Sensor Fusion Platforms for Ambient Assisted Living

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***Abstract*—Integration of ICT and sensor technologies in future Smart Homes through Ambient Assisted Living (AAL) has the potential to improve the quality and effectiveness of healthcare provided to independently living elderly persons. In this paper, we survey various categories of AAL systems, their characteristics, and show an experimental example of how a LiDAR ambient sensor and wearable sensors can be integrated to recognise a simple activity of daily living. Future research challenges in activity detection are also presented.**

Keywords—sensor fusion, ambient assisted living, smart homes, Lidar

I. INTRODUCTION

A rapid increase in the number of elderly people has been observed in all developed countries. In Australia, for example, some studies point to a 200% increase in demand for aged care and facilities [1]. A concomitant increase in elderly persons living independently in their own homes can also be expected. To maintain the quality of life and to comply with relevant government legislation, recording of daily activities, administration of medication, providing secure facilities (e.g., to monitor fall detection) and provision of cost-effective management of nursing and homecare systems will be essential [1]. Studies from Europe and the USA have found that elderly persons prefer Ambient Assisted Living (AAL) over institutional aged care [2]. Another study in Australia found that over 60% of the older population had chronic medical and psychological conditions [3]. Some of these future needs of older residents can be addressed through the integration of ICT and use of Smart Home technology [4].

Advances in information and communication technology have allowed advanced sensors (sometimes known as smart sensors) to be deployed within households, leading to the emergence of Smart Homes. AAL systems aim to process large amounts of data collected from Smart Homes and Ambient Intelligence to provide real-time monitoring and assistance in cases of emergencies. The concept of AAL incorporates "the use of information and communication technology (ICT) in peoples' daily living and working environment to enable them to stay active for longer, remain socially connected, and live independently into old age" [5]. It appears that AAL is developing as an alternative to traditional aged care [14, 15].

Although AAL has the potential to provide similar care to a nursing home (aged care home) by implementing complete monitoring solutions, there are associated privacy concerns. In [6], it was found that even though the technology was inconspicuous or transparent, users still felt that it was intruding on their lives. Nevertheless, elderly people still preferred technology as it reduces the risk of potential injuries and requiring medical attention or even hospital admission. Ambient Intelligence and AAL have the potential to assist in better decision making and for the effective use of ICT in healthcare.

II. AMBIENT INTELLIGENCE AND AMBIENT ASSISTED LIVING

A. Ambient Intelligence (AmI)

Ambient Intelligence (AmI) involves the embedding of various technologies into everyday essentials such as clothes and using this to develop an environment that assists the inhabitant's daily life [8]. In a recent paper on the Internet of Things (IoT) frameworks for healthcare [9], AmI has been deemed crucial due to the essential human element. Moreover, it points out that AmI "*allows for the continuous learning of human behaviour and responds to recognised events*." There are several advantages to an AmI system. According to [8], these include the following:

- Have a contextual awareness and employ situational information
- Can be tailored to individual needs
- Anticipates the requirements of the individual without 'conscious mediation of the individual'
- Adapts to the changing needs of the individuals as they grow old
- Can be embedded transparently into everyday items and can, therefore, be incorporated into everyday life
- Seamlessly fits into the background of the individual's daily life.

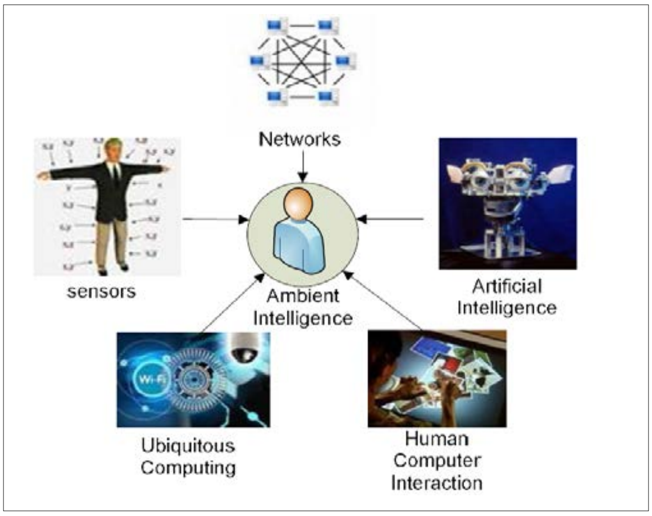

Fig. 1. Aspects of Ambient Intelligence [3].

