Inference of Hygiene Behaviours While Recognising Activities of Daily Living

Usman Naeem
School of Architecture, Computing & Engineering
University of East London
United Kingdom
U.Naeem@uel.ac.uk

Abdel-Rahman H. Tawil
School of Architecture, Computing & Engineering
University of East London
United Kingdom
A.R.Tawil@uel.ac.uk

Ivans Semelis
School of Architecture, Computing & Engineering
University of East London
United Kingdom
u0909617@uel.ac.uk

Gaby Judah
Hygiene Centre
London School of Hygiene and Tropical Medicine
United Kingdom
Gaby.Judah@lshtm.ac.uk

Robert Aunger
Hygiene Centre
London School of Hygiene and Tropical Medicine
United Kingdom
robert.aunger@lshtm.ac.uk

ABSTRACT
Many health problems are generally caused by unhealthy behaviours that occur whilst conducting everyday Activities of Daily Living (ADL), such as poor use of sanitation and hygiene. This paper describes the development of an ADL inference engine, which is able to recognise natural hygiene behaviour patterns. As opposed to traditional ADL classification approaches, the developed inference engine employs a novel hierarchal structure for the modelling, representation and recognition of the ADLs, its associated tasks, objects, dependencies and their relationships. The organisation of this information in a contextual structure plays a key role in carrying out robust ADL recognition for the detection of hygiene behaviours. The proposed work also marks a shift in feature detection methodology, as it allows actual behaviour to be studied in its natural environment within actual households, with at least two individuals per household as opposed to a laboratory based controlled setting. This paper also presents experimental results that validate the performance of the inference engine.

Categories and Subject Descriptors
D.4.8 [**Performance**]: Modeling and Prediction.

H.1.2 [**User/ Machine Systems**]: Human factors and Human information processing.

General Terms
Algorithms, Design, Human Factors, Theory.

Keywords
Human Activity Recognition, Assisted Living, Hierarchal Activities of Daily Life, Health and Well-being, Wearable Computing.

1. INTRODUCTION
Over the last century there has been a gradual increase in the life expectancy rates of people living in the UK, which in turn has led to more elderly people in the society. It has also been predicted that 25% of the European population will be made up of people aged over 65 [1]. In order to maintain the well being of an elderly person it is important that they are able to perform daily tasks such as cooking, dressing and toileting. This is also something that was recognised by gerontologists in 1963 [2], who have established a detailed lists of activities that should be carried out by elderly people on a daily basis. These lists of activities are known as Activities of Daily Living, such as personal dressing, eating, hygiene and functional movement. The ability to recognise everyday ADLs is seen as a key approach for tracking functional decline among the elderly community [3]. Additionally, many health problems are generally caused by unhealthy behaviours, such as diarrhoea and respiratory infections caused by poor use of sanitation and hygiene. These unhealthy behaviours can originate from habits that are performed frequently in constant contexts such that the behaviour proceeds automatically on encountering the relevant cues. Self-report of such behaviour can be problematic due to bias and participant burden. Useful information about the safety and healthy wellbeing of an elderly person cannot only help them lead an independent life but can also allow the possibility of instituting safeguards given a potential harmful scenario. The work in this paper aims to establish a reliable inference engine for unobtrusively monitoring and identifying hygiene related behaviours of multiple individuals within the same household over a period of several months.

This paper makes the following contributions. Firstly we introduce a novel concept of modeling and recognising ADLs as a hierarchal encapsulated entity, where each ADL has attributes that enable the inference engine to reason the internal structure and relationships of an ADL when carrying out recognition. In addition, the proposed inference engine is able to recognise ADLs being carried out by multiple people within the same area at the same time.

Feature detection mechanisms play a crucial role in achieving positive recognition rates, hence it is vital that households are equipped in such a way that data capture systems are able to yield data that would aid the recognition process. In relation to this, we also validate the way in which we carry out feature detection, as we have equipped the different households differently in order to see if they have an impact on the recognition rates.

The remainder of the paper is organised as follows. Section 2 provides an overview of the related literature, while Section 3 describes the structure and the key characteristics of a hierarchally structured ADL. Section 4 describes the inner workings of the inference engine and how it manages and recognises the hierarchally structured ADLs. Section 5 describes the experimental set up of each household and the results that validate

ICCASA 2014, October 15-16, Dubai, United Arab Emirates
Copyright © 2015 ICST
DOI 10.4108/icst.iccasa.2014.257437

findings about the inference system and the feature detection techniques employed.

2. RELATED WORK

Feature detection can be carried out using visual based systems, which can be computationally expensive when analysing video footage and can be seen as intrusive. However the contribution of vision-based systems should not be ignored, as there is a large body of work within this area. Also the activity recognition domain can be complex, hence solutions based on the fusion of multiple sensors (including vision sensors) should not be overlooked.

An alternative to visual based systems is the use of anonymous binary sensors such as: motion detectors, break-beam sensors, pressure mats, and contact switches. These can aid the process of tracking an individual around the home and complement the whole activity recognition process [4]. However, these types of systems do not have capability of remote monitoring of data. Additionally, it is not possible to have knowledge of the context or the sequence of activities being monitored.

