Remote monitoring and assessment of daily activities in the home environment

Che-Chang Yang, Yeh-Liang Hsu

Gerontechnology Research Center, Yuan Ze University, Taiwan
Department of Mechanical Engineering, Yuan Ze University, Taiwan

ABSTRACT

Background/Purpose: Quantitative analysis of daily activities measured by home monitoring systems can be helpful to assess objectively the health-related living behavior and functional ability of older adults. Advances in sensors and telecommunication technologies have prompted the concept and development of implementing diverse sensors and intelligent algorithms to monitor human/environment interactions. This paper presents the remote monitoring and assessment of daily activities of older adults living alone at home, assuming that comprehensive profiles of daily activities at home can be captured by using simple and low-cost sensors in a less diverse modality.

Methods: A passive home monitoring system with a minimal set of sensing modalities, namely human infrared and electric current, was developed and used for continuous and unobtrusive monitoring of daily activities of an elderly woman for over 6 months. Four movement detectors were deployed in different indoor locations to detect active movements, and an appliance usage detector detected television use. A set of activity features that measure the intensity, regularity and abnormalities of activity patterns is defined and demonstrated to quantify the characteristics and rhythms of daily activities of the subject.

Results: Different rhythms of daily activities can be estimated from different locations at home, and distinct behaviors were shown between weekdays and holidays. Unusual activities have been detected by the system, too. The system setup did not require modification of home furnishings that could obstruct the subject’s daily living or cause any discomfort or displeasure to the subject.

Conclusion: This study suggests that daily activities of an older adult living alone at home can be measured by means of low-cost sensors in a less-diverse sensor modality, and daily rhythms can be quantified with a simple estimation method. The activity features developed in this study are built into a home telehealth system for telecare applications.

1. Introduction

Activities of daily living (ADLs) refer to several daily tasks which are required for personal self-care and independent living, such as eating, dressing, or bathing. Lawton et al also defined the instrumental ADLs (I-ADLs) as the activities that require interaction with objects or instruments for self-care or communications with people, such as the use of telephone or basic home appliances. The ADL performance directly reflects an individual’s living independency. The ageing process is an expected cause of limiting ADL performance that changes from advanced or moderate ADLs to a lower, basic ADL level.

The performance of daily activities has been widely adopted in clinical and research fields to evaluate the level of disability, or functional status of older people. For example, ADL scales, I-ADL scales, Barthel index and the functional independence measure (FIM) scales have been developed to assess the functional ability. Traditional ADL assessment methods usually rely on self reports, diaries, questionnaires, or subjective judgments by clinical or specialized personnel. Technologies have the potentials to assist ADL measurements in an unobtrusive way without disturbing the daily life of older adults. Long-term activity profiles of the older adults monitored at a home environment can provide additional comprehensive information related to the living behaviors, and thus their functional ability can be better determined objectively. In 1993, the research group at the University of New South Wales initiated the development of a cost-effective sensor-based remote monitoring approach to identify changes of health status with...
Advances in sensors and telecommunication technologies have prompted the concept and development of “smart homes” that are achieved by implementing diverse sensors and intelligent algorithms to monitor the human-environment interactions. For healthcare purposes, such smart homes or home monitoring systems can collect health-related data to build a profile of health and the functional status of older people. In such smart homes, sophisticated instruments and sensors may be used. However, home activities can also be monitored by using a range of simple and low-cost sensors distributed in a home environment. The passive infrared (PIR) sensor is the most common sensor to detect human occupancy or active movements within specific ranges in a space. Mechanical, magnetic, or photoelectrical switches can also be used to detect location transfers at home. The estimation of energy expenditure using PIRs has also been studied, although the preliminary outcome is not acceptable. Sensors can also be used to monitor I-ADLs. The ADLife developed by Tunstall [http://www.tunstall.co.uk] is a telecare solution for elderly people. The system can detect usage of electrical appliance (e.g., oven, refrigerators) to provide more detailed information on the elder persons’ I-ADLs within their homes. A study in the monitoring of home electrical appliance usages of older people living alone showed that daily and nocturnal activities can be differentiated. ADL detection and classification of the usage of electrical appliances from power line impulses were also presented.

