

# A Smart Reminder System for Complex Human Activities

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**Abstract**— A significant number of elders live with memory impairment issues, as a result of the normal aging process. Therefore various kinds of supporting systems have been developed to help the elders, who have mild memory problems. In this paper we propose a Smart Reminder System for reminding forgotten complex activities, in home environment. Subjected complex activities are the activities, which should be completed as originally intended, after they are initiated. Due to strong relationship among initiation and conclusion activities, those activities are called as “Coupling Activities” in this paper. Reminders for forgotten Coupling Activities are predicted according to the user’s current behaviour, current location and past activity patterns. Therefore wearable sensors are used to gather required data for identifying user’s context. A reason for forgetting also is predicted with the reminder. Reminders are predicted with minimum supervision of the user, as the system learns the user’s dynamic behaviour by itself. Proposed Smart Reminder System could achieve 80% average accuracy rate for reminder prediction in a system evaluation, which was done using four subjects.

**Keywords**— Smart system, Smart home, Health care, Human activity recognition, Coupling activities, Reminder systems

## I. INTRODUCTION

With the rapid growth of elder population, new problems have been aroused related to elder caring. “Minor cognitive impairment to scheduled tasks and events”, is one of major problems occurring with ageing. Scientists have developed various memory aid systems to provide solutions for memory issues [1], [2], [3], [5], [6], [12]. But most of those systems are not designed to provide reminders for crucial complex human activities in daily life [7].

Therefore we paid attention to provide reminders for complex human activities, which are easy to forget in home environment. Subjected complex activities are the activities, which should be completed as originally intended, after initiated. Some common examples might be closing hot water flask after filling the water, buttoning up a suit after wearing, plugging off the heater after using, etc. Most of those processes exist with two clear phases; such as initiation phase and conclusion phase. For example, when a bottle is used, initiation phase is opening that bottle and conclusion phase is closing the bottle. Significant implications of these processes are “strong dependency of conclusion phase with the initiation

phase”. Therefore those kinds of activities are called Coupling Activities (CAs) in this paper.

There are many issues with those kinds of CAs in daily life, as they could be easily forgotten to be completed, after initiated. For example, forgetting to close a hot water flask after filling hot water may cause changes in water temperature, forgetting to close a hand bag after opening may cause loss of valuables, etc. Those kinds of activities can be forgotten easily by the elders, who are suffering with memory impairment issues. If there are some reasonable processes, systems and methodology to remind the user about those kinds of forgotten, critical activities within correct time, that would be beneficial. But research is yet to addresses these issues in any great detail.

Therefore the objective of our study is to develop a Smart Reminder System to predict reminders for CAs when they are going to be forgotten. Unlike previous reminder systems, proposed Smart Reminder System employs better simulation models, in order to recognize complex human behaviour. The specific case study of opening and closing various type of bottles in a home environment is addressed to represent CAs, as it is not been addressed in past reminder system research studies.

The rest of the paper is organized as follows. In Section II, background and related work of smart reminder systems are discussed. The proposed approaches for Smart Reminding are introduced in Section III. Smart Reminder System implementation and evaluation are then presented in Section IV. Finally, a brief conclusion and future work are given in Section V.

## II. BACKGROUND AND RELATED WORK

Reminder systems play a role as central component of assisted living solutions that enable people to remain active and independent in their own homes [1]. In order to perform that, reminder systems should have knowledge about the reminders such as; what to issue, at where to issue and when to issue [5], [6]. With that knowledge, adaptable reminder systems can react according to the users’ dynamically changing care needs and context [1], [4].

### A. Smart Reminder System Related Work

“Smart Reminder” [8] is a reminder system, which is composed of set of personal agents that support their user in all situations where people come together spontaneously. That system will notice the presence of another person and display

identity information like name, affiliation, etc. In cooperation with other agents it will also display information related to that person like common dates and tasks.

“Memory Glasses” [9] is another wearable, proactive, context-aware memory aid system with wearable sensors. It provides reminders with a minimum of the wearer's attention. The function of that system is to deliver reminders to the wearer in a timely, situation-appropriate way, without requiring intervention on the part of the wearer beyond the initial request to be reminded.

