Human activity recognition supporting context-appropriate reminders for elderly

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Abstract— **Dementia affects large number of elderly, manifested with memory impairment symptoms at the onset. This results in difficulties for elderly in scheduling and completing daily activities. In this respect a context-aware reminder system becomes an essential tool in helping elderly navigate their daily activities. Current work on reminder systems typically follows a set of pre-defined activities, organised into a plan. The plan is then used to prompt the elderly to execute specific activities or actions if they have not been completed. However, this is less than an ideal scheme, since the elderly sometimes choose to ignore the reminders due to being engaged in other activities that overlap with the scheduled activities. Therefore, a more flexible schedule is required, that delivers reminders in a context-appropriate manner. Such system must take into account not only the planned activities, but also the current activities of the elderly. We address this problem by monitoring the activities of the elder through our activity recognition system and using this information as a feedback to the reminder system. The reminder system can then decide whether a reminder prompt is appropriate to be delivered or should it be postponed for at a later time. We present the results of activity recognition and discuss how they affect the context-appropriate reminder system.**

I. INTRODUCTION

Ubiquitous computing is a technology that has potential to ease the symptoms associated with cognitive decline experienced by a large number of elderly. These symptoms typically begin with memory loss, however can encompass an array of other problems including speech, perception and reasoning difficulties. Memory impairment leads to inability of these patients to perform basic daily activities. Technological solutions can mitigate the need for constant care and allow elderly to remain in their home for as long as possible. The reminder systems are one of these solutions that can address the problem of memory impairment and reduce the burden on caregivers.

Current reminder systems typically have a set of activities defined into a daily plan and then deliver reminders in accordance to that plan. These plans express temporal constrains on daily activities, such as elders should have lunch between specific times of the day. However, this scheme of prompting is quite inflexible, since it does not take into account the wider context the elder might be in. Taking into consideration the wider context of the elderly is necessary since human activities in general do not exhibit sequential nature. In other words, daily activities do not occur sequentially, rather they can occur in parallel or even be interrupted by other activities. Consider the case when an elder is on the phone. It would be irritating if the reminder system prompted the elder to take a particular action, such as taking a medicine. Over time such system will become not only an annoyance, but reminders may be ignored completely by the elder. Clearly this can have a major negative impact on the elder's health (e.g. continuously forgetting or ignoring to take the prescribed medicines). Therefore, when considering delivery of the reminders, consideration must also be given to the current activities of the elder, such that the prompt is delivered in a context-appropriate manner.

The system presented in this paper takes the approach of delivering reminders by considering not only time constraints and a pre-defined plan. Rather, our system also takes into account the current context of the elder, more specifically the activities that the elder is currently engaged in.

II. RELATED WORK

The two core components of the system as evidenced from the discussion thus far are activity recognition and context-aware reminder delivery. As such, the related work section will reflect both research areas and a number of research projects will be reviewed and critiqued.

A. *Activity Recognition*

In general, human activity recognition research can be divided into two major approaches, namely machine vision based activity recognition (scene analysis) and sensor based activity recognition. This division is by no means strict and hybrid approaches also exist, for example [1], however the main focus of this work is on the latter, sensor based approach. Therefore, the most relevant systems in this domain are reviewed.

Authors in [2] describe the approach of collected data from a set of living environments instrumented with a number of motion detection sensors. The captured information is fed to statistical machine learning algorithms that are used to extract the behaviour patterns of the house occupants. However, reliance solely on the motion sensors is insufficient to deduce

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activities with high accuracy and makes it very difficult to understand specific user behaviours. In [3] authors describe a hardware platform equipped with 3-dimensional accelerometers. The results reported show only a small number of simple activities that are recognised including sitting, standing, walking, handshaking, which may be attributed to using only one type of sensors. Some activities had a high recognition rate, up to 90%, while other activities had recognition rate of only 45% depending on the position of the sensors in the body. Overall, only a very limited number of activities were recognised. The framework is heavily centralised with no support for personalisation to suit specific user behaviour. A project described in [4] also proposes recognising human activities based on accelerometers. Authors report overall recognition accuracy of 84%. However, the use of accelerometers only, limits the number of activities the system can recognise. Authors in [5] describe the issues that surround the activity inference, with a special focus on healthcare. Inferring user's activity based on the set of artefacts and other context information was found to be difficult. The authors conclude that a number of healthcare activities, such as "prescribe medicine" are triggered by sources that are too complex to capture.

