Knowledge-driven User Activity Recognition for a Smart House. Development and Validation of a Generic and Low-Cost, Resource-Efficient System

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***Abstract*—Our core interest is the development of autonomous and socially interactive robots that may support elderly users at home as part of a smart home, i.e. a home equipped with a sensor network that may detect activities of daily living such as preparing food in the kitchen, having meal in the living room, watching the television, etc. The current paper focuses on showing the design and implementation of a low-cost, resource-efficient activity recognition system that can detect user activities without the necessity of collecting a large dataset to train the system. Based on common-sense knowledge from activities of daily living, we generated a set of rules for defining user's activities in a home setting. These rules can be edited and adapted easily in order to accommodate different environments and daily life routines. The approach has been validated empirically with a pilot study in the University of Hertfordshire Robot House. The paper presents results from a study with 14 participants performing different daily life activities in the house. The results are promising, and future work will include the integration of this system in a Smart House used for Human-Robot Interaction studies. This may help develop context-aware robot companions capable of making better decisions to support users in their daily activities.**

***Keywords*-Activity Recognition; Smart Houses; Context-Aware**

I. INTRODUCTION

In the field of Human-Robot Interaction (HRI), many researchers are interested in understanding how humans interact with robots in different environments [1]. The incorporation of social skills into robots' responses to achieve smoother interaction with humans remains a significant challenge. Many studies (e.g. [2] [3] [4]) from the Adaptive Systems Research Group at University of Hertfordshire have been carried out with the aim of gathering findings that help us understand how people interact with robots in a domestic environment, and hence to develop robots which exhibit a greater awareness of context when interacting with humans. The Robot House (see Figure 1) is the naturalistic environment used by our research group to perform this variety of experiments.

Fong et al. [5] assume that humans tend to interact with robots in ways that are similar to how they interact with other humans, i.e. humans expect certain social characteristics from robots. For instance, in the area of assistive robotics, the robots will become part of people's lives, so these social skills have to be enhanced during interaction in order to increase robots' acceptance in these environments. Context-aware robot companions would have the ability to detect users' activities performed at home, but they require additional modules such as human activity recognition systems. These supply the necessary information to allow robots to adapt their behaviour to the ongoing activity, and increase their social skills aforementioned.

One of the current problems pointed out in the literature regarding these systems, is the large variety of datasets necessary to create accurate activity recognition systems [6], and the difficulties in recruiting participants for the experiments [7]. We therefore developed a different method to avoid involving users in extensive studies of data collection during the whole process of system development. This point is particularly important when working with elderly people or people with special needs, which are one of the target user groups that our research is concerned with. Asking e.g. elderly people to spend several days or weeks engaged in certain activities to generate training data for the system puts a huge burden on them. The Activity Recognition System (ARS) that will be presented in this paper takes into account this issue. The knowledge-driven approach [8] used allowed us to develop the low-cost, resource-efficient system, in which participants were involved just during the validation stage.

Our research follows two well-defined directions. Firstly, the incorporation of social skills in robot companions to create more natural human-robot interactions in living environments. Smart homes' facilities will help to develop these skills (e.g. the non-intrusive sensor network installed in the Robot House). As Chan et al. [9] mentioned, sensor-embedded houses provide context information without disturbing users' daily activities, creating greater comfort and well-being. Secondly, we avoid the involvement of users during the training phase of the development of the system by the use of knowledge-driven approach. Following these two directions, we have created a functional activity recognition system that was tested with 14 participants in its validation stage.

The remainder of this paper is organised as follows: Section 2 discusses related work. Section 3 presents the research question and goals. Section 4 describes how the activity recognition system has been created, and the structure of the set of rules defined on our system. Section 5 describes design and procedure of the experiments carried out. In Section 6, the analysis and the evaluation of these experiments are depicted. Section 7 reviews how the research questions have been accomplished. Finally, we conclude this paper in Section 8.