### B. Drawbacks of Related Work

Most of the reminder systems are predicting reminders for simple human activities in daily life [2], [3], [7]. They are unable to predict the probable reason for forgetting also. More specifically, these tools are not sufficient because they are not proactive and do not make use of rich contextual information to trigger appropriate reminders at appropriate times in appropriate locations. Most of the reminder systems are needed user's supervision in order to learn the user's dynamic behaviour [4].

## III. PROPOSED APPROACHES

The goal of our approach is providing reminders for the Coupling Activities (CAs), which are going to be forgotten. Further the probable reason for forgetting is also provided by the reminders. Reminders are predicted according to the user's dynamic changes in the life style. Rich contextual information about the user, such as current activity and current location are used to predict appropriate reminders. But in this paper we mainly concentrate on user adaptive reminder prediction process rather than the user's activity or location recognition approaches.

In order to clearly define the subjected CAs in the problem domain, we propose a new model called Coupling Activity Model (CAM). That model simulates the probable human behaviour while performing CAs, in a real world scenario. Reminder Prediction Algorithm (RPA) is designed based on the CAM to predict reminders for the CAs. Forgetting Probability (FP) factor is introduced to predict user adaptive reminders. We have described proposed approaches with more details in the following sections.

### A. Coupling Activity Model

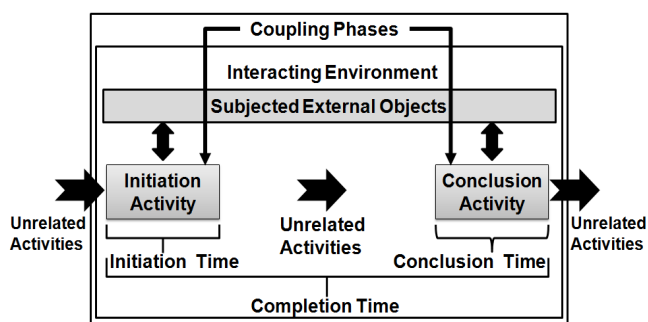


Figure 1. Coupling Activity Model

In this research, Coupling Activities are defined as mutually exclusive activities, which have strong dependency with each other. CAs should be performed physically by someone as the external object or objects are directly involving to those activities. CAs have at least initiation and conclusion phases in the entire process. Conclusion activity is always depended on the initiation activity. It is possible to have other sets of intermediate activities in between initiation and conclusion activities. But these intermediate acts are considered as unrelated activities. To complete any particular coupling activity, at least the conclusion activity should be fulfilled after initiating the process. More often than not, a critical stage in the set of activities is considered as one with initiation and conclusion activities, and they function in different manner. But interacting objects are same in both occasions. Each coupling activity has a specific time period to complete. Some coupling activities are depended on the location while some are independent from the location. Each coupling activities have their own way of performing, which is called in this paper as a “Coupling Activity Pattern”. Proposed CAM is shown in Figure 1.

### B. Activity Recognition Algorithm

Activity Recognition Algorithm is designed to recognize complex activities, which are done by using wrist areas of the both hands. Therefore simultaneous behaviour of both hands are monitored parallel in order to recognize the current activity.

Initially user's activities are captured by the three axes accelerometer sensors. They are worn on the wrist areas of both hands of the subject. Then the raw accelerometer data vectors are segmented in to frames in order to model the activities. Time domain and frequency domain features are extracted from the segmented frames to reduce the dimension of raw data. Artificial Neural Network (ANN) algorithm is used for categorizing the activities. Extracted features are used as inputs for ANN.

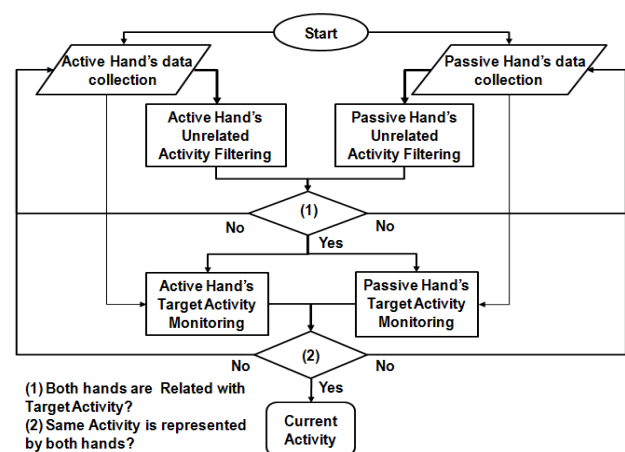


Figure 2. Activity Recognition Algorithm

In order to recognize complex activities accurately, ANN algorithms are designed for two major purposes. Initially they are used for Unrelated Activity filtering. Then filtered Related