According to [9], integration of human-computer-interaction (HCI) with autonomous control would further enhance the capabilities of future IoT frameworks for healthcare. AmI is thus essential for successful AAL implementations. AAL is "based on concepts from ambient intelligence" [7].

B. *Ambient Assisted Living (AAL)*

According to [7] and [10], when implementing multi-sensor data fusion in an AAL system, the following fundamental questions need to be addressed:

- What algorithms or techniques (including machine learning and change point detection) are appropriate for AAL application?
- What architecture should be used (where should the data processing take place; at a local server or a centralised server/hub)?
- How should the individual sensor data be processed to extract the maximum amount of information?
- What accuracy can realistically be achieved?
- How does the data collection environment affect data processing?

All of the above should be considered within a home environment where embedded sensors, along with wearable devices collect information about the subjects in two or more independent layers for better decision making. Independent information sources make the decision making process more reliable and accurate leading to more effective healthcare.

III. HOME AS AN AMBIENT SENSING PLATFORM

The primary goal of an AAL system is to extend the time which elderly or disabled people can spend living independently in their preferred environment (residential home) using ICT and sensor technologies. Essentially, the home has to be used as a sensing platform with real-time monitoring. To build a practical system, several important components (layers) need to work together. These include *activity monitoring systems* which assist residents in essential activities of daily living (ADL), such as giving reminders of important dates (doctors appointments), dressing and cooking; *health status monitoring systems* which use 'sensed information' to monitor resident's health condition and look out for any anomalous behaviour; digital patient information systems "capture health data entered by patients and provide information related to the care of those patients" [10].

Human-Computer Interaction (HCI) systems provide an interface between AAL system and its components and coordinator systems, "which communicate with constituent systems in order to achieve the global mission of the AAL system" [9]. The resident's family and friends, health care professionals and social workers can be easily connected to the system to provide instant access to data [13]. Accurate determination and recognition of ADL involve the use of multiple sensor systems; both ambient and wearable sensors need to be used in combination to optimise. Before defining the roles of sensors, we need to identify which of the ADLs are to be detected.

A. *Recognition of Activities of Daily Living*

Activities can be classified as high-level (HL-ADL) or low-level (LL-ADL). Examples of high-level activities include walking and using stairs. Retrieving a cup from a cupboard, pouring water to a cup, and bringing a cup to mouth, for example, can be classified as low-level. Combinatorial ADL such as 'making a hot beverage' consists of both HL- and LL-ADL. In this case, the HL activity is walking to each section of the kitchen to complete the task of 'making a hot beverage'. The LL activities associated with this task are (i) retrieving a cup from the cupboard, (ii) placing it on the table and (iii) pouring water into the cup. By assigning each task to either a wearable or an ambient sensor, it is possible to determine the ADL.

