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Determination of Activities of Daily Living of Independent Living Older People Using Environmentally Placed Sensors*

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Abstract— **The rapid increase in the ageing population of most developed countries is presenting significant challenges to policymakers of public healthcare. To address this problem, we propose a Smarter Safer Home solution that enables ageing Australians to live independently longer in their own homes. The primary aim of our approach is to enhance the Quality of Life (QoL) of aged citizens and the Family Quality of Life (FQoL) for the adult children supporting their aged parents. To achieve this, we use environmentally placed sensors for non-intrusive monitoring of human behaviour. The various sensors will detect and gather activity and ambience data which will be fused through specific decision support algorithms to extract Activities of Daily Living (ADLs). Subsequently, these estimated ADLs would be correlated with reported and recorded health events to predicate health decline or critical health situations from the changes in ADLs.**

I. INTRODUCTION

Like in most developed countries, ageing population in Australia is presenting substantial challenges for policymakers and public healthcare. Australian health expenditure is rising faster than economic growth, accounting for over 9% of GDP, an increase from 7.5% in 1998 [1]. Since 1990, persons aged 85 years or over doubled in mid 2010 to 1.8% of the total population, or 398,200 individuals. This was due to the increased life expectancy of older population. In two decades, the number of centenarians increased by 185%, compared with a total population growth of 31%. In 2010, 13.5% of the Australian population was 65 and over. By 2050, some 22% is projected to be aged 65 and over [2]. This ageing of population challenges the already overburdened health workforce system of Australia. It is therefore generally accepted that Australia will continue to experience increasing demand for health care workers and at a rate that will challenge Australia training and service delivery systems without significant change to its approach to workforce development [3]. Recognising these issues, in 2010, the Australian Academy of Technological Sciences and Engineering (ATSE) released a key report identifying that a suite of emerging innovative technologies offers the prospect of enhanced security, safety, diagnosis, treatment and physical assistance to improve the quality of life for elderly people, to help them remain at home, and to provide financial savings in aged care and medical treatment [4].

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Accordingly, we propose the project *Smarter Safer Homes for the Ageing*, which aims at enhancing the Quality of Life (QoL) of aged citizens and the Family Quality of Life (FQoL) for the adult children supporting their aged parents. This project seeks to not only maintain the quality of life for the aged person but improves and enhances the quality of life of the aged person's family through non-invasive monitoring and virtual engagement using environmentally placed sensors. Specifically the goals of this project are to:

- inform service providers and aged persons about the effectiveness of assistive technology on QoL and FQoL and to provide evidence about the decision support system for individualised care planning for timely intervention;
- collectively present health and well-being information of independently living elderly people in a way useful to care providers, caring relative such as adult children of the elderly person, without compromising the privacy of the elderly person;
- enable ENLIVEN platform to be tailored to varied levels of older people support needs, hence to establish a framework for designs of future homes for independent living of older people.

To this end we have designed the *ENLIVEN* platform that aggregates sensor information at environmental, cognitive, physical, and physiological levels to establish a support mechanism for decision making by service providers examining the changes/trends in ambient & ADL, psychological, behavioural and vital signs, respectively, of older people with/without chronic health conditions living at home. Figure 1 illustrates the architecture of ENLIVEN that comprises three modules, *Sensor network module*, *ADL recognition module*, and *User interface module*. The development of these modules intends to achieve the following corresponding functions of ENLIVEN:

- *Data Collection*: gathering continuous daily activity data of seniors from non-intrusive environmentally placed sensors deployed at their houses;
- *Data Analyses*: extracting daily activities from raw sensor data through human behaviour analyses, evaluating extracted activity patterns and measuring seniors' physical, health and mental function performances; determining the level and type of assistances that the elderly person requires in order to live independently and healthy for a long period of time.
- *Data Presentation*: providing self monitoring and awareness through tablet PCs at seniors' houses; en-