data are used for Target Activity recognition. Further those ANN algorithms are trained specifically for each hand as they behave in different way while performing various activities. Therefore specified ANN algorithms are named as Active Hand's ANN and Passive Hand's ANN. Process flow of the Activity Recognition Algorithm is shown in the Figure 2. When Unrelated Activity filtering and Target Activity Recognizing processes are being done, both hands' behaviours are matched with each other in order to detect whether they are belonged to same target activity, as shown in (1) and (2) steps in the Figure 2.

### C. Image Recognition Algorithm

In order to recognize capturing images, color information of each pixel are used [11]. Every image is represented as two-dimensional array, where every element of that array contains color information for one pixel. Each color is represented as a combination of three basic color components: Red, Green and Blue (RGB). According to that, three two-dimensional arrays are used, to represent some image in a RGB system.

These three arrays are merged into a single one-dimensional array, so it contains all red values, then all green and at the end all blue values. That one-dimensional array is used as input for Artificial Neural Network, and to train neural network to recognize or classify them, as shown in Figure 3. The dimension of that array is [imageHeight \* imageWidth \* 3]. Each output neuron corresponds to one image or image class.

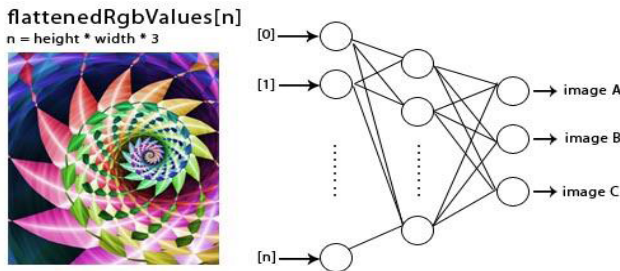


Figure 3. Image Recognition Algorithm

### D. Forgetting Probability

According to the past related literature, individuals who live alone, have same kind of activity patterns in their daily life [10]. As a result of that, they may forget a particular activity, often by nature or habit, rather than because of other activities. As the date and time also can influence on forgetting some activities, it might have to do with the extent to which the person is occupied or busy during any specific time of the day or week [10].

Therefore past activity patterns of the user are considered when the reminders are predicted in the proposed Smart Reminder System. According to that, current situation is compared with the same kind of scenarios in the past.

In order to perform that, Forgetting Probability (FP) of a particular activity in a specific time of the day or week is calculated in this work. When the FP of current Coupling

Activity is decided, numbers of forgotten turns in the past for a same scenario is considered. FP of particular activity is calculated as follows.

Where nA is the number of times that an activity A forgotten in N performances of A activity in an experiment.

$$FP = \frac{nA}{N} \quad (1)$$

### E. Reasons For Forgetting

There may have many reasons for forgetting a particular activity. But when a person forgets some activity, he or she may be involved with another task in same location or has left from the related location. In this work, those reasons are considered as "Other Task" or "Location Change". If the user is not at the related place when the completion time for a particular activity is exceeded, then it will be recorded as "Location Change". It will be recorded as "Other Task", if the user is at the same location, but occupied with some other task, when the completion time is exceeded. Location Change probability (LCP) and Other Task probability (OTP) are calculated as "(2)" and "(3)".