II. RELATED WORK

The HRI field as a distinct branch of academic activity first emerged in the mid 1990s, although the robot's behaviour and their consequences for humans have been studied in several fields. Goodrich et al. [10] present a survey of current and historical research into HRI. The field is focused on studying robotic systems that interact directly or indirectly with humans. The understanding, evaluation and appropriate design of these systems should facilitate satisfying and naturalistic social interaction between robots and humans. For an assistive robot to be useful for its user at home, the ability to recognize and respond to human activities is essential.

As we mentioned in Section I, the integration of tools such as human activity recognition systems is a first step towards the target of naturalistic interaction between users and robots. In the field of Smart Houses, we can find a huge variety of activity recognition studies, but relatively few are oriented towards robot companions and take into account the need for a reduction of time invested by users in the development of such systems, or the realistic experiments conditions pointed out by Logan et al. [11]. Our ARS has been designed and evaluated based on these principles.

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In the literature, two main categories can be found regarding activity recognition systems [8]. The first is based on visual sensors, e.g. camera-based systems to monitor behaviours and changes in the environment [12] [13]. This approach combines computer vision techniques and pattern recognition. The second category is based on sensor networks for monitoring activities in Smart Houses. It can be subdivided into data-centric, logical or semantic approaches. These approaches typically require extensive data collection with potential users of such systems. The data is then analysed using data mining or machine learning techniques to build activity models, which can then form the basis for activity recognition systems. The knowledge-driven, rule-based system approach that we describe in this article belongs to this second category. Similar approaches can be found in the literature [14] [8], but in their evaluation stages participants were told to perform certain activities following a sequence of actions. The approach here presented is capable of recognizing user activities without restricting the way in which users perform those. The use of the non-intrusive sensor network installed helped us create the natural environment the we were looking for. In our view, wearable sensors could affect users' comfort and seem particularly problematic for elderly people.

Other issues have been taken into consideration as well. The system was designed to be easy to move and install in other similar environments without the necessity of specialized knowledge on how these systems work and need to be set up. The rules and sensors are defined in the configuration files (see Section IV-B), followed by a natural language description in order to make the system more understandable. A key advantage of this approach, is that the rules are explicitly represented rather than implicitly represented (e.g. within a Bayesian network [15] [16] or a Hidden Markov Model implementation [17] [6]). This allows us to inspect and manually change or update the rules if needed. As part of the ACCOMPANY project [18], our research in the Robot House will be incrementally developing more complex HRI scenarios for home assistance, so it is important for us to be able to have a system that can be extended and modified easily by non experts, and at the time, keeping the development cost of the system down. We argue that developing a low-cost and resource-efficient system (e.g. the ARS presented), is an important prerequisite for a possible future use in real world applications.

III. Research Questions and Goals

The purpose of this article is to present the development and implementation of the knowledge-driven ARS system and its first validation study. The comparison between the activities recognized by the system, and the actual, observed activities performed by the user during several sessions, will determine the accuracy level of the system and its capacity to be integrated into future HRI studies. The data collected in the first validation study will be used to improve the first set of system parameters and to suggest new features for future versions of the system. In addition, we try to learn about users' behaviour in a natural home situation, and understand how robot companions could behave in such home environments. Our research questions are:

- Q1. Is our ARS generic enough to detect different users' activities without the system being individually trained for the users?
- Q2. Can the ARS achieve an accuracy higher than 80% in the controlled experiments?
- Q3. Can the ARS achieve an accuracy higher than 80% in the uncontrolled experiment?
- Q4. What are the advantages and disadvantages of the ARS presented in this paper?

Figure 1. The UH Robot House layout and sensor arrangement. 59 sensors are available in the house, but only 52 were used and shown here. The two cameras' locations during the experiments are represented in this picture.

