Finding Long Term Tendencies in Daily Activities of People with Dementia using RFID Slippers: An exploratory study

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Abstract

The development of Radio Frequency IDentification (RFID) technology makes it possible to track residents when installed to a house. We studied what valuable information can be extracted from location data of residents when we have carried out the data collection for years. We installed antennas into a group home, where six people with dementia lived, and asked the residents to wear slippers into which RFID tags were inserted. The data has been collected for thirty months. We found a seasonal effect for all residents such that the activity level was lowered towards summer. Looking into individual cases, we identified for a person a rapid decline three months prior to her death. As for another person who fell down, we identified a rapid decline a week prior to the incident. Both showed a change in their behavioral patterns, too. Data collection for long term is useful for assessing residents’ conditions. With sufficient data, we can detect abnormalities.

1 Introduction

Given the increasing number of aged people in advanced nations including Japan [16], it becomes an issue how to care for those aged people. The principle of self autonomy should be observed and the elderly are encouraged to support him or herself as much as possible. It is however inevitable that they need at some point a help by others as they become physically weaker. The frailter the elderly become, the more important role caregivers play.

Caregivers are required to realize what has to be done to each person for the best quality of life by observing carefully what he or she is doing. Observation is particularly important when the person in focus is cognitively impaired as he or she is often unable to express what is wrong with him or her. Good caregivers can take a precaution against a serious accident such as falling down through careful observations.

While the intuition of caregivers is appreciated for good care, the advances of caregivings lead caregivers to making a judgement based on evidences. Evidence-based care will be welcomed by both family members of the person looked after and caregivers. The point cannot be overemphasized as most engineers think it opposite, i.e., the more, the better. That is, we should keep it to minimum the amount of technologies introduced into care work so that neither persons looked after nor caregivers are threatened. The choice of location data originates from two reasons: privacy and technological issue.

Concerning the privacy issue, we have to justify data collection. There is always a trade-off between privacy and benefit when one introduces information technologies into care work. How to balance them is an important problem in itself, but surely less is better. That is, the choice of location data is relatively safe in terms of privacy as they do not capture physical images such as facial expressions, gestures, voices, and so on.

Technologically it is plausible to collect location data given the advances of Radio Frequency IDentification (RFID) technology. We inserted RFID tags into slippers and located residents’ whereabouts at a group home with antennas embedded into the flour. We narrow
the domain of data collection to a house, not a house with its surrounding area, the data collection for which requires a different kind of tracking technologies such as GPS.

Location data is rather lean. What useful information can we extract of them? We were initially interested in detecting health decline, which may lead to serious accidents such as falling down. We have seen some cases in which an elderly fell down and was transferred to hospital with his or her bone fractured as he or she was weakened. Serious accidents may lead to further losses of cognitive capabilities. We hoped that collecting location data for long term might enable us to detect the decline of health and even to prevent serious accidents such as falling.

We have never intended to replace technology for caregivers in carrying out our project. We do not think that a program may precisely predict when a person will fall down and where because accidents occur by chance. What we can do possibly is to detect increased risks and warn caregivers to prepare for accidents. The person looked after then benefits from data collection with the increased level of awareness among caregivers. It may also help caregivers to develop their abilities to notice symptoms indicating a decline of health. Subtle, slow changes developing for long term can be overlooked. Technology may assist caregivers by providing them with valuable information hard to obtain solely by human hands. Some researchers point out that the use of technologies in the dwelling for daily support shifts from the resident to the formal and informal caregiver[17].

We target in the long run to develop a formula to estimate risks of accidents, but we obviously need a vast amount of data to apply statistics to them. Given the sensitive privacy issue, we cannot jump on to data collection in large scale. We need to justify our investigation by showing an evidence that it may contribute to caregiving. The present work thus remains to be exploratory.

The development of pervasive computing led many researchers to applying the technology to enabling the elderly to live at their places as long as possible[10, 11, 13]. They install sensor networks into home to identify residents’ behaviours including abnormalities such as falling down. Behavior recognition is effective in rescuing the person monitored immediately after something went wrong[8, 9, 1, 5, 18, 19]. It is useful both for looking after a person in distance and for caring a person living within the same house.

We would like to extend the use of technology to adjusting the care level, most often to avoiding accidents. Behavior recognition works fine when an accident has occurred or is just occurring, but it is desirable to prevent accidents to occur well before they become apparent. We may replace furnitures, reconstruct some part of home, employ someone temporally to help the person to take a bath, take him or her to a day care house, relocate his or her room to easily accessible places to caregivers, and so on.

The point is that the assistance to the elderly has to be just in satisfying their needs. A person’s capability may be lost if caregivers help him or her excessively. The person is expected to do things by him or herself as much as possible to maintain his or her capabilities. Caregivers are only expected to help him or her when he or she is incapable. Assessing a person’s capability is thus of prime importance to judge to what extent a help is required.

