

HUMAN ACTIVITY RECOGNITION USING WIRELESS AMBIENT SENSOR
NETWORKS

by

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B.S., Computer Engineering, Middle East Technical University, 2010

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science

Graduate Program in Computer Engineering
Boğaziçi University

2013

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DATE OF APPROVAL: 17.01.2013

ACKNOWLEDGEMENTS

First of all, I am deeply grateful to my thesis supervisor Prof. Cem Ersoy for all his concern during my thesis. I have learnt a lot of things from him which will lead me in my future life.

I would like to thank Assist. Prof. Özlem Durmaz İncel and Hande Alemdar for their continuous support during my thesis. To work with them was a great opportunity for me. I will never forget their voluntary help in my troublesome times.

I thank to the member of my thesis jury Assist. Prof. Albert Ali Salah, for his invaluable comments and suggestions in order to improve my thesis.

I would like to thank to my colleagues and friends from NETLAB, Yunus Emre, Itır, Orhan, Bilgin and especially Can for their support and the enjoyable environment they created during my studies.

Special thanks also to my best friend Mert for his patience and collaboration during my data collection process in the home which is the main part of my thesis.

I want to thank sincerely to my family. It is the biggest chance in my life to have such a family. They have the most important portion in my achievements in my life.

Finally, I thank to my girl friend Polen for her love and invaluable support when I have needed it the most. Her existence right beside me give me an incredible energy in the hardest time of my thesis.

This research is supported by Boğaziçi University Research Fund (BAP) under the grant numbers 11A01P7 and 11A01D4 and also supported by Ericsson Turkey within Intelligent Home Gateway project under grant number TEYDEB 3110019.

ABSTRACT

HUMAN ACTIVITY RECOGNITION USING WIRELESS AMBIENT SENSOR NETWORKS

Human activity recognition in home settings provides great facilities in ambient assisted living applications. With continuous and long term monitoring, daily routines of the residents can be inferred and any abnormal situation which can be an indicator of a disease can be detected. Furthermore, health professionals can be informed in advance in such situations. Recent advances in sensor network technologies enable researchers to utilize wireless sensor networks in human activity monitoring applications. We present an ambient assisted living system which monitors the daily living of residents. For this purpose, we deployed a wireless sensor network which consists of many ambient sensors in a real house in which two residents live. Data about daily living activities of residents were collected for 30 full days accounting the privacy issues under real world conditions. Using several machine learning methods, we classified the collected data in order to model behaviours of residents and make inferences about their habits. In this thesis, we elaborate the system architecture of the wireless sensor network, share the experiences obtained during the data collection process, and the results of the classification.

ÖZET

KABLOSUZ ÇEVRESEL ALGILAYICI AĞLAR KULLANARAK İNSAN HAREKETİ ALGILAMA

Ev ortamlarında insan hareketlerinin tanınması çevresel destekli yaşama uygulamalarında büyük yarar sağlar. Sürekli ve uzun vadeli izleme ile evden yaşayan insanların günlük rutinleri hakkında çıkarımlar yapılabilir ve bir hastalığın habercisi olabilecek anormal durumlar önceden anlaşılabilir. Ek olarak, sağlık çalışanları bu tarz durumlarda önceden bilgilendirilebilir. Algılayıcı ağlarındaki son gelişmeler araştırmacıların kablosuz algılayıcı ağları insan hareketi izleme uygulamalarında kullanmasına olanak sağlamıştır. Biz, evde yaşayan insanların günlük yaşamlarını izleyen bir çevresel destekli yaşam sistemi öneriyoruz. Bu amaçla, çeşitli çevresel algılayıcılardan oluşan bir kablosuz algılayıcı ağı iki kişinin yaşadığı bir eve kurduk. 30 tam gün boyunca, gerçek yaşam koşulları altında, evde yaşayanların özel hayatlarına saygı göstererek günlük yaşam hareketleri hakkında veri topladık. Çeşitli makine öğrenimi yöntemleriyle, toplanan veriyi evde yaşayan insanların davranışlarını modellemek ve onların alışkanlıkları hakkında çıkarımlar yapabilmek için sınıflandırdık. Bu tezde, tasarladığımız kablosuz algılayıcı ağın mimarisi hakkında detaylı bilgiler verip, veri toplama boyunca edindiğimiz tecrübeleri ve sınıflandırma sonuçlarını paylaşıyoruz.

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LIST OF SYMBOLS

A	State transition matrix of a hidden Markov model
B	Observation probability matrix of a hidden Markov model
I_{gini}	Gini's diversity index
k	Nearest neighbours parameter in kNN algorithm
π	Initial state probabilities of a hidden Markov model

LIST OF ACRONYMS/ABBREVIATIONS

AAL	Ambient Assisted Living
ADL	Activities of Daily Living
ADM	Activity Discovery Method
FSR	Force Sensitive Resistor
HMM	Hidden Markov Models
IDE	Integrated Development Environment
IR	Infrared Receiver
kNN	K-nearest neighbour
PAN	Personal Area Network
RF	Radio Frequency
SMS	Short Message Service
SVM	Support Vector Machine
USB	Universal Serial Bus
WSN	Wireless Sensor Network

1. INTRODUCTION

Wireless sensor networks (WSNs) are utilized as a promising and efficient solution for various application domains, ranging from environmental monitoring to healthcare as they provide advantages with their low cost nature and collaborative sensing and intelligence capabilities. Even in unpredictable working environments, such as in industrial domains which are typical multi-path environments, examples of WSN based monitoring solutions are proved to work and provide the potential to replace their wired counterparts [1]. Home automation systems, or smart homes, appear as one of the example application areas where WSNs are utilized in the industrial domain. Light control, remote control, smart energy management, security and safety are the example applications that utilize sensing information in the home setting [2]. Besides these, remote care or ambient assisted living (AAL) applications also exploit WSNs to support elderly in their daily lives in the context of smart home systems [3, 4].

Monitoring of wellbeing is becoming an important challenge for ageing societies [5]. First of all, more investment is needed for elderly care, and secondly the decrease in the working population due to aging will cause a shortage of skilled caregivers. Therefore, solutions for the remote and automatic monitoring of the human wellbeing can contribute to address the challenges of independent living by developing smart care systems such that elderly people can have a higher quality of living standards and can live independently with minimum support from caregivers. In this regard, WSNs with their smart sensing and communication capabilities are recognized as an ideal platform [3] for ambient assisted living environments.

AAL applications are mainly based on human activity detection. Various inferences can be made through understanding the activities of people. Physical and mental conditions of people, especially elderly, can be controlled in the long term. Similarly, such applications help people sustain their life in a healthier way which is the task of AAL systems. Concerned activities are basically activities of daily living (ADL) such as cooking, toileting, and sleeping. These activities can be used to characterize

the behaviour of the elderly and with continuous monitoring, the anomalies in their behaviour can be detected early and required actions can be taken quickly. Besides the ambient assisted living domain, monitoring the ADL with ambient sensors is typically used in the healthcare domain. How much time a person spends in sleeping, how many times he/she goes out or to the toilet can be good indicators to detect medical problems and these can provide very important clues about the progress of diseases, such as Alzheimer for healthcare domain. Additionally, some emergency life threatening situations like fall or fainting detection, which are not rare for elderly, are the concern of such systems unlike the long term monitoring in AAL systems. For instance, being in the bathroom for a long time compared to the learned daily routine of an inhabitant can be a sign of such an emergency situation. Smart home applications can be considered as another prominent domain for monitoring ADL with ambient sensors. In smart home applications, recognizing the electricity or water consumption of residents or recognizing the interactions between them by following their activities are the potential examples where the systems of human activity recognition with ambient sensors can be utilized. As another usage domain, such systems can also help in inducing behaviour change for persuasive applications. For instance, if a person aims in changing unhealthy eating habits or wants to reduce the costs of domestic resource usage, such as water consumption, monitoring the ADL and identifying the habits to be changed can assist the user for a behaviour change.

The activities to be recognized and the set of sensors to be used may differ for different application domains. For instance, in a fitness tracking application, one may be interested in how active a person is and hence utilize inertial sensors and accelerometers, to identify activities like running, walking, and biking. For a more comprehensive monitoring of the behaviour of a person, identifying the activities of daily living, which are the activities that are performed on a daily basis, such as cooking, cleaning, sleeping, personal hygiene, is a more efficient and common solution. The set of sensors used in monitoring the ADL may range from sensors that are carried on the body of the users, such as acceleration sensors, RFID tags, sensors measuring physiological information (e.g., skin temperature), or ambient sensors that are deployed in the living environment of the user, such as force resistive sensors deployed under

a bed or couch to detect the sleeping or sitting patterns. Ambient sensors have the advantage of unobtrusiveness, such that they do not require the user to carry any external devices and limit the activities of users, with long term monitoring capability, compared to on-body sensors. Video recorders and cameras can be considered as another type of ADL sensing devices. However, they are not preferred commonly due to the privacy issues.

Although such an AAL system can offer a variety of benefits, there are still challenges in continuous behaviour and health monitoring using WSNs, stemming both from the wireless networking of the collaborative sensors and human activity recognition. From the perspective of wireless networking, the home is a typical multi-path environment [2] due to the walls, furniture and people moving around and it is subject to interference since ISM bands, which are usually used by WSNs for communication, are heavily utilized by cordless phones, Bluetooth and WiFi devices and even microwave ovens. Still, sensors operate using a limited battery power and hence the network lifetime is affected by this. Besides the battery limitation, sensors are resource limited in terms of processing, communication and storage. Therefore, they cannot operate complex software and provide complex services.

From the perspective of human activity recognition using sensors, the fundamental challenge is about identifying the human activities from the sensor data. The nature of human activities are usually very complex: multiple tasks can be performed concurrently and an activity can be performed in different ways, sometimes with a different sequence. Overall, these impact the activity recognition process negatively. Usually, statistical machine learning techniques are used to infer information about the human activities from sensor data. The challenge is that this requires finding an accurate model to infer activities. Furthermore, we need training sets which contain the labels of the activity data together with the raw sensor data. Obtaining these labels require human involvement, for instance the user may be asked to keep a diary or using an automatic voice recognition system the activities can be automatically labeled. Labeling the data in the training phase is usually a tedious and complex process.

In this thesis, we present an example human activity recognition system which monitors the ADL and behaviours of people in their homes with the help of ambient sensors. We deployed the system in a real house shared by two persons and collected data about their ADLs using several types of different sensors for 30 full days.

Our contributions can be summarized as follows:

- Compared to the previous examples of activity recognition systems, that were deployed in a laboratory [6–8], we deployed the system in a real house. The residents were asked to live their normal life like before the system deployment and we placed the sensor nodes to the most convenient locations without disturbing their daily life.
- Most of the similar studies take into consideration only one inhabitant [6, 7, 9]. In contrast to these examples, our main motivation while deploying the system was that most of the people spend their times in their homes and live as multiple residents. In our study, we designed a WSN for a real house shared by two inhabitants. Thus, we aim to make inferences about the relation between residents, which is an open research field.
- A collaborative system which consists of 20 sensors of seven different types was designed, unlike most of the studies which commonly utilize a small number and a few types of sensors [9].
- Our system was tested with a field test in a real house with two residents identifying a detailed set of 27 activities for 30 full days instead of focusing on a limited set of activities. This activity set includes the main daily living activities like sleeping, toileting, having a meal, cooking, watching TV, taking a shower and more detailed activities that some of them are not performed every day like hanging out laundry, having a guest, doing cleaning, having a nap.

- For the annotation of activities, we provided a simple interface for the residents and we observed that there have been between 60-100 labels for each day in total, which demonstrate that the residents recorded their activities very frequently, and hence the collected data are very detailed in contrast to some of the previous deployments, which only relied on users keeping diaries about their activities or deployments without the annotation of activities.
- The sensory data were processed using various classifiers including HMM, Decision Tree, kNN and different feature sets for performance comparisons.
- We investigated the performance of the battery lifetime. In order to increase the lifetime of the system, we offer several methods which cause significant improvements in the life time of sensor nodes.
- We present the field tests of our system continued for 30 full days together with summarizing our experiences in meeting the challenges of operating WSNs in an automated monitoring system to contribute to future studies on the acceptance and commercialization of WSN based AAL systems.

Before deploying the above mentioned WSN in a real house, some preliminary studies were conducted. Firstly, we designed a small system which consists of three sensors attached to a couch that aims to differentiate "not interacting with the couch", "sitting on the couch", "napping on the couch" and "lying on the couch" activities. The main motivation of this study is that most elderly spend most of their time on their couch in front of their favourite TV within the day. Secondly, we designed a subset of the main design in a laboratory environment, which included 10 sensor nodes, and one base station. The number of concerned activities was eight in total, including some basic ADLs like sleeping, watching TV, and going out. We collected the ADL of one volunteer subject during five days and six hours for each day. A new WSN is improved and deployed in a real house in the light of experiences we obtained from that study.

The organization of the thesis is as follows: In Chapter 2, we provide a literature review on human activity recognition systems using WSNs. In Chapter 3, we summarize the preliminary studies and introduce the utilized platform. In Chapter 4, we explain the system architecture, which is deployed in a real house, and introduce the sensor types in a detailed way. Additionally, we talk about the data collection framework and learned lessons, respectively. In Chapter 5, we describe the classification of the collected data. Additionally, possible inferences which can be made from the collected ADL data are referred to in Chapter 6. Chapter 7 concludes our study and provides possible directions for future research.

2. LITERATURE REVIEW: HUMAN ACTIVITY RECOGNITION SYSTEMS

Human activity recognition using WSNs have a wide application field ranging from AAL to persuasive systems. Other main domains are healthcare and smart home applications. In this chapter, we explain the state of the art technologies about human activity recognition together with their advantages and drawbacks, and additionally the challenges they create.

2.1. Ambient Assisted Living (AAL) Domain

AAL systems generally aim for facilitating the life of people, especially elderly in the long term by monitoring their activities and making inferences about their daily routines. Hence, abnormal situations can be detected in advance so that the necessary precautions can be taken, and furthermore health officers can be informed about the probable diseases in the long term and abnormal emergency situations in the short term [10]. For this reason, the usage of smart appliances and furnitures with sensing devices by taking into account privacy and unobtrusiveness issues are becoming widespread [11]. The user profile of such systems are mainly the elderly. For instance, Alzheimer is a mental disease which is frequently observed between elderly especially after a particular age [12]. While its occurrence ratio is 13% for above 65 years old elderly, it increases to 43% for above 85 years olds. In this regard, it is obvious that those kinds of applications will ease the life of both elderly and their relatives. In [13], a self-management system is presented for elderly who suffer from diabetes, which is a common disease among elderly, and cause the death of thousands of people around the world each year. A persuasive system which consists of both ambient and on-body sensors is designed to persuade the elderly to change their behaviours. Newsletters are utilized in the system in order to induce elderly to change their behaviours like not consuming foods with high calories or reminding them to take their medications.

Three different problems are identified in [14] for human activity monitoring (surveillance) applications. They are privacy, sheer mass of raw video data overstraining the operators, and limited flexibility. A new approach based on smart cameras focused on activity recognition and extracting only relevant information like falls is proposed in order to address the identified problems. Each smart camera is capable of embedded classification and utilize support vector machines (SVMs). It is stated that a prototype installed in a home for assisted living has been running for several months. No recognition results are stated in this study.

In another study [15], infrared motion detectors and cameras were used to collect data for 30 days for detecting a person's daily habits. In this study, they formulate the problem of extracting human activities from raw sensing data as a sequential pattern search problem and apply an exhaustive search algorithm on the collected data. 3-dimensional vectors that hold information about location, time and activity duration were used to identify the activities in that new proposed methodology.

In [16], Park *et al.* present a WSN that can recognize human behavioural patterns of the elderly who live alone in an one bedroom apartment. Accelerometers and light sensors are used in order to monitor the interactions of a person with the environment. For instance, light sensors can detect the movements of a person with the changes in the light intensity whereas accelerometers, attached to the furniture, can detect if a person is in the bed or sitting on a chair. They model episodes that are series of events which form the behaviours of a person. They measure how similar the detected episodes to the predefined episodes which they name as dictionary. For this purpose, they define several similarity metrics. Furthermore, they propose data cleaning techniques in both sensor and base station sides for the erroneous environment of wireless sensor networks.

2.2. Healthcare Domain

From the perspective of healthcare domain, human activity recognition systems can have different objectives. While some of them may support the elderly for the prevention of dangerous situations such as falls [17, 18], some focus on health issues

such as monitoring the medication intake monitoring [19].

Although falls and body movements are specific cases of activity classification, there is a significant research effort focusing on fall detection. This is due to the fact that accidental falls are among the leading causes of death over the age of 65. Most of the studies in the literature make use of accelerometers and gyroscopes for identifying sudden falls. In fact, elderly's perception about healthcare monitoring systems are that detecting emergency situations like falls is more important than monitoring ADL in the long term in order to model daily routines of people [20].

In [21], a secure fall detection system is introduced. It is indicated that the best device for fall detection are accelerometers. In this study, the sensory data which is coming from on-body accelerometers are utilized. They introduce an algorithm which aims to differentiate the falls from fall-like or normal behaviours.

The medication intake reminder and monitoring systems can help cognitively impaired people to survive independently. Similarly, medical care applications make use of medical and environmental sensors in order to obtain comprehensive health status information of the patients, including ECG, heart rate, blood pressure, skin temperature, oxygen saturation, etc. Moh *et al.* [22] integrate both sensor network and RFID technologies and design in-home medication monitoring system. It consists of three subsystems. A Medicine Monitoring Subsystem determine when and which bottle is removed or replaced by the patient and the amount of medicine taken. Patient Monitoring Subsystem alert the patient to take the necessary medicines. Lastly, a Base Station Subsystem is responsible for message relay to the Base Station Personal Computer.

The iCabiNET [23] is an indoor application that the medicine intake can be monitored over the residential network by using the RFID readers at home. The system is capable of monitoring the drugs that are bought by the user and when the presence at home is detected the smart appliances, such as TV, can be used to inform the patient about the usage and dosage. Additionally, the iCabiNET system can be

integrated with the cellular network or ordinary telephone network in order to remind the patients to take their medication correctly.

AlarmNet [24] is an another WSN example of medical care application with two main goals. Firstly, the system adapts the behaviour patterns of inhabitants, which feeds back to influence power management and privacy policy enforcement. Secondly, the system is extensible and supports a diverse collection of sensors, user interfaces, and power and privacy policies. It uses mobile body sensors like heart rate, oxygen saturation and ECG. Additionally, the deployed sensor network provides a spatial context and environmental information such as temperature, motion, humidity. Environmental, physiological, and activity sensors are integrated in a scalable, heterogeneous architecture. Healthcare professionals are able to monitor the vital signs of patients. It also provides localization of the patients via GPS.

2.3. Smart Home Domain

In this section, we discuss the existing smart home systems and applications utilizing WSNs, especially those focusing on explaining the state of the art on human activity recognition using WSNs in smart home settings.

