# Activity of Daily Living Assessment through Wireless Sensor Data

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***Abstract*— Activity of Daily Living has become a clinical de facto instrument to assess daily functional status of older people living independently at home. Almost all ADLs scales are based on subjective assessment of clinical staff and self-reported responses of the elderly person. A great deal of variability in ADL assessment is likely due to the different cultural beliefs, language and education, and over-assessment of personal capability to potentially avoid negative consequences. This paper proposes automatic and objective ADLs assessment as key component of a technology platform that supports older people to live independently in their home, called Smarter Safer Homes. The objective ADL assessment is achieved through communicating data from simple non-intrusive, wireless sensors placed in a home environment. Pilot sensor data sets were collected over six months from nine independent living homes of participants aged 70+ year. The application of a clustering based, unsupervised learning method on these data sets demonstrates the potential to automatically detect five domains of activity contributing to functional independence. Furthermore, the method provides features that support elderlys self-monitoring of daily activities more regularly, that could provide the potential for timely and early intervention from family and carers.**

## I. INTRODUCTION

Over past forty years, more than 43 indexes have been published to determine fundamental functional disability status of both patients and population [1]. Measures of functional ability outlined by the ADL have become routine in assessment of functional status of older people, believed to be a good predictor of a wide range of health-related behaviour in seniors. Among them, the Katz ADL scale is arguably the most appropriate instrument used in clinical framework to assess and flag characteristics of functional independence for elderly people in clinical and home environments [2]. Katz ADL assessment requires evaluation of activities pertaining to bathing, dressing, toileting, transferring, continence and feeding. This instrument scores each activity with 1 if an elderly person can achieve it independently, and 0 if it is dependent on assistance. Hence, the Katz ADL index scores will range from 0 to 6, indicating an elderly persons ability to function as being dependent to independent, respectively.

There are also other ADL scales to measure more sophisticated functional independence such as the full range of activities necessary for independent living in the community [3], stroke patients receiving in-patient rehabilitation [4] and patients with cognitive impairment such as Alzheimer's disease or dementia [5].

However, current approaches of ADL applications in health providers are still based on the subjective assessment from clinical staff and and self-reported responses of the elderly person [6]. Although there is some consensus across ADL evaluations, there still exists great deal of variation in the assessment that is likely to be because respondents interpret the questions differently [7]; individuals with various culture, language, and education backgrounds assess degree of difficulty in performing each ADL differently [8]; and communication barriers from cognitive impairment may also have significant implications on achieving reliable ADL assessment. Furthermore, current assessments are clinically resource intensive, particularly from a home setting, making them impractical for long term care of the elderly or disabled populations.

To address subjectivity and reduce human resource investment in assessments, wearable sensors have been designed to understand human postures [9], RFID markers tracking patients [10], wearable accelerometers detecting falls [11], etc. Wearable sensors, however, are not always convenient for users; particularly where long term monitoring is required.

Motivated by these limitations, we developed a Smarter Safer Homes platform that enables an automated approach of assessing fundamental ADLs of independent living of older people through information gathered from wireless sensors placed within their home environment. This platform thus provides longitudinal objective information about the residents day-to-day activity status, and therefore can assist self-management of residents or timely care attended from family member or carers. To achieve this, data gathered from these sensors will be used collectively to determine the residents actions through analysis of various context-related actions through our platforms human behaviour detection algorithms to automatically infer health related activities pertaining to ADLs.

## II. IN-HOME WIRELESS SENSOR NETWORK

To minimise intrusive monitoring, our sensors were placed somewhat '*invisible*' and non-intrusive to residents in their home environment. These sensors communicate in-home activity data with a local server through the ZigBee protocol that enables low-power, secure and reliable data transmission. Figure 1 illustrates an example of the data collected by the wireless sensor network.