The percentages defined in questions 2 and 3, have been set at these values in order to validate the system with an adequate confidence level. This will ensure a reasonable reliability of the environmental information that will be sent to robot companions in future HRI experiments. An accuracy over 80% seems sufficient since robots' behaviour will not solely be based on the information received from the ARS, but supported by the Robot House's system that makes decisions based on further environmental information. Therefore, we expect that this additional information supplied by the ARS will help us improve the robot's awareness of the situation and thus further enhance its abilities when interacting with users in a living environment.

IV. Human Activity Recognition Framework

A. Robot House Sensor Network Description

Two different but complementary commercially available sensor systems, the GEO System and ZigBee Sensor Network, were installed in the Robot House. Both the GEO System and ZigBee Sensor Network have a refresh rate of 1 Hz, which is deemed as adequate to detect user activities.

The GEO System [19] is a real-time energy monitoring system for electrical devices. It is used to detect the activation and deactivation of electrical appliances by the Robot House's users (e.g. opening the refrigerator or boiling water in a kettle). The status of the electrical appliances connected to this system can be queried from the GEO System database.

The ZigBee Sensor Network [20] is used to detect user activity that cannot be detected by the GEO System such as opening of drawers and doors, occupation of chairs and sofa seat places, opening of cold and hot water taps etc. The ZigBee Sensor Network consists of five ZigBee Wireless modules, which are spread across the Robot House. Together they transmit readings from a total of 26 reed contact sensors, 4 temperature sensors and 10 pressure mats to a ZigBee gateway (XBee Gateway X4). The ZigBee gateway forms an interface between ZigBee Sensor Network and the Robot House Ethernet infrastructure, where the ARS resides.

Table I
BEHAVIOUR CODING SCHEME. ACTIVITIES CONSIDERED FOR THE ACTIVITY RECOGNIZER.

Code	Behaviour	Description
ut	Using Toaster	The time that this appliance is switched on
uk	Using Kettle	The time that this appliance is switched on
pf	Preparing Food	The user is in the kitchen preparing some food
pcd	Preparing Cold Drink	The user is having some cold beverage
phd	Preparing Hot Drink	The user is preparing either tea or coffee
co	Computer ON	The time that this appliance is switched on
uc	Using Computer	The user is sitting in the dining area and using the computer
sd	Sitting Dining Area	The user is sitting in the dining area
lt	Laying Table	The user prepares the table before having meal
md	Having Meal Dining Area	The user is sitting in the dining area and having mea
std	Spare Time Dining Area	The user is reading a book or newspaper in the dining area
wt	Watching TV	The user is sitting in the living room and watching the television
t	TV ON	The time that this appliance is switched on
slr	Sitting Living Room	The user is sitting in the living room
stl	Spare Time Living Room	The user is reading a book or newspaper in the living room
ml	Having Meal Living Room	The robot reminds the user about some medicine
ct	Cleaning Table	The user finish the meal and tidy up all the objects used

B. Implementation

The ARS was developed in Java with a local MySQL database for logging purposes. The software consists of the following four different modules:

- ZigBee module. Manages sensor data from ZigBee Sensory Network.
- GeoSystem module. Pulls sensor data from GEO System Database.
- Activity Recognizer module. Analyses the sensory data retrieved from the ZigBee Module and GEO System Module to determine the user's activity.
- User Interface module. Displays and records the detected user's activities and sensory information to a local database (MySQL) and external log files.

The ARS has been tested on both Linux and Windows systems, with a local MySQL database for data logging purposes. The system is configured by using two XML files. The first configuration file contains the representation of the Robot House sensor network (i.e. mapping sensors' IDs to their symbolic names), and the second configuration file defines the semantic rules used by the ARS to detect user's activities in the Robot House (see Section IV-C). These rules were set based on an initial set of trials and the common-sense knowledge which activities of daily living (ADL's) are based on [8]. In future work, the parameters could be refined based on the information gathered after this study. We have to consider that this first experiment is part of the learning process that we have to follow to achieve our final research goals.

