

Recording Housekeeping Activities with Situated Tags and Wrist-Worn Sensors: Experiment Setup and Issues Encountered

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Abstract

RFID tag readers and accelerometers are two sensing technologies that have recently dropped in both size and cost. Assuming that key household items can easily be tagged, one could legitimately imagine a wrist-worn sensor which incorporates both, to infer Activities of Daily Living (ADL). This paper presents initial challenges in research towards this scenario by describing critical choices made in a series of data recording experiments, in which we intend to capture realistic sensor data in a lab setting, using a set of housekeeping activities as targets.

1. Introduction

As the elderly population is rapidly growing, new health care challenges are emerging. A strong desire by aging individuals to remain independent in their homes as long as possible has motivated innovative technological solutions for assisted living. In order to improve the quality of life of the senior citizens, the new solutions must offer the required medical and home care assistance.

Different kinds of cognitive impairments are a very often occurring health problem for elderly people, and their early diagnosis is highly important. First changes can be detected in the assessment of the execution of the Activities of Daily Living (ADLs) and the Instrumental Activities of Daily Living (IADLs) [1]. The ADLs are fundamental for self care, i.e. bathing, dressing, toileting, transferring, continence, and feeding. People commonly perform these activities on a daily basis, and they are signs for the functional status of the person. On the other hand, the IADLs involve interactions with the physical and social environment. This group consists of the following activities: using telephone, shopping, food preparation, housekeeping, doing a laundry, transportation, taking medications, and handling finances. Since these

activities can be delegated to the others, they are not necessary for the fundamental functioning of a person. Nevertheless, the monitoring of the IADLs' performance and detection of the abnormalities in their execution indicates the first signs of a disease.

The assessment of the ADLs/IADLs is nowadays typically done by trained caregivers and case managers. They do this manually by visiting elderly people at their homes and interviewing them. Specialized questionnaires have to be filled in during each visit. These manual assessments are time consuming and error prone because of two reasons. Firstly, the symptoms are often denied by the person for a long time [3, 13] and secondly, people might not say the truth during the interview because of the fear of being transferred to the nursing home [2].

Therefore, the automatic assessment might significantly ease the work of the caregivers and case managers and improve the accuracy of the assessments. The use of wireless sensors has a big potential for effectively and unobtrusively inferring users' activities and long term monitoring.

Researchers tried to use a wide variety of sensors to recognize user's activities in general, and the ADLs/IADLs in particular, e.g. video cameras [7, 10], microphones [8, 12] and different location systems [9, 11].

Two interesting approaches are based on complementary assumptions. The first approach assumes that the used sequence of objects during the execution of an activity can robustly categorize the activity. Thus, in this approach the sensors deployed throughout the environment enable the detection of the objects people use. Examples of sensors used for this approach are state-change sensors used in [4] and Radio Frequency Identification (RFID) tags used in [5, 11]. The second approach assumes that the motion of the body during the execution of an activity can robustly characterize the activity. Wearable sensors strapped to the human body are being used in this

approach to recognize the movement patterns while performing various activities. Sensors typically used in this approach are accelerometers [6, 12].

A promising recent approach is introduced in [14]. It combines the two previously mentioned approaches and tries to augment the recognition of the users' activities based on the actions performed on objects.

We have focused on the similar hypothesis that the recognition results could be significantly improved by using both the sensors placed in the environment and the wearable sensors. We recorded and analyzed a preliminary data set of housekeeping activities, and present in this paper choices and challenges that we faced regarding this experiment.

The rest of the paper is organized as follows. Section 2 describes the sensors we used for recording our data set. Section 3 then introduces the experiment rationale. In Section 4, we present the experience and identified challenges we obtained during the experiments and the lessons learned. Finally, we summarize in Section 5 our results and future work.

2. Sensors

We used two types of wireless wearable sensors, named iBracelet and Porcupine, for detecting object usage and arm movements respectively. Both these sensors have been designed to be as unobtrusive and easy to deploy as possible. They also operate without any calibration requirements, which make them an ideal solution for the long-term monitoring necessary for the detection of changes in human behavior.

The iBracelet is a wrist-worn RFID reader (Figure 1(a)) built at Intel Research Seattle [15] that can detect 13.56MHz RFID tags in the range of up to 10cm. We used passive adhesive 55 x 55 mm RFID tags (Figure 1(b)). When queried by a reader, tags respond with a unique identifier. The bracelet wirelessly transmits the tag ID to a base station. The received 'tag read' events are stored together with a timestamp to the persistent memory for later analysis. Therefore, if we tag the objects of interest, we can easily infer person-object interactions.