Motion sensors detect the presence of people in its vicinity. They are installed in every room to monitor the

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| ID | Type | Timestamp | Timestamp |
|---|---|---|---|
| 17 | Motion Sensor | 2013-09-07T06:24:00 | 1 |
| 31 | Power Sensor | 2013-09-07T07:05:00 | 0.239 kw |
| 148 | Humidity Sensor | 2013-09-07T08:15:00 | 58% |
| 148 | Temperature Sensor | 2013-09-07T08:15:00 | 15.6 °C |
| 177 | Reed Switch | 2013-09-07T09:38:00 | 0 |
| 193 | Acoustic Sensor | 2013-09-07T011:02:00 | 1 |

Fig. 1. Examples of sensor data collected in-home

location and transition within the home. Accelerometer sensors are attached to beds to monitor status transfers from lying/standing and sleep quality through measurement of subtle body movements in bed. Power sensors are plugged into power outlets to measure electrical power consumption of connected appliances. Acoustic sensors are attached to downpipes under the kitchen basin to detect sound generated by water flowing in pipes. A combined temperature/humidity sensor installed in the bathroom and kitchen to detect the changes in room air condition. Reed switches affixed to door contact surfaces detect opening/closing of the entrance door, wardrobes, cupboards, etc. And finally circuit meter sensors installed in the meter box monitor energy usage from kitchen stoves. Figure 2 shows which area of the home the sensors are installed on a simplified floor map of a two-bedroom unit.


Fig. 2. In-home sensor installation places

Most of the environmental sensors are powered by batteries. This makes sensor installations flexible and easy because it is untethered and can be positioned less intrusively and yet close to the activity being gathered, independent of a power source. It also benefits easy sensor maintenance. Furthermore the sensor communication generally requires little bandwidth and is relatively insensitive to latency, so that we can apply energy efficient communication protocols and event-based communication strategies, i.e. only uploading sensor data whenever an event has been detected. In this way, the sensors battery life is greatly extended lasting an average six to eight months long.

## III. Automatical activity recognition

Raw sensor data collected by our in-home wireless sensor network is initially processed to extract meaningful actions, simple human motion patterns such as entering/leaving a room, opening/closing a fridge, usually in the order of a couple of seconds [12]. This is a relatively easy task since sensors deployed at different locations usually provides obvious clues. From these actions, we want to extract basic activities that are closely related to the residents wellbeing and functional independence status as suggested in most ADLs scales. In particular, we extracted activity status relating to mobility, bathing, dressing, postural transfer (lying to standing), and preparing meals in our smart home platform, from sensors that are listed in Table I.

TABLE I
ADLs recognition from raw sensor data

| Typical activities of ADLs | Sensor types |
|---|---|
| Mobility | Motion |
| Bathing | Motion, Humidity, Temperature |
| Dressing | Motion, Reed switch |
| Postural transferring | Accelerometer, Motion |
| Preparing meals | Motion, Power, Reed switch, Acoustic |

### A. Mobility

A core part of the ADL is mobility status, computed with only one type of sensor, i.e motion sensor, deployed in each room of the house. Figure 3 shows an example of motion sensor firings from different rooms, represented in different colours of spikes over one day. Together with the topological indoor maps, we can infer the rate and changes in the mobility status of residents.

### B. Bathing, dressing, postural transferring

Although these activities involve more than one sensors, there is usually a key sensor that plays a decisive role in activity extractions. For example, bathing activity can be best inferred through abrupt changes in state of humidity/temperature sensor, as illustrated in Figure 4. Similarly, dressing activity can be inferred through changes in state of reed switches attached to the wardrobe. Postural transfer, measuring number of changes between lying and standing states, can be inferred through data value changes of accelerometer sensors affixed to bed.

### C. Preparing meals

Extracting meal activity is the most challenging of the ADLs in our platform. Since preparing a meal involves multiple actions, data from multiple sensors placed in the kitchen need to be gathered collectively to infer a major meal preparation as opposed to assuming each particular kitchen sensor activity is a meal preparing activity. Figure 5 illustrates three days sensor firings for all preparing meals related sensors in a home.