Two issues have to be pointed out in regards to the system. Firstly, the ARS is intended to trigger and present an identification at the starting point of the activities studied (see Table I). We consider that the beginning of each activity is the suitable moment at which robot companions should interact with users to offer their help. Secondly, the possibility of migrating the system to other similar environments has been considered during the development process, so that the editing, redefinition or adaptation of these two configuration files would be sufficient to run the system in these new environments.

C. Rule Definition Example

In this section, we show briefly how the ADL's rules have been defined following common-sense knowledge which make the system understandable to any researcher using it. We studied a variety of activities that will be useful in assistive robotics scenarios in future stages (see Table I). These activities can be described as the combination of sensors activated in the environment, and previously performed activities, namely context-activities. Thus, the system manages two different kinds of activities. Low-level activities are those that are detectable by a single fixed sensor (e.g. the user sitting on the sofa). High-level activities are those that can only be detected by utilising a combination of different sensors, or a combination of different sensors and low-level activities detected. Based on that, each rule is defined using the following tags:

- Duration: The maximum time the activity remains activated in the system. Some activities, e.g. *Using Computer Dining Area* and *Sitting Living Room* (described below), do not consider this tag as they are deactivated based on their associated context-activities or associated sensors' status values.
- Location: The location where the activity is performed.
- Context: Set of activities that has to be fulfilled before the activity is activated. Some activities, e.g. *Sitting Living Room*, do not have any context-activity associated with them. *Interval*: Time window in which the context-activity is relevant for the detection of the activity. *Status*: The required context-activity's state for the activation of the activity.
- Threshold (Sensors' attribute): Minimum value necessary to consider the activity as activated. It is based on the accumulated weight of the sensors triggered.
- Sensors: Each of the sensors involved directly in this activity. They have a *Status*, *NotLatching* (True: The sensor's weight will be only added to the accumulated weight while it remains on, otherwise, its weight is subtracted from the accumulated weight; False: the sensor's weight is added to the accumulated weight once it is on regardless of its later state), and *Weight* fields. Some activities, e.g. *Using Computer Dining Area*, do not have any sensors associated with them.

We can see below the examples rule *Using Computer Dining Area* and *Sitting Living Room*. More examples are available from the author on request:

```
<Activity Name="Using_Computer_Dining_Area">
    <Duration>Nil</Duration>
    <Location>Dining_Area</Location>
    <Contexts>
        <Context Interval="0" Status="activated">
         Sitting_Dining_Area</Context>
        <Context Interval="0" Status="activated">
         Computer_ON</Context>
    </Contexts>
    <Sensors Threshold="0.0"></Sensors>
</Activity>

<Activity Name="Sitting_Living_Room">
    <Duration>Nil</Duration>
    <Location>Living_Room</Location>
    <Contexts></Contexts>
    <Sensors Threshold="0.50">
     <Sensor Status="on" NotLatching="true" Weight="50">
         Sofa seatplace 0</Sensor>
     <Sensor Status="on" NotLatching="true" Weight="50">
         Sofa seatplace 1</Sensor>
    /Sensors>
</Activity>
```

In the first example, *Using Computer Dining Area*, the activity depends on *Sitting Dining Area* and *Computer On*, but no sensors are associated with the activity recognition. For this reason, *Duration* and *Threshold* tags are not considered for this activity, as the activity will be activated only when both context-activities are activated. In the second example, the activity is associated with

Table II
THE OBSERVER XT FORMATTED OUTPUT (LEFT SIDE) AND THE ACTIVITY RECOGNIZER'S EVENT LOGS (RIGHT SIDE). THIS DATA REPRESENTATION HELPED US ANALYSE THE RESULTS AND FIND BEHAVIOUR PATTERNS THAT WILL BE CONSIDERED IN FUTURE WORKS.