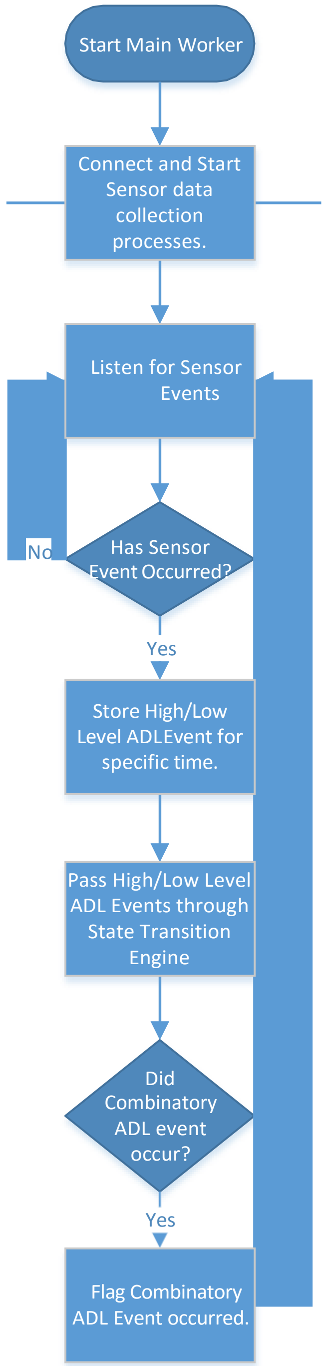

Fig. 2. ADL event detection algorithm [13]. At the connect and start step of the flow chart, parallel processes (Child Workers) start for (i) LiDAR area detection and (ii) Wearable Accelerometer ADL event detection.

In [11] researchers used both ambient and wearable sensors for activity recognition whereas in [12] a wearable was used to detect drinking activities. In this work following the methodology used in [11,12], we have utilised both ambient sensors and wearable sensors concurrently, which communicated with a computing node to validate the ADLs. Here, a LiDAR coupled with a wearable sensor is used to detect the ADL defined above.

B. Ambient Sensors

To detect high-level activities (HL-ADL) ambient sensors are used. Ambient sensors are also referred to as environment sensors or static sensors in the literature. These sensors can be placed around the kitchen, on fridge doors, cabinets and on top and bottom of stairs, among other vantage points.

Humans are detected by first mapping the area into specific regions (hot spots) as shown in Fig. 3 and counting the number of object collisions experienced by the sensor. For this project, the low-cost Hokuyo URG-04LX LiDAR was chosen as the ambient sensor. LiDAR (Light Detection And Ranging) technology uses light pulses generated by a laser source to determine the distance between an object and itself by ambient illuminance. These are also known as scanning laser range finders. The distance is measured by sending a burst of infra-red (IR) light out and measuring the time it takes to return to the object. The time is then multiplied by the velocity of light *c* to ascertain the distance.

LiDAR can detect events such as opening a cupboard or a fridge door and placing a glass on the table. More complex activities may also be detected provided that a well-defined sequence of events can be identified to be input to the algorithm. If measured HL and LL activities are combined, it can be deduced (using the ADL detection algorithm, where Figure 2 shows a typical flow chart of the main algorithm) that the ADL of ‘making a hot beverage’ had taken place. The algorithm will be briefly described in Sec. III D in conjunction with Figure 2.

Fig. 3. Hot spot areas of the kitchen.

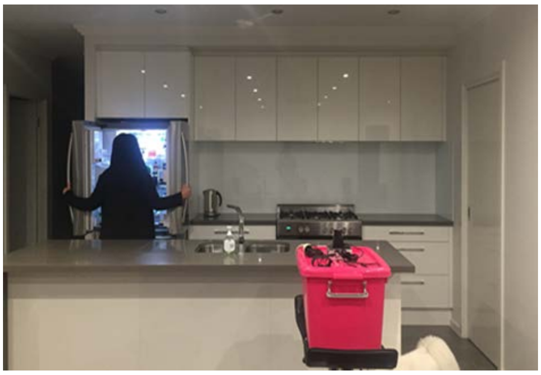

Fig. 4. The real kitchen with an open fridge and the human subject [13].

C. Wearable Sensors

Regions of the measurement area can be linked to events, which then can be analysed using temporal combinatorial methods. From these, it can be deduced with high probability that the ADL of “making a hot beverage” has taken place. The final recognition of the activity has been done by analysing a combination of well-defined events over time.