Wearing different types of sensors around the body is another technique for capturing features related to activities or posture [5]. These types of sensors are known as wearable sensors, which can range from accelerometers to audio microphones that provide data about body motion and its surroundings where the data has been collected. These sensors can be stand alone devices or incorporated into existing context aware devices such as smart phones [6], which have the ability to determine physical activities such as walking, running, climbing stairs and sitting [7][8][9]. While data maybe useful for a specific application domain (e.g. physical health and exercise), it is not very useful in isolation when trying to recognise the complex activities being conducted.

Using a combination of wearable devices and passive transponders on objects within the home environment, can achieve recognition of activities and the ability to determine the individuals that conducted them. One such approach is capturing object usage data using non-intrusive wearable sensors [10] based on Radio Frequency Identification (RFID) technologies to collect activity information. This type of feature detection is known as "Dense Sensing" [11][12], which is based around numerous individual objects such as toasters and kettles being tagged with passive wireless battery-free transponders that transmit information to a computer via a RFID reader [13], [14] when the object is used or touched. An advantage of deploying passive transponders is that they are unobtrusive, cheap, small and easy to install onto a range of different objects. In addition, these passive transponders are not reliant on battery power, hence they can be deployed within the home environment for a very long time. However "Dense Sensing" does have its share of flaws. Firstly the capturing of object usage data from the transponders is dependent on the end user (participants) to wear RFID reader on their hand or finger, which is bulky and requires regular charging. Secondly, the presence of metal or water can interfere with the signals, which can have detrimental affect on the recognition. In addition, trying to capture object usage data for small objects can be problematic, as the end user is likely to hold the object with their handing covering the passive transponder, which leads to a situation where no signal is received in order to confirm that the object has been touched [15].

Activity recognition frameworks can be divided into two main categories, inductive and deductive. Inductive frameworks such as machine learning have the potential to learn and generalize by example [16][17] while deductive methods can provide powerful means to encode semantic process knowledge [18]. Both frameworks have their benefits and limitations and the ultimate solution would be the one bringing the best of both worlds. In relation to this, the proposed hierarchal approach aims to achieve this, as the lower task recognition tier is based on an inductive framework, while the higher tier ADL recognition is based on a deductive framework.

Existing approaches for ADL inference have been focused on classification techniques that have been based on pattern recognition. The primary objective of these approaches are based on designing models that are capable of recognising activities given sequences of observable [19][20], which can be then used to deduce behavioural patterns.

One of the drawbacks of applying traditional classification techniques is that the developed inference engine employs a novel hierarchal structure for the modelling, representation and recognition of the ADLs, its associated tasks, objects, dependencies and their relationships. The organisation of this information in a contextual structure plays a key role in carrying out robust ADL recognition for the detection of hygiene behaviours.

3. HIERARCHALLY STRUCTURED ADL

For the work in this paper, the ADLs have been structured in a hierarchal structure.

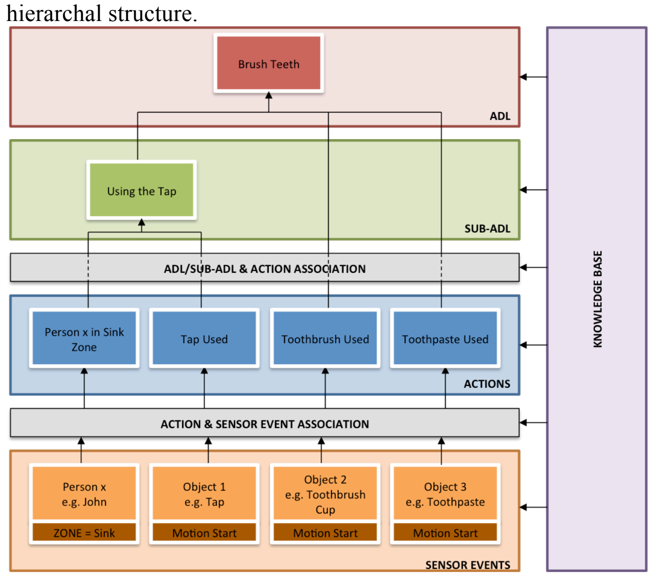

Figure 1. Hierarchal Structure of *Brush Teeth* ADL

The lowest leaf nodes level of this hierarchal structure is responsible for feature detection. Features are captured as data streams, which are known as sensor events. Each sensor event represents the movement of an object (e.g. Tap motion has started or stopped) or the presence of a person entering a zone within an environment (e.g. John has entered the toilet zone within the

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
Conference'10, Month 1–2, 2010, City, State, Country.
Copyright 2010 ACM 1-58113-000-0/00/0010 …$15.00.

bathroom). Hence, a sensor event is used to represent a person within a zone or the movement of an object (Figure 2). These sensor events are then associated with actions, while zones are associated with objects. For example, in Figure 1, a Toothpaste motion sensor event can be associated with the action Toothpaste used.

3.1 Knowledge Base of ADL Characteristics

3.1.1 Sub-ADL and Action Attributes

Before discussing the recognition algorithm, it is important to highlight the key attributes and characteristics that form the information stored in the knowledge base (see Figure 1). The attributes in the knowledge base are associated with the Sub-ADLs and actions within each ADL, as these are utilised for recognising ADLs (see Table 1) based on their characteristics.