Quantitative analysis of daily activities measured by home monitoring systems can be helpful to assess objectively the health-related living behaviors and functional ability of the older adults. This paper presents the remote monitoring and assessment of daily activities of an older adult living alone at home. It is assumed in this study that comprehensive profiles of daily activities at home can be captured by using simple and low-cost sensors in a less diverse modality. Thus, instead of using complex and multiple types of sensors, in this study a home activity monitoring system based on only human infrared sensors (PIR) and electrical current sensors (current transformer, CT) was installed in the residence of an older adult who lived alone. The movement detectors, which utilize PIRs, were deployed in different indoor locations at home to detect active movements. An appliance usage detector using a CT detected the television use. Only two types of sensors were selected because they are deemed adequate for monitoring home activities related to daily living rhythm. This approach not only simplifies the complexity in instrumentation and the sensor fitting the home environment, but also provides a unified basis for data analysis. Six-month activity data were collected through continuous and unobtrusive monitoring. A set of activity features that measure the intensity, regularity and abnormalities of activity patterns is defined and demonstrated to quantify the characteristics and rhythms of daily activities of the subject, namely, active time ratio $R_{active-time}$, activity rate $R_{act}$, daily activity rate $R_{act-day}$, coefficient of variance of daily activities $CV_{act}$, and correlation coefficient of activity profile $r$. Unusual activities can also be detected by the system. These activity features are built into a home telehealth system for telecare applications.

**Fig. 1.** The structure of the home activity monitoring system.

**Fig. 2.** The home activity detectors: (A) movement detector; (B) appliance usage detector; (C) the distributed data server.
2. Methods

2.1. Instrumentation

Fig. 1 shows the structure of the home activity monitoring system developed in this study. This system structure is based on the Decentralized Home-Telehealth System previously developed by the authors. In this system, the environment variables related to human daily activities can be measured and detected by means of the home activity detectors. The home activity detectors as shown in Fig. 2 are microcontroller-based devices, (PIC18LF6722; Microchip Co, address), and are equipped with ZigBee RF modules (XBee Series 2 OEM RF module; Digi International, address) to enable wireless sensor networking via the 2.4 GHz radio band. The home activity detectors basically support versatile and multiple sensor connectivity for specific measurement purposes. In this study only two types of sensors were selected: PIRs and CTs. The home activity detectors with PIR (movement detectors) as shown in Fig. 2A detect noticeable changes in infrared intensity due to human movements within the detection cone of the PIR. The “ON” states (active movements exist) and “OFF” states (inactive, or no movement) can be identified cyclically. The movement detectors transmit ON-state signals to the distributed data server (DDS) once human movement is sensed. The movement detectors can also measure room humidity and temperature with on-board sensors (SHT75; Sensirion AG, address). The humidity/temperature variables are also transmitted whenever the signal transmission is enabled.

As shown in Fig. 2B, the other type of home activity detector using the CT is the appliance usage detector. It measures the AC current consumed by the connected home electrical appliances. A threshold for the CT sensor output is set to distinguish the ON (in use) and OFF (not in use) states of the connected electrical appliances. Similar to the movement detectors, the appliance usage detector transmits the ON-state signals to the DDS. Note that the home activity detectors cyclically detect the sensor status every 6 seconds, and the DDS records data every 10 minutes. As a result, the DDS may receive 100 ON state counts in a 10-minute interval if the home activity detectors are continuously triggered for 10 minutes.

The DDS (Fig. 2C) is an embedded system primarily consisting of the same PIC microcontroller and ZigBee RF module. An Ethernet controller (RTL8019AS, RealTek) is also used to enable Internet communication. The DDS records the ON-state counts wirelessly received from the home activity detectors and the data are stored in an MMC memory card. Application programs or Internet browsers can access and retrieve the data in the DDS.

2.2. Subject and the residence environment for data collection

To collect home daily activities, 5 home activity detectors, including 4 movement detectors and one appliance usage detector, were installed in the residence of an older adult (female, age 75 year) in this study. The 4 movement detectors were installed in the kitchen, bedroom, and bathroom and by the doorway, respectively, where the woman frequently had her daily activities. Fig. 3 shows the setup of the movement detectors. The appliance usage detector interconnects an AC wall outlet and a television to detect the television usage. Television usage is monitored because watching television was one of the major activities of this person at home. All the home activity detectors were mains-powered and the data can be wirelessly transmitted to a DDS via the 2.4 Hz ZigBee WSN protocol in real-time. Informed consent was obtained from the
woman, although during the monitoring period, she was not aware
of the system operation, and the setup did not require modi-
fication in home furnishings or home facilities. Thus the system setup
did not obstruct, change, or interfere with her daily living routines. No
video or audio recording was used during the monitoring period so
that her privacy was preserved and protected.

