RADBOUD UNIVERSITY, NIJMEGEN

TASK 24, EINDHOVEN

MASTER THESIS

Monitoring the Elderly using Real Time Location Sensing

Author:
Erik Crombag
Thesis number:
601

Internal supervisors:
Prof.Dr.Ir. Rinus Plasmeijer
Dr. Peter Lucas
External supervisor:
Aad van Gerwen, Task 24

March 29, 2009

Preface

This thesis has been written as the result of an internship at Task 24, Eindhoven. I was sent out by my supervisor Aad van Gerwen to explore the possibilities of actively monitoring elderly people using Real Time Location Sensing technology, with a special interest in people suffering from dementia as they are among the people who need constant care and attention. At first I looked into the possibilities of an active system, intervening into the daily behaviour of elderly people, preventing them from harm.

After talking to Gerard van Glabbeek, innovation manager at Zuidzorg, Veldhoven, the attention shifted a little bit. He raised the question whether it was possible to make predictions about the onset and evolution of dementia using the information obtained from the sensory equipment. The results of my research, which was conducted in order to answer the questions raised by both Aad and Gerard are described in this thesis.

Abstract

The ratio between elderly people in need of care and the working force is in decline. In order to compensate for this loss, we need to seek for technological aids helping people in their daily lives. Elderly suffering from dementia are in need of constant care and attention, something which is becoming increasingly difficult. In this thesis two systems are presented to aid elderly people and care givers, by monitoring the movements of the elderly throughout the day in their home environments.

The first system presented uses virtual fencing to detect whether an elderly is in a potential harmful situation and raise an appropriate alarm if so. Being virtual, these fences can be conditioned to be only active in a specified context.

The second system combines the knowledge gained from observations made on the behaviour of people suffering from dementia together with the behavioural model which can be learned from the user's daily routine and make predictions about the onset or evolution of the disease.

For both systems a proof of concept had been made, using data obtained from a numerical simulation.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

> *When people get older their ability to look after themselves decreases. They start to suffer from both physical and mental discomforts. One example such a of mental discomfort is a group of diseases, which cause the decrease of cognitive capabilities, also known as dementia. People who suffer from dementia need constant monitoring. With an increasing demand on the health-care sector this is rapidly becoming a problem. By exploring new ways of monitoring these people, the health care system might be relieved.*

1.1 Smart Homes

The population in the western world is "greying". In 2001, 17% of the European Union citizens was over 65 and it is estimated that this number will reach 33% by the year 2035 [42]. This demographic trend is already causing problems. The care ratio (the ratio of the number of persons aged between 16 and 65 to those over 65) is naturally in decline. Meaning that there will be less people available to take care for an increasing amount of elderly. We may expect technology to fill the gap which is caused by this decline [35].

A trend which is currently in existence is the introduction of so called "Smart Homes" [35, 34]. Homes rigged with various sensors, monitoring the well-being of its residents. Using the information gathered by the sensors we can apply 'tele-monitoring', remotely monitoring the well-being of the residents, and even provide remote care [54].

Smart Homes have several advantages over traditional medical care. People are monitored constantly so a better insight is gained into the development of a disease. In contrary to the "snapshot" a doctor gets when a patient is visiting for a check-up. Furthermore they also get a chance to monitor the patient in their "natural" surroundings where symptoms may manifest themselves differently [43]. This may result in earlier detection of an illness, making treatments more effective [19] and this eventually may result in better treatment in general [54].

In the future other services can be launched within these Smart Homes, using the already present infrastructure; only extending the benefit of the investment. These services can also be in the direction of Ambient Assisted Living [32]; using information technology to assist people in their own home environment. Ambient Assisted Living is also a research topic supported by the European Union. In their report [45] they state:

> " *Improving the quality of life for disabled and the increasing fraction of elderly people is becoming a more and more essential task for today's European societies. The quality of life of any person, young or old, heavily depends on the efficiency, comfort and cosiness of the place he or she calls "home". Disabled people have specific requirements as for their home environment and its functionalities. For elderly people, home is a place of memories where they spend most of their time. Their demands on their home environment will increase and*

> *change with growing age - especially when their health status starts to worsen. An important aspect for all people having the need to be supported in their daily-life-activities is to remain integrated in social life - despite of their age and existing disabilities. "*

1.2 Dementia

Dementia is an acquired syndrome of decline in memory and at least one other cognitive domain, such as language, visuospatial, or executive function, that is sufficient to interfere with social or occupational function in an alert person [10]. There are many different diseases which can cause the dementia syndrome. The most common ones being Alzheimer disease and cerebrovascular ischemia. Once people start to suffer from dementia there is little hope on a 'cure'. Only 1,5% of cases of mild to moderate dementia are fully reversible [5].

When people suffer from dementia they gradually start to lose all kinds of cognitive capabilities, like short-term memory, attention, language and problem solving. In later stages of the disease people even become disorientated in time, place and even person (they don't know who they are). Often this goes together with more ubiquitous symptoms called Behavioural and Psychological Symptoms of Dementia (BPSD), such as psychosis, depression, agitation, aggression and disinhibition [7].

Patients with only mild symptoms [1] are perfectly capable of living in their own home environment, without constant monitoring from specialist care takers. Studies show that it is both better for them as the health care system in general if they do so [25, 45]. People who live at their own homes are slightly more happy than their counterparts who live in nursing homes and they cost less for society. The study shows that although cost in terms of domicile care naturally raises, the benefits gained from the reduced strain on nursing homes are far greater. People who remain living at home also tend to request less provisions for the disabled. So in all, there is a surplus which can be (partially) used for electronic aiding.

1.3 Dementia and Smart Homes

Although being capable of living on their own, people suffering from mild dementia, may exhibit behaviour which can be a danger to themselves as well as their surroundings (e.g. wandering, forgetting to turn of the stove). In order to assist people living autonomously we can apply different services which assist these people in their daily lives and provide a means for health care agencies to monitor their well-being. A Smart Home environment is suited for this application, because monitoring systems have "the potential to reduce costs and burdens of care giving while increasing safety and autonomy in old age. In the case of dementia, monitoring technologies relieve the care giver from the need to keep a vigilant eye on the elder's movements" [24].

Among others, a product on the market today is the VieDome Platform by Mextal. This system allows for various sensors and actuators to be connected to a central control unit which can be either controlled by the elderly themselves or remotely by a domicile care agency. This platform allows for various services to run on top.

An example of a such service, which targets patients suffering from dementia, aims to monitor the elderly through video telephony on the one hand and physical check-ups on the other. People who are enrolled in the program are able to connect using a video telephony to a central location where a care taker can have a little chat with them and meanwhile check whether the person still behaves normally. Participants are required to contact the service in the morning after waking up. During the day and night care takers randomly drop by in order to check whether the participants are still able to manage themselves.

[1] Tier 2 and 3 from [7]

Although being monitored daily, we still have the ‘snapshot’ situation described in the first section. In the intervals between those check-ups people may still exhibit dangerous behaviour, especially wandering. During the day we may expect the partner to keep an eye out, but in case the partner being away, distracted or sleeping at night we can explore the possibilities of monitoring their behaviour and whereabouts via Real Time Location Sensing-systems. If we can infer a behavioural pattern from the obtained location information, we also might be able to monitor the general conditions of the patient and inform the caregivers if the condition of the patient is changing.

1.4 Problem Definition

In order to create such a system various problems need to be addressed. Since this is a system which is going to be deployed in a real life environment, one needs to look into the various requirements which the system is subjected to. These requirements affect various parts of the system, for instance the Real Time Location Sensing (RTLS) method used. There are various methods available nowadays, differing from system specifications to radio-technology being used. Which one is, given the imposed requirements, the best choice?

Once the whereabouts of the users are determined, one needs to translate their movements over time into a behavioural pattern. These patterns can be very crude taking only the current time frame into account or more sophisticated using state models and probabilistic state transitions. After the behavioural model has been established this model can be used to classify the behavioural pattern.

A final issue which needs to be addressed concerns the installation of the system. It is required that the proposed system is easy to set-up and does not require any technical knowledge nor any detailed spatial knowledge about the site where the system is going to be installed. So a calibration method has to be derived which fulfils these requirements.

1.4.1 Research Aim

The aim of this research is to produce an exploration of the possibilities of various RTLS-techniques and their applicability for the proposed problem. Next to that it is an aim to get insight in different approaches which can be taken to track human movement and translate this into a behavioural pattern, eventually leading to system architecture, algorithm description and calibration method of the proposed system and a proof of concept of the proposed methods.

1.5 Research Questions

1.5.1 Main Question

Looking at the problem definition, several questions can be deduced. First of all the main research question.

> *How can patients suffering from dementia be monitored using real time location awareness and how can care takers be alarmed if the patient behaves oddly?*

1.5.2 Sub Questions

Breaking the main question down into various sub-problems leads to the following sub-questions:

- What are the requirements?
- What are different RTLS-techniques and which is most suitable?
- What does the architecture of the proposed system look like?
- How can the system be calibrated and adapted to the end user's home situation?
- How can the information form the RTLS-sensors be translated into a behavioural pattern?
- How can be the behavioural patterns be classified?

1.6 Structure

1.6.1 Approach

In order to find an answer to the sub-questions above, the following approach shall be taken. First interviews will be conducted with various stakeholders of the project in order to determine the various requirements from the end-user's perspective. Second, a survey of various RTLS techniques will be conducted in order to determine which approach is most suited regarding the system definition and requirements. Once this is determined, any requirements concerning the RTLS method will be taken into account and a system architecture will be proposed. Within this architecture two parts are addressed in depth. First of all the algorithm which is able to classify the user's behaviour. Finally a method needs to be proposed in order to install and initialize the system within the environment of the end-user, again meeting all requirements. A proof of concept will show the applicability of the proposed methods.

1.6.2 Deliverables

- An analysis of different RTLS methods and proposal for a suitable system/method.
- A high level architecture description of the proposed system.
- A description of how to install and calibrate the system at an end user's home.
- A description of an algorithm to track and classify movement patterns, plus a proof-of-concept.

Chapter 2

Requirements

> *A system which is deployed in a real-life environment is always subjected to a large number of requirements. These requirements tell us what functionality the system has to provide and which constraints the system is subjected to. These requirements are gathered through interviews with the project stakeholders. The presented taxonomy is based on the Volere Requirements Specification Template [39].*

2.1 Product Purpose

2.1.1 Problem

The challenge behind the product is described in the first chapter. It attempts to provide a means to asses the behaviour of patients suffering from dementia, who are still living on their own, and assist domicile care agencies in signalling dangerous situations.

2.1.2 Goal

The goal is to design a system which can be easily installed by a person with little technical knowledge in the patients home environment and is able to asses the patients behaviour through a wireless sensor network. If the patient's behaviour differs from his normal patterns or he performs a prohibited action an appropriate alarm is raised, which allows the domicile care agency to signal the problem and take appropriate actions.

2.2 Client, Customer and Stakeholders

2.2.1 Client

The client is Mextal, the developer of the VieDome platform. They provide the platform on which this service needs to be implemented. They can sell this service as an addition on their platform to their clients, domicile care agencies.

2.2.2 Customer

The end-customer of this service are elderly people suffering from dementia. The service is provided to them as part of the care they receive from their domicile care agency allowing them to remain living in their home environment as long as possible.

2.2.3 Stakeholders

An additional stakeholder are the domicile care agencies. They use the VieDome-platform to assist and enhance the care they can provide to their clients, the elderly. They are the ones who have the hands-on experience and are able to indicate what the current market need is.

A second stakeholder is the provider of the sensory equipment as they largely determine the interface between the sensory input and the software.

2.3 Users

2.3.1 Patient

The patient is the main user of the system, although the amount of interaction with the system will be limited, since the patient is suffering from declining cognitive abilities because of dementia. At times they do not know where they are or what they are doing, resulting in potential hazardous situations.

We may expect the patient to be an elderly person and he or she is living inside the environment. Because of the age and the dementia, it will be difficult (if not impossible) to learn the patient how to use the system. So the amount of interaction should be limited, but it would be better if there would be no interaction at all. The sensor network should be able to continuously track the patient and the system performs the assessment of his behaviour autonomous. The only interaction pattern we may expect is when a local alarm occurs. This is an alarm which is not sent to the domicile care agency, but can be used to warn the patient or the partner, for instance by emitting an auditory signal and showing a message on the Home Device. Patients can be trained to move out of the area if they hear such a signal, allowing some control over their movements. We also may assume the patient having other disabilities hampering his movement. We should take this in consideration when we require the patient to respond on an alarm, making sure that we are not too soon raising an alarm to the domicile care agency.

2.3.2 Partner

We can assume the partner having full cognitive abilities. They are the first to watch over their partner who is suffering from dementia. Still having good cognitive abilities, the partner is able to interact with the VieDome system, keeping in mind that he or she most likely is also an elderly. So the interaction patterns should not be complex and he or she might also suffer from limited mobility. We also may assume the partner to be living in the same environment as the patient.

It is of importance to know whether the patient is looked after by the partner, or that he is alone. Therefore the partner should also be continuously monitored by the wireless sensor network.

2.3.3 Care takers

Care takers are employed by a domicile care agency. They are experts on helping elderly people with their daily routine and also have a background on the symptoms and risks of dementia. They are not constantly around and respond on an emergency. In order to detect the presence of a care taker the system must also be able to monitor their movements. As soon as a care taker is present we may assume that the patient is looked after thoroughly.

2.3.4 Visitors

Visitors are mostly friends or relatives visiting the patient and his partner. We cannot assume that their visits will be frequent, although this may be the case. They have no expertise on taking care of demented people. So we cannot assume thorough supervision, although we may expect them to look after the patient. Which gives them basically the same status as the partner. Because their visits are infrequent we cannot require constant monitoring of their whereabouts by the network.

2.3.5 Operators

Operators reside at a call centre on a central location. Their task is to monitor the various VieDome systems installed at the user's homes. They receive calls, interact with patients and receive alarm messages. They are the ones who will signal a care taker to take action. They are only trained to use the system, they have no technical nor a medical background, although there is always medical assistance present at the call centre.

2.3.6 Technicians

The technician is responsible for installing the system in the user's home. They are volunteers who are trained to perform the necessary tasks. They do not have much additional technical background and are not familiar with the inner workings of the system. Furthermore their time is limited. They only have a few hours for each system to do the installation and calibration.

2.4 Mandated Constraints

2.4.1 Solution Constraints

The solution must be implemented on the existing VieDome platform. The central unit consists of a personal computer running Windows Media Centre Edition, which can be extended with additional interfaces and software.

The hardware used for the calibration process must be portable and should be usable by a technician which has little background knowledge about the inner workings of the system.

2.4.2 Implementation Environment

The sensor network must be installed within the user's home environment with as little alterations on the local infrastructure as possible. It is, for instance, not possible to create additional wiring inside the walls.

A technician should be able to complete the installation and calibration within two hours.

2.4.3 Partner Applications

The system is implemented as a service on the VieDome platform. The software will run concurrently with other services on the same platform. An additional interface can be installed in the central unit to allow for communication with the wireless sensor network.

2.4.4 Off-the-shelve Systems

It uses off-the-shelve wireless sensor technologies. Currently there are various commercial solutions available for Real Time Location Sensing. The cost of purchasing and maintaining the technology should not exceed the cost of the current service.

2.5 Relevant Facts and Assumptions

2.5.1 Facts

Within a social context, wearing a tag can be regarded as a stigma. Other people can see that the patient needs help, which can affect the patients pride. It would be recommended to find a solution where the tag can be camouflaged, for instance by putting it inside a watch.

Elderly also tend to enrol into the program, because of social pressure from their surroundings (e.g. their children). Although freely enrolled they do not see the benefits of the solution and tend the be careless regarding the use of the system. They forget to wear their tag, or deliberately refuse to wear it.

Finally there are privacy concerns. People may feel uncomfortable when constantly monitored, especially because it is 24 hours per day. For security and privacy purposes the data gathered by the system should be stored locally and should not be distributed over any network.

2.5.2 Assumptions

The software component which provides the interface between the software and the hardware of the wireless sensor network is provided by the manufacturer of the network.

The interface returns a set of coordinates for each tag at a given interval. All coordinates are expressed in the same coordinate system.

2.6 Functional Requirements

The system should be able, using a wireless sensor network, to continuously monitor the location of the patient, his partner and any care givers within the home environment of the patient.

The system should be aware of the context in which the patient is residing, meaning that it should include the current day and time and other people in the vicinity of the patient.

If the patient performs an action or resides on a location which might be potential harmful an appropriate alarm is raised, either locally (to alarm the inhabitants) or globally (to alarm the domicile care agency).

The wireless sensor network should signal the users when a the signal of a tag drops, either because the patient moves out of reach or the battery of the tag is empty.

The system should be able to infer a behavioural pattern over the course of time and is able to compare behavioural patterns acquired within varying intervals.

2.7 Usability Requirements

The system should be usable for elderly people who are not proficient with computer use, so the interface should be kept as simple as possible. For the patient the system should be ubiquitous.

In the environment of the call centre the interface of this particular service should be in line with the interface of the existing system, making it more easy for operators to learn to use the system.

2.8 Operational Requirements

The system should have an up-time of 24 hours per day. If the signal of a tag is disrupted, the system should raise a warning. If it happens because of an empty battery it would be convenient if the clients themselves can replace the battery.

The software in the home unit should be remotely maintainable.

Chapter 3

Real Time Location Sensing

> *To make the system context aware, we need to feed it with input concerning the 'state' of the environment. In our case, we want to know where the resident of our "Smart Home" are residing and what they are currently doing.*

3.1 Introduction

In order to provide context awareness to a system, we can infer many characteristics of the user. For instance we can measure his vitals, perhaps to detect whether he is agitated. If we want to know whether an elderly can get himself into trouble, we should first infer whether he is in a situation where a problem might occur. If he is just sitting in a chair or lying in bed, there is little reason for concern. It becomes a different situation when the elderly person gets up at night and starts wandering around the house.

So we should keep an eye on his current location. Where is he? And is he not in a location where he should not be? In order to detect the current location of our subject we can apply various techniques including pressure mats in floors [44] and camera systems [41]. But we could also install an array of binary sensors on objects themselves, for instance on kitchen cabinets, chairs or water taps [53].