An activity recognition system based on the '*Invisible Man*' concept was devised in [6]. It states that human activities are well characterised by the objects that are manipulated while users perform these activities. In order to identify manipulated objects during the course of an activity, each object is equipped with an RFID tag. An RFID reader mounted on hand glove, records information about objects being manipulated by a user and this information is fed to an activity inference engine. A model of activities is obtained through web data mining techniques especially mining the *how-to* websites. While the authors report positive results, with accuracy of 73%, there are a number of disadvantages to this approach; the inconvenience of wearing a glove, use of homogenous sensors and the centralised architecture design. While the first problem can be somewhat alleviated considering the technology trends in miniaturisation (authors report working on an RFID bracelet to replace the glove [7]), other problems posse a greater challenge regarding the number of activities that can be recognised and system scalability. A scalable architecture becomes critical, when considering workplace domains, for example hospitals where number of users as well as devices and sensors may range in the order of thousands.

B. Context-aware reminder delivery

Only a small number of reminder systems take into account the real time context of the elderly when delivering prompts. For example Autominder [8] adopts a plan based approach to decide the effective time of prompting the elderly. Another approach described by a number of authors [9-11] uses location awareness for reminder delivery. This work has shown that location is an important element for reminder systems. However, solely based on location does not provide enough information to make a decision whether the elderly is engaged in an ongoing activity, in which case delivering a reminder would be considered an interruption. Authors in [12] use a video camera to track users' hands, which is then fed to a rigidly pre-defined plan. CoReDA [13] takes the approach of wireless sensors nodes to obtain information about the elderly. Based on this information, they provide a personalized guidance for elders to complete the activities. However, they do not consider the current activities of the elder. A number of other systems have considered the issue of context-aware reminder delivery for other application domains, not related to elderly assistance.

The brief review of research systems show that little work has been carried out in delivering reminders that take into account real time activities of elderly. Our system, presented in the section that follows, is able to monitor daily activities of the elderly and use this information to decide on the most appropriate context to deliver reminders.

III. OUR APPROACH

One of the reasons that elderly may choose to ignore reminder prompts can be due to inadequate time when the prompt is delivered. Therefore, there is a need to monitor activities of elderly such that reminders can be delivered in a manner that is not perceived disruptive by the elderly. Our system monitors activities through the use of two major components, namely Object Networks and Decision Module. Object Networks are a network of everyday objects that provide a platform for monitoring and processing information generated as a result of user actions. User actions are typically described in terms of objects that the user is manipulating (e.g. user takes a cup). The Decision Module infers user's activities based on the events filtered through the Object Network. These events are fed to the repository of predefined user activities patterns known as the Activity Map. The Activity Map is a repository that stores activities that a user may perform (an extended explanation of these concepts can be found in [14-16]. The internal structure of an Activity Map corresponds to a directed acyclic graph (DAG) where each arc is assigned a probability value. This essentially forms a Bayesian Network. An example of a Bayesian Network defining a set of home activities is shown in Figure 1.

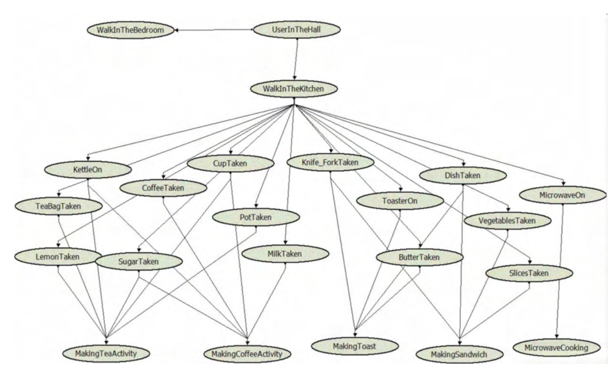

Figure 1. An example of Bayesian Network for home activities

Figure 1 shows that each activity (e.g. Making Sandwich) has a set of *causals* associated with the activity that impact the activity recognition process. Each of these causals has a specific weight on the activity, represented through the Bayesian conditional probability $P(A \mid \varphi)$ value (not

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displayed on the diagram), where A represents an activity and φ represents a causal associated with that activity. Therefore, as the events (user actions) are triggered by the object network, this is fed to the Activity Map as Bayesian evidence in order to infer the most likely activity. Human activities are modelled using Markov Chains, where *state space* defines the set of objects that are manipulated during the course of performing an activity. In addition, the Markov Chain *transition matrix* defines the probability of user manipulating an object n given that s/he is currently manipulating another object m. Each Markov Chain provides a behaviour *sequence*, extracted from the model. A sequence (λ) refers to *an ordered set of objects that the user has manipulated*, while performing an activity. Behaviour sequences are used to train the Bayesian Network in order to infer activities of a particular elderly.

Once trained the Bayesian Network can identify a number of activities based on the objects manipulated in the environment. In this paper we show results of recognising two activities, namely Making Tea and Making Sandwich as illustrated in Figure 2 and Figure 3 respectively. Results pertaining to recognition of other activities are presented in [14].