Identification of the ADL can be coupled with a wearable sensor, which can detect low-level activities (LL-ADL) such as getting a cup from a cupboard and pouring the liquid into it. However, to detect this, the initial conditions of an activity must be first defined. The defining of the initial conditions has been done by recording an activity many times and trying to find a signature for those events. If signatures cannot be uniquely identified, then the assumed signature must be pre-defined in the application.

Accelerometers are shown to be useful sensors for detecting LL-ADL activities [13]. In [11], a smartwatch with a tri-axial accelerometer, gyroscope, and a magnetometer was used for activity recognition. For simplicity, in this work, we used a single-accelerometer MbientLab’s meta motion R chip as the wearable sensor for detecting low-level activities.

D. Computational Node and ADL Detection Algorithm

The computational node or the central hub should be able to communicate with ambient and wearable sensors in a Smart Home. In this research, we use an Intel NUC5i3RYH hardware platform with the Windows 10 operating system. Data processing and ADL recognition are performed in real time using an application developed by Williams [13] using the Universal Windows Platform. MbientLab’s wearable sensor and the Hokuyo LiDAR were interfaced with the NUC using Bluetooth and virtual serial port over USB, respectively.

“The high-level overview of the ADL detection algorithm involves the Main Worker process consuming events from two parallel Child Worker processes. The Main Worker process then pushes these events through a State Transition Engine routine to determine if the appropriate sequence of events occurred for a Combinatory ADL event to be flagged” [13]. The Main Worker pairs with the wearable sensor using Bluetooth discovery mode; next, a serial connection is established with the LiDAR ambient sensor (scanning laser rangefinder). This research uses only two sensors, although more can be used for obtaining more accurate results.

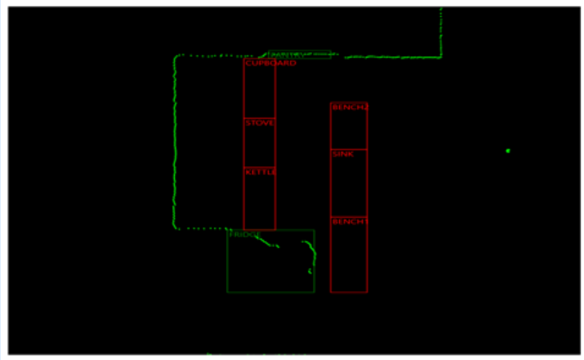

Fig. 5. Human opening the fridge as seen by the LiDAR.

IV. RESULTS AND DISCUSSION

This project detected humans by first mapping the ambient area as can be seen in Figure 3. The area was divided into specific regions. It was then assumed that any new object collisions were that of a human. Once an area had a significant number of new collisions it could be deduced that a human was indeed in that area. Figure 4 shows a human opening a fridge and Figure 5 is how that event (opening of the fridge) is represented by the LiDAR. When a human is detected in the area, the fridge regions turn green.

Regions can be linked to events, which then can be analysed using temporal combinatorial methods [13]. From these, it can be deduced with high probability that the ADL of “making a hot beverage” is taking place. The process of deduction has been done by analysing a combination of events over time as decsribed in the next section.

A. Ambient ADL

The activity of “making a hot beverage” was executed repeatedly to attain the conditions of the activity. The order of execution for the longest possible combination for ADL was:

1. START: **kettle→sink→kettle**. Retrieving the kettle, filling the kettle with water, then putting the kettle back in the kettle area to turn on;
2. **Cupboard→pantry→cupboard**. Retrieving the cup from the cupboard and placing on the table, then retrieving coffee/tea/sugar from the pantry and placing it in the cup in the cupboard section;
3. **Kettle→fridge→kettle→fridge→kettle**; END. Moving cup from cupboard area to kettle area, retrieving milk from the fridge, filling up a cup with milk and water in the kettle area, returning the milk to the fridge, then returning to kettle area to retrieve a hot beverage.

The following basic assumptions were made:

The activity would take a minimum of 2.5 minutes and a maximum of 4.5 minutes to complete. (This activity had different completion times depending on the amount of water boiled.)