Keeping in mind the requirements, we should find a solution that is as generic as possible, because we need to be able to apply it in many different environments, with as little alterations as possible to that environment. A good candidate is a range of techniques referred to as 'Real Time Location Sensing'.

These systems (mostly) consist of a sensor network which keeps track of a series of beacons (or tags) worn or attached to the object we want to track. The distance between the sensor and the tag is continuously measured and by combining the information of different sensors, the position of the tag in relation to the sensors in the network can be inferred. The amount of sensors required to track a user in his own apartment can be as little as four and require as little as four power outlets to function, provided their communication is wireless.

In the last couple of years many different methods have been proposed and different systems have been build, both for research as well as commercial purposes [20, 26]. Systems differ, among many other factors, in the technology used, calculation algorithms, the amount of sensors needed, the scalability and their cost.

3.2 Physical Properties

As stated before, currently there is no 'best' solution in existence. Many different systems have been proposed all having their own strengths and weaknesses. Systems vary with regard to their range, scalability, cost and precision.

3.2.1 Range

An important differentiator between various systems is the range in which their sensors operate. Some signals travel further than others. Consider for instance radio waves, which can travel for kilometres compared to ultrasound waves, which have a much shorter reach. In some cases, especially when using light as signal transmitter, a direct line of sight is needed between transmitter and receiver. So the environment in which the system is deployed is also an influence on the range of the system.

3.2.2 Scalability

Scalability is an indication of how easy the system is extendible. Either by extending the range of the sensors or the amount of sensors being tracked. A system which requires a very dense sensor network needs a lot of additional sensors to extend its range by only a fraction compared to a system which spans tens of meters with a single (or small group) of sensors. Another aspect of scalability is the amount of tags that can be tracked simultaneously by a single sensor. Some systems can track thousands of tags, whereas others only tens or fewer.

3.2.3 Cost

Different techniques need different hardware which of course has a different price tag. Techniques like passive RFID, which require less hardware, are cheaper than Ultra Wideband, which require tags having a battery and are able to transmit a signal itself. Another issue is the amount of sensors needed. It makes a difference whether you need only a small number of sensors (four to ten) using an Ultra Wideband system [27] or a large array when using Ultrasound [26].

3.2.4 Accuracy and Precision

Accuracy is the smallest distance a system can tell apart two separate objects [40]. The precision of the system is the percentage of measurements which actually fall within a certain accuracy. For instance a common GPS device has an accuracy of 10 meters with a precision of 95%, where as more expensive equipment achieves an accuracy of 1-3 meters with a precision of 99%.

Accuracy and prediction are a bit of a trade-off. When the one increases, the other one generally decreases. It depends on the application of the system what is most important. It should also be noted that if the accuracy of the system increases, this often leads to a decrease of the system's range.

3.3 Data Properties

In addition to the physical properties regarding the sensors, there are also some differences in how the obtained data can be handled. For some hardware this is a free choice, but other solutions impose constraints on how the data should be handled.

3.3.1 Physical or Symbolic Locations

A location system can return two kinds of location descriptions. Either physical or symbolic locations [20]. Physical locations are expressed in quantitative measurements. For instance, GPS returns latitude and longitude expressed degrees combined with a height indication in meters. Symbolic locations are more abstract. They encompass an idea where something is located. For instance: in the kitchen drawer, near the train station or in the fifth room on the left.

A system providing physical locations can usually be augmented by additional data so that it is also able to provide symbolic information. For instance, a system based on GPS can access a separate database that contains the positions and geometric service regions of other objects to provide applications with symbolic information [8].

The spatial resolution of the physical location system is of great influence of the granularity of the symbolic representations. If we have a GPS system which has an error margin of 10 meters, it is useless to make any predictions about a person standing in a room which is only a couple of meters wide.

Transforming physical location information into symbolic locations is pretty straightforward. Translating symbolic locations into physical locations can be more of a problem. Consider for instance a system using IR-sensors to detect the presence of a single person in a room. We now have the obtained the symbolic location 'Person A is in room B'. However, it is impossible to infer whether the person is sitting at his desk in a corner or walking around. We can only make an estimate of his physical location which will roughly have a spatial resolution the size of a room.

3.3.2 Absolute or Relative Positioning

An absolute location system uses the same coordinate space for all located objects. For example all GPS receivers will use latitude, longitude and altitude to represent their locations. Two GPS receivers placed on the same location will (given an error margin) yield the same result. In a relative system there is no 'greater' frame of reference. Objects are located in relation to one another, so each object has his own frame of reference. Consider a radar system. If a radar picks up a signal it returns the angle and distance of that signal.

If one knows the position of the radar in the global frame of reference (e.g. his GPS position) one can transform a relative location into an absolute location. Of course the opposite is also possible. If one knows the global coordinates of two objects we can calculate how the relate to one another. The transformation fails however if we would have relative locations and mobile reference points. In this case, there is no fixed point of reference with known absolute location. Systems which use their own sensor array mostly use relative positioning and need to be calibrated to match the (absolute) properties of the environment.

3.4 Location Sensing Techniques

Table 3.1 gives an overview of the common approaches to location sensing and their properties. As the table shows, there are differences between the various technologies.

WiFi (IEEE 802.11)/Zigbee (IEEE 802.15)

Using wireless network traffic (either via the WiFi- or Zigbee-protocol) we can deduce the location of a beacon by measuring the signal strength between this beacon (e.g. a cell phone or laptop) and the access points. If the beacon is further away from the access point, the strength of the signal arriving at the access point decreases. Using this signal strength indication we can calculate the distance to each access point and using triangulation methods we can find the position of the beacon. Unfortunately this approach suffers a lot from interference. If for instance a person steps between the beacon and the sensor (access point), the signal strength has to pass an additional obstacle and will suffer from an additional drop in strength. This effect has great influence on the achieved accuracy. It can be countered using fixed reference points (fixed beacons) to correct for interferences. We can constantly monitor the signal strength arriving at these known locations and use this information to create a map of the interference pattern. Using this map we can correct the received signals from various beacons [33]. This, however, makes the infrastructure more complex and dependent on the placing of these

RTLS Type	WiFi	UWB	Passive RFID
Cost	Medium–High	High–Very High	Low
Power Requirement	High	High	Low (Induction)
Battery Lifespan (yrs)	3–5	3–5	N/A
Range[a]	60–350 m	up to 60 m	10–15 m
Accuracy	30 cm–10 m	30–150 cm	5–10 m
Continuous Monitoring	Yes	Yes	No
Dimensions	2D	3D	2D
RTLS Type	Infrared	Ultrasound	
Cost	High	High–Very High	
Power Requirement	High	High	
Battery Lifespan (yrs)	4–7	1	
Range[b]	15 m[c]	1,2 m	
Accuracy	7–12 m	3–9 cm	
Continuous Monitoring	Yes	Yes	
Dimensions	2D	3D	

[a] Only indoors
[b] Only indoors
[c] (Combined with RF, 250 m)

Table 3.1: Different approaches to real time location sensing. Adapted from [1, 26, 46].

fixed beacons. If the infrastructure changes the whole system has to be recalibrated, which is a costly operation in terms of computational time [26].

Another method of determining the location of a beacon using WiFi, would be to take a similar approach as systems using Ultra Wideband. These systems broadcast a very short pulse and capture the shift in time of arrival between various sensors, very similar to GPS. Being independent of signal strength solves the problem of interference in a dynamic environment.

Ultra Wideband

Ultra Wideband (UWB) is a technology developed to allow for wireless applications demanding high bandwidth (e.g. wireless displays, wireless USB). Instead of normal RF-technologies which send packages in serial, UWB sends packages spread out over the a large bandwidth in parallel. It uses very short packages (only a couple of nanoseconds) reducing the chances of interference. RTLS systems based on UWB determine the distance between sensor and beacon by sending a short package from sensor to beacon and back.

The position of the beacon can be determined in two ways. Because of the short pulse there is little chance of interference from any reflections of walls and other objects, so we can use the angle of arrival as an indication of the direction from which the beacon is transmitting. Furthermore, the time that it takes for this package to travel is an indication for the distance. UWB does not suffer from interferences as signal strength does not matter and packages can travel through objects like walls. The drawback of UWB is the fact that its range is limited due to FCC regulations and it is still quite expensive.

Passive RFID

Passive RFID (sometimes also referred to as Near Field Communication) uses a proximity method to determine where tags are residing. It can determine where a tag is by checking which beacon(s) are near enough to pick up the signal. The great advantage of passive RFID is the fact that the tags are powerless, making them very cheap and last almost forever. Problem is that it is not very accurate (since it is proximity based) and does not have a large range.

Infrared

Using infrared technology, people are equipped with infrared signal transmitters which broadcast an unique code, picked up by sensors deployed on location. An implementation of such a system is the 'Active Badge'-system [52]. Users of this system carry a IR-transmitter which's broadcast is picked up by sensors in the area. The system is proximity based, so it only infers which sensor is currently picking up the user's signal. Combining this with known sensor locations, one is able to determine roughly where a user is residing.

Another system using IR is 'ALTAIR' [41]. This system uses multiple wide-angle cameras with IR-filters to detect a blinking IR-badge in the view of two or more camera's. Combining the location of the IR-led on each of the cameras together with the camera's parameters (location, field of view, etc.) the location of the badge can be calculated.

The biggest drawback of IR systems is the fact that the require a direct line of sight between the badge and the sensor, since they use light as the medium to transfer information. A thin layer of clothing is already enough to disrupt the signal, making them unusable in an environment where there are walls and such between the sensor and badge.

Ultrasound

Another way of inferring the location of a specific person or object is by using ultrasound. Systems like 'Cricket' [36] and 'Active Bat' [16] use ultrasound waves and the time of arrival of those waves to determine the position of the transmitter.

Ultrasound solutions have the advantage that high accuracy can be obtained. Active Bat has an accuracy of 9 centimetre for 99% of the time [26]. Unfortunately this comes at a cost. The range of such systems is very limited (around 10 meters) and a large sensor array is needed for accurate measurement. Furthermore in a dynamic environment, sound pulses reflecting from walls and objects may disrupt the tracking and there can be only one tag broadcasting at any time, this limits the number of maximum tags which can be tracked.

3.5 Discussion

But what is the best suited method? This depends on the purpose of the system and the corresponding requirements. Table 3.1 shows some of the most common types of RTLS-systems and their (generalized) properties.

Systems using passive RFID techniques are cheap, tags cost as much as a couple of cents and readers around $150,-. As the tags are passive, they do not have their own power source, giving them almost infinite life. But this also comes at a cost. Since they are passive, a strong signal is needed from the reader to power the tag, consuming most of the energy. So the returned signal strength is low [3], making it unreliable for signal strength measurements and thus localization, because we cannot infer a signal strength. The only remaining possibility for localization is proximity based [3]. If a tag is within the (limited) range of a sensor, we can make some assumptions on its location. Mostly these systems use a number of sensor placed around strategic locations, so the system is able to detect any user that comes near. Being linked to a location, these systems return symbolic locations.

Infrared methods use an IR-emitting tag who's light is captured by a camera or sensors. Using the multiple cameras and their parameters, we are able to infer the location where the tag is located, allowing for physical positioning. This is, however, not very accurate with an error margin of 7 to 12 meters. Using only sensors, we can detect only proximity of tags. Finally the requirement of a direct line of sight is also a big drawback.

Ultrasound is very accurate, with an error margin of only a couple of centimetres. However, in order to achieve this, one needs a dense sensor network [26], hampering the scalability of the system. Besides that, ultrasound systems are quite suitable for indoor location sensing, provided you do not need to track a lot of tags simultaneously.

Signal strength measurements can be a good solution to the problem, provided we make use of reference beacons. Otherwise, in a highly dynamic environment, the accuracy drops into the range of several meters. The advantages of using WiFi is that there is a fair chance an infrastructure is already present and common devices like cell-phones and PDA's are nowadays often equipped with WiFi-connectivity, making it a simple and cheap solution to implement.

The best solution given the requirements of the previous chapter is to use an Ultra Wideband/WiFi approach in which the time of flight is calculated. These systems achieve high accuracy and precision, are able to track many tags at once and are easily extended by adding additional sensors. Unfortunately these systems are still very expensive and often need a physical wire between the various sensors to synchronize their internal clock.

Chapter 4

Virtual Fencing

> *A system is designed which allows for virtual fences to be set-up and enforced. Although simple by design, it is already a quite powerful solution allowing for a care taker to enforce limitations on the patients whereabouts, which only apply in a specific context and are otherwise ignored.*

4.1 Introduction

A simple approach to the proposed problem of keeping an elderly person out of dangerous situations would be to constrain the area in which the patient is able to reside, keeping him only in a safe area where he is unable to harm himself. For instance the living- or the bedroom. If a patient needs to go elsewhere he needs to be guided by either his partner or a care taker.

The most direct approach to constrain the patient would be to put him in a room and lock the door, but that is not very friendly. You make the patient a prisoner in his own home and it is a nuisance to his partner or other care takers. Therefore we can use virtual fences. These only exist in a virtual environment: the topology map used in the location awareness system.

The use of virtual fences has several advantages. First and foremost, the patient is not locked in. There are no doors and such constraining his environment, so he does not get the impression of being a prisoner. Second, being virtual, it is very easy to make these fences conditional. They only exist for that particular patient and not for any other individual.

If we take it one step further, we can also introduce conditions based on time and the presence of other individuals or even past activities. For example, some fences only exist during a specific time period. Consider a rule which allows the patient only to be in his bedroom and on his way to the toilet during the night. We can also determine the fences depending on the presence of other persons. If the partner or caretaker is present the patient is allowed to enter the kitchen, which is otherwise prohibited.

4.2 Topology

Using only virtual fences, we are not interested in the topology of the environment. Marking zones which are prohibited is enough, since we are only interested in the areas where the patient can or cannot go. It is not needed to differentiate the areas from one another or having the areas map to to the topography of the house. A risk of this approach is that for each rule a separate fence has to be established, making the installation process very cumbersome.

Fences can be expressed using either a closed polygon indicating an area which is prohibited or an open polygon which acts as a border. A risk of the using only borders is the fact that due to measurement errors it might be possible for the patient to slip past the border. For instance, if we place a border between two door posts and due to a measurement error (which is on average 30 cm) not the whole of the door is covered or as soon as the patient walks by the measurement go ‘through’ the wall and past the boundary, it is possible that the patient slips past. Creating a no-go area in the corridor behind the door makes it much harder to slip past.

Another solution would be to indicate only the allowed areas. Whether to use ‘no-go’ or ‘go’-area, depends more or less on what the technician who sets up the system finds most convenient. Using logical negations we can turn a ‘no-go’ into a ‘go’-area.

The tags which are read by the sensor are classified into one of two roles. A tag belongs either to a ‘patient’ or ‘care taker’, regardless if this is the partner or somebody else. This discrimination is needed to prevent the system being fooled when there are two patients in the same area. The system might believe that there is no danger, because there are is somebody near each of the patients, but it is to be expected that both patients cannot correct each other.

4.3 Calibration

Calibrating the system is done by setting up the fenced areas. A technician uses a pocket computer which also has location awareness to indicate the corner points of a fenced area, resulting in a closed polygon made out of coordinate pairs. He then either indicates this as ‘go’ or ‘no-go’ area and gives it an unique identification. The amount of areas which need to be created depends on how the rule set is made up. One can imagine if one wants to capture many different situations a larger number of areas is needed, compared to if one reuses the same areas for each rule. Using logical and’s and or’s it is of course also possible to combine multiple areas into a more complex area, which in turn can be used as a conditional.

4.4 Architecture

Figure 4.1 shows the architecture of the proposed system. It consists of four separate components: *Patient Tag*, *Calibration Device*, *Wireless Sensor Network* and *VieDome Home Device*. These components communicate through wireless connections.

4.4.1 Patient Tag

The patients tag is a piece of hardware which is largely provided by the RTLS manufacturer and is worn by the patient, partner or caretaker. Many of these tags can be extended with an actuator, for example a speaker, to give feedback to the tags wearer. This allows us to raise a local alarm signalling the patient that he is in an area where he should not be or a partner/care taker if the patient is in trouble.

The signal sent by the RTLS tag can be picked up by the wireless sensor network.

4.4.2 Calibration Device

The calibration device is a separate piece of hardware which is used by the technician to calibrate the system after installation. In this case, this means that he uses the device to indicate the corner points of the various fences and supplies them with names. In order to do this, this device should also be able to determine its position in the sensor network. So it both contains a tag, as well as an interface to obtain its own readings. Furthermore it should contain an input modality to enter the name of the fence specified. If all fences are created, this information can be uploaded into the VieDome Home Device.

