plan library recognizer by letting three participant act a given sequence of tasks. The plan recognizer should recognize the same goal/scenario of every participant. The sequence of tasks from each participant should be recognized and by the plan library to infer the same goal/scenario. The sequence of the scenario is as follows; sit on the couch → go to the kitchen to eat dinner → go to the couch and play with the laptop → lay down on sofa → go to room and play → walk around the living room → sit down on the sofa. The duration of each action was not restricted. The total time of test sequences collected from all participants was 5461 seconds and the ground truth sequence of the given scenario was labeled by hand. The accuracy of the recognized goals of participants was evaluated by calculating the mean-squared error of the ground truth label and the labels of goals derived from the plan library after observing the participants. The accuracies are shown in Table 1, where the average accuracy was 89%

TABLE I. ACCURACY WITH GENERATED HYPOTHESIS

Participant	A	B	C
Observation Size	1660	1753	2048
Accuracy (%)	91%	85%	90%

These results show that a plan library build by DCH model could be used to recognize observed sequences to infer the goals of humans in the home environment

V. Discussion

We have proposed a new approach of plan recognition with a home environment robot system to present the potential of adapting an AI agent into the real-world. Our DCH model demonstrates high performance in building new concepts (primitives) with the relations between them to build a plan library for plan recognition. This occurs in an incremental, unsupervised manner, where observations in real-time are collected, to form the primitives necessary to build the concept

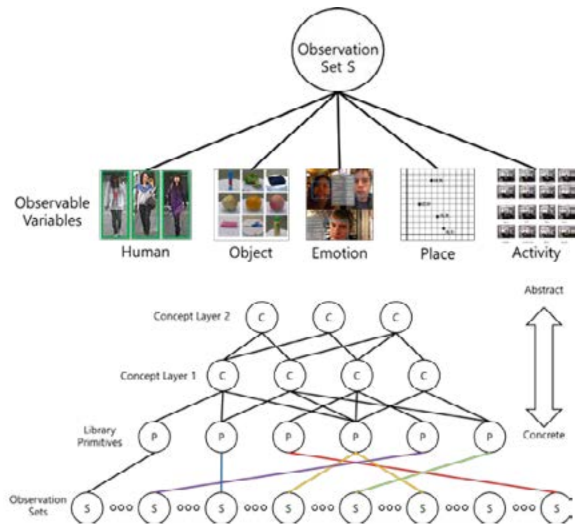

Figure 1. Architecture of Deep Concept Hierarchy

of subgoals in the plan library. The plan library was examined to validate its construction and function of recognizing plans of the observee. Through our study, we have provided some insight into how a home service robot could function in a home environment setting. However increasing the experimental scale could be a goal for future research for a more robust and flexible system. More data could be collected and tests of various scenarios may be considered.

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