Where nAlc is the number of times that an activity "A" forgotten as a result of Location Change, in "N" forgotten times of "A" activity in an experiment.

$$LCP = \frac{nAlc}{N} \quad (2)$$

Where nAot is the number of times that an activity "A" forgotten as a result of Other Task in "N" forgotten times of "A" activity in an experiment.

$$OTP = \frac{nAot}{N} \quad (3)$$

### F. Reminder Prediction Algorithm

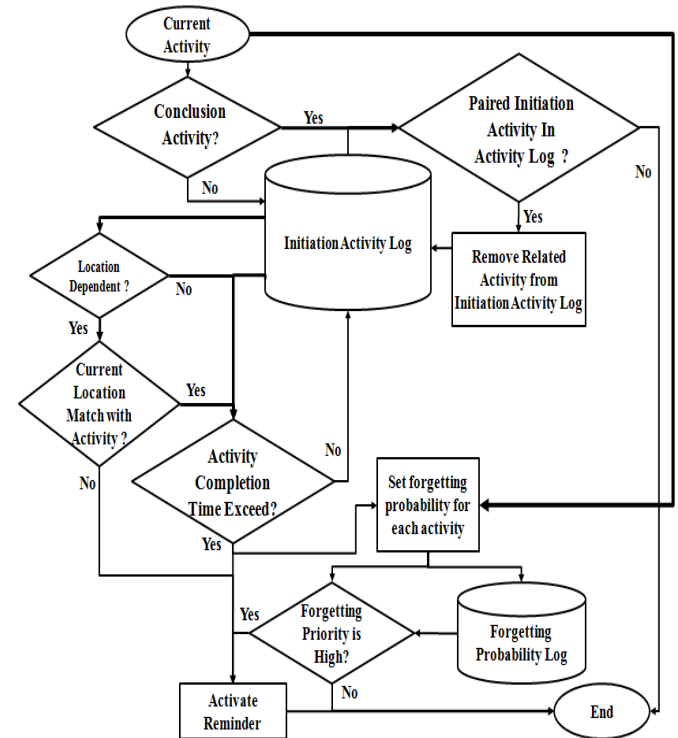


Figure 4. Reminder Prediction Algorithm

Reminder Prediction Algorithm (RPA) is designed to predict reminders using the domain knowledge about the user. Currently performing activity, current location, time line as well as past activity patterns also used as domain knowledge about the user. Designed Reminder Prediction Algorithm is shown in the Figure 4.

**1) Activity Coupling Process:** The inputs coming from Activity Recognition Layer to Reminder Prediction Layer (RPL) can be “initiation” type or “conclusion” type activity. Therefore, initially RPL try to couple the new activities with the past activities, which are stored in the Initiation Activity Log as shown in Figure 5.

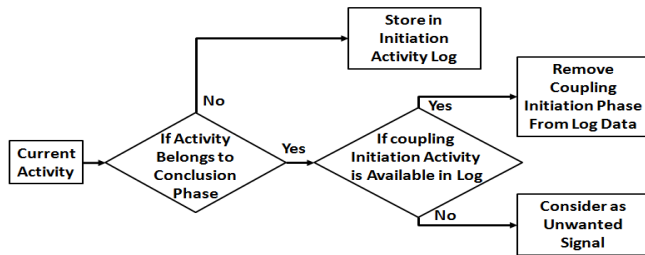


Figure 5 Activity Coupling Process

When the received input is a “conclusion” type activity, then the system checks whether it is coupling with an “initiation” activity, which is available in the past logs.

When the coupling “initiation” activity is available in the log data, then both data are mapped as “Coupling Activity” and it is considered that the activity has been completed. Then the initiation activity is removed from the Initiation Activity Log, and the system moves to new data set monitoring.

If the coupling “initiation” activity of received “conclusion” activity is not available in the Initiation Activity Log, the identified conclusion activity is ignored as there is no requirement for reminding anything. Then the process is ended from there and will move to new data set monitoring.

**2) Predict According to the Forgetting Probability:** Reminder Prediction Algorithm uses Forgetting Probability (FP) of subjected activity and reminders are activated from the beginning of the activity, when that has higher probability ( $FP > 0.5$ ) to be forgotten. Otherwise they are activated after exceeding the allocated time period. Decision making process according to the Forgetting Probability is shown in Figure 6.

**3) Reasoning for the Forgetting:** Reason for forgetting is also mentioned by the reminder. Reason is mentioned as “Location Change” when the Location Change Probability value is higher than Other Task Probability. Otherwise the reason for forgetting is mentioned as “Other Task”.

**4) Response for Location Dependency:** When a particular activity is depended on the location, then the system checks continuously whether the location limits for that activity are exceeding (or were crossing) without activity completion. Reminders are activated when the locations are exceeded (or crossed).