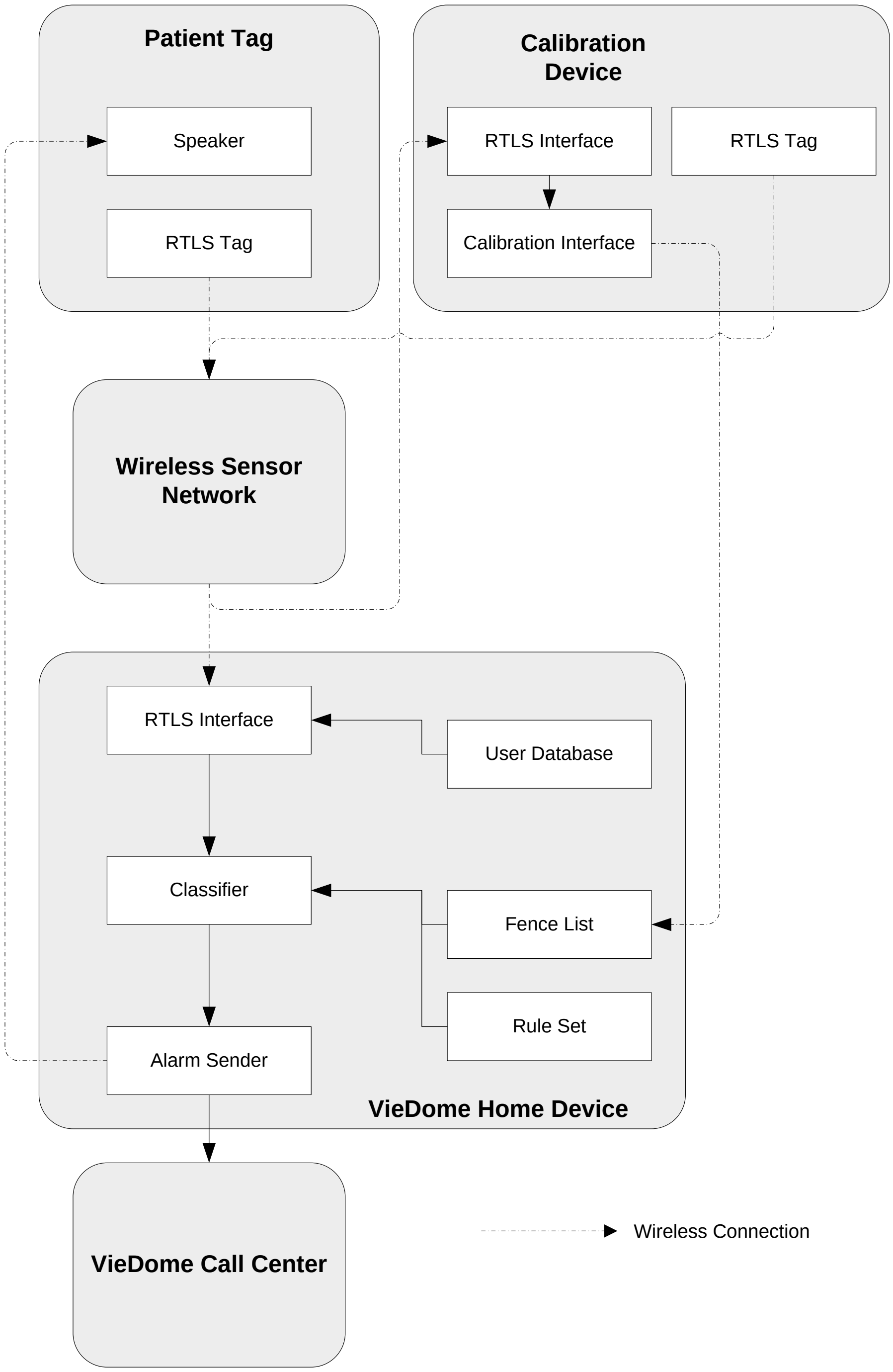


Figure 4.1: Architecture of the Virtual Fence system

4.4.3 Wireless Sensor Network

The wireless sensor network is a off-the-shelve solution provided by a separate manufacturer. This will include the sensors, the tags and an interface to allow communication between the software and the sensors.

4.4.4 VieDome Home Device

The heart of the system resides on the VieDome Home Device. The location information obtained by the wireless sensor networks are received via the RTLS interface. This information is enhanced with additional information, specifying whether a specific tag belongs to a patient or a partner/care taker. This information, combined with the fence list and the rule set, can be used by the classifier to determine whether any of the rules apply. If so, the alarm sender can either send an alarm to a (number of) local tags or to the VieDome Call Centre.

4.5 Classifier

The classifier is an evaluator of the logical implications specified in the 'Rule Set'. Let $\mathcal{R}$ be the system defined as a conjunction of rules, $\mathcal{R} = \{r_1 \wedge \ldots \wedge r_i\}$, where $i = 1 \ldots m, r_i \neq r_j$. Each rule is an implication consisting of a conjunction of 'State predicates' and 'Constraint predicates' in the antecedent and a single 'Action' in the consequent. Let r be a rule, it is defined as $r = (s_1 \wedge \ldots \wedge s_j) \wedge (c_1 \wedge \ldots \wedge c_k) \rightarrow a$, where $S = \{s_1, \ldots, s_j\} \subseteq \mathcal{S}, j = 1 \ldots n, s_i \neq s_j$, $C = \{c_1, \ldots, c_k\} \subseteq \mathcal{C}, k = 1 \ldots p, c_i \neq c_j$ and $a \in \mathcal{A}$. The sets $\mathcal{S}, \mathcal{C}$ and $\mathcal{A}$ are defined below.

All predicates take their function symbols from three sets: $\texttt{patientId} \in \mathcal{P}$, $\texttt{careId} \in \mathcal{T}$ and $\texttt{areaId} \in \mathcal{F}$, where $\mathcal{P}$ is the set containing the identification code of all patients' tags from the 'User Database', $\mathcal{T}$ is the set containing the identification code of all care takers' tags from the 'User Database' and finally $\mathcal{F}$ contains the identification tag of all the fenced areas from the 'Fence List' (See figure 4.1). These function symbols are used to quantify the predicates.

It should be noted that although we have the assumption that a predicate can only exist once in a single rule r, predicates which have different function symbols are not equal. So the set

$$S' = \{\texttt{inAreaPatient(x,y)}, \texttt{inAreaPatient(x,z)}, \texttt{inAreaPatient(y,z)}\}$$

is valid, but

$$S' = \{\texttt{inAreaPatient(x,y)}, \texttt{inAreaPatient(x,y)}\}$$

is not.

4.5.1 State predicates

Function Name	Description
inAreaPatient(patientId,areaId)	True iff the patient resides in the area.
inAreaCareTaker(careId,areaId)	True iff a care taker resides in the area.

Table 4.1: Predicate functions for virtual fencing.

In this set $\mathcal{S}$, predicates are defined which tell us something about the state of a single patient or caretaker. This can either be an indication of his location or any other feature which can apply to an individual. For instance, if we would have had a more advanced sensor model measuring the vitals of our users, we could define predicates indicating whether a specific user is excited or hungry.

In our case we can only make statements about the location of a specific user. Therefore the set only contains both the predicates listed in table 4.1 and their negations,

$$\begin{aligned}\mathcal{S} = \{&\texttt{inAreaPatient}(\mathit{patientId}, \mathit{areaId}), \neg\texttt{inAreaPatient}(\mathit{patientId}, \mathit{areaId}),\\ &\texttt{inAreaCareTaker}(\mathit{careId}, \mathit{areaId}), \neg\texttt{inAreaCareTaker}(\mathit{careId}, \mathit{areaId})\}.\end{aligned} \tag{4.1}$$

inAreaPatient and inAreaCareTaker

The predicates `inAreaPatient`(*patientId*, *areaId*) and `inAreaCareTaker`(*careId*, *areaId*) yield true if and only if the position coordinates of the patient with *patientId* or the care taker with *careId* fall within the polygon which bounds the area identified with *areaId*. Since in its current form, the antecedent of the rules indicate when an alarm should be raised, this function can be used to indicate a 'no-go'-area. If one wants to specify an area which is allowed one can apply a negation, e.g. $\neg\texttt{inAreaPatient}(x, y)$.

4.5.2 Conditional Predicates

Function Name	Description
alone(patientId)	True iff the patient is alone, no care taker is in the same area.
time(begin,end)	True iff the current time of day is between *begin* and *end*

Table 4.2: Predicate functions for virtual fencing.

The set $\mathcal{C}$, contains predicates imposing global restrictions on when a particular rule should be applied. These predicates do not concern the individual user, but either concern environmental variables such as the current time of day or the state of multiple users (e.g. the presence of multiple users in the same area). In this system we define two functions shown in table 4.2 and their negations.

$$\mathcal{C} = \{\texttt{alone}(\mathit{patientId}), \neg\texttt{alone}(\mathit{patientId}), \texttt{time}(\mathit{begin}, \mathit{end}), \neg\texttt{time}(\mathit{begin}, \mathit{end})\}. \tag{4.2}$$

Alone

This predicate yields true if the patient with *patientId* in the current area is not accompanied by a caretaker in that same area. It is specified as:

$$\begin{aligned}\texttt{alone}(\mathit{patientId}) = &\forall_{areaId\in\mathcal{F}}\forall_{careId\in\mathcal{T}}(\texttt{inAreaPatient}(\mathit{patientId}, \mathit{areaId})\\ &\rightarrow \neg\texttt{inAreaCaretaker}(\mathit{careId}, \mathit{areaId})).\end{aligned} \tag{4.3}$$

Time

This predicate yields true if the current local time is in the area specified by *begin* and *end*. It is specified as:

$$\texttt{time}(\mathit{begin}, \mathit{end}) = (\mathit{begin} <= \text{currentTime} \wedge \mathit{end} > \text{currentTime}), \tag{4.4}$$

where *currentTime* equals the current local system time.

Function Name	Description
globalAlarm(msg)	True iff a global alarm is raised with message *msg*
localAlarm(msg)	True iff a local alarm is raised with message *msg*

Table 4.3: Action functions for virtual fencing.

4.5.3 Action

The consequent of each rule consist of an action raising an alarm, either globally or locally, with a specified message *msg*.

$$\mathcal{A} = \{\texttt{globalAlarm}(msg), \texttt{localAlarm}(msg)\}. \tag{4.5}$$

A global alarm is sent to the monitoring unit in the call center of the domicile care agency. A local alarm is only sent to the VieDome Home Unit, accompanied by an auditory signal on the patient's tag.

4.6 Algorithm

Input: Set of x,y-coordinates of all tags in bounds of the sensor array.
Output: An (empty) set of alarm messages.

```
foreach Rule r_i do
    doAction:= true;
    foreach Predicate p_j from r_i do
        result ← evaluate(p_j);
        if ¬result then
            doAction:= false;
        end
    end
    if doAction then
        executeAction(a from r_i);
    end
end
```

Algorithm 4.1: The virtual fencing algorithm

As long as the system is running, the tags of various users will be polled with a certain interval. After the coordinates are obtained, the system is evaluated $\mathcal{R} \cup S' \cup C' \models A'$ and $A' \subseteq \mathcal{A}'$. S', C' and $\mathcal{A}'$ are equal to S, C and $\mathcal{A}$, but having their various function-variables initialised.

The evaluation function is described in algorithm 4.1. This algorithm checks for each of the rules whether the antecedent is true and if so, the corresponding alarm is raised.

4.7 Example

This section contains an example on how rules can be created. Assume we have an environment as shown in figure 4.2. It contains a kitchen, living room, bedroom, hallway, toilet and a bathroom. We have defined two different fences: the whole kitchen and an area near the front door. In this area there lives one patient wearing a tag with id 'p1' and his spouse who takes care of him, wearing a tag 'c1' Now let us assume that we have defined two occasions in which there is potential harm for our patient.

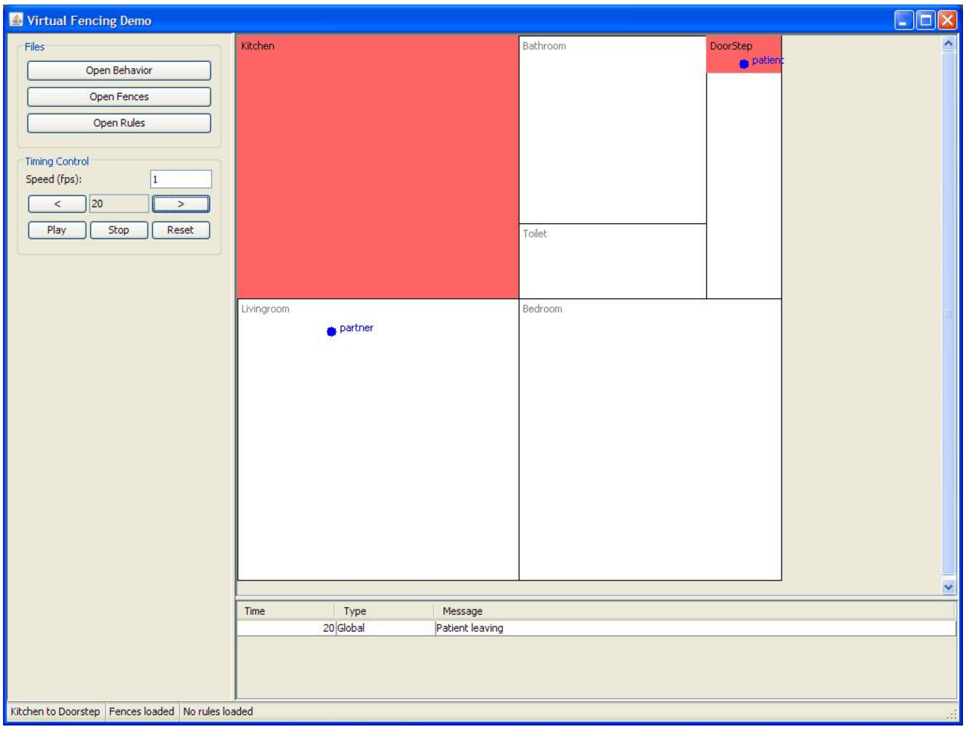


Figure 4.2: Example Environment

Either when he is alone in the kitchen and if he walks up to the front door at night. We can specify our system as $\mathcal{R} = r_1 \wedge r_2 \wedge r_3$, where

$$
\begin{aligned}
r_1 =& \texttt{inAreaPatient}(\texttt{p1}, \texttt{kitchen}) \wedge \texttt{alone}(\texttt{p1}) \rightarrow \texttt{localAlarm}(\text{Alone in kitchen}) && (4.6)\\
r_2 =& \texttt{inAreaPatient}(\texttt{p1}, \texttt{front\_door}) \wedge \texttt{time}(23:00, 0:00) \rightarrow && (4.7)\\
& \texttt{globalAlarm}(\text{Patient goes out at night}) \\
r_3 =& \texttt{inAreaPatient}(\texttt{p1}, \texttt{front\_door}) \wedge \texttt{time}(0:00, 8:00) \rightarrow && (4.8)\\
& \texttt{globalAlarm}(\text{Patient goes out at night}).
\end{aligned}
$$

Because of the definition of the `time`-function, we need to split the time interval at the beginning of a new day into two different rules. In this system

$$S' = \{\texttt{inAreaPatient}(\texttt{p1}, \texttt{kitchen}), \texttt{inAreaPatient}(\texttt{p1}, \texttt{front\_door})\}$$

,

$$C' = \{\texttt{alone}(\texttt{p1}), \texttt{time}(23:00, 0:00), \texttt{time}(0:00, 8:00)\}$$

and

$$A' = \{\texttt{localAlarm}(\text{Alone in kitchen}), \texttt{globalAlarm}(\text{Patient goes out at night}).$$

4.8 Discussion

Virtual fencing is a simple approach. There are no complex computations involved, making it a very fast algorithm, which has no problem running on a platform with already many concurrent services present. We should consider the processing time of the data received from the location sensors, because we cannot allow the algorithm to raise an alarm minutes after an accident occurs.

The usage of boolean rules makes the behaviour of the algorithm very predictable. There is no learning process involved. The rules which are stored in the system are either true or false, there is no fuzzy logic or probabilistic reasoning, which increases trust in the reliability of the system.

Giving the administrator full control over the system's behaviour also has a drawback: it makes it more complex to set up the system, because every aspect of its behaviour has to be specified. A domain expert must set up each of the rules and their corresponding fences. This raises the requirement of a very intuitive interface for this set up, as we may expect the domain expert to be not a computer expert.

These rules must be known before the installation technician can start the calibration process. Otherwise, there is no structure present which guides the technician, because there is only a link between the rules and the fences and not between the fences and the topology of the apartment.

Furthermore, the rule set is quite rigid. Once installed it may prove difficult to alter the rule set. If many rules depend on each other one cannot simply alter a rule without jeopardizing the rest of the rule set and if a new fence is needed a technician had to go on site to take new measurements. The latter can be solved by creating a virtual map (or topology) of the full apartment at the first install, making it simple to add additional constraints, since they can be drawn into the picture.

A thing that is missing in this approach is some form of memory. Each rule is checked against the current situation regardless of any previous states. Making the system less aware of the context and the behavioural patterns of the patient. Active monitoring is needed to see whether the applied rules still hold. For instance if the patient has the habit of walking towards the door, but he does not go outside, the fence which detects if the patient approaches the door might be triggered and an alarm is raised. In this case, we can assume that it is unnecessary. It is just a habit of the patient which is completely harmless. If a system would have a memory we could, for instance, create a rule which states that the patient must be returned to any other room within a certain time frame. If not we can still raise an alarm.

Another option would be to infer behavioural patterns using stochastic models like Hidden Markov Models [9, 17, 31]. These models can depending on a sequence of actions, make a more high level prediction on the activities the user is performing. Depending on the derived activities one can then asses whether this is appropriate behaviour. Being stochastic these models can adapt to an individual, matching their behavioural patterns. However, at the moment, the performance of these models is too low to be a reliable option in a real life environment. Most of these models have an accuracy of 75% when detecting low level behavioural actions, like walking or running, and their recognition rate drops when more complex actions have to be recognized.

In short, this approach is promising and applicable in a real life environment. Especially if a fixed rule set can be created which can apply for all patients, or perhaps a couple of rule sets which apply for groups of patients. It would then require some effort at first, but results in a generic solution which applies in every situation. If not, the effort required to set up the system and rigidity of the rule set would be too limiting. In order to counter these problems we might investigate the possibility of solutions including a rule set which takes the user's daily routine into account as well as some inference mechanism to adapt the rule set on the behavioural model.

Chapter 5

Predicting the Evolution of Dementia

> *By constantly tracking the movement of our subjects we can gain insight into their daily activity patterns. If we can link these activity patterns to typical behavioural patterns associated with dementia in various stages, we might be able to make predictions about the onset or evolution of the disease for a single individual.*

5.1 Introduction

With the increasing emphasis on keeping elderly people with impaired cognition to remain living in their own homes, allowing them 'to age in place', we should wonder whether it is enough to just keep an eye on them. Current systems under development mainly "emphasize managing risk of injury or death posed by the disease" [24]. They act as a safeguard preventing elderly persons from injuring themselves. But since we are already constantly capturing data about their whereabouts, would it not be possible to infer behavioural patterns and using these patterns to make predictions about the onset or evolution of their condition? Because it is important to identify dementia as early as possible, making more efficient treatment possible [6, 47].

5.2 Related Work

Suzuki et al. have conducted an experiment in which they monitored the activities of a group of elderly persons with impaired cognition (Mini Mental State Examination[1] < 24) versus a control group (MMSE ≥ 24) [47]. They supposed that in-house movement patterns could be an indication for early dementia.

They installed IR-sensors in the homes of their subjects consisting of a group of 14 elderly ranging from 67 to 90 years and monitored their movements around the house for three months. The recorded positions over time were sent to a central computer for further analysis.

They identified four different behavioural patterns: (1) going out - the subject has left his home, (2) coming home - the subject re-enters his home, (3) sleep onset - the subject goes to sleep and (4) interruption of sleep - an activation of any other sensor than the one in the bedroom, during night time. They analysed the number of outings, total sleep time, number of sleep interruptions and the patient's sleep rhythm.