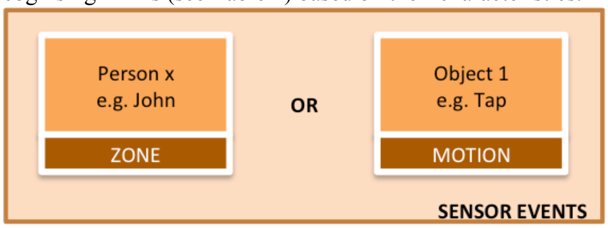

Figure 2. Sensor Event Representation

An ADL encompasses Sub-ADLs and actions, as each of them has attributes associated with the ADL they belong to. For example, the action *use of toilet roll* will be observed more frequently for *defecation* as opposed to *urination* ADL.

Table 1. Sub-ADLs and Action Attributes

Attributes	Description
Maximum Duration	This is threshold of the maximum duration of performing an action.
Minimum Duration	This is threshold of the minimum duration of performing an action.
Maximum Occurrence	This is threshold of the maximum number of times that a certain Sub-ADL or action may occur in an activity.
Minimum Occurrence	This is threshold of the minimum number of times that a certain Sub-ADL or action may occur in an activity. This also determines if an action is mandatory or optional for an activity, as an occurrence which is greater than 1 makes its mandatory that this action should be observed in order for the activity to be performed.
Mutually Exclusive Sub-ADL or Action	This states whether the Sub-ADL or action are mutually exclusive to the ADL, hence they do not occur in any other ADL. For example, Toothpaste used would only occur in *Brush Teeth* ADL.
Prerequisite Sub-ADL or Action	This determines if certain Sub-ADLs and actions need to occur before any of the Sub-ADLs and actions that will be expected to occur when this ADL is conducted.

3.1.2 ADL Attributes

Like the attributes in Table 1, ADLs have attributes that are required for the recognition process. These are based on characteristics of the relationships between all the possible ADLs that have been modelled.

The attributes described in Tables 1 and 2 collectively form the knowledge model necessary to bootstrap the system for initial ADL Recognition. The information in the knowledge model can be adjusted or modified based on the location setting in order to suit the current environment.

Table 2. ADL Attributes

Attributes	Description
Maximum Duration	This is threshold of the maximum duration of performing the ADL.
Minimum Duration	This is threshold of the minimum duration of performing the ADL.
Associative Actions	This determines whether the ADL has any Sub-ADLs and actions that are associated with other ADLs.
Interweaved ADL	This determines if the ADL can be interweaved with another ADL. For example, a person can start brushing teeth and then start flossing, which can then be followed by brushing teeth.
Shared ADL	This determines whether the ADL can be performed simultaneously with another ADL in the same zone. For example, person x and person y using the Tap in the sink zone at the same time, where person x is brushing teeth and person y is washing hands.
Assistive ADL	This determines if two people are involved while the ADL is being performed. For example, person x is brushing teeth, while person y passes toothpaste to person x.
Interruptible ADL	This determines if ADL can be suspended, while another ADL is conducted.
Repetitive ADL	This determines if certain actions or Sub ADLs are likely to be repetitive when the ADL is being carried out.

For the work in this paper, the recognition is not conducted real-time, as the recognition is conducted after the data has been collected with a real time location system. However the intention is that the proposed system will be adapted for real time recognition where a learning mechanism will be deployed in order to populate the knowledge base given the changes that take place in the behavioural patterns associated with the attributes in the model.

4. ADL RECOGNITION

The recognition of the ADLs is based on recognising the patterns and occurrences of Sub-ADLs and actions that are generated by sensor event sequences. However, there is an issue as regarding the length of the sensor event stream that should be used for recognition. The first option could be to use the entire sensor event stream captured. However, this could be very inefficient as only the most recent events are of interest within a particular time frame. The other option is to assign a sliding window of events, however this would raise an issue as to where the sliding window should start from. A sensible approach is to ensure that the sliding window starts when a person enters or exits a particular zone (e.g. toilet zone), as this could mark the end of one ADL and the start of another. However, what would happen if a person moves between zones whilst carrying out an ADL? The proposed approach has addressed by combining a series of windows in order to accommodate interweaving ADLs that might be carried out over a series of windows that are not structured sequentially. The proposed ADL recognition engine is divided into a series of functions (see Figure 3), which represent the logical steps for recognising an ADL. A description of each function follows:

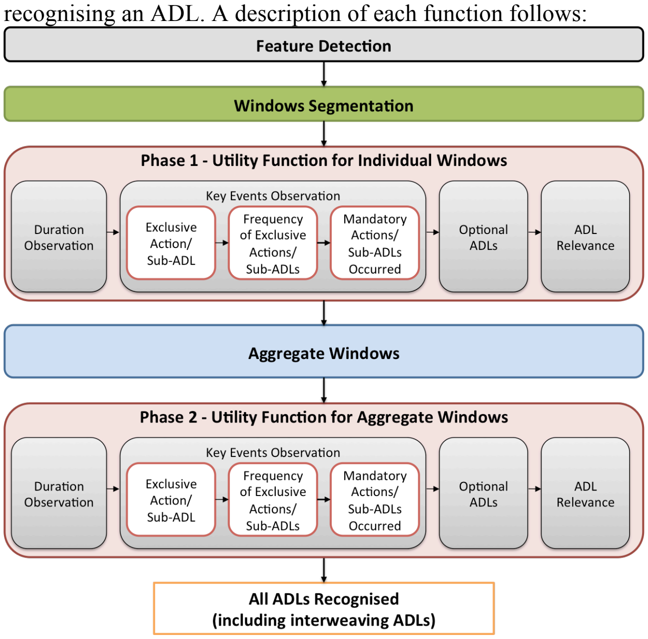

Figure 3. ADL Recognition Engine

4.1 Feature Detection

The feature detection (sensor event capture) for the work in this paper has been conducted by installing a Real-Time Location System (RTLS) [21] around the home environment. This system is traditionally used for tracking the movement of staff and equipment in hospitals, security for museums and items and for supply chain management purposes in warehouses. The main components of the system and its usage within the home environment are summarised in table 3.