Observation	Time_Relative_hms	Duration_sf	Behavior	Event_Type		System	System Events	Time	Time Relative	Delay (seconds)
								08:21:35		
User-001-S2	00:00:00	60.74	Preparing_Cold_Drink	State start		Yes	Preparing_Cold_Drink	08:22:18	00:00:43	00:00:43
User-001-S2	00:00:05	299.88	Preparing_Food	State start		Yes	Preparing_Food	08:21:39	00:00:04	00:00:01
User-001-S2	00:00:21	75.04	Using_Toaster	State start		Yes	Using_Toaster	08:21:58	00:00:23	00:00:02
User-001-S2	00:01:00	0	Preparing_Cold_Drink	State stop						
User-001-S2	00:01:28	16.96	Laying_Table	State start		Yes	Laying_Table	08:23:01	00:01:26	00:00:02
User-001-S2	00:01:36	0	Using_Toaster	State stop						
User-001-S2	00:01:45	0	Laying_Table	State stop						
User-001-S2	00:02:01	50.06	Using_Toaster	State start		Yes	Using_Toaster	08:23:36	00:02:01	00:00:00
User-001-S2	00:02:11	41.32	Sitting_Dining_Area	State start		Yes	Sitting_Dining_Area	08:23:45	00:02:10	00:00:01
						Extra	Having_Meal_Dining_Area	08:23:45	00:02:10	00:02:10

certain sensors, whose *NotLatching* field makes their activation compulsory to keep the activity activated as well. Therefore, *Duration* is not considered for this activity, since the deactivation of the associated sensors will deactivate the activity.

V. EXPERIMENTAL DESIGN AND PROCEDURE

A validation study was conducted by the Adaptive Systems Research Group at University of Hertfordshire in May 2012 to measure the accuracy of the framework previously explained. The Robot House provides a naturalistic and ecologically acceptable environment to carry out studies into ADL's. The main aim was to measure the accuracy of the system in both controlled and uncontrolled scenarios and collect data for future studies. A sample of 14 adults, unaffiliated with the ongoing research, and aged between 23 and 54 was recruited from students and staff of the University of Hertfordshire. All the subjects first completed a consent form, in which they were informed about the voluntary nature of the experiments, before they performed a two-day experiment, one session per day. Each session lasted approximately 20 minutes.

A. Experimental Setup

The experiments took place in the Robot House in which ARS were installed and configured. All the experiments were recorded on video and audio using two different cameras (see Figure 1) rather than relying on self-reporting. One camera covered the dining area and living room, and the other covered the kitchen. Those were the only rooms where the participants performed the experiments. The cupboards were labelled to make the participants aware of every object's location and create a more natural environment in the sense of knowing where things are located, as they would feel in their own houses. However, users got used to the Robot House facilities after the introductory session as will be explained in the next section.

The ARS generated two different log files for each participant, one per session. The first file stored information on all the sensors activated and deactivated during the experiment, as well as the decision-making process that the activity recognition algorithm was doing in real time. The second file represents the raw sensory data received from the system during the experiment. These raw data can be used to simulate users living in the Robot House in future experimental scenarios in which robots will be included.

B. Experimental Procedure

The experiments were led by the researcher, who introduced and explained the procedure and the house's facilities to each subject. This section took approximately 10 minutes and was only provided for the first session. After this introductory part, during the first (controlled) session the participants were led by the researcher for 20 minutes, while they were asked to perform a number of specific common ADL's using the Robot House's facilities in the way in which they felt most comfortable with. Thus, they were told what activity to perform, but not how to perform it. In the second (uncontrolled) session, we told the participants to spent around 20 minutes simulating 'living' in the house. They were asked to perform whichever activity (based on the facilities shown during the introductory session) they wished during this period of time. Consequently, we exposed the system to two different situations, controlled and uncontrolled, which would help us measure the system's accuracy and analyse human behaviour at a home environment and discover details omitted in the system, respectively. After each session, the participants were asked to complete a questionnaire. They rated the scenarios and the activities in which they were involved. Basic demographic information of each participant was collected in this questionnaire as well. Note, the order of the conditions was not counterbalanced, since the goal of the study was not to compare the two conditions. Also, it seemed important to first expose participants to the controlled condition which helped them to prepare themselves for the uncontrolled condition.