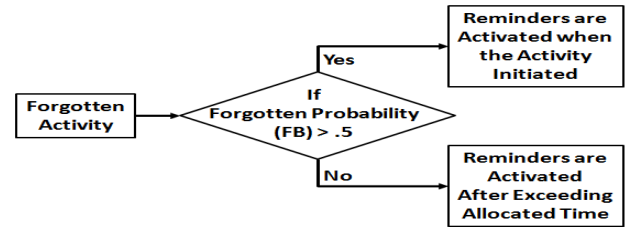


Figure 6. Forgetting Probability

## IV. SYSTEM IMPLEMENTATION AND EVALUATION

### A. Smart Reminder System

Proposed Smart Reminder System (SRS) consist three major layers such as: (1) Activity Recognition Layer (ARL), (2) Location Recognition Layer (LRL), and (3) Reminder Prediction Layer (RPL). Architecture of SRS is shown in Figure 7.

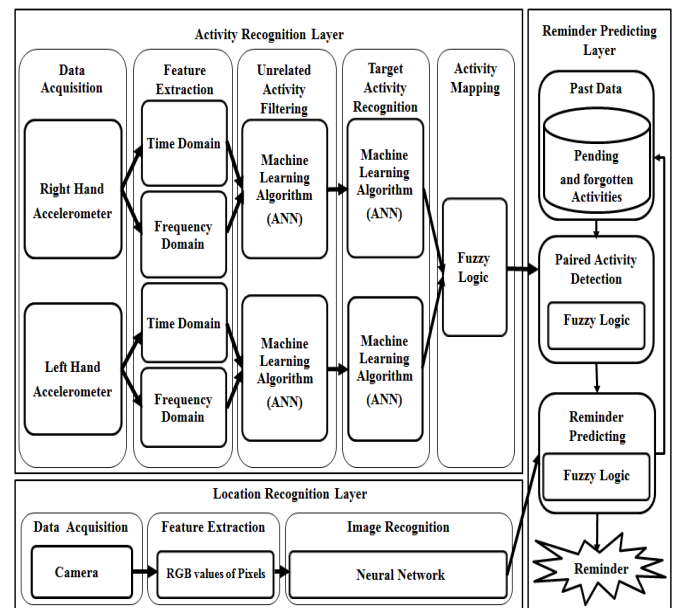


Figure 7. Architecture of Smart Reminder System

WEKA-3.6 open source library is used to develop ANN algorithms in ARL. Neuroph-2.4 open source library is used to develop Image Recognition Algorithm in LRL. “Wii Remote” devises are used as three axis accelerometers.

Activities are captured by the accelerometer sensors, which are worn on the wrist areas of both hands of the subject. Captured data is processed through Activity Recognition Algorithm. Location base images are captured by a web camera, which is worn on the chest area of the subject and recognized by the Image Recognition Algorithm.

Recognized current activity from Activity Recognition Layer and the recognized current location from Location Recognition Later are passed on to the Reminder Predicting Layer.

When the Reminder Predicting Layer is received an “initiation” activity as current activity, then it is recorded in the Initiation Activity log with the current time. Further, System continuously monitors the completion time periods of

all the initiated activities to activate reminders, when it is necessary. Finally reminder prediction is done by the Reminder Prediction Algorithm using all the domain knowledge. Further Reminder Prediction Layer keeps all the identified; forgetting probability records of each activity in “forgetting probability log” for user adaptable reminder prediction in future.

### B. Evaluation of Smart Reminder System

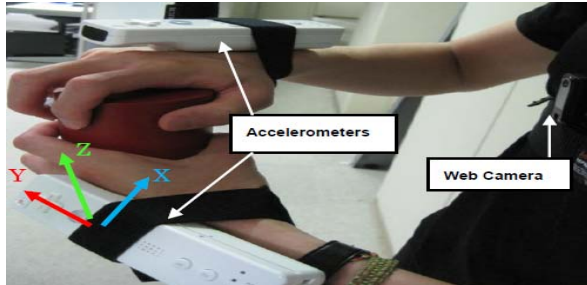


Figure 8. Experimental setup

Reminder prediction accuracy of proposed Smart Reminder System for forgotten Coupling Activities were evaluated under several test scenarios. The specific case study of opening and closing various types of bottles were performed in order to represent Coupling Activities. Sensors placements for data acquisition are shown in Figure 8. Four healthy subjects were participated for the experiments under same environmental conditions.