WSNs are gradually being utilized in the smart home systems. In [25], a ZigBee-based intelligent self-adjusting sensor together with a middleware architecture is introduced for home energy management services. For communication and networking, the sensors use the ZigBee protocol because of its low-power and low-cost characteristics. The system can adaptively reconfigure middleware, network topology, sensor density, and sensing rate based on the monitored environmental situations. The performance of the system was evaluated with a test bed deployment utilizing 10-50 sensors, consisting of temperature, light, motion, humidity sensors. The system interacts with a power management system and based on the collected data from the sensors, power manager turns off electronic appliances where no motion is monitored or adjusts the temperature and lighting according to the resident's preference. The performance results were only presented in terms of battery consumption and it is shown that situation based control-

ling of the number of active sensors achieves 8-34% reduction in battery consumption compared to periodic sampling and transmission. Similar energy management systems using WSNs for smart homes were also presented in [26, 27].

In [28], a smart home monitoring application for assisted living was introduced. The system monitors the use of electronic appliances with current sensors, the water usage with water flow sensors and the bed usage using a force sensor for determining the sleeping pattern of the elderly. The collected data is transmitted to a central server and if abnormal situations occur, such as excessive water usage, the system informs the related people by sending an SMS. A prototype of the system was deployed in a two-bedroom house with six sensors. However, no performance results were presented in the paper. Similarly in [29], well-being conditions of elderly based on the usage of house-hold appliances are monitored using ZigBee based wireless sensors. Current sensors monitor the use of electric appliances, force sensors were attached to bed, couch, toilet and dining chair to monitor their daily usage and contact sensors were attached to the grooming cabinet and fridge to monitor the opening and closing of the doors. Two wellness functions are defined according to the use of house appliances and their inactivity. The first function is determined from the non-usage or inactive duration of the appliances. The second function is determined from the over-usage of a few specific appliances. The wellness functions are calculated during the runtime of the system, and an alarm is fired when an abnormal situation is observed in the two functions. The system was deployed in four houses with six sensors for a week and collected data in real time about the wellness of the elderly.

2.4. Persuasive Systems Domain

Monitoring human behaviour in the long term forms opportunities for people to change and correct some of their behaviours, habits. In other words, human behaviour monitoring systems can also be used as persuasive systems for inducing behaviour change.

BJ Fogg *et al.* [30] indicate that three main factors must be available at the same

time in order to change a behaviour. They are trigger, ability, and motivation. The lack of any of them causes an inadequate attempt to convince subjects for changing behaviour. Triggers are the warning messages delivered to subject in order to change behaviour. Secondly, ability determines the ability of a person to change the behaviour at the time trigger received. Lastly, the motivation is the degree of being likely to change behaviour. In the light of behaviour model of BJ Fogg, human behaviour systems can induce behaviour change by sending triggers with motivated contexts to inhabitants in correct times. The study presented in [13] can be considered as an example of healthcare based persuasive system. It concerns elderly who suffer from diabetes and supplies newsletters (trigger) to the patients to what they should do with the information and reasons (motivation). Change of improper behaviours which elderly are able to perform is expected (ability). In [28], persuasion and energy management issues in the house are handled. Besides monitoring human activities, they also monitor energy consumption of the electrical appliances and water usage in the house and inform the residents. For instance, an excessive water usage is detected, a short message (SMS) is sent to the corresponding person which can be thought as a trigger.

2.5. Studies about Data Collection

Monitoring human behaviour systems provide opportunities for having a more promoted life of residents by detecting the difficulties in their life, and leading them live in a healthier way. For that purpose, they collect ADL data of residents, and process them by using machine learning algorithms in order to make inferences about daily routines of people. There are a significant number of studies which collect realistic ADL data of residents accounting that training data together with accurate labels is the essential part of human activity recognition systems. In some of them, a laboratory environment is used instead of deployment in a real house, while some of them consider only a single resident living in a house.

Cook *et al.* [31] indicate that performance of human behaviour monitoring systems is limited because of lack of rich physical datasets. For that reason, they collect a

dataset from a house which consists of three bedrooms, one bathroom, one kitchen, and one living room and make it publicly available. The house is equipped with motion sensors, digital sensors, analog sensors, and contact switch sensors. No on-body sensors are utilized. During the experiments, more than 20 students are used as the subjects. Target activities of the study are telephone use, hand washing, meal preparation, eating, medication use and cleaning. Not a full day of data are collected, they want students to perform the mentioned activities one by one. In other words, it is a session based data collection process, one activity is performed by subjects at each session. Moreover, they take into consideration a very limited activity list, which do not include some basic daily activities like sleeping, toileting, taking shower, and watching TV.

In another study [6], a more comprehensive system which include both wired and wireless sensors is designed in order to collect daily living data. They deploy 72 sensors of 10 modalities in 15 wireless and wired networked sensor systems in the environment, in objects and on the body to create a sensor-rich environment. Microphone, cameras, and several ambient sensors are deployed around the environment and on body of subjects. The sampling rate of the system is chosen as 32 Hz. It is stated that making the system ready for collecting data takes five days with a large working group, and difficulties of designing such a system is highlighted. They acquired data from 12 subjects performing morning activities. Each subject performs five times a list of predefined ADLs. Similarly, this dataset also do not represent a typical full day of a person like the previous study [31] accounting that subjects are told to perform specific activities. While inferring about high level activities like preparing breakfast, they take into account smaller component parts (gestures and locomotions) like getting knife, getting salami, opening drawer, walking. Data annotation is executed by students off-line using video cameras, and it is remarked that a 30-minutes video footage requires about 7-10 hours to be annotated, which explains that annotation is one the most tedious and difficult part of such activity recognition systems. Synchronization of the data which is another challenging part of such systems (especially when more than one central unit is receiving the sensory data) is performed during post processing. Moreover, they introduce a framework [32, 33] for activity recognition systems using

multiple sensor nodes which includes sensor goal configuration, sensor ensemble configuration, handling sensor appearing/disappearing, transfer of recognition capabilities. For that purpose, they define two parameters in [34], one of them indicates to which extent a single sensor or an ensemble can contribute to the given recognition goal, the other one indicates how trustworthy the delivered data from a sensor is. In another study of the same group [35], new methods are introduced to detect faulty or degraded sensors (due to displacement, out of energy, change in environment, etc.) in a multi sensor system and compensate it. They conclude that they achieve decreasing noise in the data by the proposed methods after testing on two different datasets.

Machine learning algorithms which are used to process the collected data need labeled data in order to make robust inferences about the activities of inhabitants. Hence, annotation of the data in data collection process is a very important factor which should not be underestimated. In [36], researchers investigate and compare four different methods for annotations mainly based on using raw sensor data, daily diaries of subjects, a visualization tool, and their combinations. The results are assessed according to three different metrics, annotation time, invasiveness, and annotation accuracy. They obtain the highest annotation accuracy together with the lowest annotation time by using a combination of a visualization tool and feedback from residents' diaries which are very invasive.

Another remarkable issue about ADL data collection is that the kind of sensors used significantly affects the perception of people for human monitoring systems [20]. Privacy, unobtrusiveness, user-friendliness, security and not limiting the movements of body are the prominent requirements. Accounting the mentioned requirements, cameras, microphones, obtrusive sensors, and on-body sensors which restrict the movements of people should not be preferable very much for human monitoring systems.

2.6. Studies about Classification of ADLs

Many different supervised machine learning methods for human activity recognition using WSNs are used in the literature in order to process ADL data [9, 37, 38].

In [37], reed switches and piezoelectric switches were installed in two different homes on doors, windows, cabinets, drawers, microwave ovens, refrigerators, stoves, sinks, toilets, showers, light switches, lamps, some containers, and electric/electronic appliances to detect more than 20 activities. The collected data was labeled by the subjects using a software running on a PDA and was processed using a naive Bayes classifier and revealed a performance of 25% to 89% depending on the evaluation metric used.

In [9], van Kasteren *et al.* deployed a WSN-based system consisting of 14 sensors in a real house and collected data for 28 days. The data were automatically labeled by the subject using a Bluetooth headset with a voice recognition software. The deployment targeted the classification of seven activities (leaving, toileting, taking a shower, sleeping, having breakfast, having dinner and drinking) and the data were processed using both hidden Markov models (HMMs) and conditional random fields (CRFs). They reported an accuracy of 79.4%.

In [38], 15 different activities were monitored using a smart home testbed which was equipped with motion and temperature sensors as well as analog sensors that monitor water and stove burner use. The system was tested in a multi-resident environment, where two students lived together. The data was processed using an HMM. In the first evaluation, they put all of the sensor data for the 15 activities into one dataset and HMM reveals 60.60% accuracy. In the second evaluation, they generate one HMM for each resident, assuming that they know the person ID for each event. In this case, the average accuracy was computed as 73.15%.

Infrared presence sensors, door contacts, temperature and hygrometry sensor in the bathroom, and microphones are used in another study [39] in order to recognize seven different activities which are hygiene, toilet use, eating, resting, sleeping, communication, and dressing/undressing respectively. They perform one hour experiments with 13 young subjects to determine the models of each behaviour. For modelling the activities, they utilize support vector machines. The classification rates change between 75% and 86% for seven activities.

Researchers propose a knowledge based approach in [8]. They take into consideration eight activities, washing hands, watching TV, having a bath, brushing teeth, and making chocolate, pasta, coffee, tea. The activities are performed by three different subjects, in predefined sequence order and in changing sequence order. Additionally, the scenario with noisy data is also tested. It is stated that overall 94% accuracy is obtained.

Rashidi *et al.* [40] introduce an approach to activity tracking that identifies frequent activities that naturally occur in a person's daily life routine. With the help of this approach, they aim to track regular activities to detect drifts in an individual's life cycle. Unlike the applications which exploit the use of probabilistic models for activity recognition for predefined activities, they combine both sequence mining and clustering algorithms and form a method named Activity Discovery Method (ADM) to detect frequent activities and cluster similar patterns together. After that, HMM model is trained in order to recognize the patterns that correspond to the cluster representatives found by ADM. They utilized from the collected data in [31]. It is indicated that their proposed method is able to recognize 77% of the original activities and 94% of the activities discovered by ADM. Moreover, this accuracy decreases from 77% to 55% when clustering is not used for the original activities.

Preece *et al.* [41] investigate the advantages/disadvantages of different machine learning methods in order to identify activities using body mounted sensors like accelerometers. Threshold based classification, decision trees, kNN, artificial neural networks, support vector machines, naive bayes, gaussian mixture models and HMM are among the concerned classification methods in the study. It is indicated that there is no classifier which performs optimally for a given classification problem. The success ratio of ADL classification change due to the used datasets. Types and numbers of concerned activities; locations, types, and numbers of used sensors are significant factors which effect the chose of classification method. Even for similar activity sets, same classification methods perform relatively different accuracy results for different two datasets. It is also stated that feature selection is another important factor on the accuracies of classification methods. It is suggested that there is a need for further stud-

ies in collecting huge realistic datasets with larger number of subjects. Furthermore, it is remarked that combining classifiers in a hybrid setting is another very promising approach.

In [42], the activity recognition process is investigated at five different steps which are preprocessing, segmentation, feature extraction, dimensionality reduction, and classification. For each step, different approaches with their advantages and disadvantages and challenges together are mentioned. In their study, they take into consideration the systems which utilize inertial sensors (accelerometers, gyroscopes) for recognizing physical activities. As a general result, they state that the activity recognition systems firstly gather the sensory data in a central unit, and then process the data offline. Thus, it is indicated that online activity recognition performance is still an open research field.

Another important point which effects the classification ratios significantly is to decide on the correct features if the concern is especially understanding the physical activities like walking, running, sitting, jumping. In [43], 14 feature extraction methods have been compared. Some of them are wavelet transform based and some of them are frequency time domain features. Two different dataset of activities are used with 20 subjects. The first set consists of three different activities: walking ,stair ascent, stair descent. And the second set consists of eight activities (level walking, walking upstairs - downstairs, jogging, running, hopping on the left and right leg, and jumping). Another issue about the study is the placement of sensors. Three different placement (ankle, thigh, waist) and their combinations are considered for the sensor locations. As the classifier, nearest-neighbour classifier (kNN) is used. First, features are derived from windows of on-body accelerometers data. The classifier is then used to identify the activity corresponding to each separate window of data which is chosen as two seconds. Although it is stated that 20 Hz sampling rate is enough to make inferences about the physical activities of a person [44], 64 Hz sampling rate is used during the experiments. Overall, the highest classification accuracy 97% is obtained for the three-activity problem while it is approximately 94% for 8-activity problem. As an important result, it is concluded that frequency/time domain features significantly outperform the wavelet features. During the experiments, the optimal place for sensors are observed as

ankle. The annotation of data during the data collection process is made by cameras.

While most of the previous work focused on achieving higher physical activity recognition performance (walking, running, sitting, falling, etc.) with indoor or outdoor applications using different sets of sensors [18, 21, 43–46], research trends are moving towards human behaviour understanding such that the habits and daily routines of people are discovered and the causes of drifts from these patterns are analysed [47].

Most of the discussed systems requires the activities to be performed sequentially in defined orders which is not realistic. In other words, they take into account the only activities, not consider them as a part of period within a standard day of a subject. Different than the previous works, in this thesis, we present a WSN system for activity recognition that concerns a full day of multiple residents in their home. The system is deployed to the real house of the residents for 30 days and we do not restrict the behaviours of the inhabitants in any way which makes the collected data realistic. Other remarkable points of our studies are utilizing a large number and variety of sensors (20 sensors of seven different types), collecting ADL data for 30 full days which is longer compared to the similar studies, high number of concerned ADLs which includes rare activities (in total 27 activities), and most importantly the multi resident design of the system by accounting that most people live as a couple in real life. Moreover, in our system, we do not assume that the person IDs for the activities are known, which is a more challenging problem compared to most of the similar studies.

3. INITIAL WORKS ON HUMAN ACTIVITY RECOGNITION

3.1. General Information About Arduino Platform

In this thesis, we mainly utilized the Arduino platform and Xbee radios in order to monitor activities of daily living (ADL) with wireless sensor networks. Arduino is an "open-source electronics prototyping platform based on flexible, easy-to-use hardware and software" [48]. It can be used in various fields from robotic to art projects. The Arduino hardware is an open-source circuit board with a microprocessor and input/output(I/O) pins for communication and controlling physical objects. The board will typically be powered via USB or an external power. Arduino also has an open-source software component which is similar to C++. It is called the Arduino Programming Language, the code written in that programming language is named as a sketch. The Arduino integrated development environment (IDE) allows you to write a sketch, compile it, and then upload it to your Arduino. The microcontroller on the board is programmed using IDE. Arduino can sense the environment by receiving input from a variety of sensors and can respond to its surroundings by controlling several actuators.

The main reason to use the Arduino platform is that, it is an open source, cost and power efficient hardware platform which helped us to quickly prototype the different sensor modalities that we required for activity recognition. We preferred to use Arduino Fio which is a member of Arduino family and it is compatible with Xbee radios unlike most of the other members of the Arduino platform. The microcontroller used in Arduino Fio is ATmega328P which runs at 3.3 V and 8 MHz. The Arduino Fio is intended for wireless applications which we require in our designs. It has 14 digital input/output pins, eight analog inputs, an on-board resonator, a reset button, given in Figure 3.1. Analog pins, each of which provide 10 bits of resolution (1024 different values) which we used as sensor values in our designs. It has connections for a Lithium Polymer battery and includes a charge circuit over USB. An Xbee socket is available

on the bottom of the board. While its voltage for charge is between 3.7 V and 7 V, the input voltage is between 3.35 V and 12 V. It has a 32 KB of flash memory for storing sketches. Its DC current per I/O pin is 40 mA. Moreover, the DTR pin is directly connected to the the sleeping pin of the Xbee module, thus it is used for controlling the sleeping mode of the Xbee module which is explained in a detailed way in Section 4.3.2.

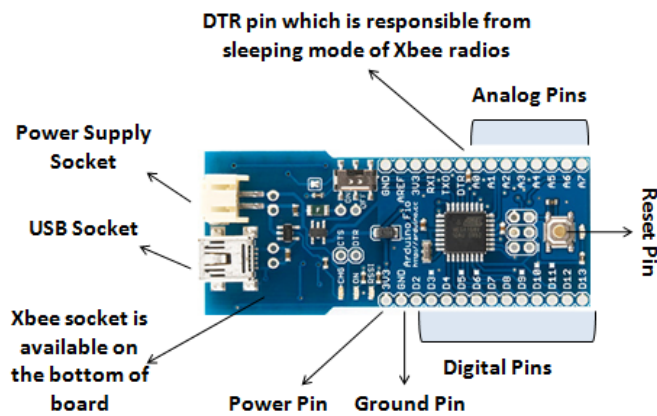


Figure 3.1. Arduino Fio [48].

We utilized standard Xbee Series 1 RF modules [49] for wireless communication in our studies. They use the ZigBee networking protocol for fast point-to-multipoint or peer-to-peer networking. They operate within the ISM 2.4 GHz frequency band, and have 30 m indoor range. The Xbee modules used in this work have 1 mW transmission power. Their RF data rate is 250,000 bps. Furthermore, they have serial interface data rate between 1200 bps - 250 kbps which we utilized in transmissions between Xbee modules and base stations in our designs. Another important point is the power requirements of Xbee modules regarding that wireless communication is one the most power consuming part of monitoring systems. Their supply voltage is 2.8-3.4 V which is convenient for Arduino Fio. While the current drawn is 45 mA in transmission position, it is 50 mA in idle or receive position. Additionally, it supports several sleeping modes including both cyclic and non-cyclic sleeping modes in order to extend the life time of batteries. With sleeping modes, the power-down current can be 10 μ A.

It supports different addressing options like PAN ID, addressing, and channel. An RF data network that consists of one Coordinator and one or more End Devices forms a PAN (Personal Area Network). In our case, one base station (central unit) and several sensor nodes constitutes a PAN. Each device in a PAN has a PAN Identifier (PAN ID) which must be unique for each PAN in order to prevent inferences if multiple PANs are used in the same area together. To send a packet to a specific module in our designs, we utilized 16-bit addressing by setting the destination address DL (Destination Address Low) to the MY (16-bit Source Address) parameter of the intended destination module. The configuration of Xbee modules are made via a software named X-CTU. We chosen to use Xbee modules with a wire antenna in our studies which can be seen in Figure 3.2.



Figure 3.2. Xbee module with wire antenna [49].

As the power supply, we utilized 3.7 V lithium polymer batteries with capacities changed between 900 mAh and 5000 mAh. The main reason to chose that kind of batteries is that they are compatible with Arduino Fio which has a built in charger mechanism for lithium polymer batteries over USB.

In our designs, we had two kinds of elements in the network which are the receivers and the sensor nodes. We formed star topology networks in which base stations performed as a receiver and the sensor nodes performed as transmitters. Base stations include an Xbee module connected to a computer with Xbee Explorer USB, and they act as receiver in the network. On the other hand, sensor nodes include Arduino Fio, Xbee module, lithium polymer battery and a sensor. Sensor nodes act as transmitter in the network. Xbee modules are the wireless communication module of the sensor

nodes, and Arduino Fio has an available socket for Xbee modules. The communication schema in the network in our studies is like in Figure 3.3.

