



International Master's Thesis

**An android based monitoring and alarm system for
patients with chronic obtrusive disease.**

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Technology

An android based monitoring and alarm system for patients with chronic obtrusive disease.

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at Örebro University 18*



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Title: An android based monitoring and alarm system for patients with
chronic obstructive disease.

ISSN

Abstract

Consistent monitoring of vital health parameters is an important issue in the medical industry. With recent technologies we are able to carry out remote monitoring of physiological parameters in patients. This allows communication between a patient and medical personnel using a smart-phone, which will collect, analyze and transfer heart rate and oxygen saturation data for subsequent review by a medical professional. Before any on-line analysis is performed on the phone it is necessary to clarify the nature of the correlation between these medical parameters. In the current thesis we establish connection between a patient wearing a pulse-oxymeter and a smart-phone running Android and perform continuous data collection. All measurements were done in consultation with medical facility and involved real patients. This data is subsequently analyzed using change point detection and anomaly detection algorithms in off-line mode. Both techniques are complementary to each other and showed reliable results which could be useful for a medical review.

Acknowledgements

I would like to express my gratitude to my supervisors: Amy Loutfi, Per Dahl and Gunnar Akner, who were consistently providing me with both good advice and technical equipment during the project. I would also like to thank personnel and patients of the Backagården medical facility for their participation and patience during the experimental part.

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Chapter 1

Introduction

The following introduction includes motivation for the current thesis work, based on major health care problems including fast aging of population. We also provide a full description of the task and introduce a structure of the thesis.

1.1 Motivation

According to the latest United Nation statistic reports, the mean age of the population is expected to grow rapidly in developed countries within the next several decades¹. This will subsequently increase the cost of the health care and result in significant loss for the national budgets. However, the latest achievements in different fields of technologies may allow us to minimize the problem and successfully integrate these technologies into the modern health care systems.

Health care is an essential part of everyday life for all human beings on the planet. Each of us requires a periodic monitoring of vital parameters and right treatments based on this data. These processes become even more crucial when people reach a certain age and are not able to follow their health condition properly without a special medical personnel or sophisticated equipment to perform the monitoring. The older a person gets, the wider spectrum of possible diseases and unexpected emergency situations might occur[3]. In order to avoid this, he or she needs to be transported to the hospital, observed by medical staff and provided with immediate help if some of the parameters are abnormal. In many cases, even a short delay might lead to the dangerous consequences including death of the patient. Nowadays, there is a wide spectrum of modern monitoring devices which possess a various number of capabilities and can assist personnel in the hospital to work with old or disabled people.

However, normally, these basic health parameters are being monitored and measured by medical personnel only at discrete intervals. This common approach can sometimes lead to the loss of crucial data (e.g. during the night).

¹World's Population, <http://www.un.org/esa/population/publications/ageing/ageing2009.htm>

Therefore, a particular interest is focused on continuous monitoring techniques. Unlike the spot checking, this type of monitoring is capable of providing a long-term information about the patient, helps to register emergency situations and react adequately to any significant change in person's health conditions in a real time. However, the correlation between certain health parameters during a long period of time is yet unclear. Therefore, this type of system could assist in studying this correlation and eventually provide us with a full and complete patients health profile, which will be subsequently analyzed by professionals.

1.2 Task description

Based on the motivation part, we can formulate the main objective of the thesis, which implies combination of the latest development in mobile phone market with signal processing techniques and sensor devices in order to create a sophisticated monitoring system. The project is based on the android mobile device (Motorola Galaxy series) and includes pulse and oximetry sensor as an additional device. An accelerometer, embedded in the phone is also used as an additional sensor. The main goal is subsequently divided into two parts: in the first part we establish a reliable connection between mobile device and a sensor to collect continuous data from patients. In the second part we examine collected data using different sorts of processing techniques and algorithms. Patient mobility is also an important aspect to consider. We want a person to maintain his normal activity level while using monitoring system. Summarizing all mentioned above we can combine a list of desired steps:

- reliable connection
- maintain patients mobility
- data collection
- correlation analysis

This project is considered as a main step towards smart monitoring system. It will serve as an assistant device measuring patients health parameters and triggering alarm in case of emergency. It is implemented through a close collaboration between Artificial Intelligence and medical experience for the benefit of the Health Care.