Four types of bottles were opened and closed in the data collection. All of those activities were called Target Activities (TAs) and all together there were 8 TAs. Gathered sample accelerometer signals of a particular TA is shown in Figure 9. Some other common activities in daily life also performed with the TAs in order to represent a real world scenario. They were called as Unrelated Activities (UAs).

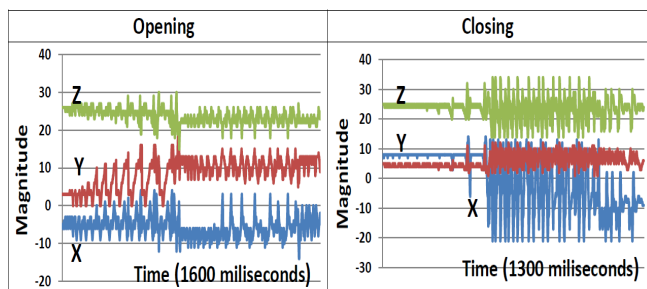


Figure 9. Accelerometer patterns of a Coupling Activity

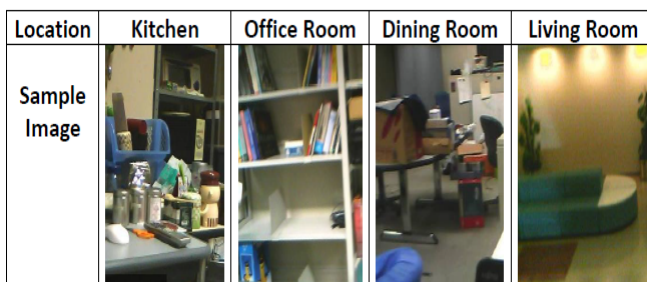


Figure 10. Captured images from different locations

Four locations were selected to perform TAs and UAs. Different locations were allocated for each TA among those four locations. Ten images, which were taken from different angles, were used to represent one location. Some sample images of each location are shown in Figure 10.

Evaluated features of the Smart Reminding System, followed test scenarios and the received average results are discussed in Table 1. In order to identify the performance of subjected feature, unwanted features were controlled in each test scenario.

TABLE 1. EVALUATION OF SMART REMINDER SYSTEM

| Monitoring Feature                                                                                             | Test Scenario                                                                                                                                                                                                                                                                                                                                                         | Received Results                                                                                                                                                      |
|----------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Reminder Prediction when the activities are delayed to be completed (Without location change or past patterns) | <ul style="list-style-type: none"> <li>Subjects were asked to perform all the Target Activities (TAs) “with a delay” (10 times)</li> <li>Again TAs were done “without delay” (10 times)</li> </ul>                                                                                                                                                                    | <ul style="list-style-type: none"> <li>70% average accuracy for uncompleted delayed activities.</li> <li>80% average accuracy for completed activities.</li> </ul>    |
| Reminder Prediction when the allocated location is changed. (Without time delay, and past patterns)            | <ul style="list-style-type: none"> <li>Subjects were asked to initiate particular TA and “leave to an unrelated location” without completing the task. (10 times)</li> <li>Again they were asked to stay in a related location after initiation the same activity. (10 times)</li> </ul>                                                                              | <ul style="list-style-type: none"> <li>80% average accuracy for location change.</li> <li>90% average accuracy with same location.</li> </ul>                         |
| Reminder prediction according to the Forgotten probability (Using user’s current and past activity patterns)   | <ul style="list-style-type: none"> <li>Subjects were asked to initiate particular TA and “delay to complete” the activity. (8 times out of 10 performances.)</li> <li>Again subjects were asked to initiate some other TA and “complete on time”. (8 times out of 10 performances.)</li> </ul>                                                                        | <ul style="list-style-type: none"> <li>For high Forgetting Probability: 70% average accuracy</li> <li>For low Forgetting Probability: 80% average accuracy</li> </ul> |
| Prediction Reason for forgetting (Using user’s current and past activity patterns)                             | <ul style="list-style-type: none"> <li>Subjects were asked to initiate particular TA and “delay to complete” the activity by performing “Other Task”, (8 times out of 10 performances.)</li> <li>Again subjects were asked to initiate some other TA and “delay to complete” the activity by moving to “Other Location”, (8 times out of 10 performances.)</li> </ul> | <ul style="list-style-type: none"> <li>For “Other Task”: 70% average accuracy</li> <li>For “Other Location”: 90% average accuracy</li> </ul>                          |