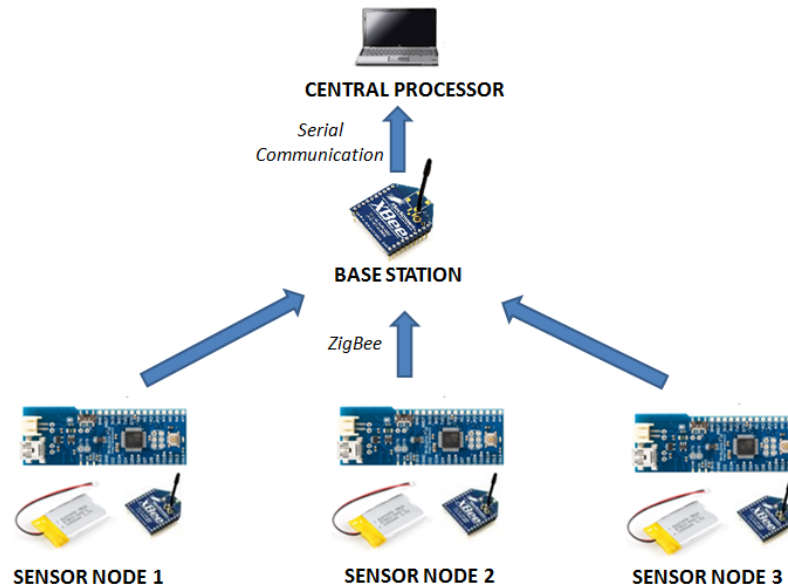


Figure 3.3. General network schema.

3.2. A Smart Couch Design For Improving the Quality of Life of the Patients with Cognitive Diseases

In this preliminary study [50], we focused on how much time people spend while sitting on a couch, napping on a couch, and lying on a couch during their daily life at homes. We aimed to differentiate these activities by detecting the transitions between these activities. In fact, it is an important part of the human activity recognition module of a home care system by accounting that people spend a significant time at couches in their homes. It is developed for especially elderly with cognitive disorders such as Alzheimer. As known mostly, elderly tend to spend very much time in front of TV in their favourite couches. Any subtle change in their sleeping and napping habits can be the sign of a serious health problem in future. To give an example, an increase at napping hours on couch or start spending more time on couch are remarkable changes in the life of elderly.

3.2.1. System Overview

We aimed to differentiate the standing, sitting on a couch, napping on a couch, and lying on a couch activities and detect the drifts from daily routines in the long term. Significant cues about how much time elderly spend time in active and inactive position at home can be achieved, as well. Furthermore, it was aimed to form warnings when a long term stationary duration is detected. Another aim to perform this preliminary study is to get familiar with wireless sensor networks and sensors in practical life for the future studies about monitoring ADL of people.

We collected data from four persons (two females and two males) whose weights are different and average age is 28. Three different sensors were utilized simultaneously, which are accelerometer, vibration sensor and force sensitive resistor (FSR), to understand and distinguish the targeted activities. These sensors are shown in Figure 3.4. All used sensors are based on Arduino Fio platform. They send the measured sensor values (values between 0-1024) to a central base station via Xbee modules with 20 Hz sampling rate.



Figure 3.4. Accelerometer, Vibration Sensor, FSR.

ADXL335 was used as an accelerometer. It has low power consumption and has $\pm 3g$ sensibility. It was placed in front of the couch in a non-disturbing way. Observation of change at the resistor due to the applied force is the working principle of FSR, and it was placed under the leg of the couch. Finally, the vibration sensor comprises of flexible piezo polymer film and a mass attached to the tip which increases the sensitivity to motion was placed on the back of the couch. The sensors and the locations can be seen in Figure 3.5. We deployed the setup at the smart home in Assisted Living Laboratory at Kandilli Campus of Boğaziçi University, and collected 15 minutes of data in total

including sitting on couch, napping on couch, and lying on couch from each of four persons. We collected five minutes of initial data in order to distinguish not interacting with the couch situation. We strongly asked for the persons to behave naturally, and did not limit their behaviours in any manner.

We mainly identified four different classes with three different types of sensors. At classification, different features and classification approaches were used. Moreover, we investigated the effects of the sensors and the features types on the success rate. Hence, we determined to most convenient combination of the sensors, the features and the classification methods in order to achieve the highest success rates.

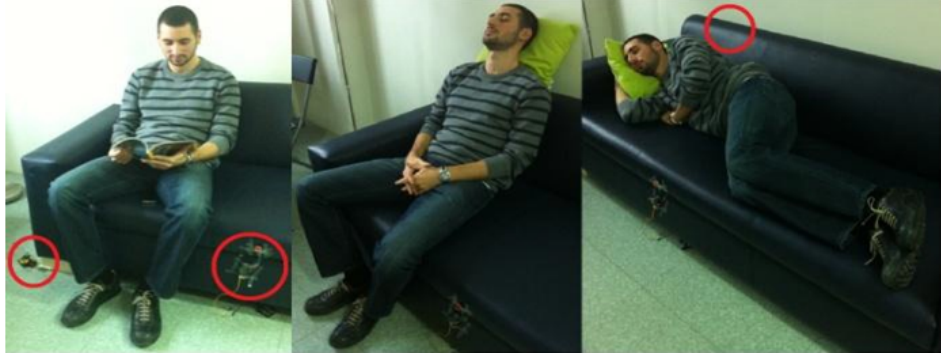


Figure 3.5. Sensor setup and a screenshot from the experiments (from left to right: FSR, accelerometer and vibration sensor).

3.2.2. Feature Extraction

We preprocessed the collected data and extracted minimum, maximum, average and standard deviation features from each window in the collected data. The reasons to choose these four features are that they are easy to implement, have low cost, and high successful rate in classification [51]. The sampling rate of the system was 20 Hz, and the window size was chosen as one second. The mentioned features of the received sensor data were calculated based on the chosen window size. We formed a vector of 20×1 sizes which compromise from four features from FSR, four features from vibration sensor, 12 features from the accelerometer (four features for each of X, Y, Z axes) after feature extraction. This vector is used while processing the collected data. While

examining the effects of different sensors and features choice on success rate, we ignored the corresponding indexes on the vector and repeated the classification methods.

3.2.3. Classification Methods

We utilized one parametric and one non parametric method in order to distinguish four different activities that are standing, sitting on couch, napping on couch and lying on couch. K-nearest neighbour (kNN) method is a non-parametric approach. In this approach, we assigned each sample in the test data to the class label of most frequent one in the k nearest neighbour samples in the training data. While calculating the distance between each sample (feature vector), we utilized the Euclidean distance. An important decision in this approach is to determine an optimal k value. We selected the k value as five after several tries.

Another used approach was Naïve Bayes method which is a kind of parametric approach. We calculated the parameters in Equation 3.1 by using the feature vectors in training data. $p(X | C_i)$ is the probability of drawing X vector from class i , and we assumed normal distribution for $p(X | C_i)$. $p(C_i)$ is the ratio of the number of samples in class i to the entire training data. $p(X)$ is the probability of coming across X vector in training data, and it was calculated like the method in Equation 3.2. $p(C_i | X)$ is the probability of selecting X vector from class i . The model which is formed by learning these parameters for each class separately is applied on each sample on test data. For each sample in test data, we calculated $p(C_i | X)$ values of the sample for four different classes, and assigned the class label with highest value to the corresponding sample in the test data.

$$\mathbf{P}(C_i | \mathbf{X}) = \frac{\mathbf{P}(\mathbf{X} | C_i) * \mathbf{P}(C_i)}{\mathbf{P}(\mathbf{X})} \quad (3.1)$$

$$\mathbf{P}(\mathbf{X}) = \sum_t \mathbf{P}(\mathbf{X} \mid \mathbf{C}_t) * \mathbf{P}(\mathbf{C}_t) \quad (3.2)$$

3.2.4. Classification Results

We utilized five-fold cross validation in the calculation of all results in this study. The entire data from four persons in the experiments were combined into one common data (approximately 24000 samples for each class are obtained), and each training data in cross validation were assured to include data from all of the persons in order to avoid generating a model which is specific to a few of the persons. We utilized the F-measure, which is the harmonic mean of precision and recall, as the evaluation metric. In Table 3.1, F-measure values of kNN and Naïve Bayes methods for each class are given. These results were valid for the situation that all sensors and all mentioned features were used together. While the average F-measure value for kNN method was approximately 83%, it was approximately 76% for Naïve Bayes method. As an overall look, we can conclude that kNN method outperforms Naïve Bayes. Especially the low F-measure value at sitting on the couch class when Naïve Bayes method is used is remarkable. Sitting was confused with napping on the couch. Another important point is that both methods almost perfectly distinguish the standing class.

Table 3.1. F-measure values of each class.

	kNN	Naïve Bayes
Standing	99.87%	99.87%
Sitting on couch	72.41%	16.41%
Napping on couch	74.53%	66.98%
Lying on couch	83.13%	89.13%

Table 3.2. Effect of sensors on the success rate.

	kNN		Naïve Bayes	
	Accuracy	F-measure	Accuracy	F-measure
FSR+Vibration S.	68.37%	74.40%	49.61%	60.20%
FSR+Accelerometer	93.96%	95.10%	67.41%	75.30%
Accelerometer+Vibration S.	58.00%	52.20%	58.52%	60.50%
FSR+Accelerometer+Vibration S.	78.54%	82.70%	67.81%	75.90%

3.2.4.1. Effect of Sensor Selection. We also investigated the effects of sensor and feature choices on the success rate in order to get a less complex and more successful design. The correct sensor selection in large scale multi sensor systems is very crucial by regarding the issues like decreasing inferences, complexity, and increasing the persistence of the entire system. For this reason, sensor activity matching is very important in such systems [52]. Accuracy and F-measure values of different sensor combinations for both methods can be seen in Table 3.2. The table presents the scenario that all mentioned features were used together. By using only FSR and accelerometer, approximately 95% F-measure value is observed. Sensitive reactions given by FSR to the changing center gravity of body on couch has an important role for achieving this success rate. The capability of the accelerometer to detect the subtle body position changing on couch can be considered as another factor that affects the success rate. We can easily conclude that FSR has a very crucial role at the classification in order to distinguish these kind of classes. Similarly, we generally obtain higher success rates with the kNN method compared to those of the Naïve Bayes.

3.2.4.2. Effect of Feature Selection. The performances of each feature are shown in Table 3.3. The table presents the results of the scenarios that each feature is used alone and all sensors are used together. We do not observe a dramatic decrease in the success rates in terms of minimum, maximum and mean features when kNN is used by accounting that 82.70% F-measure value is obtained by using all features and all sensors together as listed in the last row of Table 3.2. Hence, classifications with high successful rates can be made with only one feature by determining a correct threshold

value like in Figure 3.4.

One of our objectives is to get less complex and more successful designs. For this purpose, we repeated the experiments for each feature by using only FSR and accelerometer and by using the kNN method for the classification in the light of the information that came up with Table 3.2 and 3.3. We obtained 91% F-measure value as the highest success rate with the mean feature. The confusion matrix of this scenario can be seen in Table 3.4. Considering that we obtained 95% success rate with F-measure by using two kinds of sensors (FSR and accelerometer) and all mentioned features in Table 3.2, increasing the number of features does not increase the success rate sharply. Furthermore, another important point is that decreasing the number of used features also decrease the complexity of the overall system.

Table 3.3. Effect of features on the success rate.

	kNN		Naïve Bayes	
	Accuracy	F-measure	Accuracy	F-measure
Minimum	79.56%	83.40%	62.63%	70.40%
Maximum	77.66%	82.00%	68.90%	75.80%
Mean	79.44%	83.30%	55.79%	64.00%
Standard Deviation	63.86%	63.80%	37.71%	45.20%

Table 3.4. Confusion matrix of the scenario that FSR, accelerometer sensors and mean feature is used with kNN.

		Predictions			
		Standing	Sitting	Napping	Lying
Ground Truth	Standing	409	0	0	0
	Sitting	0	1523	34	13
	Napping	0	482	1146	2
	Lying	0	100	5	1515

3.3. Designing a Wireless Sensing System for Continuous Behaviour and Health Monitoring in Laboratory Environment

In order to understand human behaviour using a sensing system, data-driven probabilistic models can be used since they are well known and well suited for this purpose [9]. Using probabilistic models requires model parameters to be learned. Training data sets are needed for learning those parameters. However, collecting these data sets are not easy since they require both the sensor data and the activity labels at the same time. Obtaining these data sets requires special systems that allows the recording of the sensor readings and the activity labels at the same time.

In [53], we provide the details of a living lab setting for collecting training data sets in a realistic manner. We obtained significant experiences about designing a simple architecture of wireless sensor network monitoring human behaviour continuously, and have been familiar with Arduino platform and sensors through this study. Hence, it lead to a more complex wireless sensor network deployed to a real house shared by two residents for a longer period of time as the next step of our studies in Chapter 4.

3.3.1. Living Lab Setup and Concerned Human Behaviour

For the data collection process, we decorated the ambient assisted living lab in Kandilli Campus of Boğaziçi University in order to form a convenient living environment. It can be thought as a miniature house which consists of one bedroom, one living room, and one kitchen. It has basically all facilities a real house has except a bathroom. A wireless sensor network consisted of 10 sensor nodes and a base station deployed in the lab. We utilized Arduino Fio platforms and Xbee modules for wireless communication between sensor nodes and the base station. Xbee modules use the Zigbee communication protocol which is low power and has adequate bandwidth for our purposes. The base station consists of a Xbee module connected to a computer via serial communication. The subject labelled his activities using the same computer via a simple interface. Since the software which receives the sensor data and annotations of the subject is the same, and so use the same time scale, the synchronizing problem

which is one of the main problems while collecting data turns into an easy issue. Three distance sensors, three force resistive sensors, two light sensors, one vibration sensor and one contact sensor were used during the data collection process. All sensors used a common channel while communicating with the base station. We did not prefer any video recorders or on-body sensors regarding privacy and unobtrusiveness issues respectively unlike most of the similar studies. The layout of the lab environment and location of sensors are depicted in Figure 3.6. The size of the lab is approximately 55 m^2 . The sampling rate of the sensors was chosen as 2 Hz in order to increase the battery life time of sensors. When we consider the average speed of people in the home environment this sampling rate provides the necessary resolution and lowers the power consumption in the transmission mode. Additionally, the base station is located in a static position during the experiments to see each sensor directly in order to reduce the lost data rate.

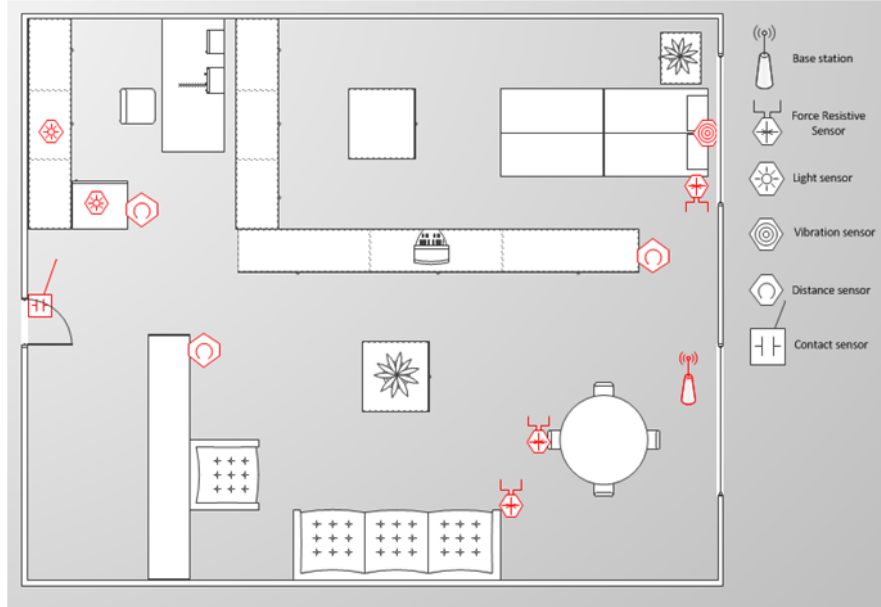


Figure 3.6. The layout of the lab environment.

The experiments are performed by a volunteer subject during five days. Approximately six hours of data is collected for each day from 12 pm to 6 pm which is generally the most active interval of a person in a standard day. During the data collection sessions, the subject does not follow a specific scenario and also he is not

instructed about how the activities should be performed. The activities are annotated by the user himself via a graphical user interface. We defined eight classes for the experiments. They are respectively, studying, using internet, watching TV, reading book, having a snack, sleeping, going outside. Also, we categorize a separate class for all the other activities which are composed of generally listening to music and speaking on the telephone. We used distance sensors for detecting passages between rooms. Sonar distance sensors which have a higher range compared to proximity sensors, were used for detecting passages between living room and kitchen; living room and hall to the door. Furthermore, sonar distance sensors are capable of sensing the activities in the living room in which the subject spends most of his time. The other distance sensor is proximity sensor and used for passing between the living room and the bedroom. Other sensors used in experiments are force resistive sensors which were located under bed, chair, and couch respectively. They were used to detect lying on the bed, sitting on the chair, and sitting on the couch. They work with the principle of resistance change due to changing applied force on them. Since they are in interaction with the subject unlike other sensors, they should have a robust wiring and keep their position stable during the data collection process. Light sensors were used for the kitchen activities. They were located in the refrigerator and the kitchen cupboard to sense the light changes stemmed from opening of refrigerator and cupboard door, so they helped making assessments about kitchen activities of the subject. Another sensor used in the experiments is the vibration sensor which was attached to the bed. With the help of vibration sensor, we aim to comprehend the sleep habits of the subject. Lastly, we used a contact sensor on the outside door to detect opening and closing of the door. So, we can understand the total time which the subject was outside or inside the lab. Some of the used sensors are shown in Figure 3.7.

We aim to form an event-based data set which consists of binary values. An event is moving inside the rooms or passing between the rooms for distance sensors; sitting on the chair, on the couch, or lying on the bed for force resistive sensors; opening refrigerator or kitchen cupboard for light sensors; rollovers and movements in the bed while sleeping for the vibration sensor; opening the door for the contact sensor. All sensor nodes sense the environment continuously without sleeping, and they start firing



Figure 3.7. Several sensors deployed in Assisted Living Lab.

sensor values to the base station when an event is detected. For this purpose, different threshold values were defined for each sensor in order to convert received sensor values which are between 0-1023 into binary values. Sample binary sensor readings with respect to the different activities of the subject during a day can be seen in Figure 3.8.