Making a judgement about care work consists of the core competence of caregivers and the role of technology is to provide them with enough information to make a correct judgement. It is thus not our intention to teach caregivers when some accident may happen. We are rather interested in informing them whether the person looked after is in good condition or requires a particular attention by estimating risks of accidents.

This article is organized as follows. Section 2 describes how we collected the data. Section 3 explains the amount of data collected and how we pre-processed them. Section 4 presents what information we can extract of the data. Following Section 5 discusses two cases to see how the location data may be used for care work.

2 Data Collection

A group home in Japan kindly allowed us to collect location data. The house was originally built about sixty years ago for a family and was converted into a group home a decade ago to accommodate up to six people with dementia. These people are cared by caregivers. Two or three caregivers usually take care for them in the daytime and one caregiver at night.

We have installed into the house twenty one antennas as shown in Figure 1 and asked the residents and caregivers to wear slippers into which RFID tags were inserted. (The antennas are numbered up to 23, but the antenna 1 and 14 are missing.) As each slipper bears an identification, we can track residents’ whereabouts when they step on one of these antennas. Caregivers use the sensor network to monitor residents’ moves. By assigning particular melodies to combinations of a resident and a place, they
can effectively know who are where by hearing
the melody. The detail of the alarm system is
described in one of our articles. [The reference
to the article is suppressed to make the authors
anonymous.]

The same sensor network with RFID slippers
was used to collect data of whereabouts for
each person. Every person was informed of the
data collection, but they were hardly informed
of long term tendencies we analyzed from the
data to avoid influencing their behaviours. We
explained them just once a tentative result in
February 2010, but have not seen any influ-
ences on their caregiving.

3 Data Collected

We have collected the data, their whereabouts,
up to now since June 2008. We limit the time
span to be considered below to the period start-
ing on the 3rd June, 2008, and ending on the
6th November, 2010, for the sake of analy-
sis. The number of entries recording moves by
each person wearing RFID slippers reached to
3,905,158 items for those thirty months. The
number of entries for the five residents, whose
data we examine below, was 1,946,264.

We preprocessed the data to identify the
time spans in which residents stayed at partic-
ular places and other time spans in which they
moved from one place to another. A RFID tag
is detected when it gets close to an antenna and
the time point of detection is recorded as IN.
The tag is tracked until it goes out of range and
the time point of leaving is recorded as OUT.

Under ideal conditions, these two time
points, IN and OUT, punctuate the time span
in which the person wearing the tag stayed at
that place, but the antenna may detect the tag
each time the person lifts up and down one of
her legs while she is seated. If it happens, we
must regard those occurrences as indicating a
continuous state in which he or she stays on
there. We take a sequence of IN-OUT pairs as
one span if the gaps between them are shorter
than 60 second. We cannot in theory exclude a
possibility such that the person walked around
the mat, but it is highly unlikely given the
modest activity levels of those residents.

Another problem may be caused by users’
wearing a pair of slippers, each of which bears a
unique ID. The same rule applies to integrating
the data from two slippers as above, that is, a
sequence of data from her slippers is regarded
to indicate the person stays on there if the gap
is shorter than 60 second. The other problem
may occur for the cases such that two anten-
as detect the same pair of slippers, which may
happen, for example, when the person stands
in between two antennas. Our algorithm in-
fers that the person stands on both mats and
does not specify a single place. The problem
is however negligible because such cases rarely
happen for the vast amount of data.

It is another matter to infer residents’
moves from a place to another. We do not have
any first-hand data of moves because the sys-
tem is not designed to detect a process. We
thus need to conjecture how she moved based
on a sequence of data obtained from several
antennas. A sequence of data from a resident
with some gaps in between may be a result of
her move if different antennas detect her slip-
ers. Our algorithm regards two consecutive
identifications of a stay by two different anten-
as as a move if the gap between them is
shorter than 30 second.

By pre-processing the raw data, the number
of incidents where a resident stays at a place is
reduced to 1,558,441 (3,905,158 items in raw),
568,517 items of which are from the residents
(1,946,264 items in raw). The algorithm above
identified 1,259,166 moves in the pre-processed
data, 432,676 items of which originates from
the residents.

Some propose sophisticated algorithms to
infer RFID tag’s location [15]. We appreci-
ate such attempts, but we do not elaborate
the procedure further. Given the huge size of
our data, it does not make significant differ-
ence what sophisticated algorithm we employ
in identifying locations.

4 Analyses

To see long term tendencies in daily activities,
we divided the 128 weeks from the 1st June,
2008, to the 6th November, 2010, into 32 sec-
tions, each of which contains four weeks. We
analyzed the data in two respects: adherence
and mobility. By adherence, we mean where
each resident tended to stay. By mobility, we
mean how often they moved in the house.