Table 3. Components for Feature Detection System

Components	Description
Positioning Sensor Tags	These tags are affixed to objects within the environment, e.g. Toothpaste. Individuals also wear these positioning tags in order to track their location within different zones. These tags also have the ability to record whether or not they are in motion.
Zone Exciters	Zones are created by LF (low frequency) Exciters, which can be set at four interval ranges between 0.15m and 15m in diameter.

In order to capture small motion of household objects, the RTLS programmed the sensor tags with a lower motion sensitivity threshold. Each sensor tag transmits the following information: motion start or motion stop, and zone information. This data transmission is carried out wirelessly using a Radio Frequency (RF) Reader, which is then uploaded to a server.

The reason for deploying a RTLS is due to its low cost and its ability to unobtrusively monitor behaviours of multiple individuals within a household via object usage data. In addition, the system is robust (sensor tags are waterproof) and is low powered, which allows continuous periods of data capture without the need of frequently charging or replacing of batteries.

4.2 Windows Segmentation

Once the data (streams of sensor events) has been captured by the feature detection component, the next step is to determine the length of the sensor event stream that is going to be used for inferring the activities and the individual that is conducting them. Hence the objective of this step is to segment the entire captured sensor event streams into individual windows, so that each window can be used for activity inference in the preceding step, which generates a utility for each window.

Site	TagSerial	TagType	TagDescription	Date	Time	MessageNote
visonic-001	007D8E	object	Toilet flush	29/11/2011	19:26:05	motion:start
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:42	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:43	motion:start
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:46	Sink Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Outside Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	motion:stop
visonic-001	001C40	object	Toilet roll	29/11/2011	23:13:33	motion:start
visonic-001	001C52	entity	Person 1	29/11/2011	23:26:08	Outside Zone
visonic-001	001C46	entity	Person 2	30/11/2011	06:49:26	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:27	motion:start
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	motion:stop
visonic-001	001C46	entity	Person 2	30/11/2011	06:49:30	Outside Zone

PHASE 1
TIME INTERVALS BETWEEN OBSERVATIONS

Site	TagSerial	TagType	TagDescription	Date	Time	MessageNote
visonic-001	007D8E	object	Toilet flush	29/11/2011	19:26:05	motion:start
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:42	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:43	motion:start
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:46	Sink Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Outside Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	motion:stop
visonic-001	001C40	object	Toilet roll	29/11/2011	23:13:33	motion:start
visonic-001	001C52	entity	Person 1	29/11/2011	23:26:08	Outside Zone
visonic-001	001C46	entity	Person 2	30/11/2011	06:49:26	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:27	motion:start
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	motion:stop
visonic-001	001C46	entity	Person 2	30/11/2011	06:49:30	Outside Zone

PHASE 2
LOCATION OF OBSERVED PERSON

visonic-001	007D8E	object	Toilet flush	29/11/2011	19:26:05	motion:start

visonic-001	001C52	entity	Person 1	29/11/2011	23:12:42	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:43	motion:start
visonic-001	007DB6	object	Toothbrush cup	29/11/2011	23:12:46	Sink Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Outside Zone
visonic-001	001C52	entity	Person 1	29/11/2011	23:12:46	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	Toilet Zone
visonic-001	007D8E	object	Toilet flush	29/11/2011	23:13:08	motion:stop
visonic-001	001C40	object	Toilet roll	29/11/2011	23:13:33	motion:start
visonic-001	001C52	entity	Person 1	29/11/2011	23:26:08	Outside Zone

visonic-001	001C46	entity	Person 2	30/11/2011	06:49:26	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:27	motion:start
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	Sink Zone
visonic-001	007DB6	object	Toothbrush cup	30/11/2011	06:49:30	motion:stop
visonic-001	001C46	entity	Person 2	30/11/2011	06:49:30	Outside Zone

Figure 4. Segmentation Phases

The windows segmentation function is dependent on two following parameters:

Time intervals between observations: This is considered when the time stamps of the sensor events indicate that there has been a significant interval between the movements of two objects. For example, the last object (e.g. toilet flush) within the sensor event stream was captured at 19:26:05, which is then followed by another object (e.g. Toothbrush cup) at 23:12:42.

Location of the observed person: This is based on the person moving from one zone to another zone. For example, moving from sink zone to toilet zone could signify the beginning or end of an activity.

The segmentation function has two phases of segmentation. First phase is to segment the captured streams into windows given the interval length between the objects observed. The next phase then carries out further segmentation of the generated windows by segmenting based on movement of a person between zones. These phases of segmentation have been illustrated in Figure 4.

4.3 Utility Function

This module is responsible for generating an initial utility for all possible ADLs being detected given the current window of sensor events. This function is computed once the sensor events have been associated with an action.