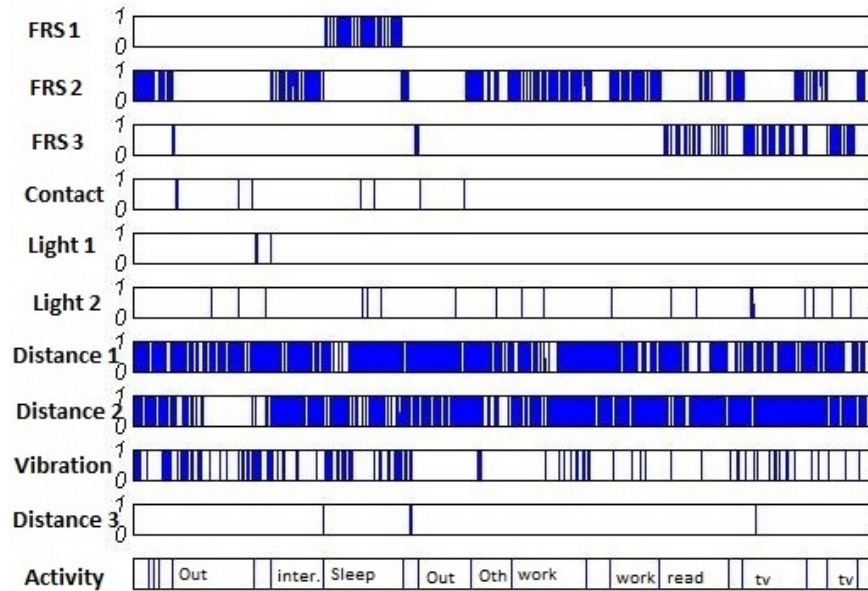


Figure 3.8. Sensor readings of binary data.

3.3.2. Classification Results and Discussions

Before the classification, we carry out preprocessing on the collected binary data. The data is discretized due to different time slice lengths which are one minute, two minutes, and three minutes accounting the average movement speed of the subject.

The selected time slice length is represented with one sample in the discretized format. In other words, we keep the summarized version of the data without any data loss by taking into account that above mentioned time slice lengths are sufficient to make any inference about the habits and daily routines of people. Secondly, we utilize three different feature representations in the discretization step of the data. They are raw data, change point, and last fired feature representations, respectively. In the raw data feature representation, the time slice length is represented by binary one for the corresponding sensor node, if that sensor node is fired for a particular time during the time slice length, and represented by binary zero if otherwise. In other words, the raw data feature representation takes into account whether the sensor node is active or not during the chosen time slice length. On the other hand, we represent the time slice by binary one in change point feature representation, if the sensor node changes its status from non-firing to firing or vice versa in that time slice. If the sensor node keeps its status stable during the time slice, that sensor node is represented by binary zero for the corresponding time slice. Finally, the last fired feature representation take into consideration only the last fired sensor node among the entire sensor nodes. Only one sensor node is represented by binary one in a sample. This feature representation is not suitable for data including multiple residents information, because it takes into account only sensor values of the last fired sensor node and ignores the other ones which can be triggered by the second resident.

Since it is five day data, we use five-fold cross validation during the classification, which means that each day is used as a test data. As the classification method, we use a Hidden Markov Model (HMM) with eight states for our case, which is very convenient for temporal data like ADL data in our case. The success rates according to F-measure is in Table 3.5.

We obtain the highest success rate 64.1% with the last fired feature representation and one minute time slice length. The last fired method outperforms both raw data and change state methods for all time slice lengths. We consider that it is closely related to the matching between activities and number of sensor nodes. We have 10 sensor nodes while there are only eight target activities which are generally performed

Table 3.5. F-measure values according to different feature representation methods and time slice lengths.

	1 minute	2 minute	3 minute
Raw Data	59.5%	55.6%	52.0%
Change State	58.8%	42.2%	39.0%
Last Fired	64.1%	62.1%	52.0%

very differently, and in different locations. The last fired method also supplies us information about the location of the subject for that time interval by stating the most recent active sensor node. Similarly, we can conclude that one minute time interval is the most convenient time interval compared to larger time intervals for this setup. The reason of that can be the small amount of data loss stemmed from the extended time slice length. Additionally, the chosen sampling rate, which is 2 Hz, also effects the success rates due to the time slice length. The worst success rates are generally obtained with the change point method and three minutes time slice lengths.

In this study, we simply perform a subset of a complete day (six hours during five days) with 10 sensor nodes deployed to a lab environment redesigned according to real life conditions. Kitchen and bathroom activities like cooking, toileting, taking shower which are the strongly necessary activities in real life are not included in this study. As the next step of our overall studies, we form a more complex and large scale wireless sensor network with 27 targeted activities to a real house with multiple residents for a longer period (30 days) in the light of gained experiences about the practical usage of the Arduino platform and sensor nodes during this study.

4. DEPLOYMENT OF A WIRELESS SENSOR NETWORK IN A REAL HOUSE

4.1. System Overview

We deployed an activity recognition system using wireless sensors in a real home in order to collect daily living data of two male persons both aged 25 for 30 full days, and we utilized the Arduino platform together with Xbee radios. The system includes 20 different ambient sensors which communicate with two different base stations to upload the collected sensory data. The utilized ambient sensors were seven different types located in the house, namely Force Sensitive Resistors (FSR), contact sensors, photocells, proximity sensors, sonar distance sensors, temperature sensor, and infrared receiver. They can be seen in Figure 4.1. The base stations are specific nodes that are attached to a computer and they assist as bridges in collecting the data coming from different sensors. The area of the house is approximately 50 m^2 . Although the communication range of the ZigBee modules have been reported as 30 m in the datasheets, due to the obstructions in the layout of the house, two base stations (PAN coordinators) were required in our deployment, one placed in the kitchen and the other one in the living room. While 13 sensor nodes were in the coverage of first base station, seven sensor nodes were in the coverage of second base station. The sensor nodes in different clusters used different channels in order to prevent probable interferences, and the destination address of base stations and sensor nodes were programmed in the convenient way. In other words, two different personal area network (PAN) which used different channels were constructed in the house in order to not missing and overlapping any sensory data. The channels were set while configuring Xbee radios. Packetization timeout which determines the time to wait before sending data, is configured as 10 character time (≈ 1.75 ms with 57600 baud rate) If this value is too short, it may cause data fragmentation and lead to unnecessary transmissions. The coverage area of the PANs can be seen in Figure 4.2 together with the layout of the house and location of used sensors. The main network architecture was designed as a star topology that

is all sensor nodes send values between 0-1023 to the relevant base station in one way. Xbee modules transmitted the received sensor values to the central units for storage and processing via serial communication whose baud rate is 57600 which is typical for Arduino Fio.

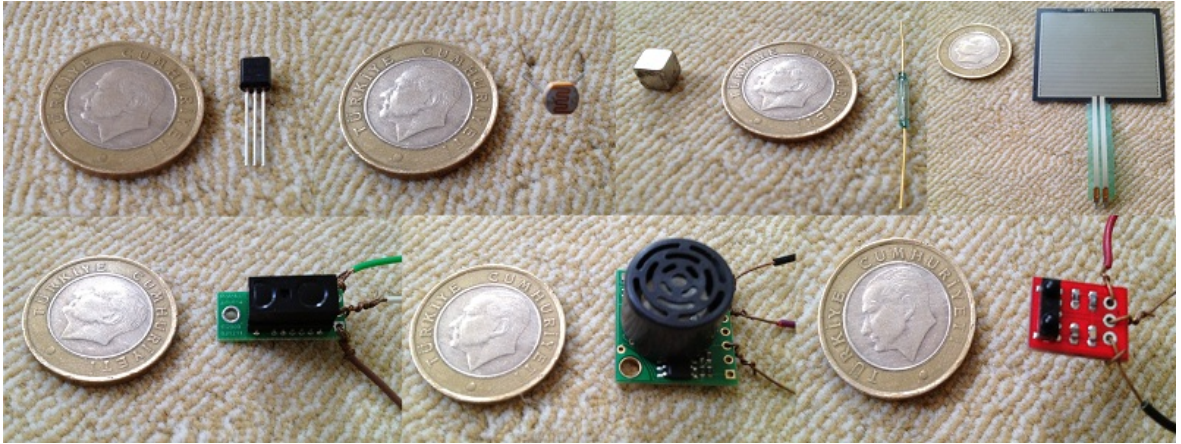


Figure 4.1. Different ambient sensors deployed in the house.

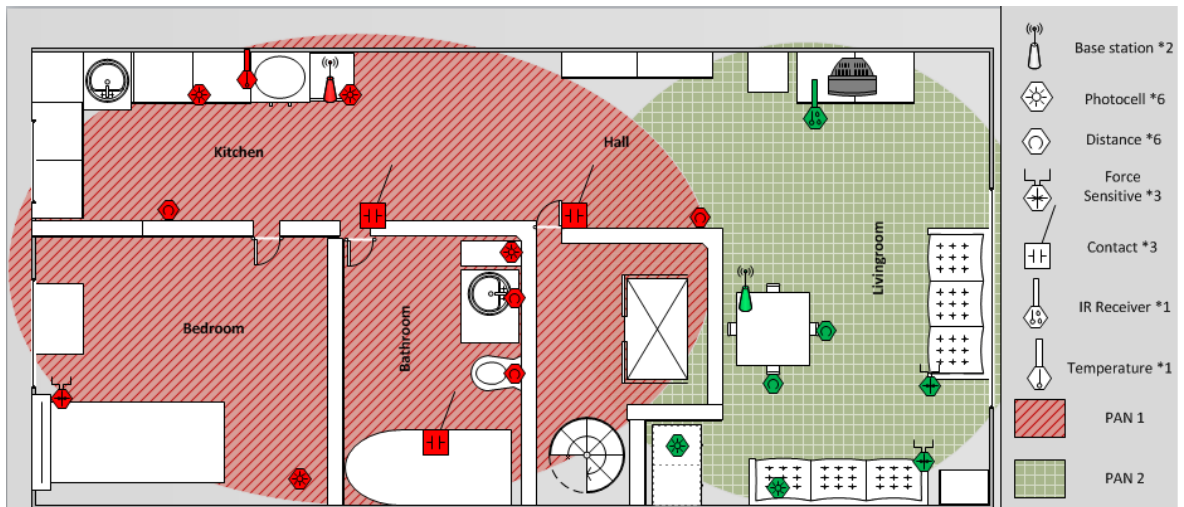


Figure 4.2. The covarege area of two PANs in the system.

We collected the sensory data in an event based format by accounting the limitations about the life time of the used batteries and life time requirements of a human activity monitoring system. Each sensor node was programmed in the way that it only sends sensory data with 10 Hz when an event was detected. Xbee modules were put into the sleeping mode in the other times. On the computers that serve as base stations,

there is a special application for both receiving the labels for the activities from the residents and sensor data coming from different parts of the house. The residents can label their current activities via a simple interface deployed on the computers served as base stations during the data collection process before starting the activity. There are 27 different activity options in the interface to label for the residents. Since we have deployed two base stations that serve different sensors, we developed a centralized software for handling the merge and synchronization of the combined data and the activity labels. We converted all collected sensor values into binary format and then, made classification and inferences about the collected data. The flow of information in the design is given in Figure 4.3.

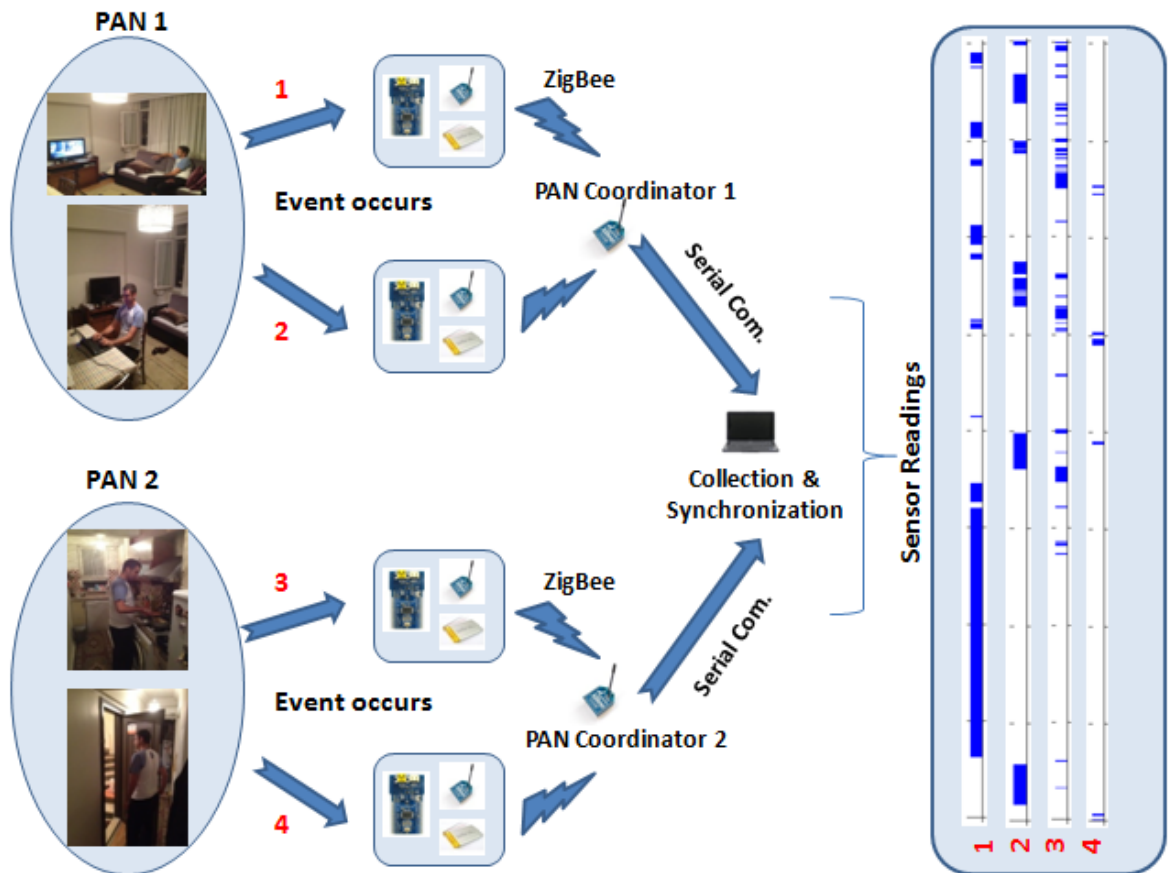


Figure 4.3. Information flow in the system.

4.2. The Ambient Sensors used in the System

The activity recognition system consists of two base stations and 20 different ambient sensor nodes, which basically comprises of seven different sensor types. These are photocells, proximity sensors, sonar distance sensors, force sensitive resistors (FSR), contact sensors, infrared receiver and temperature sensor respectively. All of them return sensor values between 0-1023 that is proportional to the amount of voltage being applied to the pin. We did not utilize any kind of cameras and on-body sensors by taking into account the privacy and unobtrusiveness issues unlike most of the similar activity recognition systems [7, 14, 15, 18, 39].

4.2.1. Base Stations

Although the communication range of Xbee radios is stated as 30 m in the datasheet, we experienced data loss due to violation in line of sight between the base station and some sensor nodes because of the not straight shape of the house. For this reason, two base stations were used in the system in order to cover the entire house. One of them was located in the kitchen. It had 13 sensor nodes in its coverage, and used the same channel for the Zigbee communication with the relevant sensor nodes. The other base station was located in the living room and used the same channel (different from the other base station) with other seven sensor nodes. While deciding on the locations of the base stations, we took into consideration not to violate the line of sight between the sensor nodes and relevant base stations in order to decrease the data loss.

The base station comprises an Xbee module connected to a computer via serial port. Xbee modules transfer the received samples of sensory data to the computer via serial communication with baud rate 57600. Then the sensory data which was transmitted to the computer and the labels of the residents were stored on the computer for being processed at the next levels. The first base station which is placed at kitchen can be seen in Figure 4.4.

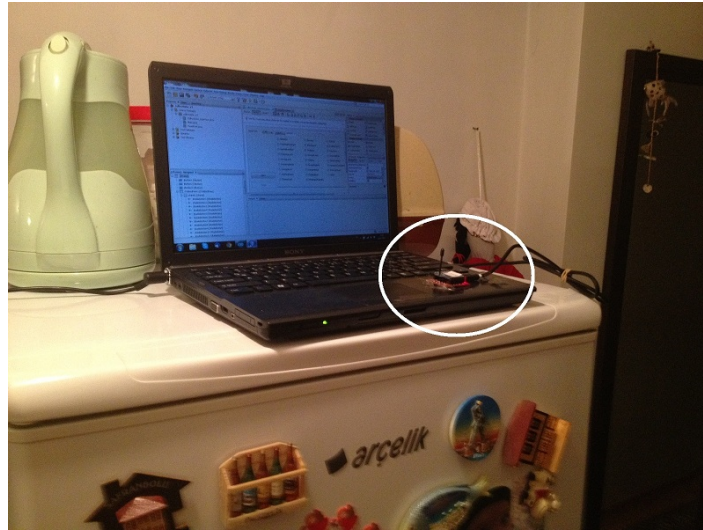


Figure 4.4. Base station 1.

4.2.2. Photocells

Photocells appeared as the most robust sensors in the system. They worked seamlessly during the data collection process. The photocell is sensitive to the change of amount of light in the environment. Arduino Fio reads higher sensor values when the amount of light in the environment increases according to our calibration to the sensors. This is the working principle of all photocells used in the system. 6 photocells were deployed on different parts of the house which can be seen in Figure 4.5 .

4.2.3. Force Sensitive Resistors

FSRs give different values due to the changing resistance. There is an inverse proportion between the resistance and applied force to the sensitive area. Thus, higher sensor values are received by increasing force. We used three square FSRs in the system which can be seen in Figure 4.6. We did not use static threshold values for FSRs like other sensors, because they are not very sensitive sensors. When sensor node starts working, it defines a threshold value according to the read initial sensor values while nobody is sitting on the couch or bed. If the read sensor values go beyond to 20 (threshold value) more of the defined initial value, it detects an event, and proceeds

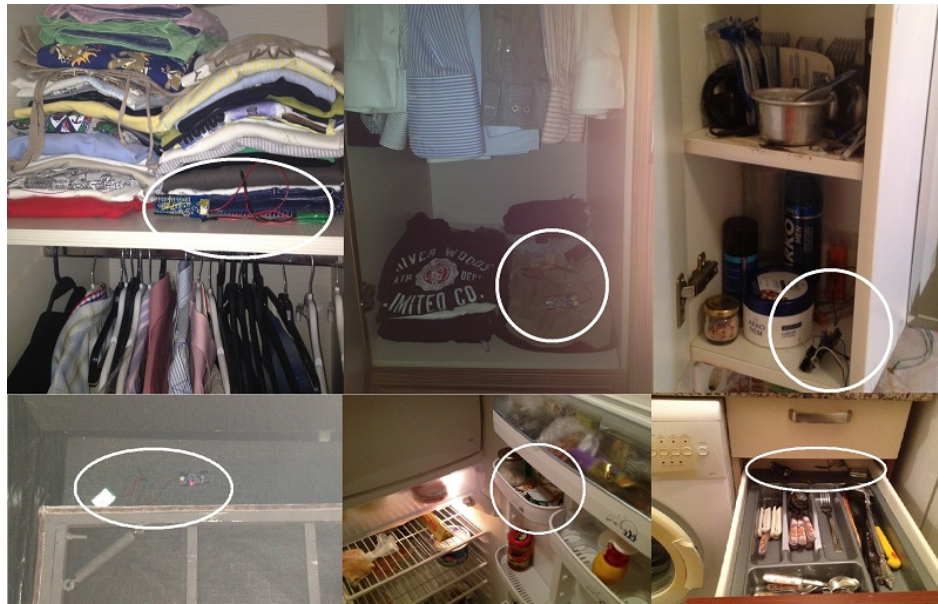


Figure 4.5. Photocells.

the normal procedure like the other sensors. We decided on this threshold value by testing the residents with all scenarios where FSRs were used. It can be changed due to the used resistances and the weights of residents. It assigns a new threshold value when it is reset and activated again. We obtained much more accurate and robust results with the mentioned method. They are the most active sensors in the system, so their power consumption is the highest. For this reason, they used 5000 mAh batteries.