4.1 Adherence

Figure 2 depicts the time trends in terms of
whereabouts as for the five residents A to E.
The sixth person was wheel-chaired and hardly
movable by herself. We thus excluded her data
of our analyses. Bars denote the total sum of
the durations of staying detected by all the anten-
as every four week. Each shading corre-
sponds to a particular antenna, whose corre-
spendence is shown in the legend.

For person A, there is a sudden change of
shades at time point 1. These shades corre-
spend to the antennas, 6 and 5, respectively,
both placed beneath the table in the dining room (Figure 1), but on the opposite sides with each other. The Figure 2-A thus tells us that person A changed her place to sit down at the table from the place 6 to another place 5. We also observe a gradual decline in the later period which ended abruptly with a drop. We know that she became quite ill in the period and spent most of her time in her room. We can see when her health started waning and how slowly her condition deteriorated, taking almost a year, until she was finally confined to her bed.

Person B shows a similar change of places at time point 2. The person broke one of her legs at that time point and the graph shows that she became to sit down at the place 5, the opposite side of the table in the dining room, after the accident. We also notice a greatly declined level in the last 5 sections, which means that she spent most of her time in her room. We recognize that the accident influenced her behavior drastically.

Person C shows a stable trend with a mild peak at time point 3. He seems to have increasingly spent most of his time in his room. Person D shows a relatively stable trend with a mild peak in the middle between time point 4 and 5. Closer look revealed that she changed her place to sit down from the place 5 to 6 at time point 4 and again changed her place from the place 6 to 7 at time point 5. The data collection from person D was abruptly ended because she started destroying slippers from curiosity.

Compared to the first four persons, person E does not show a stable trend. There is a distinctively high bar at time point 6, though, where he spent long time at place 15, that is, at the sofa in the dining room. We know that caregivers encouraged him to stay longer in the common room at that time because he tended to confine himself in his room. The graph shows that he responded positively to the action during the period although the effect did not last so long. We gave up the data collection from him in the middle because his slippers were damaged badly as the result of him stamping on the floor so strongly due to his difficulties with walking.

4.2 Mobility

Figure 3 shows the trends in terms of mobility for each resident. Bars represent the total time for which the person was moving from a particular place to another every four week. Different shadings indicate the sub-totals for different paths, i.e., combinations of two antennas between which the person was supposed to have walked. Not all paths are shaded distinctly because the differences are not visible when more than 400 distinctive patterns are required.

As for person A, we recognize two peaks, one at time point 1 and the other at time point 2. Person B used to be the most active among the residents. Her activities reached to the first peak around time point 3 and became stable at time point 4 after a mild decline from time point 3. The activity level was however drastically dropped after time point 5, when the accident occurred, followed by a gradual decline.
Figure 2: Time Trends of Residents’ Whereabouts
Figure 3: Time Trends of Residents’ Mobility
Person C shows a stable trend with two peaks at time point 6 and 8 with a mild decline around time point 7. Person D shows a stable trend with a mild peak around time point 9. Her activity dropped around time point 10, followed by a recovery up to time point 11. Person E was most active at time point 13 with bottoms around time point 12 and 14.

Interesting to these graphs is that a seasonal effect is recognizable. Time point, t1, t2, and t3 denote August, the hottest month in Japan and the activity levels in summer dropped for all the residents. They also seem to have been most active in winter, but peaks are not so distinctive compared to those drops.

5 Discussion

We have collected location data of people with dementia for thirty months at a group home and analyzed them in two respects: adherence and mobility. We now examine how these analyses might have helped caregivers to look after residents if the result had been disclosed to them. We focus on two cases of person A and B. Person A passed away during our data collection and person B fell down in her room unwitnessed. We discuss these cases in order.

5.1 Declined health

Fig. 3-A shows that person A became less mobile in her last three months. A closer look of her paths taken in the house revealed that she stayed mostly in her room in the period, rarely coming to the common room. The change is visible in the graph when we take four weeks as unit to read the long term tendency. The question is whether we could have noticed the change real time.

Fig. 4 depicts the trend concerning her mobility finer than Fig. 3-A from 4th April to 15th August by taking one week as unit. The unit of Y axis is minute. The graph indicates that her health irreversibly went into decline during the period from 16th May to 13th June, 2010. She never recovered thereafter, but her condition had been stable at low following two months. We might have noticed her decline sometime from 16th May to 13th June, 2010.

We are certain that caregivers must have recognized person A’s waning health around 13th June, after the steep decline, if they had been shown the graph depicting her mobility week by week. The change is so visible that it is difficult to miss it. But how would it look like when we set the unit shorter?

Finer grained view of the period depicted day by day however obscures the tendency (Fig. 5). The trend is not monotonic. There are mild ups and downs in the graph and it is hard to tell whether her health is in decline or recovering.