VI. ANALYSIS AND EVALUATION

A. Behaviour coding

Relatively little work (e.g Logan et al [11]) has combined behaviour coding with user activities in Smart Houses. However, many examples of different data annotation studies can be found in the field of HRI, e.g. [21], and Psychology, e.g. [22]. The coding of the video data of the participants activities helped us analyse each session and identify the important events which we were interested in. The Observer XT software supplied by Noldus Information Technology [23] is a commercial software package used for coding, analysis and presentation of observational data.

The first author of this article was the first coder of all the video material. Additionally, following conventions of behaviour coding, a second coder carried out the same process with 10% of the analysed videos in order to perform the reliability test. The Observer XT and the coding scheme shown in Table I were used by both coders, who were asked to familiarize themselves with this coding scheme before the annotation process. They were told to code activities in which users interacted with some of the sensors installed in the Robot House, in order to generate the sequence of activities that each user had been performed. The outcomes were

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exported to an Excel files in order to be compared to the events generated by our ARS during the analysis stage.

1) Inter-rater Reliability Test: The Kappa Statistic [24] was used to determine the level of agreement between the two different annotations carried out by the two coders. The annotations were paired in Observer XT, and the kappa value was generated automatically for both sessions. The time windows for the reliability analysis was defined as one second. The kappa value for the combined analysis was 0.75, with overall agreement of 76%. This result represents a good agreement rate for both annotations [25].

B. Data Analysis

A final Excel file was built based on the event lists created using Observer XT and the events generated by our ARS (see Table II). The left side of the table represents the events exported from the software. On the other side, the activities recorded by the system were written down together with their starting time. In this way, the results were shown clearly, and allowed to distinguish 'recognized', 'missed', or 'extra-recognized' activities more easily. The last category represents those activities that fulfilled all the sensor's activations required but they were not performed by the user as evident in the video data. In future experiments, the interaction between the robot companion and the user will help us clarify the real status of these kinds of activities. Moreover, additional tools to support our ARS will be integrated into the Robot House's system during the ACCOMPANY project [18].

A total of 14 participants and two sessions per participants have been considered for the data analysis. We will explain each session separately. The system performance was calculated in terms of precision, recall and accuracy [26] (see Figure 2).

$$Precision = \frac{tp}{tp + fp} \qquad Recall = \frac{tp}{tp + fn}$$

$$Accuracy = \frac{tp}{tp + fp + fn}$$

Figure 2. Precision, recall and accuracy formulas. (tp = true positives or 'recognized', fn = false negatives or 'wrongly recognized' and fp = false positives or 'extra-recognized').

1) Session 1 (controlled): We have to remember that in this scenario the user was lead by the researcher, as we described in Section V. A total of 240 events were coded in all the experiments carried out in this session. The average number of performed activities per user was 17. We got 239 correctly recognized activities, 1 missed activity, and 37 extra-recognized activities were triggered. We obtained a precision of 86,59%, a recall of 99,58% and an accuracy of 86,28%. We found some delay in the recognition of the most complex activities, i.e. those activities involving a major number of different sensors (e.g. preparing food or preparing a beverage). The rest of the activities were recognized with an average delay of two seconds, which is reasonably fast, taking into account the operating system frequency 1Hz.

2) Session 2 (uncontrolled): In the second session, good overall results were achieved too, even taking into account the openness of the scenario which we exposed our system to. A total of 216 events were coded in the experiments carried out during this session. The average number of performed activities per user was 15. We got 200 correctly recognized activities, 16 missed activities and 23 extra-activities were triggered. We obtained a precision of 89,69%, a recall of 92,59% and an accuracy of 83,68%. As stated before, some delay were found on the most complex activities. In Figure 3, we represent these averages delays per activity (e.g. Preparing Hot Drink was recognized with a delay of 35 seconds). The rest of activities were recognized with a similar average delay than in Session 1. The data collected along this experiment will help us understand human behaviour at home and improve our system.