They found that that the cognitive impaired group showed fewer outings and a clear tendency towards shorter uninterrupted sleep periods compared to the control group and concluded that number of outings and sleep rhythm might be good indicators for early detection of dementia. Although Suzuki et al. show that there is a tendency for a disturbed diurnal rhythm for patients suffering from dementia, there is no clear relation between the MMSE-scores and the severity of this disturbance [15].

---

[1] See appendix B.

Severity of cognitive impairment	Behaviour
Moderate cognitive impairment *(MMSE 10-20)*	Inappropriate or excessive walking
Moderate and Severe cognitive impairment	Attempts to leave home Pottering
Severe cognitive impairment *(MMSE < 10)*	Aimless walking Being brought back home Disturbed diurnal rhythm Moving objects from place to place Walking more

Table 5.1: Movement related behaviours in relation to severity of cognitive impairment found by Hope et al. [22].

Hayes et al. did a similar experiment [18]. They measured the walking speed and the amount of activity of mild cognitive impaired elderly and a control group using an unobtrusive sensor system. They also found a difference between between the two groups, with the cognitive impaired elderly having a greater variance in their daily activities.

Both experiments show that changes in activity patterns are an indication for an onset or deterioration of dementia. Location sensing can provide us with the data needed to build such a model. From movement patterns, activity patterns can be deduced and the higher spatial resolution of some RTLS-techniques, for instance Ultra Wideband, allows us to infer intra-room patterns, compared to the inter-room patterns which are the only possibility when using IR-sensors. This allows for a more detailed behavioural pattern.

5.3 Wandering and the evolution of Dementia

Most studies focussing on behaviour changes in dementia are concerned with the problems resulting from these changes, rather then the nature of this abnormal behaviour [22]. But if we want to diagnose any changes in the patient's condition, based on their behaviour, the nature of these problems is of vital importance. Hope et al. have conducted a study on the behaviour changes in dementia [22]. They assessed the behaviour of a population of 97 subjects. They tried to find a relationship between the time since the onset of dementia, the cognitive impairment (MMSE-score) and the exhibited behaviour of the subjects. They tried to find out whether a certain type of behaviour was either exhibited in mild (MMSE > 20), moderate (MMSE 10-20) or severe (MMSE < 10) cognitive impairment. They found that as the illness worsened (lower MMSE-scores) the subjects got more restless, walking around more and getting up more often at night. In their original research they identified 30 different different behavioural patterns. The patterns which are related to movement and thus detectable by location sensing are given in table 5.1 related to the severity of cognitive impairment of the subject.

In 2001, Hope at al. conducted a more specific research on wandering behaviour in Dementia [23]. They differentiated between different types of wandering behaviour, based on a topology by Hope and Fairburn [21]. This topology identified nine different types of wandering behaviour shown in table 5.2. They monitored the behaviour of a group of 82 participants during one year, or up to their time of death. They tried to identify the 'severity' of dementia (expressed in MMSE-scores) in which each of the different types of wandering occurs. The results are displayed in figure 5.1. Although they were unable to detect clear boundaries, there was a general trend visible. The results suggest "a progression from excessive but appropriate walking, attempts to leave home and pottering through to clear hyperactivity that becomes increasingly aimless and inappropriate. Finally, in severe dementia, the person is in danger of getting lost if he or she leaves home" [23]. Next they regarded the co-occurrence between the different wandering variables. They found that the onset of pottering preceded aimless walking and night-time walking by 14 months, increased walking by 15 months and trailing by 20 months.

Behaviour	Description
Increased Walking	Walks distinctly more than normal.
Attempting to leave home	Made any attempts to leave the house that have been prevented.
Being brought back home	Number of times brought back home.
Trailing	Tends to follow right behind carer for a total of at least 30 minutes.
Aimless walking	Walked about the house, garden or beyond without an obvious reason.
Pottering	Tended to walk around the house trying to do household chores or potter around the garden trying to do odd jobs.
Inappropriate	Walking around the house, garden, or outside for a reason that seems odd to the carer.
Excessive appropriate	Walked around the house, garden, or outside for an appropriate reason but repeated this several times.
Night-time walking	Walked during the night: includes walking aimlessly, pottering, and walking inappropriately or excessively.

Table 5.2: Various types of wandering behaviour.

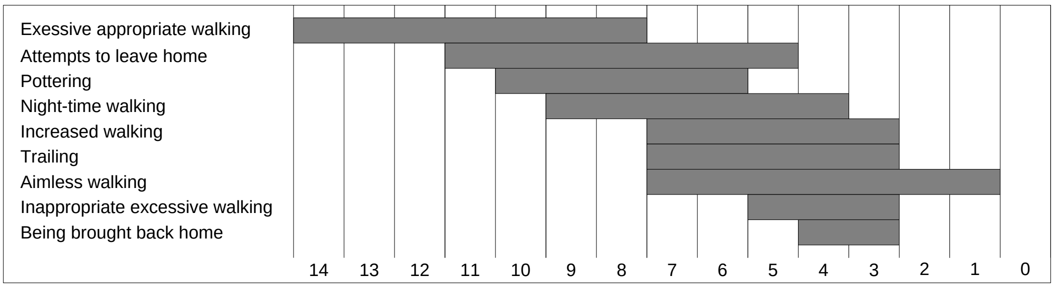


Figure 5.1: Cognitive scores (median MMSE scores) at the onset and offset behaviour. From [23].

They concluded that wandering behaviour generally starts around a MMSE-score of 13, and lasts for a period of several years. Eventually it passes and patients become progressively less active. Night-time wandering may not be part of this general picture, but more related to disturbances in the diurnal rhythm. Furthermore they found a large amount of the people with dementia (40%) were very restless. They walked constantly, apart from meal-times. If they were seated, it was for no more than 15 minutes at a time.

5.4 Circadian Rhythm and Sleeping

The circadian rhythm is a representation of our daily rhythm, our biological clock, which has a period of roughly 24 hours. During a single 24 hour cycle, we can roughly distinguish two periods. A resting-period; during which we sleep, recovering from the previous day and an active period in which we perform our daily activities. Elderly people with dementia have a disturbance in this rhythm [29], resulting less predictable sleeping and waking times and increased night-time activity. According to Gerhman et al., "they often display fragmentation in their sleep/wake patterns, such that they frequently wake up during the night and frequently fall asleep during the day. In fact, it has been shown that these patients rarely spend a full hour awake during the day or a full hour asleep during the night" [15]. If the Circadian Rhythm is impaired, it is possible that the subject starts doing day-time activities (e.g. cooking) during the night. Figure 5.2 shows the example activity patterns of four different types of circadian disturbances [29].

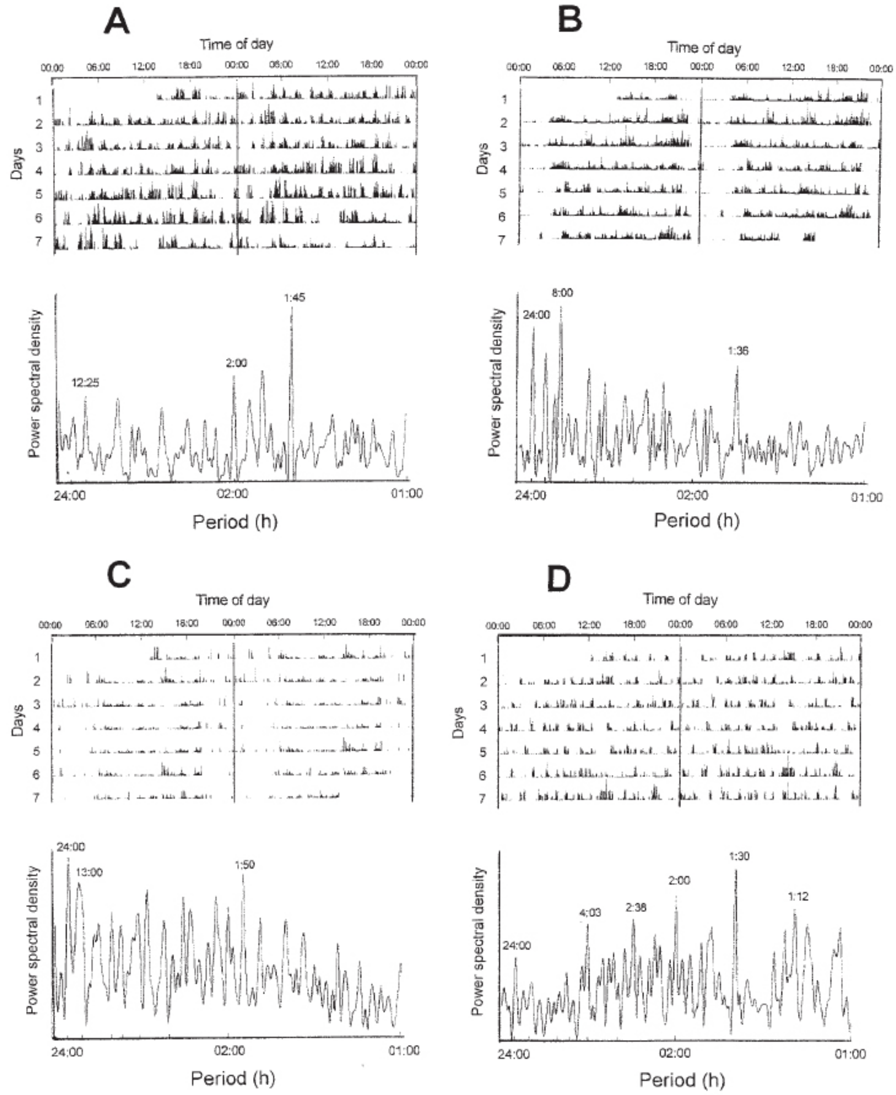


Figure 5.2: Activity charts of four types of circadian rhythm abnormalities. **A**, Severely impaired circadian rhythm with no boundary between day and night. **B**, Free-running rhythm type. **C**, Decreased circadian amplitude type. **D**, Accentuation of ultradian rhythm type.

In severe cases the circadian rhythm is fully impaired. There is no boundary any more between day and night. People are active constantly during the day only sleeping for short periods of time and they tend to wander a lot during night-time. Another type of disturbance is the so called 'free running type'. Both rising and sleeping times seem to shift on a day to day basis. So each day, the daily pattern starts and ends on a different time. A third type of disturbance is the 'decreased-amplitude-type' in which a general decrease in activity makes it hard to distinguish between periods of activity and rest. People having this disturbance exhibit a low level of activity remaining, for most of the day, in their bedrooms. Finally in the 'accentuation of ultradian rhythm' patients exhibited short "bursts" of activity of three to four hours between short sleeping periods.

Although their sleep is fragmented, people with dementia, especially nursing home patients, tend to sleep a lot. Fetveit and Bjorvatn conclude that the total amount of sleep during the day is positively correlated with an increasing degree of dementia [13]. The nursing home patients they examined, slept almost 13 hours per day during both day and night-time and their sleep was extensively fragmented. Furthermore they concluded an 'inverted U-shape' pattern in accordance with studies by Reisberg et al. [38] and van Someren et al. [51]. People with moderate dementia show more impaired sleep than people who are in the early or advanced stage of the disease.

5.5 Automated prediction of evolution

In this chapter some leads are presented which might indicate the onset or an advance in evolution of dementia. Because we are monitoring patients both during day- and night-time it would be interesting to see whether it is possible if these indication can be inferred from the obtained data. In order to do this, we first need to create a suitable model which represents the daily behaviour of a single person. We can then use classifying algorithms to draw conclusions on the evolution of the disease.

Chapter 6

Behavioural Model

> *Now that we have established what features to look for, we need to seek a way to model the daily life of the user. In this chapter this model is presented.*

6.1 Introduction

If we want our system to make any predictions about the evolution of dementia in a single individual, we first need a generalized model of the user's behaviour. The features we need to represent in this model are linked to the behavioural patterns presented in the previous chapter. Using these features we then try to make distinctions between different behavioural models. We can approach this problem in two different ways.

First we could try a nearest-neighbour approach. If we could make models which represent various stages of the disease based on observations of a large group of patients, we can measure which model is most similar to the current behaviour of our user. It is then most likely that the user's dementia has evolved to that specific stage. This approach has the advantage that it allows for an easy classification, provided that we can find a good similarity measure between the various models and that a generalized model can be made which applies to a group of individuals. This last requirement could be problematic, since there is a lot of variance in the evolution of dementia; it is unique for each person [48]. Although we can roughly assign specific types of behaviour to either mild, moderate or severe dementia, it is unlikely that we would succeed in finding a common denominator between a large group of patients which we can use as classification boundary. A final objection to this approach would be that data has to be gathered from a large number of patients which would raise privacy concerns.

So we need to limit ourselves to a single individual. What can we learn from a single person? The most important thing what we can learn is a person's history. By comparing models based on data we gathered during different periods we should be able to deduce how a person's behavioural pattern has changed over time. By looking at specific features we might even be able to classify the changes.

6.2 Behavioural Model

In this section we introduce the model which we use to represent the user's daily activities. This model is based on the well-known Hidden Markov Model, which is commonly used to make predictions about sequential information. In these models we try to predict how a the state of an internal (hidden) variable evolves over time.

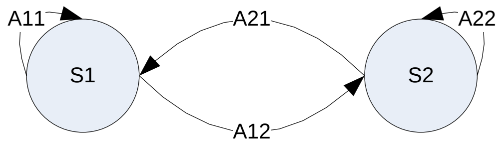


Figure 6.1: A simple Markov-chain

6.2.1 Hidden Markov Model

A Markov-model or Markov-chain is used to model the changes of a specific state variable S over time. It is described at any time as being one one of a set on N distinct states [37], $S_1, S_2, \ldots, S_N$. In figure 6.1, $N = 2$. At a predefined interval the system state is updated. The actual system state at a given time t is defined as S_t. In a full probabilistic evaluation of the system, the probability of the system being in state s_j at a given time t depends on all its predecessors, $P(S_t = s_j | S_{t-1} = s_i, S_{t-2} = s_k \ldots)$. However the Markov assumption states that every system state depends only on his N previous predecessors. So in the case of a first order Markov-chain, $N = 1$ and we can truncate our equation,

$$P(S_t = s_j | S_{t-1} = s_i, S_{t-2} = s_k \ldots) = P(S_t = s_j | S_{t-1} = s_i). \tag{6.1}$$

The truncated function is computationally still tractable, even if the number of time steps becomes large. Next to that we assume all probabilities to be stationary, so they are independent of time. So for each pair t, r,

$$P(S_t = s_j | S_{t-1} = s_i) = P(S_r = s_j | S_{r-1} = s_i). \tag{6.2}$$

Because of both assumptions, we can express the state transition probabilities as a single matrix A where $A_{ij} = P(S_t = s_j | S_{t-1} = s_i)$.

When applying such a model we could observe the system-state $S_1, \ldots, S_t$ and use the model (1) to predict the probability of this sequence of events or (2) find a model which matches this sequence best. However, we cannot guarantee that what we observe is also the 'real' system state. Consider for instance a noisy sensor which returns occasionally a wrong value. We can compensate for this by assigning a probability distribution to our observations as well. So the true system state becomes 'hidden' from us and we only observe the system state indirectly. This is modelled by introducing an additional set of observation symbols $O = \{o_1, \ldots, o_M\}$. We define the probability distribution of these observations in a particular state s_j as:

$$B_j(k) = P(O_t = k | S_t = s_j), \tag{6.3}$$

where $1 \leq j \leq N, 1 \leq k \leq M$. And finally we need an initial state distribution π,

$$\pi_i = P(S_1 = s_i), \tag{6.4}$$

where $1 \leq i \leq N$.

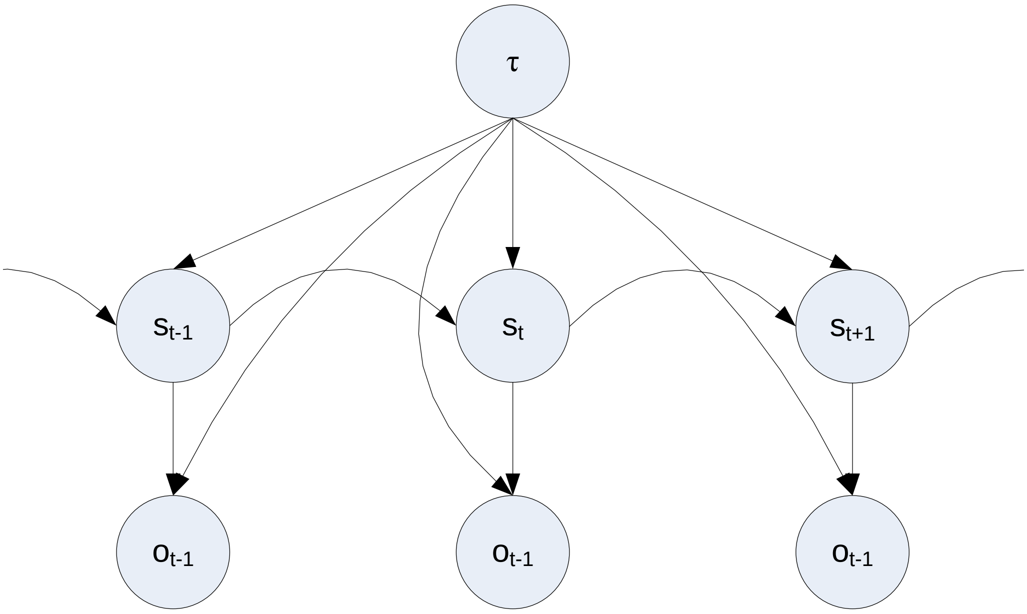


Figure 6.2: The behavioural model

6.2.2 System Model

Problems when using a Hidden Markov Model arise because of the assumption that the model is stationary. In our case this means that the probability of a person taking a shower is equal during the whole day, which is of course not true [1].

A better solution being to relax the stationary principle of the HMM by making the transition probabilities depend on the current time, also known as Non Stationary Hidden Markov Models (NS-HMM). In short, observation sequences of continuous time are made discrete by dividing them into bins of fixed width, which share the same temporal information. For each bin, separate transition probabilities can be learned using the same learning algorithms which apply on regular HMM's [55].