Therefore to accurately and efficiently extract this activity we need advanced, well researched, data mining and statistical analysis techniques, such as those described in [13]. In

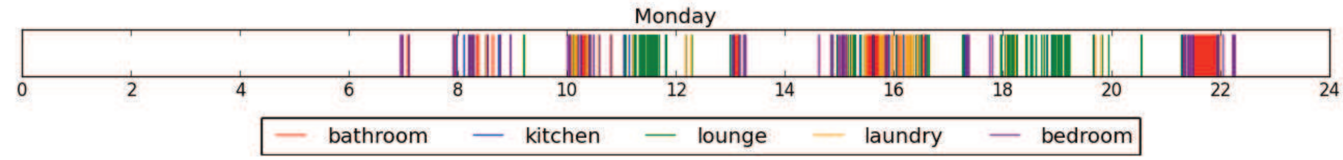


Fig. 3. An example of one day's motion sensor firings in a home, (00:00:00 $\sim$ 23:59:59)

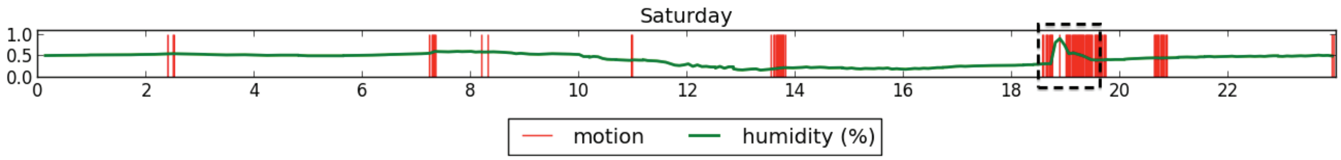


Fig. 4. An example of one day's bathing related sensor firings in a home (00:00:00 $\sim$ 23:59:59), the box indicates an inferred bathing event.

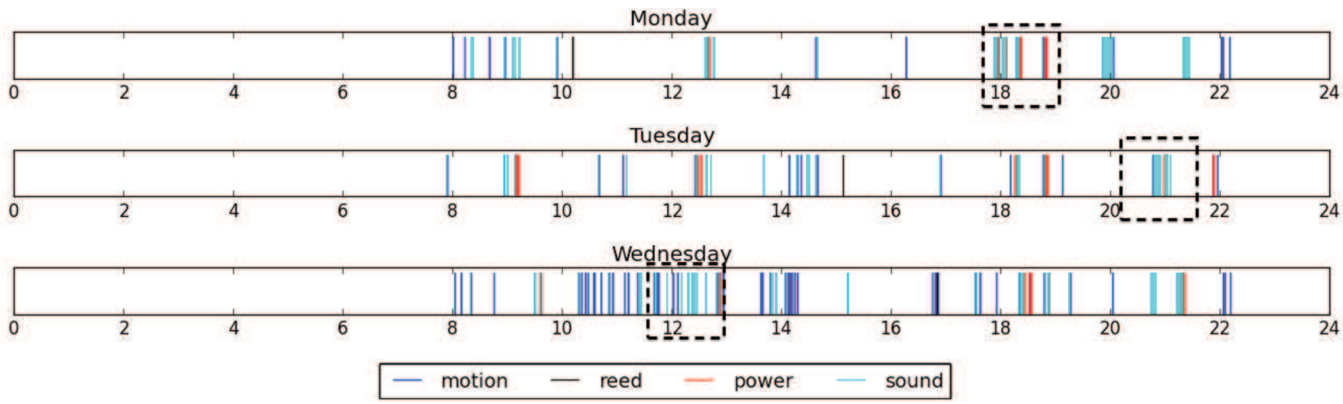


Fig. 5. Three days preparing meals related sensor firings in a home, boxes indicate inferred meal preparations with high confidence.

brief, we can divide existing activity recognition algorithms into three categories:

**Supervised learning:** requires labelled sensor data to train a pattern recognition learning algorithm. A probabilistic and reasoning model can be thus constructed by this algorithm from the training data set to infer activities happened on unknown new sensor data sets. Compared against typical activities measured in general ADLs scales, these are usually fine-grained activities such as making a phone call, brewing a coffee, reading a book, etc. Examples of techniques used in this category includes Dynamic and naïve Bayes networks [14], Conditional Random Fields (CRFs) [15], Hidden Markov Models (HMMs) [16], and support vector machines (SVMs) [17]. In many scenarios, collecting labelled sensor data can be time consuming, tedious, and almost prohibitive, especially when deploying sensors in a large-scale trial environment.

**Unsupervised learning:** constructs activity recognition models directly from unlabelled sensor data. This approach either estimates probability of activities through clustering techniques such as Hierarchical methods [18] allowing multi-resolution activity modelling on possible related actions, or adaptive methods [19] where a stochastic model can update the likelihoods of activities according to new observations of action clusters. There are other algorithms for unsupervised learning which include the use of graphical models [20] and multiple eigenspaces [21].