Figure 4.6. Force sensitive resistors.

4.2.4. Distance Sensors

We used two kinds of distance sensors as proximity sensors and ultrasonic distance sensors (range finder). There are two ultrasonic distance sensors and four proximity sensors in the system.

4.2.4.1. Ultrasonic Distance Sensors (Range Finder). These sensors are much more complex and developed than what we need. They measure the distance of the objects up to 6.45 meters. However, we used them to detect whether someone passes in front of them or not in our system. Initially, they give constant sensor values in a certain interval when nobody is passing in front of them. Thus, we defined threshold intervals for each of them initially. If someone passes in front of the sensor, it gives different sensor values outside of the threshold interval. They are shown in Figure 4.7.

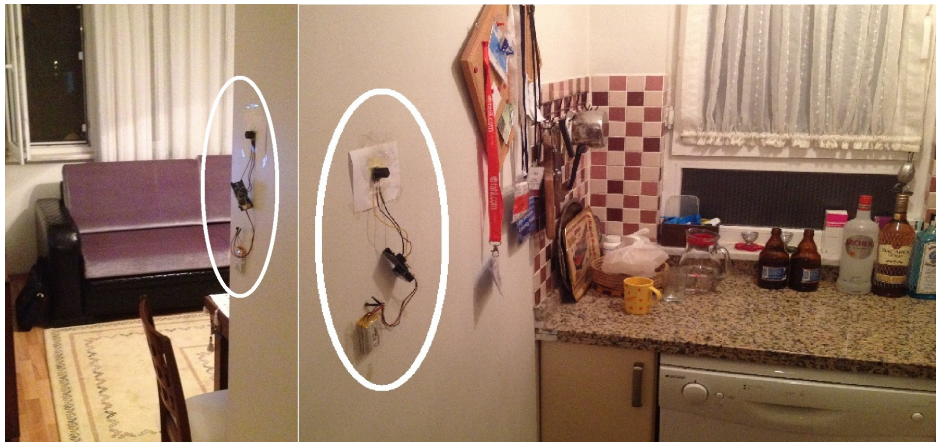


Figure 4.7. Sonar distance sensors.

4.2.4.2. Proximity Sensors. Proximity sensors have very small ranges like 10 cm. They give high sensor values around 1000 by default and small sensor values around 130 when they see an object in their range. These values are generally valid for the proximity sensors in our system. For this reason, we defined a common threshold value as 200 for all proximity sensors in the system. It means that if the read sensor values are smaller than 200, the sensor node detects an event. Four proximity sensors were used in the deployment. They can be seen in Figure 4.8.



Figure 4.8. Proximity sensors.

4.2.5. Contact Sensors

We used three contact sensors in our system. Contact sensors are generally used for detecting opening or closing doors, drawers. Their working principle is simple. They include two metal pins in opposite positions in a way that they are not touching each other. However they are influenced by a magnetic area, and convey the current, if they are sufficiently close to each other. A magnet is used together with the contact sensor. Magnet is typically located on the door and the contact sensor is located on a stable point. According to our calibrations, contact sensor gives high sensor values around 1023 when the contact sensor is not influenced by a magnetic area, and oppositely it gives small sensor values between 0-100 when it is influenced by a magnetic area (condition of being sufficiently close to each other). For this reason, we defined different threshold values for each contact sensor due to their usage aim. For example, opening of a door can be an event for some activities, while closing of a door can be an event for another activity. The contact sensors deployed in the house are shown in Figure 4.9.



Figure 4.9. Contact sensors.

4.2.6. Temperature Sensor

The temperature sensor was located above the oven in the kitchen. It gives sensor values directly proportional to the temperature in the environment. It is obvious that the environment temperature and seasons are an important factor for the temperature sensor due to its nature. We collected all data during the summer. After several tests, we decided on 105 as the threshold value which equals to approximately 33.8 centigrade. While residents are preparing a meal, most of the time the temperature of the environment increases as a result of heating any food. The temperature of the kitchen never exceeds 33.8 centigrade in normal situations. If the residents begin to heat any food while preparing a meal, the temperature of the environment go beyond the predefined threshold value and the sensor node detects an event that the temperature of the environment is increasing. In such a condition, sensor node wakes up the wireless communication module and starts firing to the relevant base station in the kitchen. One note about using the temperature sensor is that it continues to fire for a while, after

preparing a meal is over. The reason is that the environment does not cool down the threshold value immediately. However, it lasts only 4-5 minutes at most. By the help of the temperature sensor, we can get significant results about preparing and having meal habits of the residents. You can see the temperature sensor in Figure 4.10.



Figure 4.10. Temperature sensor.

4.2.7. Infrared Receiver

The infrared receiver (IR) was placed above the decoder of the TV. It is sensitive to infrared and, since the TV remote control use infrared for working, it is obvious that IR can detect easily that a button is pushed on the remote control. Hence, we can get significant information about TV usage habits of the residents. Actually, IR supplies much more than what we mentioned above. It can be known even which button is pushed specifically by using the instruction manuals supplied for different brands of TV remote controls. However, we are just interested in whether the TV remote control is used or not. IR samples at 100 Hz unlike other sensors, because we can miss any valuable data if we work with less sampling rate accounting that pushing a button is a much faster activity compared to all other concerned activities in the system. Sensor node controls the related pin every 10 ms, and transmits with 10 Hz like the other sensors in the system upon detecting an event. We defined the threshold as 1000, because sensor values around 1023 is read from IR by default. When a button

is pushed on the remote control, very low sensor values around 100 are read. The IR sensor is shown in Figure 4.11. All basic properties of the sensors in the deployment are summarized in Table 4.1 and 4.2 with respect to the base stations they are connected.



Figure 4.11. Infrared receiver.

4.3. Data Collection Process

4.3.1. Sensor Selection and Deployment

20 sensors of seven different types are utilized during the data collection process. We selected the most convenient sensors which enable us to understand the aimed activities in a more robust and easy manner. In other words, we took into consideration sensor activity matching while selecting sensors and locations for deployment. We utilized photocells, FSRs, proximity sensors, ultrasonic distance sensors, contact sensors, temperature sensor and infrared receiver during the data collection process. The locations of each sensor and base stations are depicted in Figure 4.12.

Table 4.1. Basic properties of sensors which are connected to the base station in the kitchen.

Sensors	Location	Threshold	Resistance
Photocell 3	Inside refrigerator in kitchen	>150	10k ohm
Photocell 4	Inside drawer in kitchen	>200	10k ohm
Photocell 5	Inside wardrobe in bedroom	>80	10k ohm
Photocell 6	Inside bathroom cabinet	>150	10k ohm
FSR 3	Under bed in bedroom	Dynamic Thr.	1k ohm
Sonar Dist. 1	On wall in hall	<70 or >90	No res.
Sonar Dist. 2	On wall in kitchen	<80 or >90	No res.
Proximity Sen. 1	Just above tap in bathroom	<200	No res.
Proximity Sen. 2	On closet in bathroom	<200	No res.
Contact 1	Side of outside door	>1000	1k ohm
Contact 2	Side of bathroom door	<300	1k ohm
Contact 3	Side of shower cabin	>1000	1k ohm
Temperature 1	Above oven in kitchen	>105	No res.

Table 4.2. Basic properties of sensors which are connected to the base station in the living room.

Sensors	Location	Threshold	Resistance
Photocell 1	Inside wardrobe in living room	>250	10k ohm
Photocell 2	Inside couch in living room	>70	10k ohm
FSR 1	Under couch in living room	Dynamic Thr.	1k ohm
FSR 2	Under couch in living room	Dynamic Thr.	1k ohm
Proximity Sen. 3	Back of chair in living room	<200	No res.
Proximity Sen. 4	Back of chair in living room	<200	No res.
Infrared Rec. 1	Just below TV decoder	<1000	560 ohm

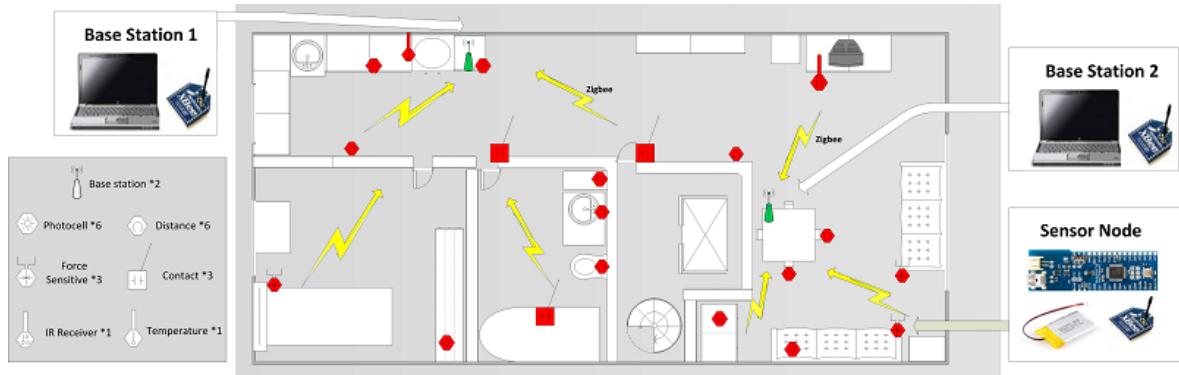


Figure 4.12. Layout of the house and the place of the sensors.

To give a straightforward example to understand sensor activity matching, we can handle the toileting activity. When a person is performing the toileting activity, we expect several actions occur at the same time or in succession during the time interval of toileting. Firstly, the person closes the bathroom door that triggers the first action. The contact sensor which is located on the side of bathroom door is activated and starts firing. It continues firing during the toileting mostly since we expect the bathroom door to be closed during the toileting. After a while, we expect the proximity sensor located on closet to be activated when the person lifts the closet cover. It is also expected to be active during toileting. After the end of the toileting, we expect the proximity sensor and the contact sensor to stop firing respectively. Additionally, other proximity sensor which is just over the tap is expected to fire for a short time while the person is washing his hands. In brief, all of the actions comes together and forms toileting behaviour. Closing the bathroom door while closet cover is closed or lifting the closet cover while bathroom door is open does not mean toileting behaviour. The sensor activity matching table is shown in Table 4.3.

We also took into account privacy and unobtrusiveness issues while deciding on the sensors and their locations. As mentioned before, we did not use any cameras or video recorders in the data collection process which significantly violate the privacy of individuals. Furthermore, there were no sensors on body which disturb people and limit the movements of people most of the time. Thus, we preferred ambient sensors

Table 4.3. Sensor locations and targeted activities.

Type	Sensor ID	Location	Target Activity
Contact Sen.	Co1	Outside door	Going outside, receiving guest
	Co2	Bathroom door	Taking shower, toileting
	Co3	Shower cabin	Taking shower
Proximity Sen.	Di1	Back of the chair in living room	Sitting on chair
	Di2	Back of the chair in living room	Sitting on chair
	Di3	Just above tap in bathroom	Washing hands
	Di4	On closet in bathroom	Toileting habits
Sonar Dist. Sen.	So1	On wall in hall	Passing along the hall
	So2	On wall in kitchen	Kitchen activities
FSR	Fo1	Under the leg of couch	Sitting, lying, napping
	Fo2	Under the leg of couch	Sitting, lying, napping
	Fo3	Under the leg of bed	Sleeping of second person
Inf. Reader	Ir1	Just below TV	Watching TV
Photocell	Ph1	Inside the wardrobe	Dressing of first person
	Ph2	Inside the couch	Sleeping of first person
	Ph3	Inside the refrigerator	Using refrigerator
	Ph4	Inside the drawer	Kitchen activities
	Ph5	Inside the wardrobe	Dressing of second person
	Ph6	Inside the bathroom cabinet	Bathroom activities
Temp. Sen.	Te1	Above oven in kitchen	Cooking, having meal

during our data collection process. All sensors were located in the environment as stated before, and the size of them are so small to distinguish as depicted in Figure 4.1. Moreover, the line of sight between the base stations and sensor nodes is another important point while especially determining the locations of sensors and base stations in order to decrease probable data loss.

Additionally, we interviewed with the residents about usage habits of the goods at home to make the sensor activity matching in a more accurate way. For example, they stated that they always keep the shower door closed, and always keep the closet cover closed during the other times except toileting. These statements have been helpful while choosing sensor types and deployment locations of sensors.

4.3.2. The Problem: Life Time of Batteries

One of the most important criteria while choosing the sensors and designing the system is the life time of the system, i.e. the life time of batteries, because a long life time of the system without any replacement in the batteries are required in such human behaviour monitoring systems. Similarly, we took into consideration the low power consumption of Arduino Fio platforms and Xbee radios for the consistency of the system. The power requirement of the sensor nodes are supplied by lithium polymer batteries and Arduino Fios have the property of charging the lithium polymer batteries without requiring any external device. Three important factors which effect significantly the life time of the batteries are sampling rate of the system, active sleeping mode of Xbee radios (wireless communication module), and duty cycle of each sensor nodes.

4.3.2.1. Sampling Rate. All sensors were sampled at 10 Hz. In the preliminary field tests, lower sampling rates were observed to cause some data loss. On the other hand, given the speed of several human activities, higher sampling rates were shown not to provide any benefits but resulted in higher power consumption. As a result of these preliminary experimentations, we defined the sampling rate of the system as 10 Hz. In order not to miss any pressing button of remote controller, which is a much faster activity compared to the natural human activities, the infrared receiver was sampled at 100 Hz, however the sensor values were transmitted with 10 Hz like the other sensor nodes.

4.3.2.2. Sleeping mode of Xbee Radios. In the conducted preliminary tests, we realized that the active sleeping mode of Xbee radios increases the life time of batteries dramatically. Thus, to extend the battery lifetime of the batteries, we programmed the sensors in a way that if they did not have new data to be sent, they did not activate their wireless communication modules considering that the wireless communication is one of the most power consuming actions. Moreover, we preferred using the low-power ZigBee wireless communication protocol. In the light of the above mentioned issues,

we designed an event based data collection system. To give details about it, all wireless communication modules of the sensor nodes sleep initially. However, Arduino Fios continue to receive and assess the sensor values meanwhile with 10 Hz, and the sensor value is compared with the predefined threshold value specific for that sensor. If the sensor value is not in the predefined range, an event is detected. Upon detection, the wireless communication modules are woken up and start sending sensor values to the relevant base stations. The threshold values for each sensor are stated in Section 4.2. An event definition varies according to each sensor. For instance, it can be sitting on the chair for a proximity sensor, pushing a button of remote controller for an infrared receiver, opening refrigerator for a photocell. After the detected event ends, the sensor values are returned within the predefined thresholds. In this case, data transmission stops and the wireless communication modules switch to sleep mode again. When there is not a sensed event, no transmission takes place to reduce the power consumption. We chose the first sleep mode while configuring Xbee radios, by accounting that it is the most power saving mode and additionally not a cyclic sleeping mode like we require. The only drawback of the sleeping mode is that the reassociation with the network can take as long as 300 ms, though the wake up time for the Xbee radio is 13.2 ms. On the other hand, given the huge increase in the battery life time and the longer duration of human activities, this delay does not very much affect the performance of the system and using sleep mode is more preferable.

4.3.2.3. Duty Cycle of Sensors. Some of the sensor nodes were active during a long time interval within the day while some of them were active for only a small time interval. To give an example, FSRs were active during the whole sleeping duration whereas the photocells in the kitchen drawer were much less active like at most 10 minutes in a day. For this reason, we utilized lithium polymer batteries with capacities ranging from 1800 mAh to 5000 mAh due to the duty cycles of sensor nodes. With these improvements, we got a battery replacement frequency between 2-8 times during our 30-day field study depending on how frequently a sensor detects an event and transmit the readings.

Table 4.4. Experiment results about lifetime of batteries.

		Sampling Rate	
		10Hz	100Hz
Idle Mode Duty Cycle	10%	24h19m	24h11m
	50%	24h29m	23h57m
	90%	24h10m	24h02m
Sleep Mode Duty Cycle	10%	145h21m	146h43m
	50%	49h23m	45h32m
	90%	28h30m	27h07m

4.3.2.4. Performance of Networking, Lifetime. In order to evaluate the performance of network lifetime under different configurations we conducted experiments before the deployment. We investigated the effect of sensor sampling rate and keeping the Xbee radios in the sleep mode instead of keeping them in the idle mode. In the experiments, we used 1800 mAh batteries and a photocell sensor node. We experimented with three different duty cycle values 10%, 50% and 90% and with two different sampling rates at 10 Hz and 100 Hz. In the first experiment, the wireless communication modules were kept in the idle mode when they were not transmitting. In a time frame of 100 seconds, the sensors transmitted data for 10 seconds, 50 seconds and 90 seconds and waited in the idle mode for the rest of the time for 10%, 50% and 90% duty cycle operations, respectively. In the second experiment, ZigBee modules were switched to the sleep mode when there is no transmission. The results of the experiments are summarized in Table 4.4.

According to the results, we obtain approximately one day of lifetime when idle mode is used. The effect of sampling rate and using different duty cycles are negligible. The results are consistent with the specifications of the hardware. In the transmission mode, the current consumption is 45 mA and in the idle mode it is 50 mA. Therefore, there is not much improvement space with lower sampling rates since the sensors being used have very little power consumption compared to the radio. On the other hand, when we use the sleep mode, we see huge differences in the life time. In the sleep mode,

the current consumption is below $10\ \mu\text{A}$. Therefore the gain in the lifetime duration is visible even for the 90% duty cycle, which is a relatively high rate. Moreover, the increased effect in life time when using lower sampling rates and lower duty cycles is another key finding. In the experiments before the actual deployment, we observed that higher sampling rates do not provide any extra information given the durations of the human activities. Therefore, we preferred using the 10 Hz sampling rate for a prolonged life time.

4.3.3. Labeling Activities

Collecting robust, realistic and detailed data with detailed annotations is the critical point of the systems that understand human behaviours. Moreover, getting correct and detailed annotations for the collected data is the most crucial, at the same time the most tedious part of this data collection process. For the annotation of activities, we provided a simple interface for the residents and observed that there have been between 60-100 labels for each day in total, which demonstrate that the residents recorded their activities very frequently, and hence the collected data is very detailed in contrast to some of the previous deployments which only relied on users keeping diaries about their activities or deployments without the annotation of activities.