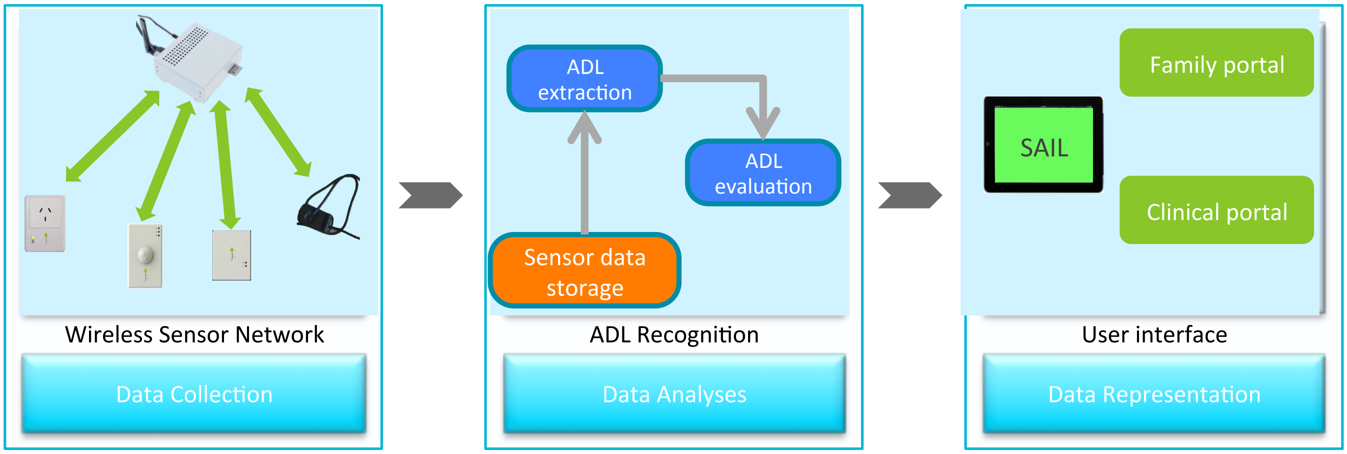

Fig. 1. The ENLIVEN platform architecture

abling family members to gain an insight of their elderly parent living alone; assisting health care providers getting a picture of seniors' daily lives, routines and health care status, and provide timely intervention through tele-health.

Since details on the data presentation function of ENLIVEN are beyond the scope of this paper, we will focus only on the data collection and analyses functions from hereafter.

II. Wireless sensor network

Although there exist many previous works on monitoring ADL through intrusive sensors, such as video camera understanding human postures [5], RFID markers tracking patients [6], wearable accelerometers detecting falls [7], etc, our focus is on using environmentally placed sensors for non-intrusive monitoring of human behaviours. The reasons are three-fold:

- First, wearable sensors are not always convenient for users carrying around;
- Second, environmentally placed sensors can be deployed to be out of the sight of users, less frequently interfering with their daily lives;
- Third, the data recorded by sensors are anonymous, containing very little information about personal privacy.

Table I describes all types of in-house environmentally placed sensors that are used in ENLIVEN. Motion sensors detect the presence of people in its vicinity. They would be installed in every room to monitor the in-house movements of seniors. Accelerometer sensors would be installed around the bed/mattress to measure subtle body movements during sleeps, and thus infer sleeping quality of seniors. Power sensors attached to power inlets of microwave, hot plates, coffee machine, toaster etc. would infer meal preparation by detecting their switching on and off corresponding with meals. Similarly, power meter sensors attached to the dishwasher would detect the dish cleaning activities. Acoustic

TABLE I

List of environmentally placed sensors

Sensor type	Data collected
Motion sensor	Incidents of movements
Accelerometer	Mattress movements
Power sensor	Electrical powers draw by appliances
Acoustic sensor	Water flows in pipes
Temperature sensor	Temperature readings
Humidity sensor	Humidity readings
Reed switch	Doors open/closed
Pressure sensor	sofa/couch being attended

sensors attached to pipes would detect sound signals generated by water flowing in vanity pipes. Temperature/humidity sensor installed in the bathroom would detect bathing (from the increase of temperature and humidity). It would also record ambient temperature/humidity of the house. Reed switch attached to doors would detect opening/closing of the entrance door, wardrobes, cupboards, etc. The pressure sensor would detect the sitting and leaving of the couch and bed, which would infer transfer. Also acoustic sensors in the living room would detect social interactions, inferred by human voice recorded. Note that the acoustic sensor detects a noise signal only, it does not record speech as a microphone. Figure 2 collectively shows sensor installation places on a simplified floor map of a one-bedroom unit.

Most of those environmentally placed sensors, if not all, are powered by batteries. This makes sensor installations flexible for placement in the home, particularly to maintain an non-intrusive environment, and also maintenance. The sensor communication generally requires little bandwidth and is relatively insensitive to latency, so that we could apply energy efficient communication protocols, as introduced in [8]. It is also possible to save power by using event-based communication strategies, i.e. only uploading sensor data whenever an event has been detected.