In our case we could divide the observations of a whole day into 24 bins each containing the observations of a single hour or create 4 bins if we want to divide our day into morning, afternoon, evening and night. The amount of bins created is important as too few bins would make the model too general (e.g. if we only have one bin, we still cannot detect whether our user showers during the day or during the night) and too much bins would make the model over fit.

In order to relax the non-stationary requirement a global switching variable τ is introduced, which value depends on the 'actual' time of the day.

Let Λ be a non-stationary Hidden Markov Model of the daily routine of a single user, we can define $\Lambda = \{\vec{\pi}, \vec{A}, \vec{B}, f(T)\}$, where $\vec{\pi}, \vec{A}$ and $\vec{B}$ contain elements π^i, A^i and B^i specifying the behavioural pattern at a specific time i of the day. This can either be a specific hour of the day or perhaps even a single hour on specific day of the week, depending on our temporal granularity. If we would increase the granularity we get a more accurate representation of the user's behaviour, but at the risk of over fitting. Plus, we need a large corpus of training data if we want a more fine grained system.

There exists a function $f(T) = \tau$, indicating which sub-model is currently in effect, depending on the time of the day, T. A graphical representation of Λ is shown in figure 6.2. In this model the state S_t

[1] We all shower in the middle of the night, don't we?

depends on both the previous state, as well as the switching variable τ:

$$P(S_t = i | S_{t-1} = j, \tau) = A^{\tau}_{ij} \quad t = 1, 2, \dots \tag{6.5}$$

$$P(S_0 = i) = \pi^0_i \tag{6.6}$$

and the observation probability distributions are defined as:

$$P(O_t = i | S_t = j, \tau) = B^{\tau}_j(i). \tag{6.7}$$

6.3 Observations

When using real time location sensing, the location of a specific tag is obtained at a fixed interval. A RTLS-observation at time t is defined as $O_t = < o_i, T >$. It is a tuple containing both location information as well as a time stamp of the real time. Using $f(T)$ we can calculate to which τ an observation belongs and assign it to the set O_τ, containing observations which are captured in the same real-time interval. The total set of observations contains all observations $O = \{O_1, \dots, O_{\tau_{max}}\}$.

6.4 Learning

Now we have defined our model, we need to find a way to adjust all probability distributions such they match the observations if our sensors. In short, which model Λ is most suited to predict our observed sequence of sensor data O. So we seek

$$\underset{\Lambda}{\operatorname{argmax}} P(O|\Lambda), \tag{6.8}$$

the configuration Λ which is most likely to output the same sequence of observation-values as what we have observed via our sensors. A way of estimating this model is by using a generalized Expectation-Maximization algorithm called the *Baum-Welch algorithm* or *Forward-Backward learning*. The algorithm is described in detail in [37]. We need, however, to make sure that we group all the observations for a single value of τ and use only these observations to learn the probability distributions belonging to that value of τ;

$$\underset{\Lambda}{\operatorname{argmax}} P(O|\Lambda) = \underset{\vec{\pi}, \vec{A}, \vec{B}}{\operatorname{argmax}} \prod_{\tau=1}^{\tau_{max}} P(O_\tau | \pi^\tau, A^\tau, B^\tau). \tag{6.9}$$

The algorithm consists of two steps, Expectation and Maximization which are repeated until the model converges to a local maximum solution. In the expectation step we calculate the current fit of the model on to the observed data, so we wish to calculate $P(O|\Lambda)$. We can do this using the *Forward-Backward procedure*. We calculate a forward probability $\alpha_t(i)$, defined as

$$\alpha_t(i) = P(o_1, o_2, \dots, o_t, S_t = s_i | \Lambda), \tag{6.10}$$

which is the probability of a partial sequence of observations up to time t given the current model. We can solve this inductively, as follows:

$$\alpha_1(i) = \pi_i^{\tau_t} b_i^{\tau_t}(O_1), \quad 1 \le i \le N, \tag{6.11}$$

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) A_{ij}^{\tau_t}\right] B_j^{\tau_t}(O_{t+1}), \quad 1 \le t \le t_{max}-1, 1 \le j \le N, \tag{6.12}$$

$$P(O|\Lambda) = \prod_{i=1}^{N} \alpha_{t_{max}}(i), \tag{6.13}$$

where τ_t is defined by the observation $O_t =< o_i, T >$, using $\tau_t = f(T)$. Next to the forward probability, we can also calculate a backward probability $\beta_t(i)$, defined as

$$\beta_t(i) = P(O_{t+1}, O_{t+2}, \ldots, O_{t_{max}} | S_t = s_i, \Lambda), \tag{6.14}$$

which is the probability of observing the partial sequence from $t+1$ to the end, given $S_t = s_i$ and our current model. We can also solve this inductively as follows:

$$\beta_{t_{max}}(i) = 1, \quad 1 \le i \le N \tag{6.15}$$

$$\beta_t(i) = \sum_{j=1}^{N} A_{ij}^{\tau_{t+1}} B_i^{\tau_{t+1}}(O_{t+1}) \beta_{t+1}(j), \qquad t = t_{max}-1, t_{max}-2, \ldots, 1, 1 \le i \le N. \tag{6.16}$$

Using α and β, we can calculate the expected number of transitions to state $S_t = s_j$ from $S_{t-1} = s_i$, and if we divide this by the total number of expected transitions from that state, $S_{t-1} = s_i$ we get an estimation of the probability $A_{ij}^{\tau_t}$. So we define

$$\xi_t^{\tau_t}(i,j) = \frac{\alpha_t(i) A_{ij}^{\tau_{t+1}} B_j^{\tau_{t+1}}(O_{t+1}) \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) A_{ij}^{\tau_{t+1}} B_j^{\tau_{t+1}}(O_{t+1}) \beta_{t+1}(j)}, \tag{6.17}$$

$$\gamma_t^{\tau_t}(i) = \sum_{j=1}^{N} \xi_t(i,j). \tag{6.18}$$

Using the above we can re-estimate the probability distributions (the Maximization-step), as follows

$$\bar{\pi}_i^{\tau_0} = \gamma_1^{\tau_0}(i), \tag{6.19}$$

$$\bar{A}_{ij}^{\tau_t} = \frac{\sum_{t=1}^{t_{max}-1} \xi_t^{\tau_t}(i,j)}{\sum_{t=1}^{t_{max}-1} \gamma_t^{\tau_t}(i)}, \tag{6.20}$$

$$\bar{B}_j^{\tau_t}(k) = \frac{\sum_{t=1, O_t = o_k}^{t_{max}-1} \gamma_t^{\tau_t}(i)}{\sum_{t=1}^{t_{max}-1} \gamma_t^{\tau_t}(i)}. \tag{6.21}$$

If we repeat this process until convergence we obtain a model Λ which matches our observations.

6.5 Related Work

Various methods have been proposed to derive and asses the behaviour of humans, using a range of stochastic models. Van Kasteren and Kröse [50] propose a Dynamic Bayesian Network using a large number of binary sensors as main input. They first create a static 'naive' Bayesian network which is independent of time. Next they extend this model using only the previous time step using a transition model and finally they look k-steps into the past. At best they gained an recognition rate of 58% using the static model. They found that the way in which the 'continuous' time was split into discrete intervals largely influenced the performance. The best result was achieved if they chose intervals which exactly matched the length of the various activities.

Wilson and Atkeson use a similar approach [53]. They use a generic dynamic Bayesian network, based on the input of a large number of binary sensors. Their model is capable of tracking multiple people in the same environment, although the performance greatly decreases if the number of occupants increases. They conclude that people behave differently in groups and generic activity patterns do not apply any more.

Lymberopoulos et al. take a different approach [28]. They use an algorithm by Agrawal and Srikant [2], which detects frequent occurring patterns in a sequential dataset. The algorithm finds patterns which co-occur in different sequences of data. When applied to the spatio-temporal data gathered from the movement of a user through the apartment they were able to infer which places in the apartment were visited most often and if there were specific sequences of actions (visited places). When taking into account the duration and timing of these sequences a general model of the user's daily activities can be build. This approach well suited if one wants to seek sequences of patterns which occur frequently, regardless of any temporal information, yet we are also interested in distribution of activities over time.

Duong et al. introduce an additional top-layer to the HMM managing the switching between various 'modes' of the bottom layer of the network [11]. Depending on the state on the top layer, the network at the bottom layer is configured differently, which is similar to the τ-variable presented in this chapter. However their switching variable is independent of the global time of the day.

Furthermore their network has the property that the duration of the network staying in the same state is not exponentially (or geometrically) distributed. Instead they use the Coxian distribution which is more flexible. They named it Switching Hidden Semi-Markov Model (S-HSMM). This flexible Coxian distribution makes the network more flexible, but also harder to learn the probability distribution.

Chung and Lui propose an extension which they named the Hierarchical Context Hidden Markov Model (HC-HMM) [9]. Their model is actually not a single HMM but includes three reasoning components which are 'executed' in sequence transforming lower level data into higher-level behavioural patterns, allow for equal sequences of low level information to have a different meaning given a specific context. Because we can already learn a lot of our patient from the low-level data obtained, there is no need to incorporate a notion of higher-level activities as this would only introduce additional classification errors.

A general difference between current systems in existence and the system presented in this research is the fact that, although abnormality detection has been explored, there is not yet a system which actively links features of dementia with observed behavioural patterns and tries to make an assessment of the onset or evolution of the disease.

Chapter 7

Behavioural Analysis

> *Once we have established our model, we can seek ways to compare different models and classify them according to the behavioural features of the user. We can compare different models using the Kullback-Leibler-divergence and if there is significant difference we can extract features to see how the behavioural pattern has changed.*

7.1 Numerical Simulation

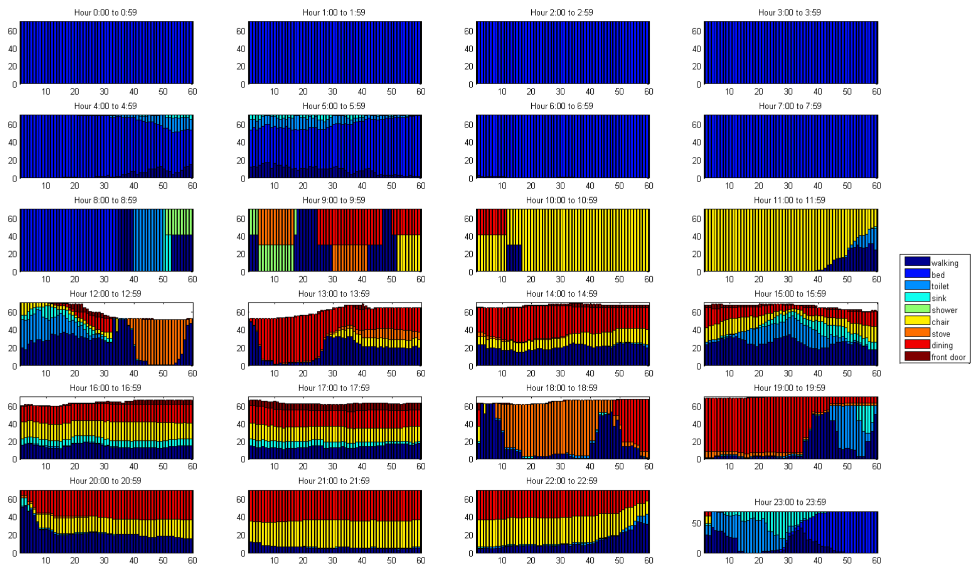
Unfortunately, because of time and budget constraints, it was not possible to conduct an experiment in a real life environment. So we have to resort to a simulation. For that purpose the simulator, described in appendix C has been written. In this simulator we track the 'life' of a virtual agent. This agent has two different behavioural patterns. It acts either normal or mild cognitive impaired. When acting normal, the agent follows a regular behavioural pattern with few deviations. The mild cognitive agent behaves more restless, switching faster between activities. It also is more restless at night, occasionally exhibiting wandering behaviour, and has a circadian rhythm disturbance of the "free running rhythm"-type, making its sleeping and waking times more unpredictable.

The movements of the agent in his environment are recorded as if there were sensors present. For this experiment we assume a perfect sensor model, but this can easily be altered by adding Gaussian noise to the observed values.

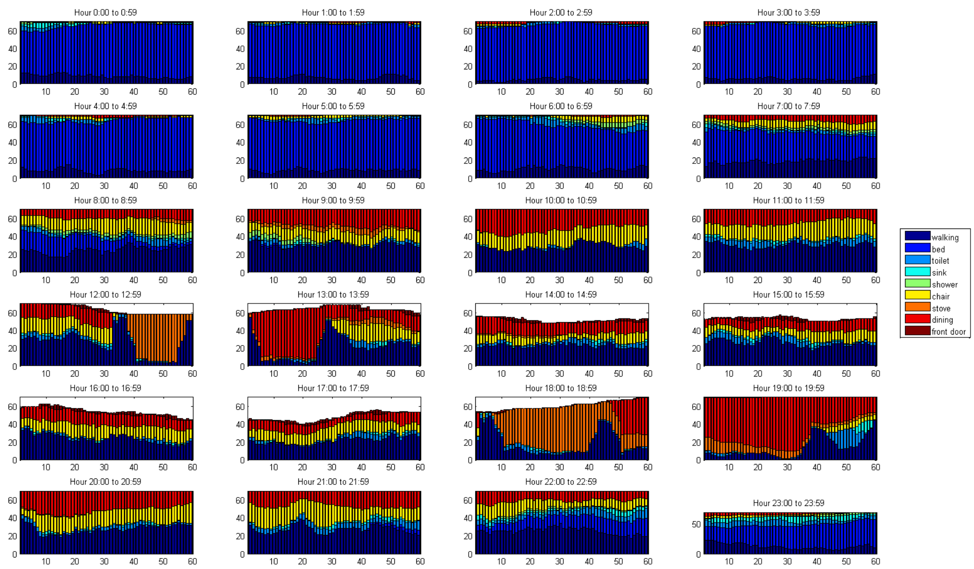
7.2 Applying the Behavioural Model

Using the simulator, data sets have been created of various length, ranging from 10 days to 70 days. These datasets contain a sequence of (x,y)-coordinate pairs, as well as a time-stamp and are captured with an interval of one minute. These coordinate pairs are then mapped on regions of interest in the environment of the agent, which act as our observations. We assume that activities generally are executed in a specific location (e.g. cooking near the stove, sleeping in bed). These specific locations can be seen as regions of interest. We are not interested in the specific activity conducted at a particular location, because we cannot infer this from location information alone. Our movement between the different regions of interest, however, should provide us with enough information to infer a general behavioural (or movement) pattern. In our simulation environment these regions of interest have been manually defined. The regions defined in the simulation are: *Bed*, *Toilet*, *Sink*, *Shower*, *Dining Table*, *Chair*, *Couch*, *Stove* and *Front Door* (see also figure C.2, page 56). Figure 7.1 shows how the various activities are distributed over the day for both types of behaviour.

The final set of observations O equals the list of regions of interest appended with two additional observations; *Outside* and *Walking*. If the agent is not within the environment we observe this as *Outside*. And if the agent is in the environment, but his location cannot be mapped to one of the regions of interest, we assume that it is *Walking* from one place to another. Once the data is transformed we obtain

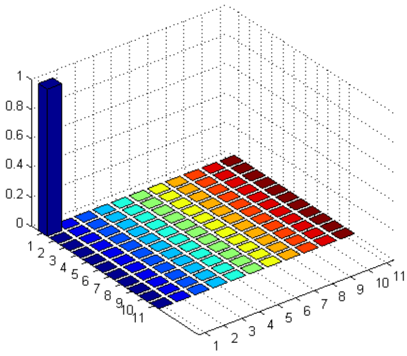


(a) Normal Behaviour

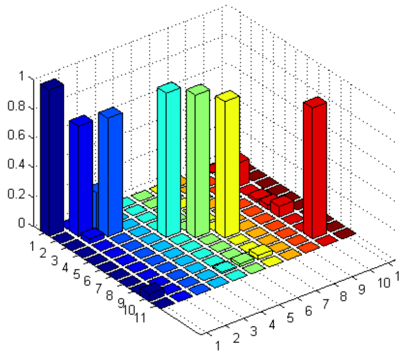


(b) Impaired Behaviour

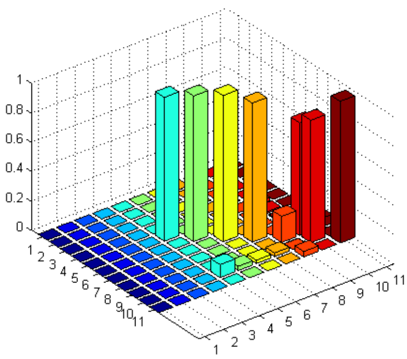
Figure 7.1: Daily behaviour. Both graphs show the probability distributions of the activities at each minute, obtained from 70 days of simulation. Each colour represents a different location. There is a clear distinction between both types of behaviour: The normal model has much sharper boundaries between daily activities.



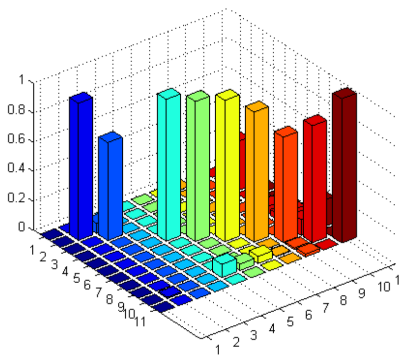
(a) Normal Behaviour - $\tau = 0$



(b) Impaired Behaviour - $\tau = 0$



(c) Normal Behaviour - $\tau = 13$



(d) Impaired Behaviour - $\tau = 13$

Figure 7.2: Example of two learned state-transition matrices A^0 and A^{13} for both types of behaviour. The left axis represents the 'from'-states i and the bottom axis the 'to'-state j in $A^{\tau}_{ij} = P(S_t = j | S_{t-1} = i, \tau)$. *1 = Bed, 2 = Toilet, 3 = Sink, 4 = Shower, 5 = Dining Table, 6 = Couch, 7 = Chair, 8 = Stove, 9 = Front Door, 10 = Walking, 11 = Outside*

a sequence of locations. Using the learning algorithm described in the previous chapter, we can then infer a general model reflecting the users behaviour over time.

Figure 7.2 shows an example of four state transition matrices A. At night there is a clear distinction between the normal and impaired behaviour. In case of normal behaviour, the agent remains in bed, whereas in the case of impaired behaviour there is a small chance on a transition from *Bed* to *Walking* ($P(S_t = 10 | S_{t-1} = 1) > 0$) and from *Walking* to various other activities.