The result suggests that the time scale is important for the case of person A. The trend becomes obscure if the graph depicts the trend day by day. We need at least to look at the data by taking one week as unit and to examine the data for four or five months.

We believe that the analysis demonstrated here is useful for caregiving. The gradual change spanning four to five months is hard to perceive. We might recognize that a person has become less active for half a year, but cannot tell how rapid or slow the change is. Neither can we tell whether the change is irreversible.

We could have served person A better if we had prepared for her last months in advance. Some caregivers might have been alerted while she was going though her terminal period, but it must have been difficult to discuss her terminal care among caregivers including family members without evidence. The analysis of location data as above must have helped caregivers to focus on terminal care.

5.2 Falling down

Every effort has to be made to prevent the elderly from falling down since the accident often leads to serious problems due to their already poor health. They may not be able to walk, for example, having spent long time on the bed. Loss of mobility easily leads to cognitive incapability.

Many researchers hope to remove the risk of falling down as much as possible. We will see how the data collected may be utilized to decreasing the risks by examining the case of person B, who fell down in her room during our experiment.

The graph depicting B’s mobility (Fig. 3-B) shows that her recovery after the second summer, at time point 4, was slow. Her level of mobility just before time point 5 did not recover to the level as it had been one year ago, around time point 3. Her level of mobility had been lowered by twenty percent for a year, from time point 3 to 5. The analysis shows that she became weaker than previous year, but the information is not enough to predict when she falls down.

We closely examine her data for two months prior to the accident. Fig. 6 shows her mobility from 13th December, 2009, to 7th March, 2010, week by week. She fell down on 5th February, 2010, which is included in the 8th bar from left. The figure shows that there was a steep
Figure 4: Person A’s mobility week by week from 4th April to 15th August

Figure 5: Person A’s mobility day by day from 16th May to 15th June

Figure 6: Person B’s mobility week by week from 13th December to 7th March
We take another view of the same data to see how person B has changed her behaviour. Fig. 7 shows person B's path frequencies within the house in matrix. The antennas in the house (Fig. 1) are linearized from the top right (the dining room) to the bottom (towards the entrance), that is, 5, 6, 15, 20, 7, 11, 19, 18, 2, 16, 8, 21, 17, 13, 4, 9, 3, 22, 23, 10, and 12. The verticals are IN point while the horizontals OUT point. The diagonal line is thus left blank. The matrices are arranged from top left to bottom right.

We focus on the week from 31st January to 7th February, the matrix in the bottom right, to find any subtle difference distinctive of the week, in which person B fell down. Unique to the matrix is the filled part in the middle, delineated with the bold rectangle. The feature shows that the area was covered by person B quite often, namely, the area into which the antennas, 8, 21, 17, 13, 4, and 9 are installed. These antennas are all placed in the corridor near her room. Of those, the antenna 17 is placed in front of her room.

The drop found in Fig. 6 and the feature in Fig. 7 jointly indicate that person B often went out of her room, but soon returned there after walking around the corridor. That is, the area she moved around was narrowed down. We imagine that she was not tempted to go far possibly due to some problem related to her mobility.

Backing to her mobility, we take a finer grained view of the data than Fig. 6, shortening the period examined from 24th January to 5th February. Fig. 8 depicts the data day by day during the period. Two downs are recognizable in the graph. The first trend spans the dates from the 26th to the 28th January and the second trend from the 30th January to the 4th February, with slight ups on the 1st and 3rd February. Of these trends, the second one led her to fall down on the 5th February.

Can we predict the fall down by referring to the trend as shown in the graph? The first down and the second are only different in their spans. The second one lasted longer than the first one. We looked into the path frequencies of these periods day by day, but no recognizable difference was found there.

The result shows that the trend is only visible when we analyze the data on weekly basis, the trend which led person B to a falling down. The current study does not enable us to predict when the person falls down, but may help us to make a rough estimation of risks, when we analyze the data on weekly basis. The risk in-
Figure 7: Person B’s path frequencies week by week from 13th December to 7th March

Figure 8: Person B’s mobility day by day from 24th January to 5th February
nized a risk. There are a number of proposals for the kind of wearable devices[4, 3, 2, 6]. Employing a mobile alert system may be useful as well[7], but we need carefully examine how necessarily it is because wearing a device all the time can be a stress to the person.

Some researchers warn that providers of smart homes have been very focused on the technical possibilities, rather than solving the everyday problems of end-users[14]. Although many useful technologies have been developed to assist the elderly and caregivers, few discuss which one to choose and when. People usually talk about it, but it is sometimes difficult to reach an agreement because they project their (often idealized) images onto the person. Evidence should help caregivers to judge what kind of monitoring is required.

References