While the data are collected, the residents tag their activities via a simple interface which were deployed on the computers used as base stations. It can be seen in Figure 4.13. There were 27 different activities on the interface in total generally including main daily living activities like sleeping, toileting, having meal, cooking, watching TV, taking a shower. Furthermore, it includes more detailed activities that some of them are not performed every day like hanging out laundry, having a guest, doing cleaning, having napping. One of the most important things which should be stated is that the residents are not required to follow a specific scenario; we strongly asked for them to live their normal life like before deploying the setup around. For this purpose, we placed the sensor nodes to the most convenient locations in order not to disturb the daily life of residents.

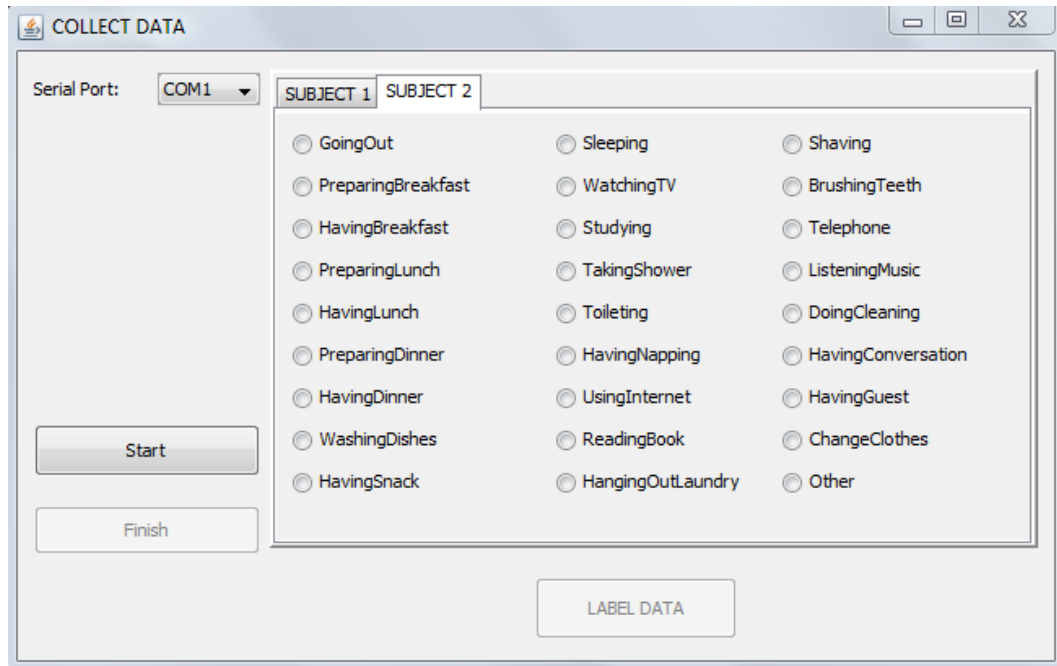


Figure 4.13. Interface of activity labels.

The interface is user friendly and very simple to use by anyone including elderly. Starting of labeling process begin by clicking "START" button and finish by clicking "FINISH" button after 24 hours from starting. There are the same interfaces deployed on the different base stations, and residents can label themselves by using any of them. First of all, inhabitant chooses himself from the panel options as "subject 1" or "subject 2". Then he selects the most suitable activity from the radio button options due to what he is performing currently. There are 26 separate activities which are supposed to be performed by the residents generally in the home. Moreover, another class named as "other" is defined for all other activities performed by the residents. After selecting the activity, inhabitant clicks on the "LABEL DATA" button. He finishes the labeling after a small confirmation menu which shows subject ID and activity name. As it can be seen in Figure 4.13, there is also serial port option on the interface. It specifies the serial port number for the serial communication between computer and Xbee radio for the transmission of the sensor data. Making changes on this option by residents is not expected unless otherwise is stated. One of the residents can be seen in Figure 4.14 while tagging himself on the interface.



Figure 4.14. One of the residents is tagging himself.

The data collection process for each day started at midnight and covers a 24 hours span lasting until the next midnight. Both interfaces which are deployed on different base stations were activated at the same time. All received sensor data were recorded into text files on the computers which are used as base stations separately along 24 hours. Similarly, labels were recorded into the text files. The recording format of the sensor data can be seen in Table 4.6a. As it can be seen, there are three columns which are sensor ID, sensor value, and received time of the sensor data respectively. At the next steps, we converted the received samples into binary samples, nevertheless we kept the sensor values in text files. In future studies, we may utilize them in other fields like modelling the sleep cycles of residents by using the changes in sensor values. Additionally, format of the text files which includes labels of the residents is depicted in Table 4.6b. Similarly, it also has three columns which are name of the activity, time of the activity, and subject ID respectively. All time values in the system are in milliseconds granularity. Approximately 60-100 labels are recorded for each day in total for two residents. It shows that the collected data has very detailed information about daily life of the residents.

Table 4.5. Recording format of data.

Sensor ID	Sensor Value	Received Time
...
Co2	36	58688277
Di2	137	58688341
Co2	36	58688373
Di2	137	58688453
Co2	36	58688485
Di2	137	58688549
Co2	36	58688581
Di2	137	58688661
Co2	36	58688677
Di2	137	58688757
Co2	36	58688789
Di2	137	58688853
Co2	36	58688885
Di2	137	58688965
Co2	36	58688981
Di2	137	58689061
Co2	36	58689093
Di2	137	58689157
Co2	36	58689189
Di2	137	58689269
...

Activity Name	Received Time	Person ID
...
HavingNapping	10684	SUBJECT_2
BrushingTeeth	22463	SUBJECT_1
Toileting	269960	SUBJECT_1
Other	604326	SUBJECT_1
PreparingDinner	646284	SUBJECT_2
WashingDishes	1844074	SUBJECT_2
HavingSnack	2181123	SUBJECT_2
BrushingTeeth	2367053	SUBJECT_2
Toileting	2639439	SUBJECT_2
HavingSnack	3532509	SUBJECT_2
Sleeping	3825365	SUBJECT_2
Toileting	22439029	SUBJECT_2
Other	23511765	SUBJECT_2
ChangeClothes	23646996	SUBJECT_2
GoingOut	23920609	SUBJECT_2
Toileting	31991077	SUBJECT_1
PreparingBreakfast	32273467	SUBJECT_1
WashingDishes	35620492	SUBJECT_1
Telephone	41165606	SUBJECT_2
ChangeClothes	41812838	SUBJECT_2
...

(a) Recording sensor data.

(b) Recording labels.

4.3.4. Synchronization and Discretization of the Data

The main steps we performed from the collected data to be able to make inferences is depicted in Figure 4.15. We will talk about the first and second steps in this part. We will mention about the third and fourth steps in Chapter 5, and the last step in Chapter 6 respectively. Since we deployed two base stations that serve different sensors, we developed a centralized software for handling the merge and synchronization of the combined data and the activity labels. We made the data ready for being processed. It basically contains three steps. Firstly, the sensor data and activity labels from different base stations are combined, then they are synchronized, and lastly, they are discretized in terms of different window size and different feature representations.

Firstly, we merged the sensor data and labels recorded on different base stations.

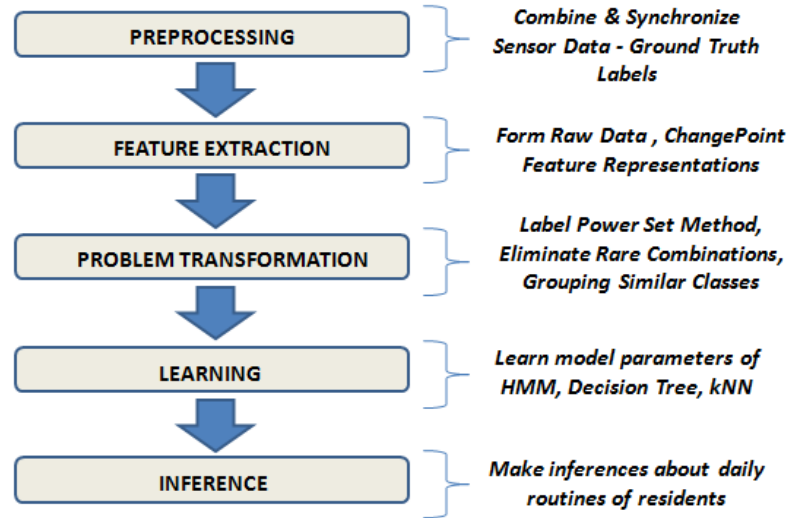


Figure 4.15. Performed main steps from data collection to inference.

We simply combined and then ordered the sensor data and activity labels in an ascending way in terms of received time. Then, we divided 24 hours time into 100 ms separations due to sampling rate which is 10 Hz. We found the nearest separation according to the received time of the sensor data and place the sensor data to that separation. To make it more clear, if we think about a sensor data whose received time is 10040 ms, there are two options to place it. These are 10000 ms and 10100 ms. However, we place it to 10000 ms, because it is nearer to the former separation. We place all sensor data to 10000 ms whose received time is between 9950 ms and 10050 ms. We expect one sensor data for each sensor in that time interval according to used sampling rate. If more than one sensor data occurs at that time interval for any one of sensors, we ignore one of them. While forming the data which is ready for classification, we did not focus on the sensor values. If there were any received sensor values in that time interval for any sensor, we assessed it as that sensor was active in the specified time interval and we kept it as one, otherwise we kept it as zero. Thus, we converted the collected data into a binary format on which we implemented several machine learning algorithms. The synchronization procedure can be seen in Figure 4.16.

T_i = receiving time of the sample S_i ,

Divide 24 hours of data into 100 ms slots, $Slot_{0:N}$ where N is the total number of slots in 24 hours, which is 864000 due to 10 Hz sampling rate,

if $T_i(mod100) < 50$ **then**

$Slot_k \leftarrow S_i$;

else

$Slot_{k+1} \leftarrow S_i$ where $k = \lfloor T_i \div 100 \rfloor$;

end if

Figure 4.16. Synchronization procedure.

In the discretization, we took into account two factors which are the window size and the discretization method (feature representation). We used three different options as the window size; one minute, two minutes and three minutes respectively by accounting the average human activity duration. In other words, we divided the all data into windows whose lengths are the chosen window size. We represented the specified window with only zero or one for each sensor according to whether they are active or not in the specified window. If we found any received sensor data in the specified time interval for particular times for any sensor, we concluded that the sensor was active along the specified time interval and kept it as one; otherwise it was kept as zero. To state the condition of the sensor as one for the relevant time interval, we took into account the frequency of the sensor data at that time interval. If it was higher than the predefined threshold value specifically for that sensor, then we concluded that the sensor was active during that relevant time period. The reason of such an implementation is to decrease the effect of probable misfired sensor values. For instance, the infrared receiver sometimes sent sensor values for just one or second times in an hour when there were no events around. We experimented with two types of feature representations, namely, raw and change point feature representations. In the raw data feature representation, the feature value for a sensor is one if that sensor is fired at any point during a given time step and zero otherwise. In the change point feature representation, on the other hand, the feature value for a sensor is one only if

Table 4.6. Data format.

Time	Ph1	Ph2	Ir1	Fo1	Fo2	Di3	Di4	Ph3	Ph4	Ph5	Ph6	Co1	Co2	Co3	So1	So2	Di1	Di2	Te1	Fo3	Sub. 1 Label	Sub. 2 Label
...
19:25	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:26	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:27	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:28	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:29	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:30	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	11
19:31	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0	0	16	27
19:32	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	16	18
19:33	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	18
19:34	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	18
19:35	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	16	18
19:36	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	16	18
19:37	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	18
19:38	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	18
19:39	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	16	18
19:40	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	16	14
...

the sensor changes its status from either firing to non firing or the other way around during the given time step.

After combining sensor values and labels from two separate base stations, and then synchronizing and discretizing the collected data, we get the data format as seen in Table 4.6, which is ready for classification. It consists of 23 columns. First column indicates the time information, then 20 subsequent columns represents values of 20 different sensors deployed at the home. The last two columns specify the labels of first inhabitant and second inhabitant respectively. The starting time of all days is 00:00 am and consists of 24 hours daily living data of the residents. The first column gives hour minutes and seconds information of the data. Since we converted sensor values to binary format, data sensor values are just zero or one. Sensor readings from a random day is depicted in Figure 4.17. We implemented several machine learning methods on the data depicted in Table 4.6. At the final step, healthier inferences can be made with the high accuracy classification.

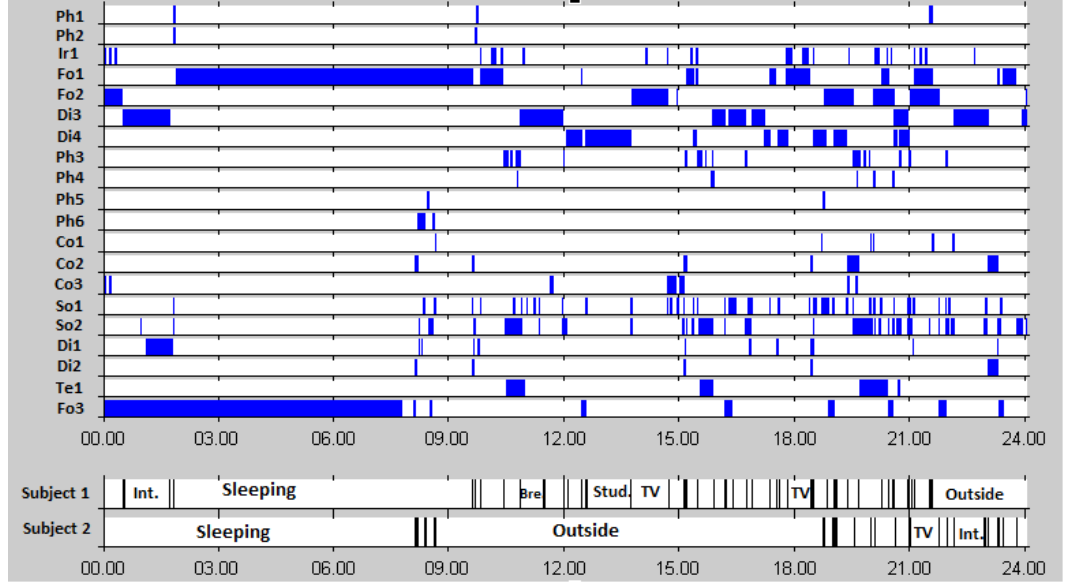


Figure 4.17. Sensor readings for a random day.

4.4. Learned Lessons

We experienced a lot of difficulties about the usage of sensors during system deployment and system process. In this section, we share these experiences for future works. We give information about the usage of each kind of sensors which are not written at the user manuals of sensors. And then, we share the experiences about detecting some specific activities. Finally, we give general information for probable solutions of the problems that can be encountered.

4.4.1. Sensors Based

While using FSR, we can utilize small boards to get more robust results. Their two near pins are more compatible with the holes on the boards, and can be wired directly to the boards. Another important issue about FSR is to avoid them using on moveable furniture like chairs. We generally placed the FSRs under the legs or upholstery surface of chairs, and chairs were generally moved by the inhabitants very frequently within the day. For this reason, they were broken very easily. We preferred to use FSRs with the couches or beds, because they are much more static furnitures

and far from moving during the day. Additionally, different resistors values can be tried to determine a static threshold value to detect events more easily. In this manner, you can even find that the person is sitting on which side of the couch. If the aim is to detect just whether the person is sitting or not like in our case, determining a dynamic threshold value which is determined when a sensor node is activated can be much more robust for the persistence of the system.

Contact sensors are very sensitive and fragile sensors which require very much attention. The opposite wires inside contact sensor are wired due to the magnetic force and start to transmit current, when the contact sensor is affected by a magnetic force caused by a magnet. Contact sensors are used together with magnets, and generally placed on the wall which is static position. On the other hand, magnets are placed on the edge of the door which is moving. The direction of the magnet due to the contact sensor is very crucial, contact sensors are not affected from the magnet at some situations even if the magnet is just next to the contact sensor. It is a very important matter and not included in the user manuals. If it is possible, magnets should be placed in a way that it should cover half of the periphery of the contact sensor to get more accurate results when the door is closed so that an event is obtained. Consequently, positions of the contact sensor and magnet according to each other are very sensitive and it should be taken into consideration. Another point is that the usage of contact sensors with metal surfaces. It should be noted that contact sensors can be affected by metal surfaces, and touch of a contact sensor directly to the metal surface should be avoided.

Another used sensor is the infrared reader for detecting whether any button on the remote controller is pushed or not. Actually, we can get much more by the help of infrared reader like learning which button is pushed. We made it work with 100 Hz to not miss any push buttons as mentioned before in Section 4.2.7. It was noticed that infrared reader sometimes fires and sends one sample even if no event occurs. We ignored these kinds of lone samples while processing the data. Furthermore, it should be placed by considering the line of sight between the television and the remote controller.

We can think of photocells as the most robust and user friendly sensors in the system. They can work at low temperatures like inside the refrigerator. Moreover, their power consumption is very low; they can generally work during at least 10 days with 1800 mAh lithium polymer batteries due to the usage aim. In our study, the usage field of contact sensors and photocells overlapped mostly, and we preferred to use photocells for every possible conditions.

Since their three legs are compatible with the holes on the boards, we utilized a small board with the temperature sensor. Their main drawback is that they still fire for a while after the person is finished with the oven. This can be solved with simple software which is embedded to Arduino Fio. So it can halt firing in a case of serious decrease in sensor values for a certain time, even if the values are still higher than the threshold.

Another sensor group is the sonar distance sensors which are used to detect passes along the hall. The main aim of sonar distance is much more complex in fact. They can compute the distance of objects in their range which is 6.45 m. While using the sonar distance sensors, we focused on the change of sensor values which is very sensitive. For this reason, we had to place the sensors to predetermined locations on the wall and take care of not changing the locations of them during collecting data. A small change on the location of sonar distance sensor generated erroneous results. The sensors can be stuck directly to the wall in order to immobilize them. One shortcoming of sonar distance sensors occurs when someone walks past it faster than a certain speed. As we mentioned before, wireless communication module sleeps by default in order to increase the lifetime of batteries. To wake it up and connect to the network again lasts approximately 300 ms, and they can send samples after they are connected to the system. Thus, sonar distance sensors can send very few samples when a very fast passing (near to running) occurs, which is unlikely most of the time.

Lastly, another kind of sensors which is used in the system is proximity sensors. Their range is 10 cm, which is so small compared to sonar distance sensors. One advantage is that their small red led turns on, when they detect an object in their

range. Hence we can understand easily whether it is working correctly or not. When we use one thick wire for pins of the sensor, sometimes loose connection occurs. Hence, using multiple thin wires rather than one thick wire is recommended while connecting proximity sensors with Arduino Fio. Each relevant wire touch to the metal parts of the relevant pins at the sensor, and not touch to each other is another important point which require attention.

4.4.2. Activity Based

Before recording the actual data, we have worked with the sensors for a few days as a dry run to observe the efficiency of sensors in real life. After trying several different sensor combinations for particular activities, we decided on the final set of sensors and their locations to achieve the best performance. At this part, we mention about the experiences which we got at this dry run process. The challenging activities during this process were sitting on the chair, toileting, and taking a shower.