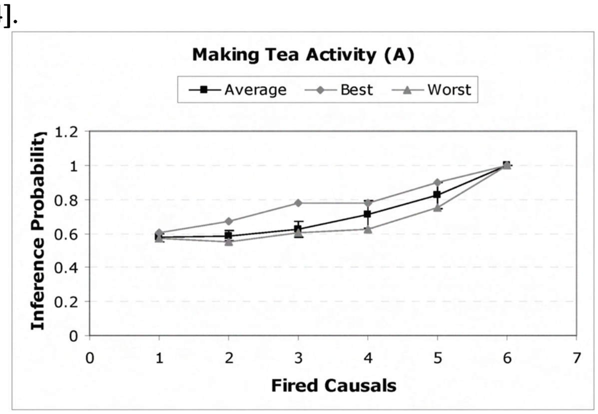

Figure 2. Making Tea activity

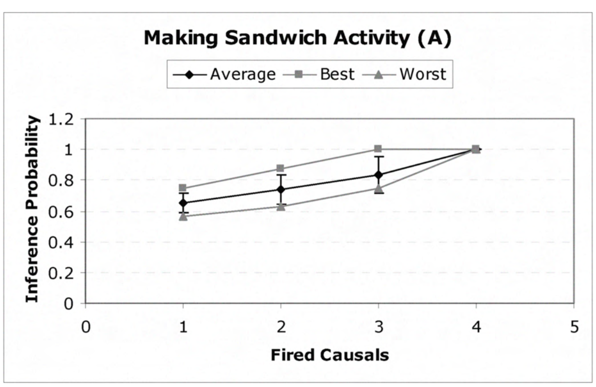

Figure 3. Making Sandwich activity

In these results, the x-axis represents the number of fired causals for the corresponding activities, which are essentially causals generated as a result of user actions. The y-axis represents the Bayesian belief value that a particular human activity is being performed, given a set of causals. The Average line includes standard deviation of the values, represented as error bars in the graphs. Standard deviation is used to measure the inference consistency, under varying user behaviour input. The best and worst case in the graph, represent the two extremes in recognition of the activity that occur as a result of variations in behaviour of the elderly.

In general, the Bayesian Network achieved an 80% recognition rate on average when one causal was missing. This can be seen on the 5th causal of Making Tea activity where the average inference probability was 0.82. The inference probability value climbs close to 1 at the best case scenario.

Once the activity is recognised, the reminder system uses this information to decide whether to deliver a prompt. Reminder system adopts an Event-Condition-Action (ECA) rules to describe context-aware prompting rules. An example rule that delivers a prompt to the elder to take medicine before eating, while s/he is preparing lunch is as follows:

$$\begin{aligned}&\mathit{Later}(\mathit{current\ time}, \mathit{anchor\ time}) \wedge \\ &\mathit{Earlier}(\mathit{current\ time}, \mathit{anchor\ time} + \mathit{delay\ window}) \\ &\wedge\ \mathit{LocatedIn}(\mathit{elder}, \mathit{Home}) \wedge \\ &\mathit{IsMakingSandwich}(\mathit{elder}, \mathit{yes}) \Rightarrow \mathit{medicine\ prompt}\end{aligned}$$

The ECA rules allow for a flexible programming of events, such that they are delivered at the appropriate time, taking into consideration elder's context. We have created a software tool that allows creating and editing of the prompting rules. This tool may be used by caregivers to define rules that minimise the perceived disruption by the elderly. A screenshot of the tool is shown in Figure 3.

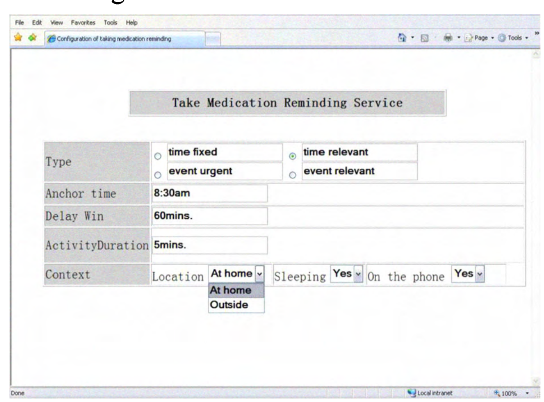

Figure 4. Software tool for editing ECA rules

We have already carried out preliminary experiments for activity recognition and context-aware reminders. Our plan is to carry out further experiments with a view of measuring the disruption of current activities perceived by the elderly and also record the rate of adherence to reminders produced by the system.

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IV. Conclusion

This paper has presented a preliminary work on context-aware reminder system that takes into consideration the wider context of the elderly, namely their activities, when delivering reminders. We have taken a synergic approach between the activity recognition system and the context-aware reminder system, enabling delivery of prompts in a context-appropriate manner. This is important issue to ensure that elderly accept the system and not feel irritated by it and also adhere to the prompts delivered by the system.

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