The ADL that has the highest utility is considered to be the most probable ADL that is being conducted given the sensor event stream in each window. Figure 3 shows the structure of the utility function, which is divided into four steps that will determine the initial utility of each ADL. The output of the four steps is used to compute the initial utility. A brief description for each step is described as follows:

4.3.1 Step 1 – Duration Observation

The ability to recognise the duration of an action plays an important role in determining the ADL being carried out. The objective of this step is to see if the duration of the observed actions are within the maximum and minimum duration thresholds that are stored in the ADL characteristics knowledge base. If the observed duration is within the threshold then the output of this function would be computed as 1. However for cases where the observed duration is not within the threshold are computed as follows:

Case 1: Observed duration is less than the minimum duration threshold

If an observed duration for action (e.g. tap used) associated with ADL (e.g. wash hands) is less than the minimum duration threshold that is currently stored in the knowledge base then a linear probability scale is computed which is based on the linear difference between the observed start time and the minimum accepted duration.

For example in Figure 5, the minimum duration for *Tap used* is 00:00:50, while the observed duration is 00:00:25. In this instance the linear probability scale will be computed based on the observed action and the associated threshold data stored in knowledge base, in this case it would be 0.5.

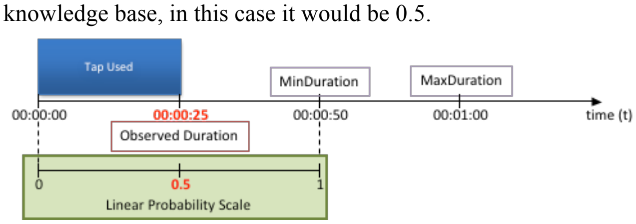

Figure 5. Observed duration less than the minimum duration threshold

This can be simplified as,

$$\frac{x_t}{y_t} = p \qquad (1)$$

where x is the observed duration, y is the minimum duration in the knowledge base and t represents the unit of time. For example:

$$\frac{25_{sec}}{50_{sec}} = 0.5$$

Case 2: Observed duration is greater than the maximum duration threshold

If an observed duration for action (e.g. using floss) associated with ADL (e.g. flossing) is greater than the maximum duration threshold that is currently stored in the knowledge base then another linear probability scale is computed as;

$$1 - \left(\frac{x_t - y_t}{z_t + 2z_t}\right) = p \qquad (2)$$

where x is the observed duration, y is the minimum duration, z is the maximum duration while tt represents the unit of time. For example:

$$1 - \left(\frac{240_{sec} - 60_{sec}}{120_{sec} + 240_{sec}}\right) = 0.5$$

In Figure 6, the minimum duration is 00:01:00, maximum duration is 00:02:00, while the observed duration is 00:04:00. The output of this function (2) based on the observation and the data in knowledge base would 0.5.

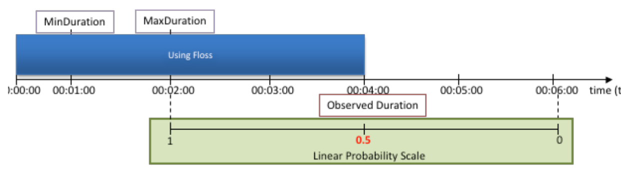

Figure 6. Observed duration greater than the maximum duration threshold

4.3.2 Step 2 – Key Events Observation

2a. Exclusive Action/Sub-ADL

This step determines the proportion of actions and Sub-ADLs that are exclusive to the possible ADLs given the window of sensor events. For example, *Toothpaste used* would **only** occur in *Brush Teeth* ADL, hence this action would also be considered mandatory for this ADL to be recognised. This would be computed as:

$$\frac{x}{\sum y_1, y_2 \dots y_n} = p \qquad (3)$$

where x is the observed exclusive action and $\sum y_1, y_2 \dots y_n$are the total number of associated exclusive actions with possible ADLs given the window of sensor events.

2b. Frequency of Exclusive Actions/Sub-ADLs

The objective of this step is to determine the frequency of observed exclusive actions and Sub-ADLs, where the frequency is above the expected mandatory threshold of actions and Sub-ADLs for the possible ADLs given the window of events. For example, the ADL characteristics knowledge would identify the frequency of the action *loo roll* used to be in the range of 1 – 5 for the ADL defecation, which would be considered mandatory. However if the captured frequency event for this action were greater than 5 then this action would be considered optional. This is computed as the in Function (3), where x is the observed optional exclusive action and $\sum y_1, y_2 \dots y_n$are the total number of optional exclusive actions that are associated with the all possible ADLs given the window of sensor events.

2c. Mandatory Actions/Sub-ADLs Occurred

This step determines the proportion of mandatory actions and Sub-ADLs that have been observed given all the possible ADLs that could occur within the current window of sensor events. This is computed as in Function (3), where x is the observed mandatory actions and Sub-ADLs and $\sum y_1, y_2 \dots y_n$ are the total number of actions and Sub-ADLs that are associated with all possible ADLs within the current window of sensor events.

4.3.3 Step 3 – Optional ADLs

This step determines the proportional of optional actions and Sub-ADLs that have been observed given all the possible ADLs that could occur within the current window of sensor events.

4.3.4 Step 4 – ADL Relevance

This step determines the proportion of unrelated actions and Sub-ADLs that have been observed given all the possible ADLs that could occur within the current window of events.