7.3 Kullback-Leibler Divergence

The Kullback-Leibler Divergence or KL-divergence is a measure of *relative entropy* between two probability distributions [4]. Relative entropy is a measure of the amount of uncertainty that arises when approximating a probability distribution $P(\mathbf{x})$ with $Q(\mathbf{x})$. A lower entropy means fewer additional information is needed to explain $P(\mathbf{x})$ with $Q(\mathbf{x})$, in other words $Q(\mathbf{x})$ is a better approximation of $P(\mathbf{x})$, provided our data equals $\mathbf{x}$. The KL-divergence, for discrete probability distributions, is defined as

$$\mathrm{KL}(p||q) = \sum_{\mathbf{x}} p(\mathbf{x}) \ln \frac{q(\mathbf{x})}{p(\mathbf{x})} d\mathbf{x}, \tag{7.1}$$

and has the following properties:

- If $p = q$, $\mathrm{KL}(p||q) = 0$
- $\mathrm{KL}(p||q) > 0$, if $p \neq q$

The KL-divergence by itself is no distance measure, because $\mathrm{KL}(p||q) \neq \mathrm{KL}(q||p)$, but we can use it as a distance measure by summing both possibilities $\mathrm{KLD}(p||q) = \mathrm{KL}(p||q) + \mathrm{KL}(q||p)$.

Can we use the Kullback-Leibler distance as an indication of change in our behavioural model? Before we can implement the KLD, there are two issues which need to be addressed. First, how do we define $\mathbf{x}$ in equation 7.1? It is not possible for us describe all possible deviations of a daily routine and second, if $P(q(\mathbf{x})) = 0$ or $P(p(\mathbf{x})) = 0$, $\mathrm{KLD} = \infty$ which makes it hard to express in a programming language. To overcome the first problem we estimate the KL-divergence using a Monte Carlo method in which we use distribution $p(x)$ to generate data samples $\mathbf{x}_1, \ldots, \mathbf{x}_N$. The true KL-divergence can then be approximated by averaging over the distances obtained from the individual samples,

$$\mathrm{KL}(p||q) \simeq \frac{1}{N} \sum_{n=1}^{N} \{-\ln q(\mathbf{x}_n|\Theta) + \ln p(\mathbf{x}_n)\}. \tag{7.2}$$

where Θ is a model, which describes $q(\mathbf{x})$. The second problem can be addressed by introducing an additional parameter $\epsilon, 0 \leq \epsilon < 1$, imposing an upper bound on the amount of entropy,

$$\mathrm{KL}(p||q) \simeq \frac{1}{N} \sum_{n=1}^{N} \{-\ln((1-\epsilon) q(\mathbf{x}_n|\Theta) + \epsilon) + \ln((1-\epsilon) p(\mathbf{x}_n) + \epsilon)\}. \tag{7.3}$$

If ϵ is set to 0, the original unconstrained estimation is obtained. If $\epsilon \neq 0$, the logarithm is taken from a value which is at least ϵ, so $\ln(\ldots) < \infty$. When applied to our datasets we obtain clear differences in distance measures. As is shown in table 7.1.

P	Q	$\mathrm{KL}(p\|\|q) + \mathrm{KL}(q\|\|p)$
normal 10 days	normal 10 days	0
normal 50 days	normal 10 days	0.46
impaired 50 days	impaired 10 days	38
normal 50 days	impaired 50 days	2149
normal 10 days	impaired 10 days	2763

Table 7.1: Kullback-Leibler Distances, where $N = 20$, $1 \leq \tau \leq 24$, $\epsilon = 0.1$ and $|\mathbf{x}| = 1440$

We can infer from these distance measures that there is little variance in the behaviour of the normal agent. The impaired agent already shows some more difference when comparing two different data sets, but when comparing a normal agent with an impaired agent there is a clear difference. So the Kullback-Leibner distance can act as a measure for behavioural change.

7.4 Feature Analysis

If we have established the fact that the behavioural pattern of our subject has changed, so $\text{KLD}(\Lambda||\Lambda') >> 0$, we need to establish what caused this change. In order to do this, we need to extract features from the learned behavioural models. We can do this by generating a number daily location patterns from our probability distributions Λ(the 'old' behavioural model) and Λ' (the 'new' behavioural model), which should be a good approximation of the subject's average day of the period over which the model was captured, and extract the features from these generated patterns. These features can then be fed to a Bayesian network which can make a decision on the subject's condition. What features to choose has already been explored in chapter 5.

7.4.1 Circadian Rhythm

The circadian rhythm can either be normal or be disturbed in four ways. If we assume the sleeping and waking times to be Gaussian distributed, we can use the standard deviation σ as a measure of variety in sleeping and waking times. A σ' from Λ' being significantly larger then σ from Λ, might be an indication of further impairment of the circadian rhythm.

Next to the distribution of sleeping and waking times we can look at the number of sleep interruptions at night and the length-distribution of uninterrupted sleep periods, because in case of severe impairment or accentuation of the ultradian rhythm it is hard to speak about sleeping and waking times at all.

7.4.2 Activity Level

Another set of features which should be taken into account are the ones concerning the daily activity level of the user. Suzuki et al. [47] identified the number of outings and general restlessness as potential measures for dementia. The number of outings can simply be counted from our generated observation sequence. As a measure of activity we can look at the total distance covered during a day.

A final measure concerning activity patterns would be the average time spend on a single activity. Cognitive impaired elderly tend to be very restless, so we may expect that they spend little time on a single activity.

7.4.3 Wandering

The final set of features we should concern are those related to wandering behaviour. It is hard to identify real wandering from only the location information of the user, but we can identify a few features. We can define night time wandering as an activity when the user goes out during the night to perform activities which are unexpected, e.g. to go and sit in the living room. We should be careful not to classify every night-time activity as wandering, because we can expect someone going to the toilet. But there also may be occasions when a person deliberately goes out at night (e.g. to fetch something to drink). We may however expect that these incidental actions are averaged out when creating a model over a long period of time.

To detect whether a person is repeating himself, we can use the algorithm by Lymberopoulos et al. [28] on the orignal dataset, not on the model, to find the most common sequences of activities. We use the original dataset, because in our model we only take into account the probability on a certain action, so any temporal information is omitted. If we find a specific activity sequence which occurs multiple times per day, we can look at the time difference between these activities. If this difference is small, we may assume a person performing a set of activities in sequence.

7.5 Bayesian Network

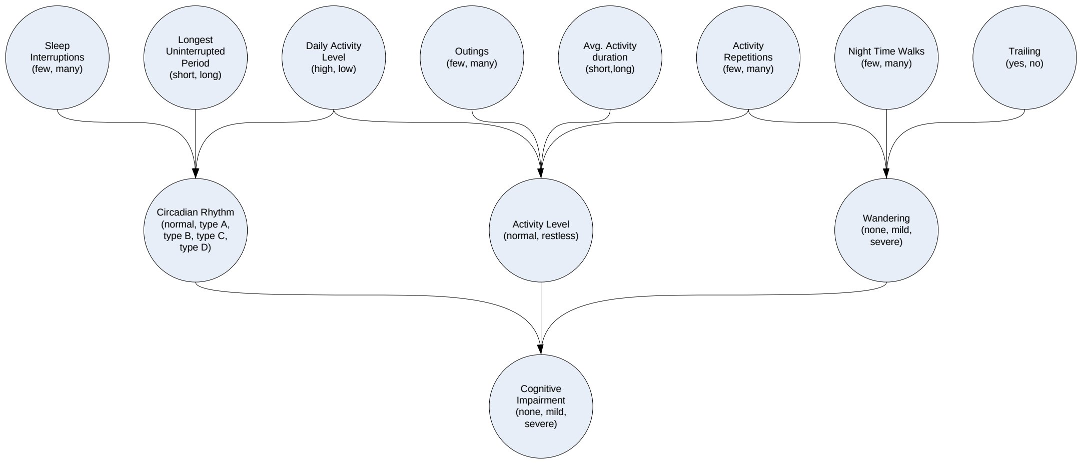


Figure 7.3: Bayesian network for classification

To make a prediction about the condition of the user, we can combine the features described above in the Bayesian network shown in figure 7.3. We combine corresponding features into three main categories, those concerning the circadian rhythm, general activity level and wandering behaviour. Eventually an assessment about the patients condition can be made.

7.6 Discussion

In this chapter an overview has been given on how the information obtained from the real time location sensors can be combined with the medical knowledge presented in chapter 5. In this research only the generation of the models and predicting a difference using the KL-distance has been implemented. Because of the numerical simulation, it is more or less a self-fulfilling prophecy. We know already that there will be differences in the models, because we programmed the agent's behaviour to be different. Yet these differences are based on observations taken from scientific literature on the behaviour of cognitive impaired elderly, so we may expect some correlation with 'real' behaviour. More research, however is needed to conduct some experiments in real life situations to see how well the sensors perform and whether we can model the activities of daily life in the way described in the previous chapters.

Another research which has to be conducted is one on the features described. Studies show that these features are indications of dementia, but how the behaviour of people translates onto the sensor data is still unknown, yet an attempt has been made to predict how such a classifier would look like. This prediction could be used as guidance for any future research.

Chapter 8

Social implications

> *When installed into the home environment, intelligent systems have significant impact on the daily lives of its inhabitants. This chapter briefly addresses some issues that may arise.*

8.1 Impact on Daily Life

When introducing assistant technology into the daily life of elderly people, it will not go without an impact on their lives. Even though we aim for the technology to be as ubiquitous as possible, it always requires some form of adaptation from a user's perspective. If we want to track peoples' movements throughout the day, we must require them to wear some kind of tag.

But wearing this tag can make the people very uncomfortable. They can get anxious as they get the feeling that someone is watching their every move. They get the feeling their privacy is invaded. Furthermore there also the practical discomfort of wearing such a tag. They cannot leave it off, because this would disrupt the functioning of the system. If we could manage to put a tag in an everyday device like a watch, people are less likely to be reminded that they are tracked and also tend to wear it more, as a watch is something they always wear.

Another advantage of hiding the system as much as possible is the fact that there is less chance, it will act as a stigma for the users. When clearly visible, their social surroundings might perceive this and know that these people are suffering from some form of disease. This might give the users a feeling of discomfort.

A last point of attention is the change of social relation between patient and care giver. As care givers start to rely on technological assistance, it may start to function as a barrier between patient and care giver. It is mainly a matter of trust. We lay something that is very dear to us, our own health, in the hands of technology. When trusted, it may enhance the relation between patient and care giver as they get the impression that there is always someone watching over them and is able to respond quickly. When mistrusted, this would work quite the opposite. Patients get the impression that the care giver is further away, sitting behind his computer screen. They get the feeling that it is not about people any more. The following quote is a good summary of how those people generally feel about assisted living:

> *" The reluctance of older adults and policymakers to adopt technological change may be described by the ancient proverb: "Better a known devil than an unknown god." New technologies may promise great savings to policymakers, but in lean economic times their unproven status is seen as an unacceptable risk. Likewise, older adults may view the technological option as 'gilding the lily', replacing a perfectly good and well-known alternative (for instance a lever switch) with an unnecessarily complicated one (for instance, a menu), which offers slight or no advantage [49]. "*

The amount of trust, from both care giver and patient, is strongly related to the reliability of the system. There is always the risk of potential failure of the system. So we should aim to make these systems as robust as possible. Another aspect of robustness is the reliability of the predictions the system makes. Only when the system achieves a high performance, care givers will trust its judgement.

8.2 Privacy

A final concern is the privacy of the user. By monitoring his movements 24 hours per day, we obtain al lot of valuable information, which can potentially be abused. People find the idea of inviting a Big-Brother into their homes very discomforting. As concluded by Zagler et al. [56], they want a “guardian-angel”, but without any sensors, which is of course a paradox. It is a good example of the fragile balance we have to keep between invasion of privacy and the security of remote monitoring.

We can increase the privacy of the users by making sure that the captured raw data is not accessible from outside the home environment, so it cannot be stolen by any remote attack. Any processing of the data should occur on-site making sure that when a remote call is needed (in case of an emergency) one only has to send appropriate information from which sensitive information is already subtracted.

8.3 Use Case

In all it seems that there is a lot of reluctance against ambient intelligence in the home environment. Yet there are also examples of successful use cases. One such example is the research conducted by Evans et al. [12]. They enabled a flat in London with sensory equipment to assist its occupant; an 82-year old male, suffering from moderate to severe dementia, who lived there by himself. It had sensory equipment installed to detect movement throughout the apartment, bed occupancy, night-time wandering and going outside and the use of the cooker and water taps. It incorporated technologies to enable automatic lighting, automatic cooker and tap shut-off, voice prompts and reminders, and detection and warning about hot cooker hobs. And finally the system was able to send a warning to the warden of in case of night-time restlessness.

Immediately from the start of the experiment they learned some behavioural treats which were yet unknown to the care takers, e.g. the patient getting very little sleep at night. After an initialisation period in which they only monitored the behaviour of the tenant, they switched on the assistant technology. The interventions the system made when, for instance, the tenant got up at night, were quite successful. When reminded not to go outside during the night, the tenant did not do so on many occasions. His night-time sleep period increased to six hours, which was a big improvement.

From questionnaires with his daughter and care takers, they learned that his average quality of life increased. He was able to more easily navigate around the apartment, because of guidance by the automatic lighting system and he had fewer accidents with the stove and water taps. The tenant itself also got the impression his life got easier. He did not notice that there was any technology present, but he could remember the voice prompts his daughter recorded and responded to them. So he was not aware, but when reminded he could remember experiencing the assistant technology.

In this case the technology enabled the tenant to remain living autonomous in a way which would otherwise be impossible.

8.4 Guidelines

As shown from the use case, smart technology can enhance peoples lives. Yet we should be aware that it is still about people. Zagler et al. [56] identified a few guidelines which one must consider when designing or implementing smart home technology.

8.4.1 Offer Perfect Transparency

Explain clearly what the system can and cannot do and what will happen once the system is enabled. Not only to the end-users, but also to their surroundings. Make sure to highlight the benefits of the system.

8.4.2 Make the User the Master

Allow the user to enable or disable (part of) the system in case he or she feels the need to do so. This keeps the user in the drivers-seat, making it easier for him to accept the technology. Also make sure that there is a balance between unobtrusive and completely hidden technology. Too much sensors on display is not good, but completely concealed, the system might also become eerie and threatening. People want to get the feeling they can keep an eye on the technology as well: "You can see me, but I can see you as well".

8.4.3 Fight Laziness

People should not become to reliant on ambient technology. If the system is too perfect people become more careless and inactive, relying on the system to intervene. Especially for elderly people it is important to keep their minds and bodies agile by performing every day activities.

We should be careful not to rush the applications of Ambient Assisted Living in our everyday lives, even though their applications can be promising and even proven to be beneficial. When applied these systems have great impact on the lives of their users. We need to make sure our guidelines and protocols keep up with current trends, allowing us to apply these promising technological aids in a smart and sensible way.

Chapter 9

Conclusions

> *Now that we have described the results of this research, we can draw some conclusions. The possibilities of monitoring elderly people using RTLS-techniques have been explored and two approaches have been presented.*

9.1 Conclusions

In this research an exploration has be made on the possibilities of applying real time location sensing to monitor people suffering from dementia. Two approaches were presented: a system to actively prevent the elderly from harm and a system to make predictions on the onset or evolution of the disease.

A proof-of-concept has been made using numerical simulation as it was not possible to conduct experiments in a real life situation, but as these simulations were aimed to match observations made in clinical studies we may expect a correlation between the behaviour of our agents and the behaviour of our prospective end-users.

Compared to other research in this field, this research distinguishes itself by seeking for ways to model the behaviour of a user and to combine this model with results of medical research on the behaviour of people suffering from dementia, making an attempt to create a system which is able to make predictions about the onset or evolution of dementia based on behavioural patterns.

9.2 Questions

In the first chapter some research questions were raised. The main question was:

> *How can patients suffering from dementia be monitored using real time location awareness and how can care takers be alarmed if the patient behaves oddly?*

As stated before, two different approaches have been proposed to address this problem. The 'virtual fencing'-approach is simple, yet promising. It is easy to set up and through the rule set, the care taker has full control over the functionality of the system. As shown in the use case by Evans et al. [12] using prompts to guide the user when he or she is lost is an effective way to influence the user's behaviour for the better. The 'virtual fencing'-system allows us to define situations in which such a prompt should be uttered, either locally or by signalling the warden. Furthermore the system is easily extendible by defining additional functions or incorporating more sensory information.

The 'behaviour-modelling' approach allows for a more intelligent adaptive system which incorporates the daily behaviour of the user. The system does not actively tries to intervene, but it can be used to signal any care givers if there are significant deviations in the user's behavioural pattern.

Signalling the care takers happens through the infrastructure which is already present in the VieDome platform. This platform allows for communication between devices installed in users' homes and a centralized call centre at the domicile care agency.

What are the requirements? The requirements of the system are described in chapter 2. It is key that the system is easy to use, especially for elderly people and it should refrain from requiring too much infrastructural changes.

What are different RTLS-techniques and which is most suitable? Different techniques have been discussed in chapter 3. Eventually Ultra Wideband seems the most promising techniques as it achieves very high accuracy, is easily extendible and requires few adaptations of the infrastructure of the home environment. Unfortunately it is also the most costly solution.

What does the architecture of the proposed system look like? In chapter 4, the 'virtual-fencing'-system is described in detail, including an architecture. Basically the system will consist of three main components: The sensor network, a central unit doing the processing and a separate calibration unit, which is only required when setting up the system.

How can the system be calibrated and adapted to the end user's home situation? This is also described in chapter 4. Calibration will be done by creating regions of interest or virtual fences by walking around the environment and indicating where these regions should be placed.

How can the information form the RTLS-sensors be translated into a behavioural pattern? The behavioural model is described in chapter 6. We store the probability of a user being on a specific location at a specific time into a Non-Stationary Hidden Markov Model. This model can be trained using the 'Baum-Welch algorithm'.

How can be the behavioural patterns be classified? In chapter 5 we explore what behavioural features we should look for when trying to classify dementia. The circadian rhythm, general activity level and wandering behaviour are features which can be measured using location information. From the model these features are extracted and are then fed to the Bayesian network described in chapter 7.