### C. Discussion

| Prediction<br>Actual ↓ | SLCO | SLCC | SSCO | SSCC | PLCO | PLCC | PSCO | PSCC | UAs | Prediction |
|------------------------|------|------|------|------|------|------|------|------|-----|------------|
| SLCO                   | 10   | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0   | 1          |
| SLCC                   | 0    | 10   | 0    | 0    | 0    | 0    | 0    | 0    | 0   | 1          |
| SSCO                   | 0    | 0    | 10   | 0    | 0    | 0    | 0    | 0    | 0   | 1          |
| SSCC                   | 0    | 1    | 0    | 8    | 0    | 0    | 0    | 0    | 1   | .8         |
| PLCO                   | 0    | 0    | 0    | 0    | 9    | 0    | 0    | 0    | 1   | .9         |
| PLCC                   | 0    | 0    | 0    | 0    | 0    | 10   | 0    | 0    | 0   | 1          |
| PSCO                   | 0    | 0    | 0    | 0    | 0    | 0    | 9    | 0    | 1   | .9         |
| PSCC                   | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 10   | 0   | 1          |
| UAs                    | 0    | 0    | 0    | 0    | 1    | 0    | 1    | 0    | 8   | .8         |

Figure 11. Activity Recognition Performance (Performed all TAs and UAs are shown in the confusion matrix)

1) **Performance of Activity Recognition Algorithm:** Received results by the proposed Activity Recognition Algorithm are shown in the confusion matrix in Figure 11. Performance of activity recognition algorithm was depended on the performed activities and the nature of working environment. Activity recognition performance was reduced when the Unrelated Activities were performed with Target Activities. However it could achieve 93% average recognition accuracy rate for performed activities. Only few activities were confused as other activities.

2) **Performance of Location Recognition Algorithm:** Average recognition accuracy of Location Recognition Algorithm was in higher level (90%). But always recognition performance was depended on the quality of captured images. Image quality changed with the background lighting effect and movement speed of the subjects.

3) **Performance of Reminder Predicting Algorithm:** In the first test scenario, reminder prediction was done according to the taken time to complete the Coupling Activity. Therefore reminder prediction performance was directly depended on the activity recognition performance.

In the second test scenario, reminder prediction was evaluated according to the location changes done by the subject while performing particular Coupling Activity. Therefore performance of reminder prediction was depended on the location recognition performance.

In the third test scenario, reminder prediction was done according to the user's past activity patterns. Therefore always reminders were predicted according to the user's current context as well as past forgetting probabilities. But in real time test scenarios, incorrectly recognized activities were also stored in the log data. Therefore reminders were activated in wrong order when the system was interacting with the activities, which were difficult to be recognized.

In the fourth test scenario, "Location Change" reason could be predicted in higher accuracy rather than the "Other Task" reason, as the location recognition performance was higher than the activity recognition performance.

### V. CONCLUSION AND FUTURE WORK

We have presented a Smart Reminder System (SRS) to predict reminders for Coupling Activities, which are easy to forget. User's current behaviour, current location and past activity patterns were used to predict user adaptable reminders. Proposed SRS performed well in the experiments and could achieve 80% average accuracy rate for reminder prediction. It reacted accurately with minimum supervision by the user and could predict reminders adapting to the user's dynamic behaviour. But always reminder prediction performance was depended on the performances of activity recognition and location recognition.

Therefore in future, activity recognition and location recognition algorithms should be improved to recognize activities more accurately. In order to monitor the performances of proposed approaches more clearly, system should be trained and tested with large number of data sets of various subjects.

In the future developments we are planning to use human emotions also for predicting the reason for forgetting more accurately. Further, reminders will be sent to the mobile phones of the appropriate parties. Eventually, reminders will be provided to more general Coupling Activities in daily life.

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