The user would

- always return to the kettle area before continuing each logical step
- always retrieve a new cup from the pantry
- retrieve the ingredients from the pantry and return to the kettle area
- retrieve the milk last from the fridge
- return the milk to the fridge after making the hot beverage.

If all the above conditions hold within the allocated time, then an alert will appear in the application developed confirming the ADL conditions have been met. Thus the experiment focusses on one particular case only; other permutations, for example, not having milk with the hot beverage is not considered. The wearable sensor’s low-level activity detection capability can be utilised to allow for alternate combinations of “making a hot beverage.”

B. Wearable ADL

The first ADL involved the person pouring water into a cup (Water-Pouring- W-P ADL). Out of the wearable ADLs, this one was the longest one to be recorded. It was found, that there were many different ways to pour water into a cup. This required further investigation on how a typical elderly person poured hot water into the cup. One such difference would be the distance that the kettle was held from the cup. It was found that as long as the kettle was held between 15 cm to 27 cm from the cup, it did not drastically alter the data. Another variable tested was the cup being placed on the edge of the bench. These distances did not appear to affect the model. Also, various weights for the kettle were also tested. The weight of the kettle would change depending on the amount of water in the kettle. For this project, the water was kept at a weight that allowed to stay the same without disrupting the model.

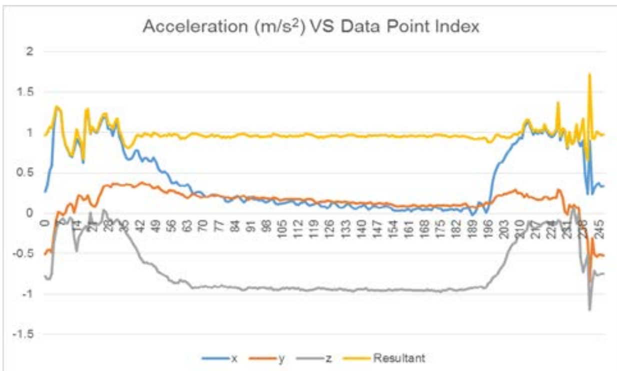

Fig. 6. Acceleration v^s data point index for Water-Pouring ADL Test 1.

The second ADL involved pouring water from the kettle into a cup. To formulate the model, water was poured from different distances. Through empirical testing, it was found that if the distance the kettle was held above the cup was within 15 cm to 27 cm, then it did not significantly affect the data. The same was repeated for the movement of placing the cup to the edge of the bench, and it was found that these distance also did not significantly affect the model.

For the experiment the kettle was kept at a constant weight of 1515g, approximately 750 ml being water. It was found, that different volumes of water in the kettle did affect the model. This affected the time component of the model as it would change the time it took to pour. As a result of these learnings, the weight of water in the kettle was kept at a level that would allow for two hot beverages to be poured. This did not disrupt the model and was also dependent on the elderly person's strength.

The graphs below were produced by randomly selecting ten repetitions. The graphs are based on the accelerometer magnitude versus data point index. Data point index can be substituted for time using the following: Time (sec) = data point index/25, where 25 is the sampling frequency. Fig. 6 and Fig. 7 can be broken up into three distinct windows. The first window is the lifting of the kettle, the second window is the pouring of water, and the third window is placing the kettle back onto the table. These distinct windows could be seen in the other samples only differing in length. In Fig. 6 windows are from point 0 to 40, 41 to 195, and 196 to 247. In Fig. 8, the windows are from 0 to 48; 49 to 167, and 196 to 220. These results were typical of the other windows tested.