2.3. The use of simple estimates for daily activity analysis

A selection of simple estimates (activity features) is used to
quantify the daily activities in terms of the activity frequency and
the activity regularity. Fig. 4 shows an example of the activity data
collected in one day in the kitchen. As the data were recorded every
10 minutes, there are a total of 144 time periods (or epochs) in
a day. The activity counts in each epoch are shown chronologically
in Fig. 4A. The maximum activity count collected in one epoch is
100. The same data can be re-arranged in the frequency order by
ranking the activity counts in the epochs, as shown in Fig. 4B. The
activity features in terms of activity frequency can thus be derived
from the frequency-ranked activity data.

2.4. Feature 1: active time ratio

People may perform their daily activities at varied time periods
in a day. The first focus of interest is how frequently the subject
performs activities on a daily scale. As shown in the frequency-
ranked activities in Fig. 5, $c_i$ is the activity count at the $i$th epoch.
The epochs that have activity counts ($c_i \neq 0$) are called “active
epochs”, and the other epochs without activity counts ($c_i = 0$) are
called “inactive epochs”. As a result, the total epochs can be divided
into the “active period ($T_{act}$)” and “inactive period ($T_{ina}$)”.

The “active time ratio” is a measure to indicate how frequently
the subject performs activities over the entire day. The active time
ratio $R_{active-time}$ is defined as the ratio of the number of active
epochs ($T_{act}$) to overall epochs ($T_{act} + T_{ina}$), as expressed in
Equation (1). For example, the number of $T_{act}$ in Fig. 5 is 47 and the
total number of epochs is 144. This corresponds to $R_{active-time}$ 32.6%.

<table>
<thead>
<tr>
<th>ADL features</th>
<th>Kitchen</th>
<th>Bedroom</th>
<th>Doorway</th>
<th>Bathroom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily activity rate</td>
<td>2.19%</td>
<td>0.11%</td>
<td>0.19%</td>
<td>0.93%</td>
</tr>
<tr>
<td>Active time ratio</td>
<td>0.19</td>
<td>0.06</td>
<td>0.09</td>
<td>0.10</td>
</tr>
<tr>
<td>Activity rate</td>
<td>11.73%</td>
<td>1.79%</td>
<td>1.89%</td>
<td>9.29%</td>
</tr>
<tr>
<td>Coefficient of variance of daily activities</td>
<td>0.89</td>
<td>4.73</td>
<td>4.55</td>
<td>4.72</td>
</tr>
<tr>
<td>Correlation coefficient of activity profile</td>
<td>0.35</td>
<td>0.22</td>
<td>0.20</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Table 1 Comparison of the activity features computed from the 6-month average activity profile in the four home locations.

Fig. 6. The long-term profile of daily activities in the kitchen.

Fig. 7. The long-term average activity profiles in (A) kitchen, (B) bedroom, (C) doorway, and (D) bathroom of the elderly subject’s residence.

Fig. 8. The long-term average profile of TV usage.
A high active time ratio generally indicates a more frequent activity profile, regardless of the activity intensity in the active epochs.

\[ R_{\text{active-time}} = \frac{T_{\text{act}}}{T_{\text{act}} + T_{\text{ina}}} \]  

(1)

2.5. Feature 2: activity rate (or usage rate for appliances)

In addition to the active time ratio, it is also important to have estimates regarding the intensity of activities. The “activity rate” and “daily activity rate” are defined for this purpose. The activity rate measures the intensity of activity over the active period, while the daily activity rate measures the intensity of activity over the entire day.

The activity rate \( (R_{\text{act}}, \text{or the usage rate for appliances}) \) which is calculated according to Equation 2, is the total activity counts in the active period \( T_{\text{act}} \) divided by the maximum number of the active epochs \( T_{\text{act}} \) (i.e., \( T_{\text{act}} \times 100 \)). Note that in Equation 2, if there is no activity in a day, both the sum of \( c_i \) and \( T_{\text{act}} \) are zero. Therefore the activity rate here is defined as zero.

\[
R_{\text{act}} = \begin{cases} 
\frac{\sum_{i=1}^{k} c_i}{100} & \text{if } T_{\text{act}} > 0 \\
0 & \text{if } T_{\text{act}} = 0 
\end{cases}
\]  

(2)

For the same example shown in Fig. 5, the total activity count was 528 from the 47 active epochs. As a result, the activity rate is 11.2%, which means that the woman was active for an average of 11.2% of the time in an active epoch. A higher activity rate indicates that the intensity of the activity is higher during the active epochs.