Figure 1. (a) iBracelet, (b) RFID tag

The RFID tags are durable, small sized and inexpensive. The RFID technology has gained a growing interest in recent years, due to its potential in supply chain management. Thus, in the near future, consumer goods could be permanently embedded with the RFID tags, which will make the deployment of this technology feasible in the home environments. Meanwhile, controlled deployment might still be feasible in the environments of the elderly, where they live semi-independently with occasional help of care givers who could add tags to accommodate the RFID monitoring.

The Porcupine is a wearable multi-sensor platform (Figure 2) developed at the Darmstadt University of Technology [18], which includes the following sensors: 3-axis accelerometer, 9 tilt switches, 1 temperature sensor, and 2 ambient light sensors. Additionally, it has a real-time clock, serial flash memory, mini USB port, 3 buttons for annotations, 3 LEDs and automatic power switching between battery and USB powered modes.

We attached the Porcupine to the wrist of the users by a strap in order to infer the fine grained arm movements. In the future, we plan to integrate it in a bracelet or watch to make it more unobtrusive for a user. For our recordings, we wanted to have an as high and accurate sampling frequency as possible for raw acceleration data, so we used the Porcupine in the USB powered mode by attaching it to a hip-worn OOO pocket-sized computer that was also used for logging the data.



Figure 2. Porcupine

3. Experiment Rationale

In our experiment, we focused on one specific class of the IADLs, i.e. housekeeping activities. So far, most researchers have been concentrating their efforts on recognizing various selected instances of different ADL/IADL classes. There have been efforts on recognizing different instances of the same ADL/IADL classes, e.g. bathroom activities [8], cooking [17], and taking medications [16], but there were no attempts to recognize in-depth the housekeeping activities, which are an important and often occurring IADL class. Although, this type of activities is not done by the

elderly people in the later stages of a disease, its assessment can detect the highly important beginning of a disease. Also, housekeeping consists typically of localized indoor activities which make it a very good candidate for the evaluation of our approach and usage of the sensors, described in the previous section.

In our experiments, we target the following housekeeping activities: vacuuming, ironing, dish washing, dusting, cleaning windows, watering plants, mopping, brooming, setting the table, and bed making. At the time of writing, we have the data set consisting of the 4 activities (vacuuming, ironing, dusting and brooming), but we're still in the process of recording the data for the remaining 6 activities. The overall length of the current data set is 112 min (1534 sec of vacuuming, 3213 sec of ironing, 1339 sec of dusting, and 635 sec of brooming). Vacuuming was performed 7 times, ironing 5 times, dusting 9 times, and brooming 4 times. We plan to make the final data set public.

Subjects that participated in the experiment are the employees of the Darmstadt University of Technology, mostly researchers. This might have introduced a significant bias into our data set, but at this early stage it was impractical to ask elderly people to participate in the experiment. However, we argue that the results of our current experiment can be generalized for other housekeeping activities and different classes of users. To date, the participants in our current experiment were 10 subjects, 3 females and 7 males. We had 2 left handed subjects and 8 right handed subjects. All the subjects wore the iBracelet and the Porcupine at the dominant wrist only (Figure 3(a)). In that way we are able to recognize the key person-object interactions within activities and still have the satisfactory level of the wearability and unobtrusiveness, as well as maintain as many factors from our scenario as possible.



Figure 3. Experiment setup: (a) Sensors, (b) Laboratory

For our recordings we used a controlled lab environment, at the Darmstadt University of Technology (Figure 3(b)). We furnished the laboratory with typical objects found and used in a domestic setting, to make it resemble a common home environment. None of the subjects felt uncomfortable performing the home activities at the laboratory or wearing the sensors during the execution of the activities. We recorded the whole process by video

camera for later annotations, to avoid bias in the data set by the subjects' online annotations. The subjects did not have any complaints about possible privacy issues at this stage, though we assume this might be different if the recordings were done in real home environments over longer stretches of time.

We deployed multiple tags on as many objects as possible for several reasons. Firstly, we wanted to evaluate the best placement of the tags for different objects. Secondly, to increase the likelihood of identifying the key objects used in different activities. Thirdly, we want to see the influence of the number of deployed tags to the later recognition results by simulating different amounts of the detected tags in our data set. So far, we tagged 36 objects with 113 tags (Table 1). We plan to deploy more tags for the objects relevant for further activities we are planning to record. Maximum number of deployed tags per object is 18 (for a pillow). Only 7 objects were tagged with a single tag. On average, 3 tags were deployed per object. Optimizing for detection, we tried to tag various parts of the objects that we considered being hard for the interaction detection due to their size, the way they are usually being used by users, and the short range of the RFID reader antenna embedded in the iBracelet.