Finally we also briefly explored the social implications of installing such a system in the home environment of the user. We should be aware that these technologies have a significant impact on the daily life of people and they should not be applied carelessly.

9.3 Future Work

For the proposed system to become usable in real-life, we first need to conduct additional research. First and foremost, the proposed methods should be tested using real sensory equipment and probably adaptations have to be made to the model to match the measured data. Another point of research should be the feature extraction and Bayesian network. Because of the limitations of the numerical simulation, these classification-features are only suggested, but not actively explored. It is important that more medical research is conducted on qualitative measures to differentiate between these features. Finally we should seek ways to obtain the structure and probability distribution underlying the Bayesian network described in chapter 7.

Appendix A

Virtual Fencing Demonstrator

> *In order to demonstrate the functionality described in chapter 4, a little demonstration program has been created. This program takes inputs from configuration files describing the behavior, fences and behavior-rules and visualizes the different actors, fences and possible alarms.*

A.1 Introduction

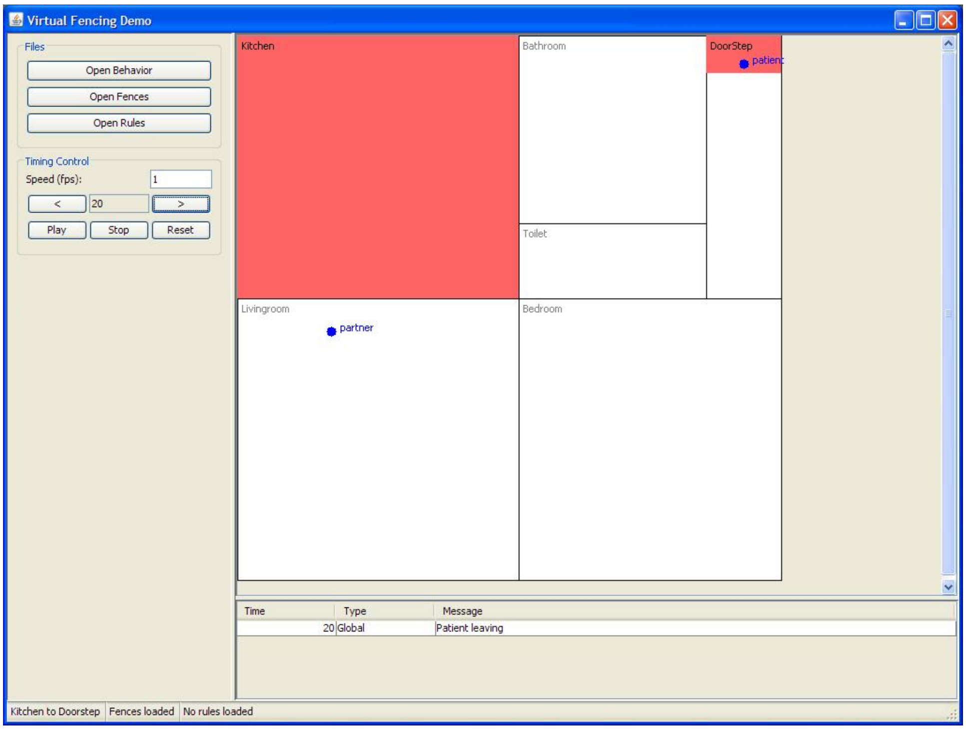


Figure A.1: The Virtual Fencing Demonstrator

Chapter 4 describes an implementation which uses virtual fencing to constrain the movement of the patient. Being virtual these fences, or borders, are invisible to the patient and they can be context dependable. In order to visualize this implementation a little demonstrator has been created, which takes its inputs from various configuration files and shows the behavior of the various actors within a virtual apartment, which is made up for the purpose of this demonstrator.

A.2 Behavior

For this demonstrator we assume the presence of a RTLS-system already tracking the whereabouts of our actors. The position of the various people in the scene are expressed as (x,y)-coordinate pairs. The position of the origin is of little importance as long as both the fences as the positions are expressed in the same coordinate space. In order to simulate the presence of such a system, coordinates are expressed in a configuration file binding them to a specific time frame. Time frames are expressed using natural numbers, starting from frame 0. This file is formatted using the CSV-format (semicolon separation) and has the following grammar:

behavior	=	**name** **comment** **persons**
name	=	`#name;` behavior_name :: *String*
comment	=	`#comment;` comments_text :: *String*
persons	=	**person** **person** | ϵ
person	=	`#person;` person_name :: *String* **coordinates**
coordinates	=	time_frame :: *Integer*; x-coordinate :: *Integer*; y-coordinate :: *Integer* **coordinates** | ϵ

Once loaded the behavior of the different actors can be 'played' as a movie using the timing control buttons. The actors are shown as blue dots moving around within the virtual apartment. Using the 'Speed'-field the user can control the playing speed, which is by default one frame per second.

A.3 Fences

Alike the behavior coordinates, the fences are also specified using a configuration file. In this file, each fence is specified as a polygon using x,y coordinate pairs of each corner point. Each separate fence is identified by a unique name. This configuration file is specified according to:

fences	=	**fence** **fence** | ϵ
fence	=	name :: *String*; **coordinates**
coordinates	=	**coordinate; coordinates | coordinate**
coordinate	=	x-coordinate :: *Integer*; y-coordinate :: *Integer*

The fences are displayed as red polygons in the overview window.

A.4 Rules

The Rules indicating the different states in which the system should raise an alarm are specified in a third (and final) CSV-file. These rules are expressed in logic using the disjunctive normal form. The alarm which should be raised is separated from the conditions by a semicolon. Specified in gramar the file is formatted as follows:

rules	=	**rule**
		rule | ϵ
rule	=	**antecedents ; consequent**
antecedents	=	**condition** `OR` **antecedents** | **condition**
condition	=	**not function** `AND` **condition** | **not function**
function	=	`inAreaPatient(patientId,areaId)` |
		`inAreaCareTaker(careTakerId,areaId)` |
		`alone(patientId)` |
		`time(beginTime, endTime)`
not	=	**!** | ϵ
consequent	=	`localAlarm(message)` | `globalAlarm(message)`

A.5 Running the Algorithm

Using the 'Play' and 'Stop' buttons the user is able to start and stop the simulation. Once started the actors start moving according to the loaded behavior. After each time step the rules are evaluated using the algorithm described in section 4.6. If an alarm is raised it is shown in the bottom of the screen. If the last line in the behavior file is reached, the simulator is stopped.

Using the arrow buttons next to the frame counter, the user is able to step a single frame forward or backward and the 'Reset'-button will return the simulator to its starting configuration.

Appendix B

Mini Mental State Examination

The Mini Mental State Examination is a questionnaire developed by Folstein in 1975 [14]. It consists of 11 questions each worth a specific number of points. A total of 30 points can be scored. Figure B.1 shows an example of such a questionnaire. It tests various areas of memory and cognitive functioning. A score over 27 indicates no impairment at all. Scores between 26 and 20 are a sign of mild cognitive impairment; between 19 and 10 moderate to severe cognitive impairment and below 10, severe cognitive impairment. The test score has to be corrected for degree of schooling and age. Also physical hindrances might interfere with the test.

Low scores in the test are an indication of cognitive impairment, although the test does not conclude which specific disorder is causing the impairment. Still the MMSE is "considered a to be a valid assessment instrument, because it correlates well with other tests of cognitive functioning, shows longitudinal changes that parallel cognitive decline in dementia, and has moderate to high sensitivity and specificity" [15].

MINI MENTAL STATE EXAMINATION (MMSE)

Patient's name:

Hospital number:

ONE POINT FOR EACH ANSWER	DATE			
ORIENTATION				
Year Month Day Date Time	____/5	____/5	____/5	____/5
Country Town District Hospital Ward	____/5	____/5	____/5	____/5
REGISTRATION				
Examiner names 3 objects (eg apple, table, penny) Patient asked to repeat (1 point for each correct). THEN patient to learn the 3 names repeating until correct.	____/3	____/3	____/3	____/3
ATTENTION AND CALCULATION				
Subtract 7 from 100, then repeat from result. Continue 5 times: 100 93 86 79 65 Alternative: spell "WORLD" backwards - dlrow.	____/5	____/5	____/5	____/5
RECALL				
Ask for names of 3 objects learned earlier.	____/3	____/3	____/3	____/3
LANGUAGE				
Name a pencil and watch.	____/2	____/2	____/2	____/2
Repeat "No ifs, ands, or buts".	____/1	____/1	____/1	____/1
Give a 3 stage command. Score 1 for each stage. Eg. "Place index finger of right hand on your nose and then on your left ear".	____/3	____/3	____/3	____/3
Ask patient to read and obey a written command on a piece of paper stating "Close your eyes".	____/1	____/1	____/1	____/1
Ask the patient to write a sentence. Score if it is sensible and has a subject and a verb.	____/1	____/1	____/1	____/1
COPYING				
Ask the patient to copy a pair of intersecting pentagons:	____/1	____/1	____/1	____/1
TOTAL	____/30	____/30	____/30	____/30

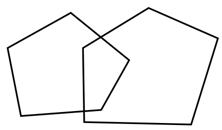


Figure B.1: An example of a Mini Mental State Examination

Appendix C

Behaviour Simulator

Because a real user test was infeasible due to cost and time restrictions, a simulator was created to generate location data of an agent living in a virtual environment. The agent represents an elderly who behaves either normal or according to a pattern which might be expected when a person has mild cognitive impairments. This movements of this agent can then be stored as if it was tracked in real life by a RTLS-system and be used for further processing.

C.1 Introduction

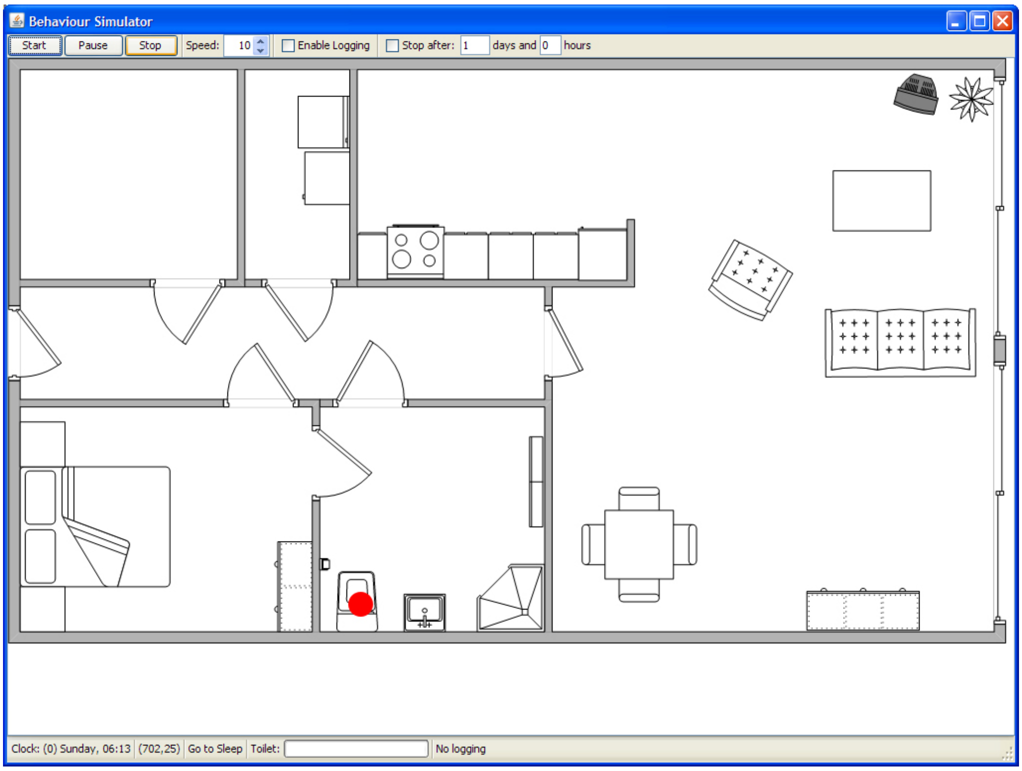


Figure C.1: Behaviour Simulator

Due to time and budget restrictions it was not possible to conduct an experiment using real subjects. So an alternative had to be sought. In order to obtain data on which various algorithms could be tested a simulation was created in which an agent, representing an elderly, was moving around in an environment representing an elderly home apartment. Depending on either the time of day, or the need to go to the toilet, the agent moves to a specific location within the apartment to 'perform' an activity. We are only interested in the movement patterns as that is what we are able to measure when using an RTLS-system.

C.2 Simulator

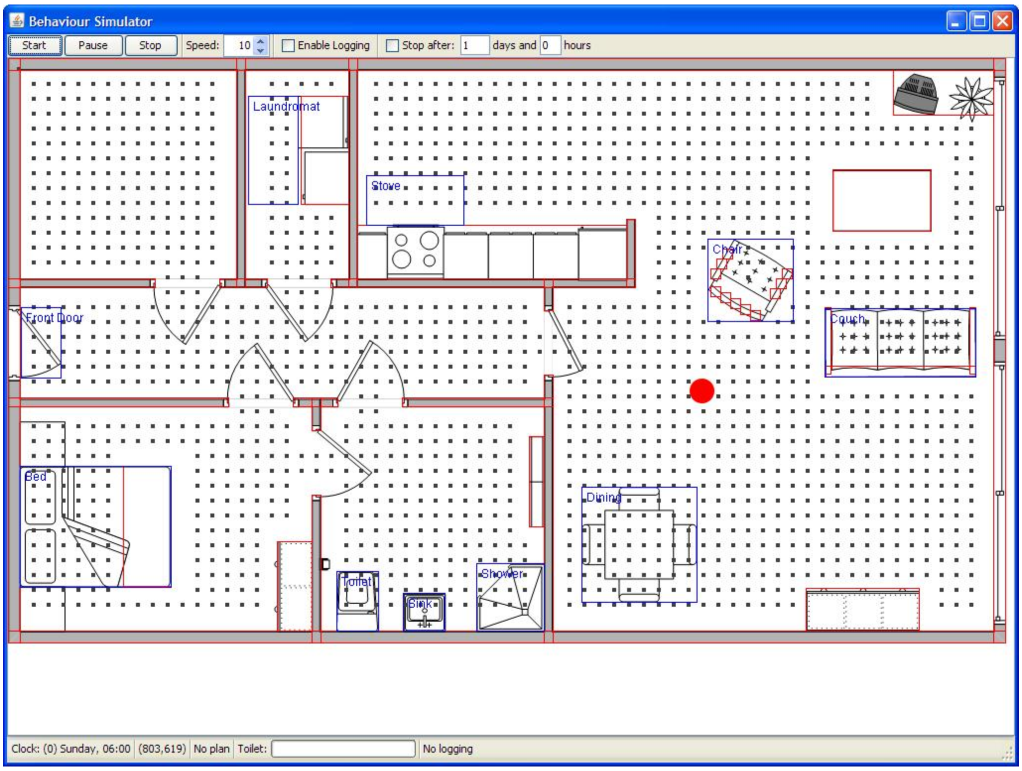


Figure C.2: Behaviour Simulator, the meta-data made visible

The environment is represented by a floor plan of the apartment (see figure C.1). It was inspired by looking at blueprints of existing elderly apartments. The floorplan was augmented with meta-data so the agent could navigate (figure C.2). The red areas depict blocked areas through which the agent cannot pass, such ass walls and furniture. The agent finds its way using by planning a route using A* pathfinding on the waypoints which are shown as grey blocks. At start up these waypoints are dynamically generated starting from the top left corner at a fixed spatial resolution in the direction of all legal steps an agent can take from that point, creating a graph of which each point is connected to all his direct neighbours. This graph represents all possible routes through the apartment the agent can take. Finally the blue areas indicate areas of interest where the agent can perform an activity (e.g. the toilet or the stove).

Using the buttons at the top of the interface, the user can start, stop or reset the agent, set the speed of the clock, enable the logging of his movements and finally set an upper bound after which the simulation stops automatically.

C.3 Behaviour

Flag	Description
toilet	Indicating how high the need is for the agent to go to the bathroom
isAwake	Indicating that the agent is awake
isToBed	Indicating that the agent has gone to bed in the evening
hunger	Indicating that the agent is hungry
isNewDay	Indicating that it is a new day
outAtNight	Indicating that the agent wakes up at night without reason and starts wandering (applies to the mild cognitive impaired agent only)

Table C.1: Agent behaviour: Internal flags

Once the simulation is started the agent starts his daily routine according to his behaviour, depending on his 'mental condition'. We distinguish between a normal agent and a mild cognitive impaired agent. The behaviour of the agent is specified according to the hierachical paradigm [30]. The agent is aware of the current time, day of the week and some internal flags indicating his current state (see table C.1). All of these flags are boolean except 'toilet'. This is a floating-point value that slowly increases over time (when sleeping, this increase is slower) and if a certain threshold is exceeded the agent has to go to the bathroom. The flag 'isNewDay' is set if the clock reaches 0:00 and is reset once the agent gets up in the morning. The flag 'outAtNight' applies to the mild cognitive impaired agent only and has a chance of being set during each time step, indicating that the agent gets up during the night without apparent reason. In correspondence with these flags an appropriate plan is selected and this plan is then executed in full. A plan can consist of one or multiple actions performed in sequence. Plans which involve staying stationary for a long time: 'Sit in Chair', 'Sit on Couch' and 'Sit at Table' can be interrupted if the agent needs to go to the bathroom, is hungry or needs to go to sleep. Once the agent is done performing an action, a new action is selected. If no conditions apply the agent remains idle and the conditions are evaluated on each time step until a new plan can be selected.

C.3.1 Normal behaviour

Figure C.3 (page 59), shows the behavioural rules for an agent which behaves normally. The grey blocks indicate an action which the agent performs if the specific rule applies. For a more detailed description of the actions, see table C.2 (page 58).

C.3.2 Mild Cognitive Impaired Behaviour

Being mild cognitive impaired, the agent exhibits certain behaviours which we might expect according to the studies discussed in chapter 5. Its general feature is that it is more restless than a normal agent. The agent spends less time on a single activity, which increases his general wandering around the house from one activity to another. Furthermore, there is a small chance that the agent starts to wander around, aimlessly visiting some places within the apartment. Furthermore there is a slight disturbance in his circadian rhythm. His waking and sleeping times are less fixed, the agent wakes up somewhere between 6:00 and 10:00 and goes to sleep between 21:00 and 1:00, and there is a possibility that the agent wakes up at night without any purpose. For a more detailed description of his behaviour, see table C.2 (page 58) and figure C.3 (page 59). Finally the chance of going out is reduced to 1 to 3 compared with other actions during the afternoon.