2.6. Feature 3: daily activity rate (or daily usage rate for appliance usage)

Similar to Feature 2, the daily activity rate (or daily usage rate for appliances) \( R \) generally shows the intensity of the activities the subject performs over a whole day. For the sample data in Fig. 5, the daily activity rate is 3.67%, which is an indicator of the intensity of activity of the day.

\[
R_{\text{act-day}} = \frac{\sum_{i=1}^{k} c_i}{144 \times 100}
\]  

(3)

2.7. Feature 4: coefficient of variance of daily activities (or coefficient of variance of daily appliance usage)

People may perform activities of varied frequency at different time periods of the day, which results in varied activity patterns. The coefficient of variance of the activity counts distributed over a whole day \( (CV_{\text{act}}) \) defined in Equation 4 can provide an estimate of how uniformly the subject performs activities in a day. For the example data in Fig. 4, the coefficient of variance is 2.28.
CV_{act} = \frac{\text{Standard deviation of } c_i}{R_{act-day \times 100}} \tag{4}

2.8. Feature 5: correlation coefficient of activity profile (or correlation coefficient of appliance usage profile)

It has been reported that elderly people tend to have a stable lifestyle.\textsuperscript{15} Hence, the regularity of daily activities compared with the long-term profile can be an important estimate of whether the subject follows his/her own regular activity rhythms (behavior patterns). The correlation coefficient \( r \) is a common statistical measure of the interdependence of two or more variables. Therefore, the correlation coefficient is used to compare a daily profile to the long-term average profile. The correlation coefficient ranges from \(-1\) to \(1\), and a higher value in the correlation coefficient of two profiles means a more similar or correlated trend between the two profiles. For example, the correlation coefficient of the one-day activity profile shown in Fig. 4, and the 6-month average profile as shown in Fig. 6 is 0.17.

3. Results

3.1. The long-term activity profiles

Table 1 lists the activity features analyzed from the 6-month activity data in the kitchen, bedroom, doorway and bathroom, and the long-term average profiles are also shown graphically in Fig. 7. The activities in the kitchen have a greater daily activity rate, active time ratio, and activity rate. These activity features indicate a relatively greater activity frequency in the kitchen than the other three locations. The smallest coefficient of variance of daily activities and highest correlation coefficient of activity profile are also found in the kitchen activities, indicating a more regular activity rhythm. In contrast, the activities by the doorway show the least correlation coefficient of activity profile and highest coefficient of variance of daily activities among the locations. These activity features show that the activities by the doorway are least regular, which is also expected. According to the activity features, the woman had relatively intense activities in the kitchen, and this may imply that she still preserves a good performance level in the I-ADLs.

Fig. 8 shows the long-term average profile of TV usage, and its activity features are listed in Table 2. The most intensive TV usages are at 9:40 in the morning and 19:20 in the evening. From the high correlation coefficient of daily TV usage 0.74, the subject showed regular behavior in TV usage.

Fig. 9 shows the long-term average activity profiles on weekdays and holidays in the kitchen, bedroom, doorway, and bathroom. Moderate differences between the profiles on weekdays and holidays can be observed from this figure. Table 3 lists the detailed ADL features from Fig. 9. In general, daily activities remained similar on weekdays and holidays, indicating that there is no significant difference regarding the subject’s activity rhythm between weekdays and holidays.

Fig. 10 shows the long-term average TV usage on weekdays and holidays, and Table 4 lists its activity features. The higher daily usage rate of 55.29% on weekdays means that the TV is ON more than half of the day, indicating that watching TV is the major activity at home. Compared with the weekday profile, the holiday profile has lower daily usage rate and active time ratio. This shows that the subject used TV more on weekdays than on holidays.

| Table 4  |
|----------------------|----------------|----------------|
| Activity features    | Weekdays       | Holidays       |
| Daily usage rate     | 55.29%         | 42.76%         |
| Active time ratio    | 0.56           | 0.44           |
| Usage rate           | 98.83%         | 95.72%         |
| Coefficient of variance of daily appliance usage | 0.92 | 1.19 |
| Correlation coefficient of appliance usage profile | 0.82 | 0.67 |
greater coefficient of variance of daily appliance usage and the lower correlation coefficient of appliance usage in the holiday profile also indicate less regular TV usage than weekdays. By interviewing the woman, it was confirmed that she usually watches TV news and programs to help handle finances (stock market and transactions) in the morning during weekdays. This is considered a major cause of the different performance in the activity features and the significant changes observed from the two profiles.