Tagged objects	Number of tags per object
Pillow	18
Vacuum cleaner, bucket	9
Mop, TV, big broom	7
Small pillow case, big pillow case	6
Ironing board	5
Sewing machine, dusters box	4
Fan, iron, window cleaning liquid, pot for distilled water, bottle for distilled water, cleaning cloth	2
Sewing machine utensils box, sewing machine mechanism box, dust pan, sponge, glove for left hand, glove for right hand, small broom	1
Dusting cloths 1-8	1 each
Wall sockets 1-4	1 each

Table 1. Number of tags per objects

The scenario we introduced to the subjects was kept as vague as possible. We specifically did not give the detailed description of the required object interactions and sequences of actions to be performed within each activity, as we wanted to avoid biasing our data set with same sequences of tagged objects and artificially staged actions. The subjects were encouraged to perform the activities as naturally and using their own routines as much as possible. We will

specifically evaluate the diversity of ways different people performed the same activity.

Our final goal is the recognition of the performed activities and different stages of the activities together with their duration and the way they were performed by different people. This way, recognition methods can be primed as much as possible for long term monitoring and detection of changes in the behaviour of elderly people before actual deployment. In this early stage, we came across several issues during the experiments and we present them in the following section.

4. Lessons learned - Experience

The challenges encountered during the experiment can be categorized in three groups: deployment issues, reliability of tag detection during the activities' execution, and the diversity of ways different people perform the same activity. In the rest of the paper, we will address all of these issues.

4.1. Deployment issues

In terms of the deployment, we faced some difficulties during the process of tagging a large number of objects and manually mapping the tag ID to the object it has been attached to. This process is tedious and a few errors occurred during the cataloging procedure. The errors were discovered afterwards during the analysis of the recorded data. This might not be an issue if in the future objects we buy are already equipped with RFID tags.

Another problem that appeared during the recordings was synchronization of data coming from the iBracelet, the Porcupine, and the video camera, which all produce data at different speeds. Data streams coming from the iBracelet and the Porcupine were timestamped, so their synchronization was almost straight forward, but yet, a significant time drift occurred now and then. We successfully recovered the data by identifying the time drift from the recorded videos. For future recordings, we plan logging the both data streams on the same computer, and preferably performing the sensor fusion by logging the data in the same log file. Another option would be to use the detection of a test tag at the beginning of the recording. For the synchronization of the video stream with the rest of the data, we asked the subjects to make 3 repetitive arm movements before starting with an activity. These movements are represented in the raw acceleration data by 3 distinguishable peaks, and can be easily synchronized by visual inspection of the acceleration plots.

4.2. Reliability of tag detection

Regarding the reliability of tag detection, we analyzed the logged tag IDs in 3 different ways: overall and per activity number of tag detections, how many different tags were detected overall and per activity, and in the end we made the analysis of the tag detections and how many different tags were detected per subject.

Throughout the whole data set, the iBracelet detected tags on 4917 occasions. On average, 0.73 tag detections happened per second. Distribution of tag detections over the recorded activities is as follows. During the ironing activities tags were detected 2556 times, i.e. 0.79 tags detected per second. During the vacuuming activities tags were detected 1504 times, i.e. 0.98 tags detected per second. During the dusting activities tags were detected 551 times, i.e. 0.41 tags detected per second. And during the brooming activities tags were detected 306 times, or on average 0.48 tags detected per second. Thus, the vacuuming is the most extensive activity in terms of the tag detections. This is because of the fact that the tag placed on the vacuum cleaner stick was detected very often during the vacuuming. A similar situation occurred with the tag placed on the handle of the iron. That is why the ironing activity also has very high tag detection score. On contrary, the dusting and brooming activities have lower tag detection scores, because the tags placed on the dusting cloths and the broom were rarely detected. The reason for that is probably the way how the tags had to be mounted to the dusting cloths and the broom, which affected their reading. The detection of tags might have been improved if we used the longer range RFID reader, but, at the same time that would also introduce more false positives, i.e. the number of tags detected accidentally near the hand. In our data set, there were only 16 false positives, and we think the better tradeoff between the range of the antenna and tag detection precision could be achieved in the future. Another issue might be the object's material properties, especially for the metal handle of the broom that we used. A smaller plastic hand broom was much easier to detect, but the subjects used it only occasionally at the end of the brooming activity to gather the dust in a dust pan.

Overall, the iBracelet detected 33 different tags, which is not much considering the 113 deployed tags. Two reasons can be found from the video footage. On the one hand, the short range of the RFID reader caused many false negatives, i.e. tags were not detected even though the subjects were interacting with the tagged objects. On the other hand, many of the tagged objects were not involved in the execution of the

recorded set of activities, and we think that the overall number of detected different tags will be much higher in the final data set.