**Logical modelling and reasoning** exploits logical and domain knowledge representation for activity and sensor data modelling, and to use logical reasoning to perform activity recognition [13]. We omit further detailed discussions as it is beyond the scope of this paper.

Due to the age of our residents and their difficult in self-reporting, unsupervised learning techniques are the most practical and suitable for our trial. We therefore used clustering techniques to extract the meal preparing activity from related sensor data. Note that instead of using an approximate clustering methods such as K-means, we developed a dynamic programming based optimal clustering algorithm using the time ordering property of the sensor data. Specifically, let $\mathbf{X}_i$ represent the array of firing records of sensor $i$ per minute of a day, with $|\mathbf{X}_i| = 1440$. Let $a_i$ represent the probability of sensor $i$ involved in meal preparation, which can be determined through data gathered from scheduled interviews of the routine meal preparation activity with participants. Then the total sensor firing record array $\mathbf{X}$ can be represented as $\mathbf{X} = \sum_{i=1}^{n} a_i * \mathbf{X}_i$. Our developed clustering algorithm thus computes $\mathbf{X}$ to find $k$ clusters that minimise the summation of root mean squares of all clusters. These $k$ clusters are output as possible time intervals of meal preparation during the day with confidence rates represented as probabilities. Figure 6 shows an example of the preparing meals activity extracted by our method from the sensor data listed in Figure 5. To test the accuracy of our clustering based

| Date | Preparing meal time | Confidence |
|---|---|---|
| Monday | 17:52 ~ 18:49 | 100% |
| | 08:40 ~ 09:13 | 50% |
| Tuesday | 20:46 ~ 21:04 | 100% |
| | 13:40 ~ 15:07 | 66% |
| | 18:10 ~ 18:19 | 55% |
| Wednesday | 11:07 ~ 12:55 | 100% |
| | 20:01 ~ 22:10 | 31% |

Fig. 6. Three days preparing meals related sensor firings in a home

method, we compared sensor data sets collected from nine independent living homes with ground truth about routine meal preparations obtained residents through home interviews. Then we extracted meal preparation information from these nine homes over six month sensor data to be compared against two weeks of ground truth information provided by the residents. Our comparison resulted in precision rate of 82% and 78% recall rates shows great potential for the application of this clustering based unsupervised learning model.

## IV. Discussion and Future Works

Automatic determination of ADLs enables objective assessment of functional independence, particularly in a home environment for the elderly people living independently. These daily activities are presented in an intuitive way in our Smarter Safer Homes platform, as illustrated in Figure 8. Supposing Monday's ADL is representative of expected

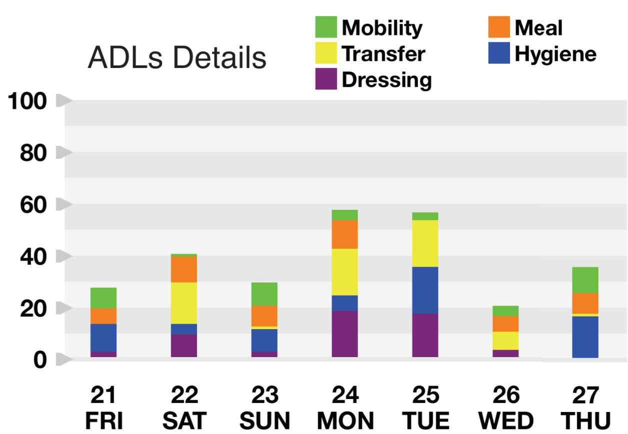


Fig. 7. Five domains of automatically extracted ADLs

healthy functional status of the senior person, the ADL shown on Wednesday may warrant investigation of their decline in functional status, should it recur more regularly. Our Smarter Safer Homes platform can support older people living alone in self-management of their functional independence; and simultaneously provide the capacity for family members to provide better support to their elderly parents living alone remotely. Furthermore, an automated ADL assessment feature could also provide health care providers, the capacity to monitor older peoples' health care status more regularly, and provide a more timely and early intervention through telehealth.

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