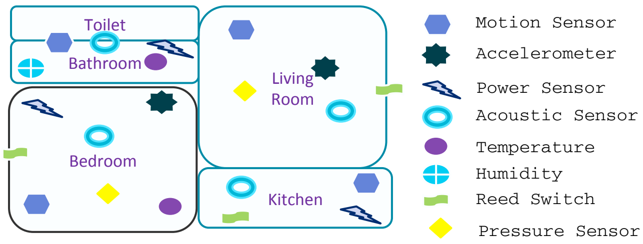

Fig. 2. Typical places where sensors installed

III. Extract ADLs from Sensor Data

Raw sensor data is initially processed at the in-house local server. The output is converted to semantically meaningful representation of observed actions. As suggested in [16], we define an action as a simple human motion pattern usually in the order of a couple of seconds. These actions, along with their temporal features, are then transmitted to the database server for more complex activity extractions. An activity is a more complex motion pattern, typically of longer duration. For example, turning on the microwave is considered an action, while preparing a meal is an activity. Typical activities of daily living, as a concept that is first established by Katz [17], include Bathing, Dressing, Toileting, Transferring, Continence and Feeding. Table II shows a non-exhaustive list of ADLs that could be extracted from related sensors in our project.

TABLE II
Extracting ADLs from Sensors

Daily activities	Sensor types
Sleep	Motion sensor, Accelerometer
Preparing meals	Motion, Power, Acoustic sensors
Dishwashing	Power, Motion sensors, Reed switch
House cleaning	Motion, Power, Acoustic sensors
Visiting bathroom	Motion, Temperature, Humidity sensors
Indoor walking	Motion sensors
Sit-stand transition	Pressure, Motion sensors

The extraction of some of the ADLs from the sensor data is rather intuitive and straightforward. For instance, dish washing or indoor movement are relatively easy to detect from the actions that are observed from the sensor data. A firing of the motion sensor strongly indicates human movement in a single-occupancy environment, and a noticeable power consumption from the dishwasher relates to the actual usage of dishwasher. However there exist some other ADLs that may consist of a more complicated set of actions, such as preparing meals, house cleaning, etc. Efficiently recognising these activities from sensor data is an active topic of research [10] in recent years. In literature, the ADL recognition techniques can be categorised into two major types: rule-based activity recognition [11], [12] and probabilistic recognition models [13], [14], [15]. In our project, we harness the strengths of methods of both types by using rule-based recognition for simpler activities and using probabilistic method to recognise more complex daily activities. Specifically we apply Bayesian-based methods [18], [19] and Hidden Markov Model to model the uncertainty of human behaviour [20], [21]. Figure 3 briefly illustrates steps of extracting ADLs from sensor data.

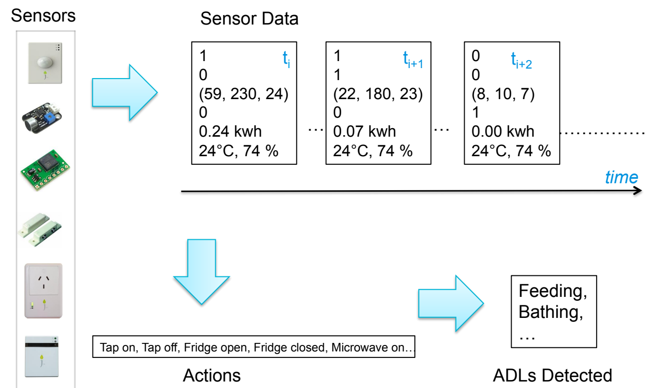

Fig. 3. Extracting ADLs from sensor data

IV. Discussion

Accurately detecting and extracting ADLs from sensor data would lay solid foundations for later ADL evaluations and health status assessments. It will benefit:

- designing an evaluation tool to assess health status of seniors from their ADLs;
- building predictive models for triage and wellbeing support to provide timely and supportive model for seniors;
- constructing feedback models to enable self-management, empowerment, and community engagement for seniors to live longer e.g. improve cognitive levels and reduce depression.

The ENLIVEN platform will be piloted over 6-9 months among 20 independent living homes in Armidale, Australia. Each home will be fitted with environmentally placed sensors, as described above, integrated with a wireless sensor network. This would enable the evaluation and testing of our sensor network, ADL recognition algorithms, to demonstrate the benefits and barriers of adopting the ENLIVEN platform by independent living seniors.

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