The outputs of the four steps described are used to compute the utility of all the possible ADLs given the current window of events. The computation of the utility (u) is based on the average of the outputs of the 4 steps (s), which is as follows:

$$\frac{\sum_{i=1}^{n} s_i}{n} = u \qquad (4)$$

Based on the recognition environment the ratio of importance for each step can be changed, however for the following example (Table 4) the ratios are considered all equal.

Table 4. Initial Utility for ADL x given window of events

Steps	Ratio	Output
(s_1) Duration observation	1:4	1
(s_2) Key Events Observation	1:4	0.8
(s_3) Optional ADLs	1:4	0.3
(s_4) ADL Relevance	1:4	0.7
	Initial Utility (u)	0.7

This utility function is applied in two phases, where the first phase is for individual windows to determine the ADLs given each window of events. While the second phase is applied to aggregate windows in order to determine ADLs that are interweaved. For example if window 1 is ADL x, window 2 is ADL y, and window 3 is ADL x, then this implies that ADL x is interweaved with ADL y.

4.4 Construction of Aggregate Windows

There can be many instances where an activity can be carried out in parallel with another activity. For example, a person could be brushing his/her teeth while they floss their teeth. The recognition of these types of interweaving instances is made possible by grouping the detected windows into aggregate of related windows, which reflect the interweaved activities.

Construction of the related aggregate windows is carried out by assigning the first recognised window w_1 as a starting point for the newly constructed aggregate window a_1. A linear search is then performed on the rest of detected windows to see if it is possible to add a related window w_n to the current aggregate window a_1. The construction of the aggregate window is dependent on timing interval between the individual windows, because if the timing interval between two individual windows is over a certain threshold (e.g. 15 minutes) then the current aggregate window a_1 can be finalised (Figure 7).

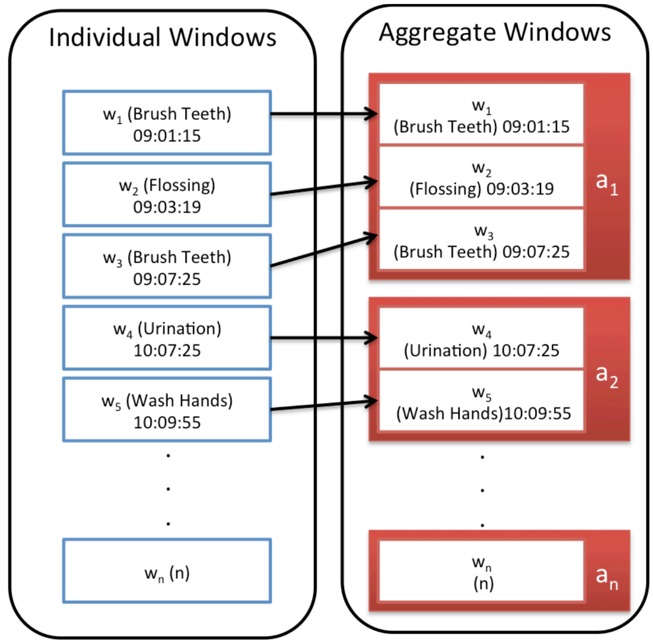

Figure 7. Construction of Aggregate Windows

Once all of the aggregate windows $a_1 \dots a_n$ have been constructed, the utility function is then applied in order to carry out the second phase of classification based on the new constructed aggregate windows.

5. EXPERIMENT AND RESULTS

The objective of the conducted experiments was to validate the performance of the inference engine given data collected from three households. This performance was measured by calculating the precision and recall rates of the ADLs recognised given the aggregate windows.

The precision (P) and recall (R) for this experiment has been calculated as follows:

$$P = \frac{True\ Positive}{True\ Positive + False\ Positive}$$
$$R = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (5)$$

RTLSs were installed in three households in order to collect data for validating the inference engine. At least two individuals were occupying each household. Sensors of different sensitivity were used to reflect the different expected motion patterns of the different objects. For example, toothbrush cup use would only effect a slight movement, toilet flush a slightly greater movement, and toothpaste an even greater movement. Participants were told to wear the sensors on their dominant wrist continuously during the trial. They were also given a behavior recording sheet, which was left inside the bathroom. Every time they left the bathroom participants were required to record in their ID number (self-selected to ensure anonymity), the date and time, whether anyone else was present in the bathroom at the same time, and which hygiene related activities they undertook while in the bathroom: toilet (defecation or urination), tap use, soap use, toothbrushing, flossing, shower, other. This reported information was then used as ground truth, which is used to measure the accuracy rate of the inference engine. When there were discrepancies between the sensor and self-reported data (coded manually), adjustments were made to the sensitivity of sensors used, or the location of the exciters until an acceptable level of recognition was reached. Each household setup is different, hence was equipped differently, which will help give us an indication of what impact this has on the recognition rates. The experimental set up of the three households was as follows:

Household 1: Home with 2 people living there. RF Reader on same floor as bathroom.

Objects tagged: toilet flush, toilet roll holder, tap, toothbrush cup, toothpaste (which is sometimes kept in the toothbrush cup, and sometime not), soap, and floss.