Table 5
The activity features from the activities collected in the bedroom on April 29, and the 6-month long-term activity average.

<table>
<thead>
<tr>
<th>Date</th>
<th>Activity features</th>
<th>April 29</th>
<th>Long-term average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Daily activity rate</td>
<td>0.7%</td>
<td>0.1%</td>
</tr>
<tr>
<td></td>
<td>Active time ratio</td>
<td>0.11</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Activity rate</td>
<td>5.94%</td>
<td>1.8%</td>
</tr>
<tr>
<td></td>
<td>Coefficient of variance of daily activities</td>
<td>4.87</td>
<td>4.73</td>
</tr>
<tr>
<td></td>
<td>Correlation coefficient of daily activities</td>
<td>0.01</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Table 6
Comparison of activity features in TV usages on on-day profile and 6-month long-term average profile.

<table>
<thead>
<tr>
<th>Activity features</th>
<th>July 12</th>
<th>Long-term average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily usage rate</td>
<td>44.8%</td>
<td>49.0%</td>
</tr>
<tr>
<td>Active time ratio</td>
<td>0.47</td>
<td>0.50</td>
</tr>
<tr>
<td>Usage rate</td>
<td>96.2%</td>
<td>97.3%</td>
</tr>
<tr>
<td>Coefficient of variance of daily appliance usage</td>
<td>1.11</td>
<td>1.1</td>
</tr>
<tr>
<td>Correlation coefficient of daily appliance usage</td>
<td>0.59</td>
<td>0.74</td>
</tr>
</tbody>
</table>

3.2. Unusual activities

Unusual activities were detected during the monitoring period. For example, Fig. 11 shows the activities in the bedroom collected on April 29, 2010. Unusual activities were found during 3:10 to 3:50am as the subject actually fell accidentally in her bedroom in the early morning and could not get up. Table 5 shows the activity features of the collected activities on that day and the 6-month long-term activity average. The unusual activities caused a higher activity rate, daily activity rate, and active time ratio. Although the coefficients of variance of daily activities from both profiles are similar, the correlation coefficient of daily activities on that day was 0.01, which is greatly lower than the counterpart 0.22 from the 6-month long-term average.

Fig. 12 shows unusual TV usage from 2:00 to 2:40 detected on July 12, 2010. It was later confirmed that the subject was watching TV in the early morning on that day because she could not fall asleep. As listed in Table 6, the correlation coefficient of daily appliance usage on that day ($r = 0.59$) is lower than that from the 6-month long-term average ($r = 0.74$). The other ADL features roughly remain similar.

4. Discussion

In this paper, a home activity monitoring system is presented. This system was installed in a residence of an elderly woman living alone to monitor her daily home activities. In this system only two types of home activity detector, the movement detectors using PIRs and an appliance usage detector using CT, were used because this approach is considered to not only simplify the instrumentation and sensor fitting in the home environment, but also to provide a unified basis for data analysis. The movement detector senses apparent human movements in different locations at home. The appliance usage detector was connected to a television to measure the television use. During the monitoring period, the woman was not aware of the operation of the system. The system setup did not require modification of home furnishings that could obstruct her daily living or cause any discomfort or displeasure. The wireless data transmission using ZigBee WSN in a home environment is also reliable. Although the particular living characteristics and rhythms were obtained from the monitoring system in such a single-person study, home visitors or cohabitants (e.g., families, home nurses) living together at home cannot be distinguished by those simple sensors. This technical issue limits the system usability if the system is considered to be used in family residences or for community-dwelling people.

A set of activity features in terms of activity frequency and regularity was adopted to provide quantitative estimates regarding the home activity characteristics by analyzing the 6-month activity data collected by the system installed in a residence of an older adult (female, age 75 years) in this study. These simple estimates can indicate the characteristics and the long-term living rhythms of daily activities of the subject living alone at home. Unusual activities have been detected by the system, too. The results from this study also suggest that the use of less-diverse and simple sensors may be sufficient for remote home activity monitoring. The older adult is actually the mother of one of the authors of this paper, and she was fully aware of the test and agreed with it. The woman and her son actually welcomed the test because the sensors are gathering information not only for healthcare purposes. Knowing the living rhythms of the older adult also enriches the content of interaction and communication with her son.

The activity features developed in this study are built into the home telehealth system. The monitoring system and the analysis method presented in this paper can be a cost-effective approach to evaluating functional status of older adults for personal home healthcare applications.

References