We used FSR which is placed under the leg of a chair to detect sitting on the chair, however it was not so robust even if we placed it in a stable position. Residents were not told to restrict their behaviours, thus they behaved like the previous days before the deployment. They moved the chair most of the time before and while sitting on the chair. Since, FSR is in contact with the ground while moving; this situation increases the probability of change in the position of the sensor and failure in connection between FSR and Arduino Fio. Therefore, it caused to false positives and false negatives. After that, we placed it under the upholstery of the chair, and got the same non satisfactory results. It is seen in Figure 4.18. Finally, we tried proximity sensor with 10 cm range instead of FSR. We placed the proximity sensor at the back of the chair, so it could see back of the person in its range while sitting. According to the sitting habits of residents, the range of the proximity sensor was enough. We detected all sitting cases with the proximity sensor except abnormal sitting positions. We can state that it is much more robust than FSR in order to detect whether someone is sitting on the chair or not, because its position is stable and have no interaction with any other objects while someone is sitting on the chair. One drawback occurs in the situation that some

bag or objects are put on the chair while someone is not sitting on the chair. In such a case, the proximity sensor can fire although nobody is sitting. However, we did not encounter such a scenario during the data collection process.



Figure 4.18. FSR located under the upholstery of chair.

Another concern is about taking a shower. At the beginning, we utilized the humidity sensor to detect taking a shower, and placed a humidity sensor in the bathroom. There was a visible increase at the sensor values while one of the residents was taking a shower; which helped us understand whether one of the residents was taking a shower or not. However, there were a few points which cause ambiguity in taking a shower activity. First of all, sensor values of the humidity sensor did not increase immediately when the inhabitant started to take a shower. For this reason, we could not state the start time of the activity precisely. Secondly and similarly, sensor values did not decrease in a short time after the activity was completed. This period could last up to 30-40 minutes and vary in terms of different conditions like ventilation of the bathroom. Obviously, such a length of time causes misleading inferences. We could not clearly define the time period of activity including the starting and ending time of the activity. Alternatively, we decided to use a contact sensor after interviews with the residents. Residents indicated that they keep the shower cabin closed by default when they do not use the shower cabin. In the light of habits of residents, we placed a contact sensor on the door of shower cabin to detect whether it is open or closed.

So, the start time and the finish time of the taking a shower activity can be defined precisely. Residents can also open the shower cabin for other reasons than taking a shower. However, it should not be forgotten that we do not decide on whether the person is taking a shower or not by the help of just one contact sensor placed on the shower cabin door. For instance, residents generally take a shower with the bathroom door closed, and we have also a contact sensor for that.

To understand the toileting activity, we utilized a flex sensor as the first try. The flex sensor gives reactions when it is bended. We placed the flex sensor on the button which serves for flushing, in a way that person has to bend the flex sensor to push the button. As a second try, we used a contact sensor on the side of button serves for flushing again, and a magnet was placed on the button. When the button which serves for flushing was pushed, a height difference occurred with its side, which cause firing of the contact sensor. However, these two tries were unsuccessful and not robust enough. Two main reasons for that are they were all in contact with the person while using which made them less robust, and they did not give the exact information about the starting time of the toileting activity. They supplied the information about the finishing time of the toileting process, because most people flush after toileting. So, we could not determine the length of the toileting process of the residents which is an important issue for us. Finally, we decided to use a proximity sensor. During the interviews, residents stated that they keep the toilet lid as closed when it is not used. The proximity sensor was placed in such a location that it could see the toilet lid in its range when it was open. Thus, we could understand the beginning time and finishing time of the toileting activity exactly. Additionally, the proximity sensor had no interaction with the residents while in usage unlike the former tried sensors. This condition makes it much more robust compared to the former tried sensors. All arrangements are done based on the statement that the residents keep the toilet lid as closed when they do not use it. However, it is not always the case. Some people can have different toileting habits, and in that conditions new arrangements can be done according to the shape of the toilet specifically.

4.4.3. Solutions to Probable Problems in the Deployment of the WSN

We mention about several solution steps for probable problems which can be encountered during the data collection process. For instance, the sensor does not fire in an event condition or fires when there is no event condition in the environment at that time. When something about sensors goes wrong, firstly remaining life of the battery should be considered. If the battery is not out of charge, the connections between Arduino Fio and the sensor should be controlled carefully. There are sometimes lacks of contact which are not visible. For that reason, using thin multiple wires between the sensor and Arduino Fio is suggested instead of just one thick wire. It is especially valid for sensors like proximity sensors which do not have distinctive and smooth pins. Moreover, the male-female jumper wires can be chosen if it is possible to use them with that kind of sensors. They are much more robust compared to using normal wires or glue. Another probable reason of the problem can be change in the location of the sensor during the data collection process. It is an important concern for especially sensors like FSR, sonar distance sensors, and contact sensors. A subtle difference in the location can lead to problems for such kind of sensors. They should be placed in a very stable manner which cannot be moved easily. Alternatively, Arduino Fios connected to FSRs can be reset in a problematic condition while nobody is sitting on the couch if they are using a dynamic threshold value. The Arduino Fio will redetermine a new threshold value at such a condition by itself. Finally, if problems still continue after going through all of the mentioned conditions, there can be a problem related to waking up the Xbee radio like a lack of contact in the wake up connection. Furthermore, change in the condition of environment affects some sensors. For instance, the temperature sensor will be affected from a sharp temperature change in the environment if a static threshold is assigned for it.

5. CLASSIFICATION OF THE DATA

One of the main challenges in recognizing human behaviour is inferring the human activities from sensor data. It has two requirements, namely finding the accurate model and learning the parameters for that model. Human activities are very complex in nature therefore it is a challenge to find an accurate model that accounts for this complexity and still provide a good level of generalizability. Because complex models are usually less generalizable and prone to over fitting. On the other hand, when we want to use the human behaviour recognition systems worldwide, we need more generalizable models.

While finding an accurate model is a requirement, it is not sufficient. We need to find the appropriate parameters of our model. For this purpose, we need training data sets which are enriched versions of the sensor data to contain the activity labels as well. The used models for classification are k-nearest neighbour (kNN), decision tree and hidden Markov model (HMM).

5.1. Machine Learning Methods

kNN [54] is a very simple classifier which has an easy reasoning and is used widespread in the classification problems. All samples in the training data are searched and the nearest k neighbours of the test sample are determined. Then, predictions are made about the test sample by using the majority voting of the k nearest training samples. Choosing a proper k value is essential and requires experimentation on the training data. In our problem, we chose k as 80 after several tries, and utilized Euclidean distance as the distance metric while calculating the distance between the samples.

Decision tree [54] is a frequently used nonparametric approach in classification like kNN. It is preferred because it can produce good results even when there is a limited amount of training data and it provides an easier interpretation of the classification

rules. Decision tree mainly consists of a tree structure with branch nodes and leaf nodes, and has a rule based structure. We used a binary decision tree in which each branch node has exactly two children nodes. One of the critical points in decision trees which substantially affects the success rate of the classification is the splitting decision. For the collected daily living data, Gini's diversity index is used as the split criterion while deciding on the rules to form child nodes from the parent nodes. It is an index of node impurity and calculated in Equation 5.1

$$\mathbf{I}_{\text{gini}} = 1 - \sum_i \mathbf{p}^2(i) \quad (5.1)$$

where $p(i)$ is the observed fraction of classes with class i that reach the node. A node with just one class (a pure node) has a Gini index zero. The aim of the Gini index is to minimize the impurity contained in the training subsets generated after splitting the decision tree. Since we do not have any missing values in the data, any surrogate rule is not used while building the decision tree. Each branch node has at least 100 observations which satisfy its conditions and the number of total nodes including branch and leaf nodes varies between 265 and 581 due to the discretized time interval and feature representations for the classification with original labels. After building the decision tree, the inference is made using the rules. The test sample is first placed in a leaf node according to the rules of the tree. The label for the leaf node is then assigned to the test sample.

HMMs [55] are widely used in natural language processing and also they have been shown to work well for human activity recognition tasks because of their capability to grasp the temporal nature of human activities. It is a temporal probabilistic model that jointly maximizes the probability of the observations and the hidden states.

The hidden states correspond to the activities performed and the observations

correspond to features, in other words, the sensor values which are composed of zero and one in our binary data. $p(S_{1:T})$ is the sequence of hidden states, and $p(O_{1:T}^{1:K})$ is the sequence of corresponding observations where T is the number of data samples and K is the number of features, which is the number of sensors in our case and equals to 20. There are three main parameters in a basic HMM structure which are π , A and B . The first parameter π is $p(S_0 = n) = \pi_n$ where π_n indicates the probability of starting with state n in the model. This parameter represents the initial state probabilities and can be kept in an $N \times 1$ vector where N is the number of states, which is activities in our case. The second parameter A is the transition distribution between the states in the model, $p(S_t | S_{t-1})$. It represents the probability of going from one state to the next. It can be shown with an $N \times N$ matrix. The third parameter B is the observation probability distribution $\prod_{i=1}^K p(O_t^i | S_t)$. It represents the probability that state S_t would generate observation vector $O_t^{1:K}$. It can be represented with an $N \times K$ matrix. Our aim is to find the sequence $S_{1:T}$ that maximizes $p(S_{1:T} | O_{1:T}^{1:K})$. As seen in Figure 5.1, the hidden state at time t , namely S_t , depends only on the previous hidden state S_{t-1} . It is valid for the first order Markov assumption in which we utilized in the classification with HMM. Furthermore, the observable variable, which is a 20×1 sensor data vector in our situation, depends only on the hidden state on that time interval. We used the maximum likelihood method for learning the parameters and the well known Viterbi algorithm [56] for inference.

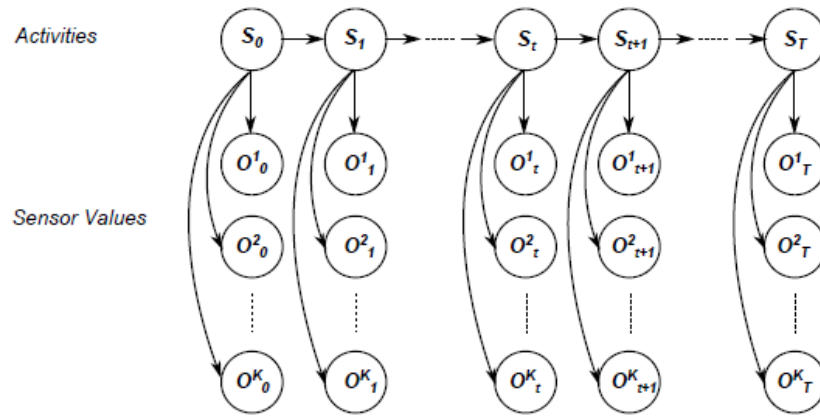


Figure 5.1. HMM structure.

5.2. Original Labels

With multiple resident activity recognition, we can name two different versions of the problem formulation. First, we can provide the concurrent two activities that are being performed in the house without differentiating between the residents. Secondly, we can also identify the activities of the residents separately. Generally, the second problem formulation is more challenging especially when there is no information about which sensor is activated by which resident, as in our case. We handled the first approach in our study which can be thought as a special form of the multi-label classification problem [57]. In the multi-label classification problem, there is no limitation about the number of labels for per samples, however we have two labels for each samples in our collected data, and one label if the two persons are performing the same activity at that time. Moreover, observations in the multi-label classification problem are not temporal unlike the observations in the daily living data of residents. We implemented the problem transformation on the collected data, which is one of the widespread approaches in multi-label classification. We preferred the label power set method [58] in the problem transformation approach by accounting the above mentioned differences between classical multi-label classification data and the daily living data of multiple persons, and the large size of the collected data. The idea is based on converting the multi-label data format into a standard single label data format. We represent the two-label data with a larger variety single label data. The number of possible combinations reduces to N^2 , where N is the number of activities. However, in our case, we get 190 different combinations of behaviours according to the discretized data due to one minute time interval by considering all behaviour combinations of two persons. Some of the combinations do not occur at all. For example, the bathroom activities do not occur concurrently therefore, we do not have combinations like one resident is taking a shower and the other one is brushing teeth. Moreover, a significant portion of these combinations occur very rarely, making them impossible to learn with any kind of classifier due to the insufficient amount of training data. Besides, these combinations do not carry significant information. As the second step, we reduced the number of combinations to 86 by ignoring the combinations lower than 30 minutes in total during 30 days. The reduced combinations cover the 97.2% of the entire data, and

the rest of the combinations which is about 2.8% does not carry significant information about the behaviours and habits of persons. They are not even performed along one minute on average per day, and we labelled them as "other" in the new transformed data. Hence, we can ignore this small part of the data to improve the general success rate of predictions all over the data. At the last step, we applied well known classifiers HMM, decision tree, and kNN on the transformed single label data.

The results in 5.1 include two different feature representation methods using three different time step intervals. We evaluated the recognition performance using the accuracy metric. We performed a leave-one-out cross validation over all days and reported the average accuracy of 30 different tests. The performed classifications aim to differentiate 86 different activity combinations for 1 minute window size, 89 different activity combinations for 2 and 3 minutes window size.

We obtained the highest accuracy rate as 57.6% with the decision tree method, two minutes window size, and the raw data feature representation. Another remarkable observation was that the dramatic decrease in the accuracy rates except HMM when the change point feature representation was used. The change point feature representation with a non-temporal classifier cause a significant data loss when it is used on a temporal data like our collected daily living data of two inhabitants which explains the reason of this dramatic decrease. On the other hand, we did not observe such a decrease when HMM is used, because HMM is mainly a temporal data classifier which takes into account the sequential order of samples unlike the other used classifiers. Very low

Table 5.1. Classification results according to accuracy.

		Discretization Interval		
		1min	2min	3min
HMM	Raw	49.0 \pm 11.9%	52.8 \pm 11.9%	55.8 \pm 11.6%
	Change Point	43.3 \pm 16.0%	40.3 \pm 15.2%	42.8 \pm 17.3%
Dec. Tree	Raw	57.0 \pm 11.1%	57.6 \pm 10.8%	57.5 \pm 10.8%
	Change Point	22.0 \pm 8.2%	23.0 \pm 8.5%	24.0 \pm 8.6%
kNN	Raw	54.1 \pm 10.9%	54.7 \pm 11.1%	55.6 \pm 11.3%
	Change Point	21.0 \pm 8.8%	21.5 \pm 8.6%	22.7 \pm 8.7%

accuracy rates were obtained when kNN and decision tree were used together with the change point feature representation, because we lost a large amount of information in data. For instance, in the change point representation, the value of the corresponding sensor is all zeros while a person is sitting on the chair and it is only one for a short time when the person start sitting or leave the chair. There is no extra information in the data while sitting on the chair in order to infer anything about the activity of the person. Besides, if we decrease k parameter of kNN to 10, we obtain 5%-6% average accuracy rates which is close to predicting randomly. Since the decision tree has a hierarchical rule based structure, it performs slightly better than kNN for both feature representations. We make less detailed predictions by increasing the window size, and thus higher accuracy rates are obtained with wider window sizes. We can conclude that the raw data feature representation outperforms the change point feature representation for all used methods. We did not use the last fired feature representation which we utilized in the initial work [53] with this data, because it is not suitable for the nature of multi-resident datasets. Only the information of one of the residents can be shown in the data if the last fired feature representation was used. Thus, any inferences cannot be made for the other resident.

5.3. Combined Labels

We have a very large number of different labels for 27 activities. The problem with the large number of activity labels is that they require a larger number of training data which is difficult to obtain. In order to handle this problem, we grouped the activities into more general groups so that instead of having breakfast, having lunch, having dinner, and having snack, we described the having meal activity. In this way, we had 11 more general categories of activities. The grouping of the all labels are shown in Table 5.2.

Table 5.2. Grouping labels into more general groups.

Original Labels	New Label	Activity ID
Going Out	Going Out	1
Pre. Breakfast, Pre. Lunch, Pre. Dinner, Washing Dishes	Preparing Meal	2
Hav. Breakfast, Hav. Lunch, Hav. Dinner, Hav. Snack	Having Meal	3
Sleeping, Napping	Sleeping	4
Toileting	Toileting	5
Taking Shower	Taking Shower	6
Studying, Using Internet	Studying	7
Watching TV, Reading book, Listening Mu- sic	Relaxing	8
Hanging Out Laundry, Cleaning, Hav. Guest, Telephone, Conversation, Other	Rare Activities	9
Change Clothes	Change Clothes	10
Brushing Teeth, Shaving	Bathroom Activities	11

Similarly, we preprocessed the new labelled data with the label power set method, and got 61 different combinations of labels. After reducing the number of combinations (eliminating the combinations which lasted lower than 30 minutes in total), we obtained 48 classes which represented 99.71% of the entire data due to the one minute window size. The results are shown in Table 5.3. The feature representation and used method for the highest accuracy classification changed. We obtained the highest accuracy 70.3% with HMM, raw data feature representation, and three minutes window size. When the raw data representation is used, performances of HMM and the decision tree are very close. There is a significant increase in the accuracy rates for all methods compared to the classification with non-grouped labels as expected. HMM outperforms the decision tree slightly for all window sizes unlike the previous non-grouped labels case.

The confusion matrix in the heat map representation can be seen in Figure 5.2. The value inside cell(i,j) is the percentage value which indicates the rates of prediction j for label i . We relabeled the other activities which is 0.29% as "other" class, for this reason, we had 49 classes in the confusion matrix. Activity combinations with low class IDs appear more frequently in the data. Thus, accuracy for the activity combinations with high class IDs which are more rare decreases due to the small amount of training data.

Table 5.3. Classification results according to accuracy with grouped labels.

		Discretization Interval		
		1min	2min	3min
HMM	Raw	$66.8 \pm 10.4\%$	$69.2 \pm 10.4\%$	$70.3 \pm 9.6\%$
	Change Point	$51.2 \pm 15.6\%$	$47.3 \pm 14.8\%$	$49.2 \pm 16.2\%$
Dec. Tree	Raw	$66.6 \pm 10.3\%$	$67.2 \pm 9.9\%$	$67.0 \pm 9.9\%$
	Change Point	$24.8 \pm 8.4\%$	$25.5 \pm 8.4\%$	$26.2 \pm 8.5\%$
kNN	Raw	$64.8 \pm 10.6\%$	$63.7 \pm 11.2\%$	$66.1 \pm 10.7\%$
	Change Point	$23.6 \pm 8.7\%$	$24.6 \pm 8.5\%$	$24.9 \pm 8.6\%$

While combining the activities, we take into account similar activities which trigger similar sensors. For this reason, we benefited from the activity sensor matching table in Table 4.3. To give an example, preparing breakfast, preparing lunch, preparing dinner and washing dishes were grouped into one class, because their classification are typically performed by the sonar distance sensor placed on the wall in the kitchen, the photocell in the kitchen drawer, and the temperature sensor above the oven for preparing meal activities. Additionally, type of meal can be understood easily by including the time of the day as another feature in the data. Some activities like going out, toileting, taking shower, change clothes are unique in the design of the system due to the activity sensor matching. For instance, we expect the contact sensor on the bathroom door, the proximity sensor on the closet, and the proximity sensor above the tap to fire in a sequence for the toileting activity. Making an activity unique is not possible for some activities due to its nature like calling on the telephone. Moreover, it is obvious that making every possible activity unique will raise the complexity of the system design heavily. With combining similar activities into one class, we had some information loss about the details of activities. However, we still keep the main

Table 5.4. Comparison of some similar studies in the literature.