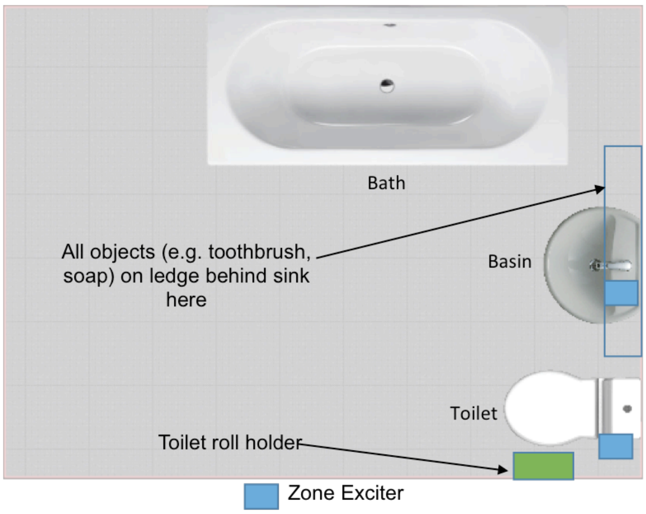

Figure 8. Household 1 Setup

Household 2: Home with 2 people living in it (not a couple, so don't use bathroom at same time). Concrete walls, so even though RF reader was on the same floor as the bathroom, some signals might not have gotten through.

Objects tagged: toilet flush, toilet roll holder, soap (bar and liquid) toothbrush cup, toothpaste 1, and toothpaste 2.

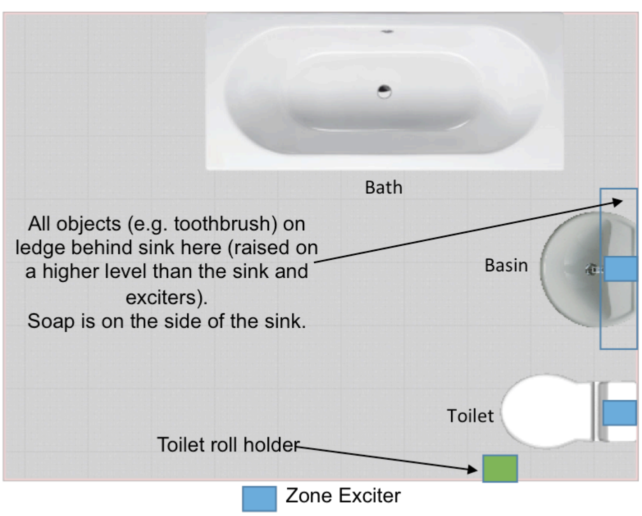

Figure 9. Household 2 Setup

Household 3: Home with 2 people living there. RF reader on the same floor as bathroom (adjacent room).

Objects tagged: toilet flush, toilet roll, soap, toothbrush holder, toothpaste 1, toothpaste 2, upstairs tap, floss.

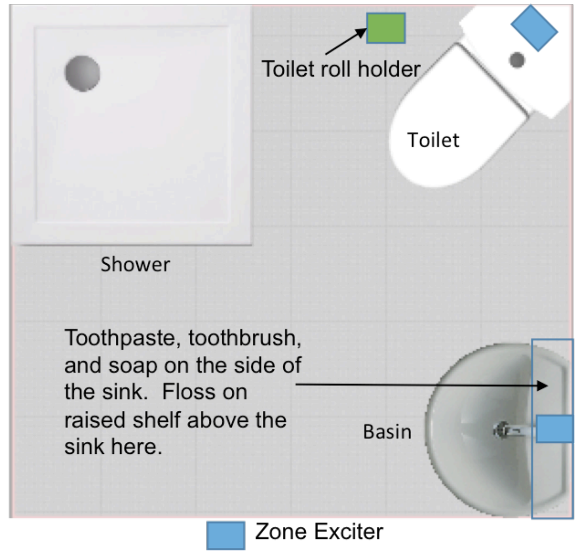

Figure 10. Household 3 Setup

The results in Table 5 show that the precision rates for each of the households ranged from 67% to 80%. The recognition rate for household 2 was good, however the other two households had significantly lower recognition rates. This was down to how the households were equipped, as well as the sites characteristics (e.g. walls), which could possibly be the reason for the drop in recognition rates.

Table 5. Experiment Results

Household	Precision [%]	Recall [%]
1	75	81
2	80	75
3	67	66

One of the reasons for the lower recognition rate for household 1, was down to the soap button press mechanism, which was not reliable, hence soap use was measured primarily by motion only, which is not as effective when capturing data. Household 3 had the lowest recognition rates, which was expected as this site was an old building, hence there was always the possibility that the many false positives would occur due to floors creaking. The results indicate that the setup of the household and the building characteristics (wall, floor boards) can have impact on the recognition rates. In addition to developing a robust activity recognition algorithm, these results highlight the importance of feature detection techniques for reliable activity recognition.

6. CONCLUSION

The work described in this paper looked at how hygiene related ADLs such as brushing teeth could be modeled and recognised as a hierarchal encapsulated entity, where each ADL has attributes that enable the inference engine to reason the internal structure and relationships of an ADL when carrying out recognition. The work also looked at how to infer activities that are conducted by multiple people at the same time within households (bathroom) using RTLSs. The experiment results highlighted the important of how household setup and site characteristics can have an impact on activity recognition rates.