1.3 Thesis outline

The following thesis work contains four main chapters

- **Chapter 1** represents the introduction part of the current research, contains subsections for motivation and a full task description

- **Chapter 2** gives an overview of the related work that has been done in the area and results of the background search. The chapter is based on a project's description for the Ubiquitous Healthcare systems, followed by some significant works in Fuzzy logic applied for the medical purposes.
- **Chapter 3** represents a full system set up realized before the actual testing of the application and signal processing. Contains a full description of the main sensor device involved in the experimental part.
- **Chapter 4** depicts a full overview of the analytic part of the work. Data processing including "change point detection" and "anomaly detection" is followed by "activity correlation".
- **Chapter 5** is based on a testing of the system in a real environment involving patient trial together with stress testing beforehand. The conditions and details of the experiment is followed by conclusion, drawn on the achieved results.

Chapter 2

Background

The following chapter will provide a current state of the art in monitoring systems development focusing on the following aspects: Health-Care systems general overview, sensors, devices communication, data processing. A separate part will analyze a usability and reliability of the fuzzy logic approach and show various number of examples where this particular type of logic was successfully implemented in medicine.

2.1 Remote Monitoring of Physiological Parameters

As a part of the Ubiquitous Health-care Information System (UHS) Remote Monitoring has three objectives, which are to reduce time loss due to lag, reduce the medium cost, and reduce inaccuracy in traditional medical flow¹. In addition, it has to fully realize that events and changes in the real environment must be reflected in UHS, and changes and decisions made in UHS must be forwarded to the real life. In other words, ubiquitous health-care consumers will send out data from various sources, receive real-time medical information, knowledge, and relevant expertise and search out relevant and useful information, especially for remote monitoring of physiological parameters. All the systems developed and currently used in this area can be categorized by several aspects: type of sensors, type of connection between sensors, monitoring/processing device and signal processing.

The choice of sensors in many cases is the most essential step while creating a monitoring systems. Implementing different scenarios(indoor or outdoor monitoring) demands deploying different types of sensors. However, there are two major categories: wearable and non-wearable. The first includes all devices which require contact with the patient's body in order to provide measurements. They can often be attached to a different body parts or integrated with some clothes and represent, for instance, a common article of T-shirt [24]. A main reason for close communication with person's body is peculiarity of the

¹Korea IT Times, http://www.kdcstaffs.com/it/main_news_print.php?num=5414

medical data, measured by wearable sensors. The most considerable parameters are: heart rate, oxygen saturation, blood pressure and sugar rate. It is possible in some cases to avoid using wearable devices for measuring this data, and use, for instance, sensors embedded in pillows or blankets [34], however this approach is highly limited in terms of usage and can only be employed for monitoring at night.

The second category contains all the sensors that can be appropriately used to provide information about surrounding environment. In many situations this data can make a huge impact for the overall analyzes and play a vital role in maintaining patient's health condition. One of the examples could be CO₂ sensor [32] which was incorporated into a wireless platform and provide user with information on carbon dioxide level in the room. In this particular project it is embedded into the user's piece of equipment (e.g. firefighter boot), however other ways of usage are not excluded. There is also a several number of techniques for posture recognition and activity measurements implemented with cameras integrated in the living environment[8]. Usually non-wearable sensors are combined into a sensor network which provides all kind of information, appropriate for overall analysis, but at the same time can significantly reduce patient's mobility and monitoring area. At the same time, one of the major aims of the project is to provide a person with a sophisticated system which will maintain his/her activity level including outdoor activities (like shopping or taking a promenade). The second type of sensors are not capable of working in terms of permanently changing environment and therefore can not be used.