VII. Discussion

The results presented above allow us to answer the research questions presented in Section III. The approach followed has demonstrated the possibility of creating a low-cost, resource-efficient ARS and presenting it to real users without the necessity of previous training. This is directly related to the reduction of time spent by participants in HRI studies as it was mentioned in Section I. The accuracy in both controlled and uncontrolled sessions exceeded the 80% threshold previously defined in our research questions, which was considered as adequate for the kind of study. Some of the advantages presented by this approach are the creation of a non-restricted and naturalistic system that allows users to behave as they would in their own houses. As we mentioned, in other approaches experiments were typically much more constrained. The use of hidden, non-intrusive sensors installed around the Robot House helped us create this natural environment, as we focussed on avoiding wearable sensors that could make users uncomfortable. In addition, the system can be easily migrated and setting in a similar environment without the necessity of specialized knowledge. The rules and sensors were defined using a natural language in order to make the system more understandable.

On the other hand, the system does have some disadvantages. Firstly, the types of sensors currently used do not allow to determine accurately where the user is located in the house. Therefore, the recognition of activities for two or more users simultaneously cannot be detected directly, as the system is not able to match activities with users. An extra tool (e.g. a camera recognition system) may solve the problem, so that it will be considered in future work. However, this will increase cost and complexity of the system and involve privacy issues. Secondly, the semantic rules used by the ARS were defined based on common-sense knowledge of how a person would carry out the ADL's. A module to modified these initial definitions as the user interact with the system will be considered in future stages of our research.

Once the ARS has been integrated into the Robot House system, we will be able to create much richer scenarios in which robot companions will be aware of users' activities. This will allow us to adapt robots' behaviour to their needs in each situation,

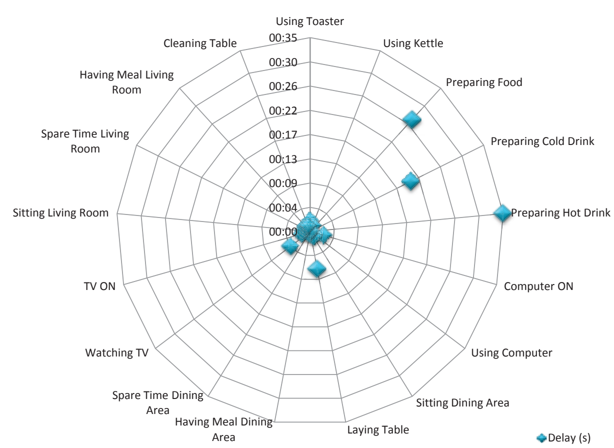

Figure 3. Overall delay per activity in the uncontrolled scenario.

and increase robot companions' autonomy to make decisions. A variety of challenging studies will be targeted in future stages of our research.

VIII. Conclusion and Future Work

We have presented the development and validation of a knowledge-driven rule system to identify user activities in home scenarios. We tried to build a low-cost, resource-efficient and easily understandable and re-configurable system that is accurate enough to detect a set of ADL's. This approach was evaluated empirically by means of the studies carried out in the Robot House. The experimental environment allowed participants to behave in a similar way that they would in their own homes, as it was reported in the questionnaires. Although the participants did not belong to our target user group, i.e. elderly people, we claim that, due to the general design of our system, the results can be generalized, and if necessary, can be easily adapted to this users group. In future work, the adaptation to individual users and their specific life styles and routines may also be considered. The results achieved fulfil our expectations and answer fully the research questions defined in Section III. These findings motivate us to progress towards our final research target of designing context-aware companion robots for home environments. It can be concluded that the developed ARS could be integrated into future experiments of our research.

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