Further work will be carried out, as the current approach has the potential to be adapted for real time recognition. As a learning mechanism will be deployed in order to populate the knowledge base given the changes that take place in the behavioural patterns associated with the attributes in the model.

7. REFERENCES

[1] Mann, W.C. 2004. The Aging Population and Its Needs. *IEEE Pervasive Computing*. 3, 2 (Apr.-Jun. 2004), 12-14.

[2] Katz, S., Ford, A.B., Moskowitz, R.W., Jackson, B.A., and Jaffe, M.W. 1963. Studies of illness in the aged: The index of ADL: A standardized measure of biological and psychosocial function. *Journal of the American Medical Association*. 185, 12 (Sept. 1963), 914-919.

[3] Fleury, A., Vacher, M., and Noury, N. 2010. SVM-Based Multimodal Classification of Activities of Daily Living in Health Smart Homes: Sensors, Algorithms, and First Experimental Results. *IEEE Transactions on Information Technology in Biomedicine*. 14, 2 (Mar. 2010).

[4] Wilson, D.H., and Atkeson, C. 2005. Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors. In *Proceedings of the Third international conference on Pervasive Computing (PERVASIVE'05)*, Hans-W. Gellersen, Roy Want, and Albrecht Schmidt (Eds.). Springer-Verlag, Berlin, Heidelberg, 62-79.

[5] Kern, N., Schiele, B., and Schmidt, A. 2003. Multi-sensor activity context detection for wearable computing. *Ambient intelligence Lecture Notes in Computer Science*. 2875, 220-232.

[6] Dernbach, S., Das, B., Krishnan, N. C., Thomas, B. L., & Cook, D. J. 2012. Simple and Complex Activity Recognition through Smart Phones. In *Proceedings of the Eigth International Conference on Intelligent Environments*,214–221. IEEE. doi:10.1109/IE.2012.39

[7] Khan, A. M., Lee, Y.-K., Lee, S. Y., & Kim, T.-S. 2010. Human Activity Recognition via an Accelerometer-Enabled-Smartphone Using Kernel Discriminant Analysis. In *Proceedings of the 5th International Conference on Future Information Technology*, 1–6.

[8] Jennifer R. Kwapisz, Gary M. Weiss, and Samuel A. Moore. 2011. Activity recognition using cell phone accelerometers. *SIGKDD Explor. Newsl.* 12, 2 (March 2011), 74-82. DOI=10.1145/1964897.1964918

[9] Jun Yang. 2009. Toward physical activity diary: motion recognition using simple acceleration features with mobile phones. In *Proceedings of the 1st international workshop on Interactive multimedia for consumer electronics (IMCE '09)*. ACM, New York, NY, USA, 1-10. DOI=10.1145/1631040.1631042

[10] Tapia, E., Intille, S., and Larson, K. 2004. Activity recognition in the home using simple and ubiquitous sensors. *Pervasive LNCS 3001*, 158–175.

[11] Buettner, M., Prasad, R., Philipose, M. and Wetherall, D. 2009. Recognizing Daily Activities with RFID-Based Sensors. In *Proceedings of the 11th International Conference on Ubiqitous Computing*, Orlando, 51-60.

[12] Philipose, M., Fishkin, K.P., Perkowitz, M. , Patterson, D.J. , Kautz, H. and Hahnel, D. 2004. Inferring Activities from Interactions with Objects. *IEEE Pervasive Computing Magazine*, 3, 4, 50-57.

[13] Kalimeri, K., Matic, A., and Cappelletti, A. 2010. RFID: Recognizing failures in dressing activity. In *Proceedings of the 4th International Conference on Pervasive Computing Technlogies for Healthcare (PervasiveHealth)*, 1-4.

[14] Philipose, M., Smith, J.R., Jiang, B., Mamishev, A., Roy, S. and Sundara-Rajan, K. 2005. Battery-Free Wireless Identification and Sensing, *Pervasive Computing IEEE Journal*, 4, 1, 33-45.

[15] Buettner, M., Prasad, R., Philipose, M., & Wetherall, D. 2009. Recognizing daily activities with RFID-based sensors. In *Proceedings of the 11th international conference on Ubiquitous computing - Ubicomp '09*, 51. doi:10.1145/1620545.1620553

[16] Delgado, M., Ros, M., and Vila, A. 2009. Correct behaviour identification system in a tagged world. *Expert Systems with Applications*, 36, 6, 9899-9906.

[17] Ros, M., Delgado, M. and Vila, A. 2011. Fuzzy method to disclose behaviour patterns in a tagged world. *Expert Systems with Applications*, 38, 4, 3600-3612.

[18] Suzuki, M., Matsushima, T. and Hirasawa, S. 1999. On a deductive reasoning model and method for uncertainty. In *Proceeding of the IEEE Conference on Tools with Artificial Intelligence*, 161-164.

[19] Naeem, U. and Bigham, J. 2009. Activity Recognition in the Home using a Hierarchal Framework with Object Usage Data. *Journal of Ambient Intelligence and Smart Environments*, IOS Press.

[20] Naeem, U., Tawil, A.H.R, Bashroush, R. and Al-Nemrat, A. 2012. Achieving Model Completeness for Hierarchally Structured Activities of Daily Life. In *Proceedings of the 2nd International Conference on Pervasive and Embedded Computing and Communication Systems*, Rome.

[21] www.elpas.com, Suppliers of the Real Time Location Systems.