Another important issue is the number of measuring devices. The more sensors we use the wider spectrum of possible scenarios and events we are able to cover. However, overloading patient with electronics can cause inconvenience and affect his mental condition. Moreover, a power consumption problem is a serious consequence in this case, which was previously addressed and leads to unnecessary complexity of the system [5] [38].

At the next stage, sensor layer of every remote monitoring system is typically connected to the processing device. This communication can be either wired [14] or wireless, depending on initial goal of the application. The wireless communication is usually provided by Bluetooth or ZigBee confection [42]. However, there are some alternative approaches, and one of them was described in IEEE journal on selected areas in communications [13]. Systems, designed in this project are capable of integrating different types of sensors with Radio Frequency Identification into a Radio Frequency board through a programmable interface chip. This chip can use a comprehensive signal processing to extract bio-signal feature parameters and only transmit them. These systems, however, have an additional aggregation node for signal processing and data converting. In our case it is replaced with a mobile phone device, which provides more computational power and wider range of functionality.

The opposite to wireless is a wired sensor networks, where each sensor in the system is connected to a processing device. Normally, it is a wearable sensor

network which integrates sensors, electrodes and wired means of communication in order to monitor patients health [14].

Since the overall mobility and unobtrusiveness of the system together with patients active life are among the highest priorities of the project, we have to consider wireless communication as the only appropriate approach.

2.2 Processing Device

A processing device is an essential part for most of the health care systems. The initial choice can vary depending on the application purposes. Generally, medical personnel requires collection and displaying the information measured by sensors in order to make decisions about patient's health conditions. This requirement can be fulfilled with PDA (Personal Data Assistant), which can serve as an aggregation node in these cases [13]. This approach has been successfully implemented in the project by Fei Hu and Yang Xioa where they used a special device to integrate all sensor data into database records and send it out.

Moreover, several attempts to perform on-line analyzes were made before the data was sent further to the assisting group [14]. In the project by Zhengand Zhang, system provides real-time visualization, memorizing, analysis, diagnosis and three degrees of alarm. It was implemented through the PPU (Portable Patient Unit) device which has a wireless connection to the wearable sensor network.

At the same time, an approach where a mobile device is used as processing node has not been popular in healthcare project. However, mobile service was involved in designing of systems described in "U-Health system with use of smart phone and sensor network"[42] and practical case of "MyHeart" project[24]. In first case, a signal from each sensor is transferred to the the base mote, which is connected to Client PC. At this stage, a body-information data is extracted and sent further to the Server PC. In case of abnormality, Server PC transfers a text message and patient's condition to family and medical center. It furthermore offers a web and mobile service to confirm patient's condition.

The second project considers a cellular phone as a transmitter of the signal, acquired from the sensors and processed by on-body electronics to a monitoring center. It allows professional care-givers to consult the patient's data and interact with him[24].

2.3 Data Processing for Ubiquitous systems

Besides monitoring feature one of the main goals of the current project is to create a reliable platform for the future extensive research towards on-line monitoring system. This implies collecting a continuous dataset and perform a certain level of analysis, based on received measurements, which can lead to serious restrictions in terms of algorithm complexity. In other words, we are not interested in computationally expensive methods which might slow down the

process. Thus, for processing purposes, we employ particular methods: change point and anomaly detection. Both procedures are commonly used in data mining area and have been studied before [21][17][19][15][20][43].

2.3.1 Change point detection

Generally, change points are abrupt variations in the generative parameters of a data sequence[2]. In other words every rapid drop/jump in time series is represented by a certain point, which plays an important role in processing of this data. Therefore, on-line detection of change points is useful in modeling and prediction of time series in application areas such as finance, biometrics, and robotics. In our case, this procedure indicates a situation, which can potentially be dangerous for a patient, and, hence should be an integral part of data processing.