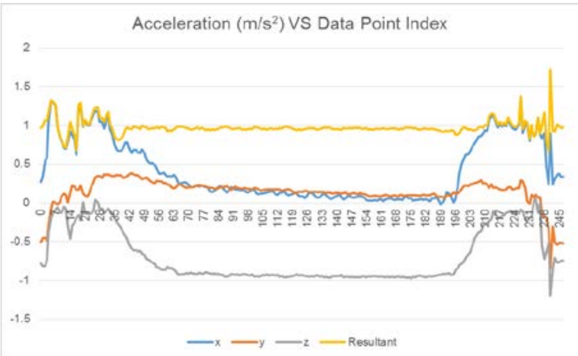

Fig. 7. Acceleration versus data point index for Water-Pouring Test 2.

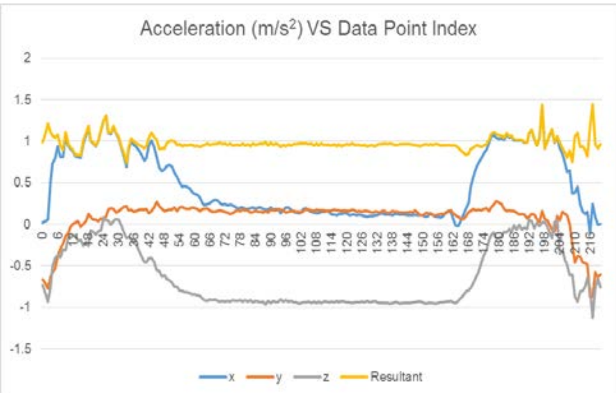

Fig. 8. Acceleration versus data point index for Water-Pouring Test 3.

The results given in Table 1 contain three basic statistical parameter values for each of the ADL experiments performed. The minimum and maximum values are found which are used to test against the real-time data for Window 1 for W-P ADL and the variance is 0.0077 and 0.0299. The variance is used to test the accuracy of the minimum and maximum values and to ensure the accuracy of the true minimum and maximum attributes. During the experiment, activity recognition was based on three additional statistical attributes: Standard deviation, mean absolute deviation and root mean square (rms) value (not shown in Table 1).

Table 1. Consolidated Water-Pouring ADL Window 1 test.

TEST	Mean	Std. Dev	Variance
1	1.0020	0.0878	0.0077
2	1.0100	0.1058	0.0112
3	1.0160	0.1729	0.0299
4	1.0020	0.1501	0.0225
5	1.0150	0.1309	0.0171
6	1.0070	0.1124	0.0126
7	1.0170	0.1222	0.0149
8	1.0100	0.1163	0.0135
9	1.0120	0.1160	0.0135
10	1.0090	0.1477	0.0218
Minimum	**1.0020**	**0.0878**	**0.0077**
Maximum	**1.0170**	**0.1729**	**0.0299**

C. Combined Ambient and Wearable ADL

Mapping an area of interest (Fig. 3) and determining whether that area is occupied via hot spots, is evidently advantageous. Employing this technique mitigated the issues associated with sensor placement and intrusiveness, but lacked the ability to identify object interaction. A combination of both the wearable data and the LiDAR data are required in order to eliminate the false positives detected in the Water-Pouring ADL and applications can be developed incorporating algorithms to determine whether all possible combinations of a given ADL will be detected under the various conditions mentioned in Sec. IV *A*.

V. CONCLUSION

In this paper, we surveyed some important characteristics of Ambient Assisted Living. A LiDAR used (in association with other low-cost components) as an ambient sensor has been shown to successfully recognise a simple activity of daily living (ADL): "making a hot beverage." A wearable sensor on the wrist of a subject was used to detect low-level activities related to the same ADL. An Intel NUC was used as the hardware platform to integrate the two sensors. The results reiterate studies in the literature claiming combinational systems are more effective. In a more general sense, the following are a few of the challenges facing the research community: (i) How to optimise the health and well-being of elderly persons through the integration of ICT and sensor technologies in Ambient Assisted Living. (ii) Iplementing accurate real-time monitoring and response systems with Smart Home technology. (iii) How to recognise the activities of daily living (ADLs) through judicious selection of both ambient and wearable sensors. (iv) Clinical studies of combinatory activity recognition systems for Smart Homes.

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