Study	Sens. Num.	Sens. Type	Day	Activity	Accuracy
[37]	77-84	reed switches, piezo electronic	14	>20	25%-89%
[9]	14	analog sensors	28	7	79%
[38]	-	motion, temperature, analog, contact switch	not a full day	15	73%
[39]	21	infrared presence, door contact	1 hour exp.	7	75%-86%
[8]	40	tilt sen., pressure, contact	not a full day	8	94%
Our study	20	photocells, contact, distance, FSR, temperature, infrared rec.	30	48 act. combinations	70%

activities which mainly shape the daily routines and habits of residents during a typical day. Besides, even with the combined activities, our study takes into account more activities (48 activity combinations of two residents with 11 main activities) compared to the similar studies in the literature [8,9,37–39]. A comparison of the similar studies in the literature can be seen in Table 5.4. As it can be seen, we achieve a high accuracy with many more concerned activities compared to other studies. Furthermore, a higher variety in sensor types, collecting 30 full days of ADLs of multiple residents unlike other studies which concern round based activities (collecting the data of a specific activity for a particular time, not a full day data) are other significant properties of our study.

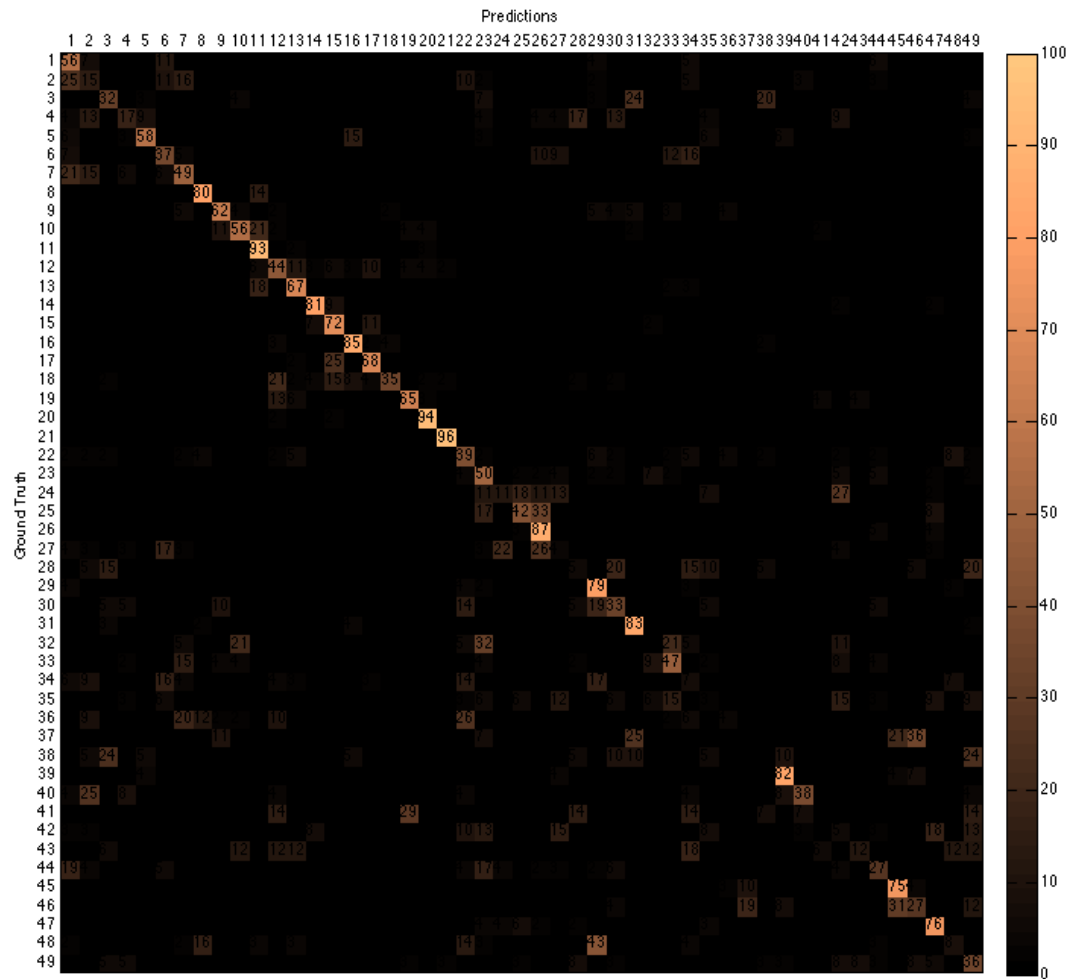


Figure 5.2. Confusion matrix in heat map representation (HMM, Raw data feature representation, 3 min. window size, combined labels).

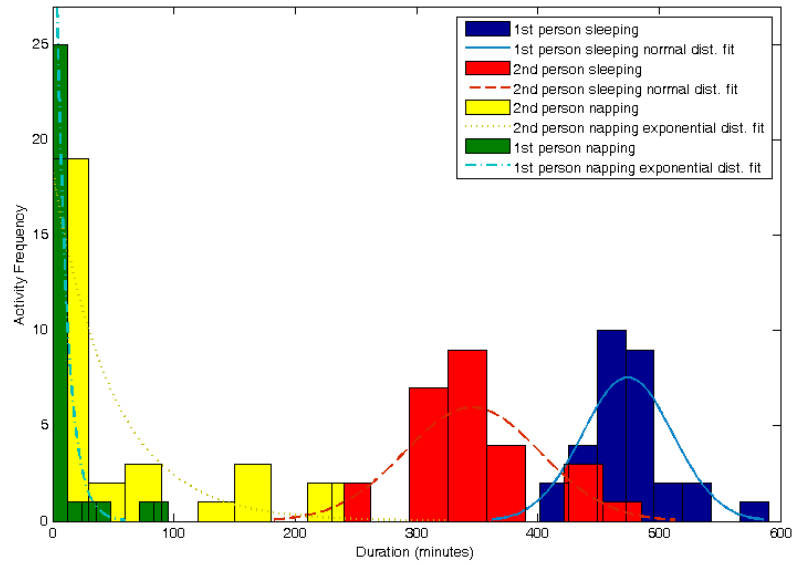
6. INFERENCES ABOUT THE DATA

In this chapter, we talk about the inferences which can be made after a successful classification in order to give an insight about assessing ADLs of residents in the long term. Our main target is to improve the life quality of people by understanding their behaviours and learning the habits and drifts from daily routines of people. The improvement in life quality can be investigated in three main aspects, namely, health, social interaction, and personal finance. These promotions can affect the life of people in the short term or the long term. In order to improve the life standards of people, we can work with health officers closely and inform them about any negative situations in the life of monitored persons. Furthermore, the residents can be contacted directly and persuaded to change their behaviours. While learning the habits and detecting the drifts from the daily routines, we basically focus on activity durations, activity times, and activity frequencies which we consider as the main factors that shape the daily living of people.

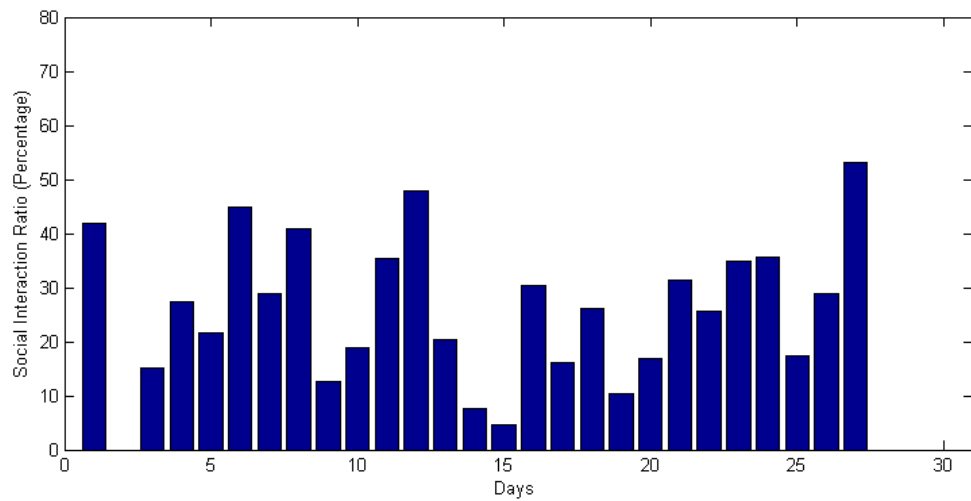
Health issues are the first degree matters that should be considered especially for the elderly. Most of the studies about understanding the activities of people concern mainly the elderly [13, 16, 17, 29]. We aim to detect abnormal situations in advance so that the necessary precautions can be taken, and furthermore health officers can be informed about the probable diseases in the long term and abnormal emergency situations in the short term. As an important case, take sleeping and napping behaviours of residents during a day. In Figure 6.1a, sleeping durations are fitted to a normal distribution and napping durations are fitted to an exponential distribution for both residents. The first person sleeps more than the second person. On the other hand, the second person closes the gap by napping within the day much more. Moreover, people can be warned about their insufficient sleeping durations. For instance, the average sleeping duration of the second person over a month is approximately five and a half hours, which is very low. We can inform the person that he should increase the average

sleeping durations for a healthier lifestyle.

Furthermore, we can improve the social life of persons by highlighting the points where they are socially weak. For this purpose, there are "having a guest" and "having a conversation" activities which are used by persons while data is being collected.



(a)



(b)

Figure 6.1. Activity and social interaction behaviour patterns: (a) Sleeping and napping durations. (b) Social interaction.

They give useful clues about their social interactions. Collecting daily living data from a real house with multiple residents enables us to study the social interactions of persons which cannot be investigated in similar studies in which the data is collected from a single resident. For this purpose, we can utilize the common activity and conversation durations of persons. Additionally, it can be inferred from the data that who is performing the housework, like washing the dishes, doing cleaning and hanging out laundry, or are they shared between the residents. Hence, people can be informed about the common activities to trim their workloads at home, which is especially valid for young persons who share the same house.

On top of the social interactions between the residents, the interaction with other people can be investigated by detecting the guest visit durations and frequencies. If a person spends most of the time at home, and not having a guest very often, it can be a sign of weak social life. Additionally, we can detect excessive usage of using the Internet at home which is a popular reason of unsocial tendencies nowadays, and warn the inhabitant to decrease it to a reasonable level. In Figure 6.1b, we depict the ratio of the time (in percentages) the residents spend together to the amount of time they stay at home. The time spent together includes the durations of having conversations with each other, and the duration of common activities performed by the two persons together, like preparing a meal, having a meal, having a conversation, watching TV except sleeping and going outside together. The average ratio of interacting with each other was calculated as 25.6%. One of the residents was not at home on the second, next to last and the last day, therefore, no interaction behaviour exists on those days.

Activity starting times are as important as activity durations in some situations in order to infer probable health problems. You can see the starting time of having meals of the first person during 30 days in Figure 6.2. There is not a smooth horizontal line for the starting time of each meal along the days. For some days, the person has breakfast at 1 pm, lunch on 6 pm and dinner on 11 pm. The worse one is that he sleeps approximately one hour later after having the dinner for some days which can trigger other serious diseases. Furthermore, the person does not have some of the meals within the day on some days, or he is outside between the related time intervals. Learning

that the person is outside or not, we can decide that the person skips the meal or not. For instance, the person does not have lunch at home for five consecutive days while at home. We can persuade the person to have a healthier life by preventing the irregular starting time of meals or skipping the meal.

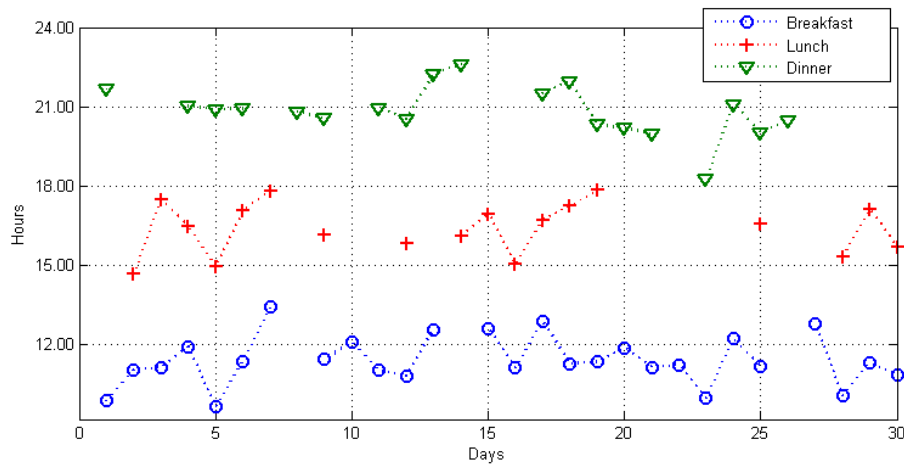


Figure 6.2. Starting times of breakfast, lunch and dinner for the first person during 30 days.

Another important case that we consider about the health issues is the short term emergency conditions. To give an example, being in the bathroom for more than 30 minutes can be a sign of an emergency case for most people. The person could fall and faint which is not very rare especially for elderly. Such an unconsciousness condition can be detected through the sensors deployed in the bathroom, like more than 30 minutes the bathroom door is closed after the person enters the bathroom, and health officers can be informed immediately. The distribution of the toileting duration in the histogram for the residents can be seen in Figure 6.3. By learning the toileting habits of each inhabitant, emergency situations can be inferred separately regarding the durations of continuously being in the bathroom. For instance, being in the bathroom for 30 minutes may be an emergency case for the second inhabitant while it may not be for the first inhabitant.

With smart activity recognition systems, it is also possible to reduce the domestic energy and resource consumption. For instance, forgetting the television on very often

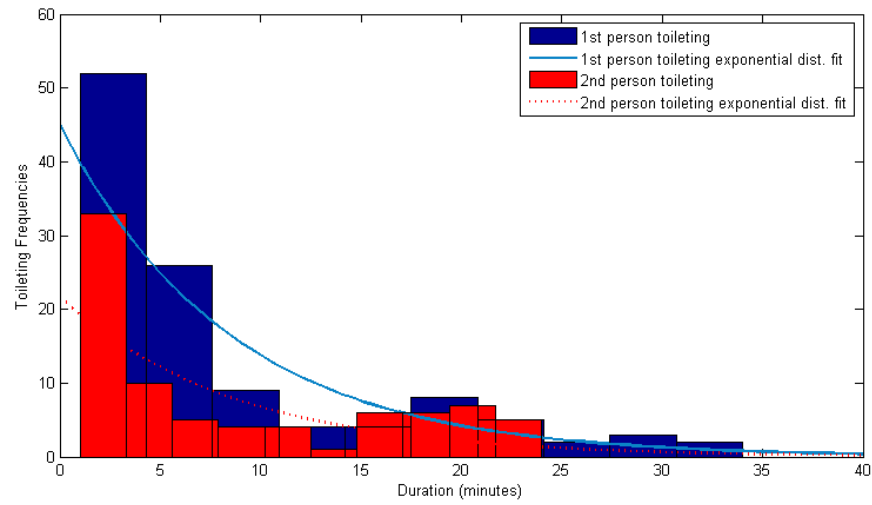


Figure 6.3. Spending time at toileting for residents in histogram.

while taking a shower can be detected, and the person can be persuaded to change this behaviour or the television can be shut down automatically. Similarly, water usage while showering or washing hands can be monitored and excessive levels can be reported to the user. By inducing this sort of behaviour change, we can both reduce the bills and contribute to the green planet.

7. CONCLUSION

With the increase in the average living age of people in the world, more investments are needed for elderly care. Moreover, the decrease in the working population due to aging will cause a shortage of skilled caregivers. For this reason, monitoring and recognizing human activities remotely is gradually becoming a popular research field. On the other hand, there have been serious improvements in sensor technologies in last decades which induce inexpensive low power sensors with the ability of collaboratively process and make inferences from the acquired data about behaviours of residents. These improvements enable sensor technologies to be utilized in AAL applications as a part of WSN which monitors human activities continuously in order to deduce emergency situations like falls in the short term and detect drifts from the daily living patterns of residents in the long term. Thus human activity monitoring systems using WSNs support independent living of people with disabilities and other elderly. Additionally, health officers can be informed about abnormal situations in advance. It is obvious that such systems will relieve the workload from both family caregivers and health officers. Other utilization domains of such WSNs are healthcare applications like supervising medication intake, smart home applications like controlling excessive electricity and water usage in homes, and persuasive systems like aiming to convince residents to change and correct their behaviours by the help of several notifications.

The task of AAL systems based on WSNs is basically modelling human behaviours and detecting drifts from daily living routines of residents in the long term. Several machine learning methods can be utilized to model human behaviours from acquired sensory data. These methods need large, accurate and realistic training data sets with their corresponding annotations for learning model parameters. For this reason, collecting realistic data sets with accurate annotations is the key feature of such AAL systems. In order to address these challenges, we present a WSN based automated assisted living system which has been tested in a real house, shared by two residents, and collected ADL data from 20 different sensors for 30 full days. In the light of experiences from initial studies, we utilized the Arduino framework for designing the

WSN. Unlike similar studies in the literature, we concern multiple residents in our system accounting that living alone is not very often in real life, even for elderly. The multiple residents setting also enables us to investigate the relations between residents. Furthermore, we aim to detect a very large set of daily activities (27 activities in total) which include both basic activities like sleeping, toileting, cooking and rare activities which are not performed every day like hanging out laundry, doing cleaning, having guest. We collected an invaluable huge data including two residents' ADLs of 30 full days with average 60-100 accurate labels for each day. The sensor data has been classified with kNN, decision tree, and HMM methods. According to the performance evaluations, we obtained 70% accuracy rate with HMM. Besides, we also evaluated the system performance in terms of battery life time and showed duty cycling event based sensing and data transmission increases the life time of the system. We also shared our experiences and key lessons from deployment of WSN to a real house and the data collection process.

We observe that classifiers which take into account the temporal information in the data like HMM are much more successful in the classification of ADL data. Moreover, we do not have the assumption of person ID activity matching in our design which turns the activity recognition for multiple residents into a challenging problem. For this reason, the recognition performance can be improved by using more sophisticated methods like hierarchical factorial hidden Markov models [59]. Secondly, tackling scalability issues arising when these systems are to be deployed in large scale can be considered as a future work. Accounting that obtaining activity labels is a burdensome and costly task, and additionally, the model parameters are subject to change across different people and home, the reuse of the knowledge obtained previously is essential in order to disseminate AAL systems based on WSNs. Using transfer learning across different settings can be considered to handle this problem [60]. In this way, we will be able to transfer the knowledge we obtained in this thesis to new settings.

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