Action	Description	Norm.		Imp.	
		x	y	x	y
Go to Toilet	The agent first goes to the toilet and then moves to the sink.				
Go to Sleep	The agent goes to the toilet, then to the sink and finally into the bed.				
Go to Bed	The agent goes to the bed.				
Make Breakfast	The agent moves to the stove for x minutes and then to the dining table for y minutes.	10	20	10	20
Make Lunch	The agent moves to the stove for x minutes and then to the dining table for y minutes.	15	20	15	20
Make Diner	The agent moves to the stove for x minutes and then to the dining table for y minutes.	30	45	30	45
Take Shower	The agent moves to the shower.				
Sit in Chair (m,a)	The agent moves to the chair and remains there for x to y minutes.	15	60	10	20
Sit in Chair (e)	The agent moves to the chair and remains there for x to y minutes.	120	240	10	20
Sit on Couch (m,a)	The agent moves to the couch and remains there for x to y minutes.	30	90	10	20
Sit on Couch (e)	The agent moves to the couch and remains there for x to y minutes.	120	240	10	20
Sit at Table (a)	The agent moves to the dining table and remains there for x to y minutes.	5	20	5	15
Sit at Table (m,e)	The agent moves to the dining table and remains there for x to y minutes.	30	60	10	20
Go Outside	The agent moves to the front door and after 3 minutes, he goes outside for x to y minutes.	30	75	30	75
Random Walk	The agent randomly walks along x to y locations in the apartment. *(Only available to the cognitive impaired agent.)*	-	-	2	6

Table C.2: Agent behaviour: Side-by-side comparison of the normal and the cognitive impaired agent. *(m) = morning, (a) = afternoon* and *(e) = evening*

C.4 Logging

When enabled, the simulator creates a log-file containing the coordinates of the agent at an interval of one minute as if the agent was tracked by a RTLS-system, with the exception that the measurements of this sensor system have no error margin. If necessary this error margin can be introduced by adding Gaussian noise on each of the measurements. Once recorded, these log-files can then be used for further processing and inference of behavioural patterns.

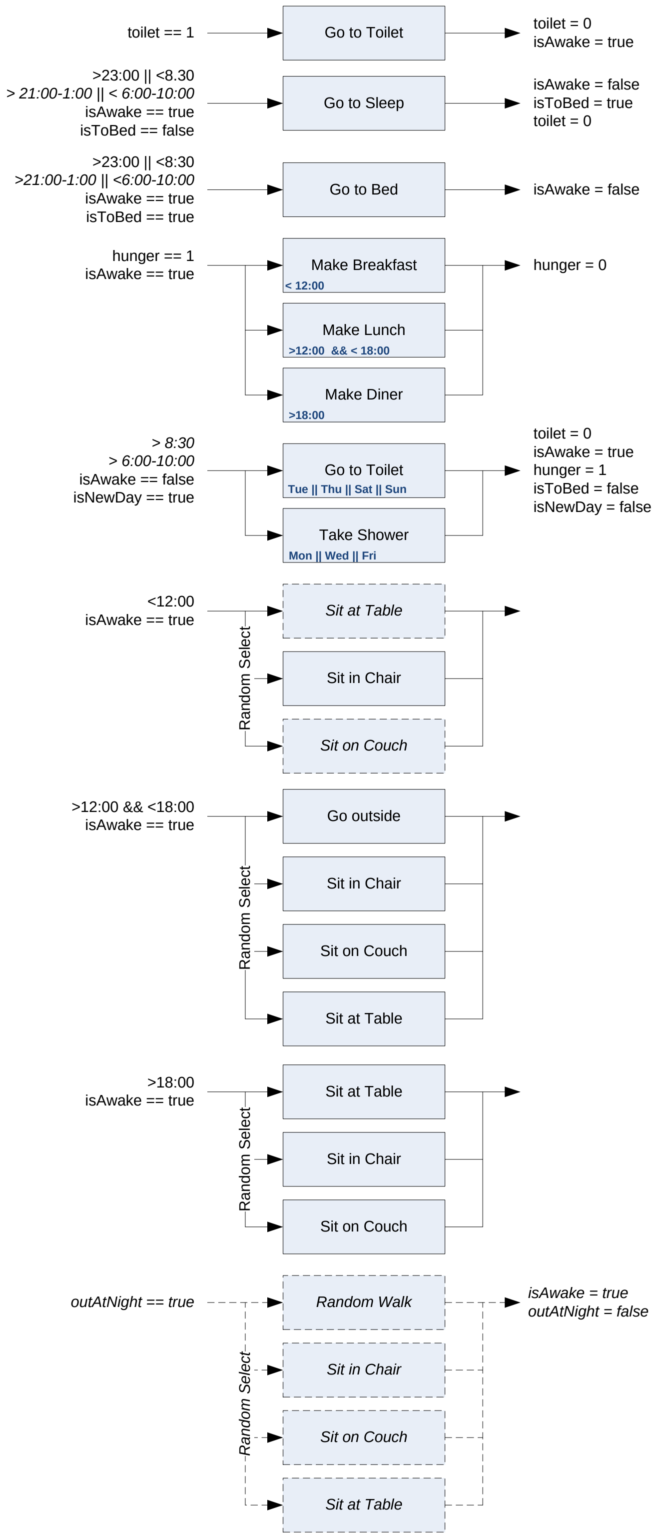


Figure C.3: Agent's behavioural pattern. The italic and dashed blocks only apply to the cognitive impaired agent.

Bibliography

[1] Mike Addlesee, Rupert Curwen, Steve Hodges, Joe Newman, Pete Steggles, Andy Ward, and Andy Hopper. Implementing a sentient computing system. *IEEE Computer Magazine*, 34:50–56, 2001.

[2] Rakesh Agrawal and Ramakrishnan Srikant. Mining sequential patterns. In *Proc. of the Int'l Conference on Data Engineering (ICDE)*, pages 3–14, 1995.

[3] Autoid.org. Active and passive rfid: Two distinct, but complementary, technologies for real-time supply chain visibility. `http://www.autoid.org/2002_Documents/sc31_wg4/docs_501-520/520_18000-7_WhitePaper.pdf`, 2002. White paper [Accessed online: 15-12-2008].

[4] Christopher M. Bishop. *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer, August 2006.

[5] M Boustani, B Peterson, L Hanson, R Harris, and C Krasnov. Screening for dementia. a systematic evidence review. Rockville, MD: Agency for Healthcare Reasearch and Quality. [Online: `http://www.ahrq.gov/clinic/uspstfix.htm`], 2002.

[6] Malaz Boustani, Britt Peterson, Laura Hanson, Russell Harris, and Kathleen N. Lohr. Screening for Dementia in Primary Care: A Summary of the Evidence for the U.S. Preventive Services Task Force. *Annals of Internal Medicine*, 138(11):927–937, June 2003.

[7] Henry Brodaty, Brian M. Draper, and Lee-Fay Low. Behavioural and psychological symptoms of dementia: a seven-tiered model of service delivery. *Medical journal of Australia*, 178(5):231–234, 2003.

[8] Barry Brumitt, John Krumm, B. Meyers, and S. Shafer. Ubiquitous computing and the role of geometry. *IEEE Personal Communications*, 7:41–43, October 2000.

[9] Pau-Choo Chung and Chin-De Lui. A daily behavior enabled hidden markov model for human bahavior understanding. *Pattern Recognition*, 41:1572–1580, 2008.

[10] *Diagnostic and Statistical Manual of Mental Disorders*. American Psychiatric Association, 4th edition, 1994.

[11] Thi V. Duong, Hung H. Bui, Dinh Q. Phung, and Svetha Venkatesh. Activity recognition and abnormality detection with the switching hidden semi-markov model. In *CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Volume 1*, pages 838–845, Washington, DC, USA, 2005. IEEE Computer Society.

[12] N Evans, R Orpwood, T Adlam, J Chadd, and D Self. Evaluation of an enabling smart flat for people with dementia. *Journal of Dementia Care*, 15:33–36, 2007.

[13] Arne Fetveit and Bjorn Bjorvatn. Sleep duration during the 24-hour day is associated with the severity of dementia in nursing home patients. *International Journal of Geriatric Psychiatry*, 21:945–950, 2006.

[14] Marshal F. Folstein, Susan E. Folstein, and Paul R. McHugh. “mini-mental state” : A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*, 12:189–198, 1975.

[15] Phil Gehrman, Matthew Marler, Jennifer L Martin, Tamar Shochat, Jody Corey-Bloom, , and Sonia Ancoli-Israel. The relationship between dementia severity and rest/activity circadian rhythms. *Neuropsychiatr Dis Treat.*, 1:155–163, 2005.

[16] Andy Harter, Andy Hopper, Pete Steggles, Andy Ward, and Paul Webster. The anatomy of a context-aware application. In *MobiCom '99: Proceedings of the 5th annual ACM/IEEE international conference on Mobile computing and networking*, pages 59–68, New York, NY, USA, 1999. ACM.

[17] Kamrul Hasan, Husne Ara Rubaiyeat, Yong-Koo Lee, and Sungyoung Lee. A Reconfigurable HMM for Activity Recognition. In *ICACT*, 2008.

[18] Tamara L. Hayes, Francena Abendroth, Andre Adami, Misha Pavel, Tracy A. Zitzelberger, and Jeffrey A. Kaye. Unobtrusive assessment of activity patterns associated with mild cognitive impairment. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association*, 4(6):395–405, November 2008.

[19] PA Heidenreich, CM Ruggerio, and BM Massie. Effect of a home monitoring system on hospitalization and resource use for patients with heart failure. *American Heart Journal*, 138:633–640, 2000.

[20] J. Hightower and G. Borriello. Location systems for ubiquitous computing. *Computer*, 34(8):57–66, 2001.

[21] R.A. Hope and C.G. Fairburn. The nature of wandering in dementia: A communtiy-based study. *International Journal of Geriatric Psychiatry*, 5:239–245, 1990.

[22] Tony Hope, Janet Keene, Kathy Gedling, Sandra Cooper, Christopher Fairburn, and Robin Jacoby. Behaviour changes in dementia 1: Point of entry data of a prospective study. *International Journal of Geriatric Psychiatry*, 12:1062–1073, 1997.

[23] Tony Hope, Janet Keene, Rupert H. McShane, Christopher G. Fairburn, Kathy Gedling, and Robin Jacoby. Wandering in dementia: A longitudinal study. *International Psychogeriatrics*, 13:137–147, 2001.

[24] Alison Marie Kenner. Securing the elderly body: Dementia, surveillance, and the politics of “aging in place”. *Surveillance & Society*, 5(3):252–269, 2008.

[25] Lucy Kok, John Stevens, Natasja Brouwer, Edwin van Gameren, Klarita Sadiraj, and Isolde Woittiez. *Kosten en baten van extramuralisering - De gevolgen voor de Regeling hulpmiddelen*. Number 109 in Werkdocumenten. Sociaal Cultureel Planbureau, 2004.

[26] Anothony LaMarca and Eyal de Lara. *Location Systems: An Introduction to the Technology Behind Location Awareness*. Morgan & Claypool Publishers, 2008.

[27] B. P. Lo, J. L. Wang, and G.-Z.Yang. From imaging networks to behavior profiling: Ubiquitous sensing for managed homecare of the elderly. In *Adjunct Proceedings Of the 3rd International Conference on Pervasive Computing*, May 2005.

[28] Dimitrios Lymberopoulos, Athanasios Bamis, and Andreas Savvides. Extracting spatiotemporal human activity patterns in assisted living using a home sensor network. In *PETRA '08: Proceedings of the 1st international conference on PErvasive Technologies Related to Assistive Environments*, pages 1–8, New York, NY, USA, 2008. ACM.

[29] Yutaka Motohashi, Akira Meada, Hideki Wakamatsu, Shigekazu Higuchi, and Takao Yuasa. Circadian rhythm abnormalities of wrist activity of institutionalized dependent elderly persons with dementia. *Journal of Gerontology*, 55A:740–743, 2000.

[30] Robin R. Murphy. *Introduction to AI Robotics.* MIT Press, Cambridge, MA, USA, 2000.

[31] Paradeep Natarajan and Ramakant Nevatia. Coupled hidden semi markov models for activity recognition. In *IEEE Workshop on Motion and Video Computing (WMVC'07)*, 2007.

[32] Jürgen Nehmer, Martin Becker, Arthur Karshmer, and Rosemarie Lamm. Living assistance systems: an ambient intelligence approach. In *ICSE '06: Proceedings of the 28th international conference on Software engineering*, pages 43–50, New York, NY, USA, 2006. ACM.

[33] Lionel M. Ni, Yunhao Liu, Yiu Cho Lau, and Abhishek P. Patil. Landmarc: Indoor location sensing using active rfid. *Pervasive Computing and Communications, IEEE International Conference on*, 0:407, 2003.

[34] N. Noury, G. Virone, J. Ye, V. Rialle, and J. Demongeot. New trends in health smart homes. *ITBM-RBM (RBM)*, 24:122–135(14), 2003.

[35] Institute of Medicine. *Crossing the Quality Chasm: A New Health System for the 21st Century.* National Academy Press, July 2001.

[36] Nissanka B. Priyantha, Anit Chakraborty, and Hari Balakrishnan. The cricket location-support system. pages 32–43, 2000.

[37] Lawrence R. Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. pages 267–296, 1990.

[38] B. Reisberg, E. Franssen, and S.G. Sclan. Stage specific incidence of potentially remediable behavioral symptoms in aging and Alzheimer's disease: a study of 120 patients using the BEHAVE-AD. *Bulletin of Clinical Neuroscience*, 54:95–112, 1989.

[39] James Robertson and Suzanne Robertson. Volere Requirements Specification Template Edition 6.0. Technical report, Atlantic Systems Guild, 1998.

[40] George Roussos. Location sensing technologies and applications. Technical Report November, School of Computer Science & Information Systems Birkbeck College, University of London, 2002.

[41] M. Sakata, Y. Yasumuro, Y. Manabe, and K. Chihara. ALTAIR: automatic location tracking system using active ir-tag. In *Proceedings of IEEE Internation Conference on Multisensor Fusion and Integration for Intelligent Systems*, pages 299–304, 2003.

[42] Cliodhna Ní Scanaill, Sheila Carew, Pierre Barralon, Norbert Noury, Declan Lyons, and Gerard M. Lyons. A review of approaches to mobility telemonitoring of the elderly in their living environment. *Annals of Biomedical Engineering*, 34(4):547–563, 2006.

[43] R. J. Shephard. Limits to the measurement of habitual physical activity by questionnaires. *British Journal of Sports Medicine*, 37:197–206, 2003.

[44] Prashant Srinivasan, David Birchfield, Gang Qian, and Assegid Kidané. A pressure sensing floor for interactive media applications. In *ACE '05: Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology*, pages 278–281, New York, NY, USA, 2005. ACM.

[45] Horst Steg, Hartmut Strese, Claudia Loroff, Jérôme Hull, and Sophie Schmidt. Europe Is Facing a Demographic Challenge. Ambient Assisted Living Offers Solutions. `http://www.aal-europe.eu/Published/Final%20Version.pdf`, March 2006. [Accessed online: 15-10-2008].

[46] Frost & Sullivan. RTLS Market Overview. `http://rfidwizards.com/index.php?option=com_content&task=view&id=378&Itemid=350`. White Paper [Accessed online: 25-09-2008].

[47] Toshiro Suzuki, Sumio Murase, Tomoyuki Tanaka, and Takako Okazawa. New approach for the early detection of dementia by recording in-house activities. *Telemedicine journal and e-health*, 13(1):41–45, Feb 2007.

[48] Reeti Tandon, Sudeshna Adak, and Jeffrey A. Kaye. Neural networks for longitudinal studies in alzheimer's disease. *Artificial Intelligence in Medicine*, 36:245–255, 2006.

[49] J.E.M.H van Bronswijk, W Kearns, and L Normie. Ict infrastructures in the aging society. *Gerontechnology*, 6(3):129–134, 2007.

[50] T. van Kasteren and B. Krose. Bayesian activity recognition in residence for elders. In *Intelligent Environments, 2007. IE 07. 3rd IET International Conference on*, pages 209–212, 2007.

[51] E.J. van Someren, E.E. Hagebeuk, and C. Lijzenga. Circadian rest-activity rhythm disturbances in alzheimer's disease. *Biol. Psychiatry*, 40:259–270, 1996.

[52] Roy Want, Andy Hopper, Veronica Falc, and Jonathan Gibbons. The active badge location system. *ACM Trans. Inf. Syst.*, 10(1):91–102, 1992.

[53] D.H. Wilson and C. Atkeson. Simultaneous tracking and activity recognition (star) using many anonymous, binary sensors. In *Proceedings of Third International Conference, PERVASIVE 2005*, pages 62–79. Springer Berlin / Heidelberg, 2005.

[54] Winston H. Wu, Alex A.T. Buia, Maxim A. Batalina, Lawrence K. Aua, Jonathan D. Binneya, and William J. Kaisera. Medic: Medical embedded device for individualized care. *Artificial Intelligence in Medicine*, 42(2):137–152, February 2008.

[55] J. H. Xiao, B. Q. Liuu, and X. L. D Wang. Principles of a non-stationary hidden markov model and its applications to the sequence labeling task. In *Proceedings of the 2nd International Joint Conference on Natural Language Processing (IJCNLP 2005, Jeju, Korea)*, Lecture Notes in Artificial Intelligence. Springer Verlag, New York, 2005.

[56] Wolfgang L. Zagler, Paul Panek, and Marjo Rauhala. Ambient assisted living systems - the conflicts between technology, acceptance, ethics and privacy. In Arthur I. Karshmer, Jürgen Nehmer, Hartmut Raffler, and Gerhard Tröster, editors, *Assisted Living Systems - Models, Architectures and Engineering Approaches*, number 07462 in Dagstuhl Seminar Proceedings, Dagstuhl, Germany, 2008. Internationales Begegnungs- und Forschungszentrum für Informatik (IBFI), Schloss Dagstuhl, Germany.