The number of different detected tags per activities is 18 for dusting, 6 for vacuuming, 5 for ironing, and 4 for brooming. Dusting activity in its nature includes interaction with different objects being dusted, which is why the more different tags were detected during the performance of dusting comparing to the other activities. Even though ironing activity also includes interaction with the clothes being ironed, it is not reflected in our data set as we omitted tagging the clothes.

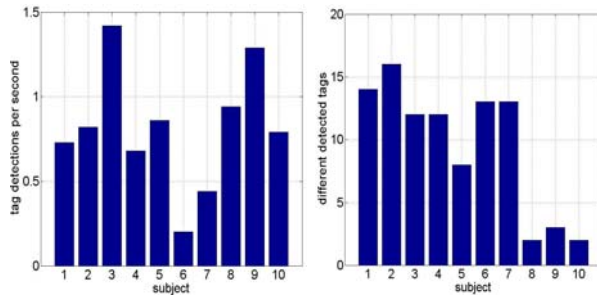


Figure 4. (a) Tag detections per subject, (b) Different detected tags per subject

We evaluated how much the number of tag detections (Figure 4(a)) and different detected tags (Figure 4(b)) varies among the subjects. 3 subjects (subjects 8, 9, and 10 in the Figure 4) participated only in ironing activity, and that’s why they have the lowest scores for the number of different detected tags. On contrary, they have among the highest scores for the number of tag detections per second. That’s due to the high tag detection score for the ironing activity. The authors of the paper (subject 1 and subject 2 in the Figure 4) also participated in the experiment, but they didn’t introduce the bias into the data, even though they knew how the system works and they spent considerable time preparing the laboratory and tagging the objects. The only noticeable bias occurred during the brooming activity of subject 2. We had a few problems with the data synchronization for that specific recording, so the subject had to repeat the activity a couple of times. This is probably the reason for the occurred bias.

4.3. Activity performance diversity

We kept our scenario presented to the subjects very general. That resulted in a variety of ways subjects performed the activities. Subjects had different interpretations of the activities. For example, 2 subjects used the vacuum cleaner not only to vacuum the floor,

but also to clean the sofa. Surprisingly, 5 of the subjects did detailed vacuuming of the floor under the sofa. In two cases, the iBracelet could not recognize turning the vacuum cleaner on and off, because the subjects did these actions by their leg. Some of the typical actions that have to be done during the activity, such as pulling out the vacuum cleaner cable consisted of very different movements among the subjects. During the ironing activities, only one subject used the distilled water. None of the subjects placed the iron on the side handle of the ironing board. That significantly decreased the detection of the interactions with the ironing board, because the tags were placed close to the handle in hope that the subjects would use it during the ironing. Also, repetitive cleaning movements during activities such as brooming and vacuuming varied in intensity among different subjects. All this will most probably influence the recognition results in the end.

All our subjects wore the sensors on their dominant wrist. Still, during the ironing activity 2 subjects occasionally used their non-dominant hand for ironing some parts of the clothes that were easily reachable in that way. The same pattern occurred when one of the subjects was using both hands during the dusting. Another problem is that in many situations, the dominant hand was occupied with another action, and the subjects had to interact with the necessary objects by using the non dominant hand. The iBracelet couldn’t detect those events, which introduced additional false negatives. One solution to this problem would be to wear the sensors on both the left and the right wrist. But, in our scenario, we assume that the wearer would prefer to wear just one bracelet, and will therefore leave it to the inference engine to deal with this issue.

5. Conclusions and Future Work

In this paper, we report on the issues that appeared during the experiment of recording the execution of 4 housekeeping activities by 10 subjects. For the recording, we used 3 different types of sensors, which introduced synchronization issues, as well as the deployment challenges of tagging the everyday objects with RFID tags. We also analyzed the reliability of tag detection per activities and per subjects who participated in the experiment. We had much more false negatives than false positives in our data set, because of the antenna range but also because of the fact that the subjects wore the sensors only on the dominant wrist. Both, the longer antenna range and sensors on the non-dominant wrist and on the ankles would improve the tag detection results. Wearing

multiple sensors would be too obtrusive, but longer antenna range seems to be feasible. In the end, we also tried to conclude different ways the subjects executed 4 activities that we recorded and their influence on the data set.

In the future, we plan to continue our experiment having in mind the lessons that we learned in this initial stage. After we have the complete data set of the activities we're interested in, we will further analyze the data, especially acceleration and other Porcupine's data in order to recognize the relevant arm movements and combine it with the object interaction data to recognize the activities.

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7. References

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