Popular approach, which incorporates several relative studies[20][43] is based on Bayesian on-line change point detection and focused on the retrospective segmentation problem[2][10]. In project by Ryan Prescott Adams and David J.C.MacKay a particular case is examined: the model parameters before and after the change point are independent. Later, an on-line algorithm for exact inference of the most recent change point is derived. Authors compute the probability distribution of the length of the current “run,” or time since the last change point, using a simple message-passing algorithm. This implementation is highly modular so that the algorithm may be applied to a variety of types of data[2]. The whole procedure is based on different calculations and can be combined into the following steps: (1) Initialize, (2) Observe New Datum, (3) Evaluate Predictive Probability, (4) Calculate Growth Probabilities, (5) Calculate Changepoint Probabilities, (6) Calculate Evidence, (7) Determine Run Length Distribution, (8) Update Sufficient Statistics, (9) Perform Prediction, (10) Return to step 2.

The concern is to estimate the posterior distribution over the current “run length” or time since the last change point, given the data so far observed [2]. It is implemented in step seven:

$$P(r_t|x_{1:t}) = P(r_t, x_{1:t})/P(x_{1:t})$$

With the last step a marginal predictive distribution is calculated using the following equation.

$$P(x_{t+1}|x_{1:t}) = \sum_{i=1} P(x_{t+1}|x_t, r_t)P(r_t|x_{1:t})$$

in both cases x refers to observations and r is a length of the current run. The result after applying described algorithm are expected to look as it shown on figure 2.1 bellow.

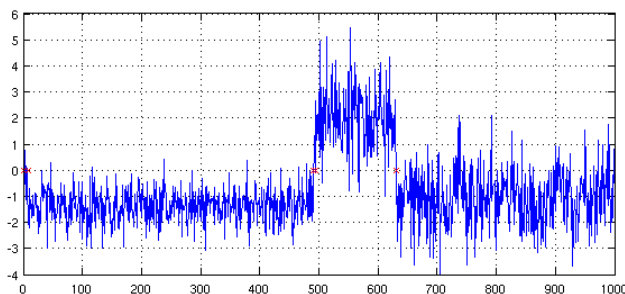


Figure 2.1: Bayesian on-line change point detection results

Another method was proposed by Allen B. Downey in his work "Change-point detection in network measurements" [10]. The main idea behind this work is also based on Bayesian theorem and implies an algorithm for simultaneous detection and location of the change points in a time series, and a framework for predicting the distribution of the next point in the series. The kernel of the algorithm is a system of equations that computes, for each index i , the probability that the last (most recent) change point occurred at i [10]. This algorithm is later evaluated by applying it to the change point detection problem and comparing it to the generalized likelihood ratio (GLR) algorithm.

However, there is one serious drawback, considered by author in the conclusion section of the paper: the proposed algorithm requires time proportional to n^2 at each time step, where n is the number of steps since the second-to-last change point. If the time between change points is more than a few thousand steps, it may be necessary to desample the data to control run time [10]. Assuming the specific requirement, announced in the beginning of this section, the proposed algorithm is computationally expensive for the current project.

In spite of the fact that, change point detection algorithm plays an essential role in data processing for our particular case, it won't be able to satisfy all the requirements. When it comes to personal health care, a large number of different scenarios can not be covered by a single processing technique. Therefore, these scenarios should be considered in conjunction and processed by multiple data mining methods.

2.3.2 Anomaly detection

Unlike change point detection, which only registers abrupt variation of time series, anomaly detection provides us with a wider spectrum of information about the signal. Normally this procedure refers to detecting patterns in a given data set that do not conform to an established normal behavior. We assume, that if any particular section differs from the rest of the signal, it could potentially

represent a dangerous situation and should be analyzed by a medical specialist. At the same time, anomaly detection itself would not be able to register rapid changes in a processed data if they repeat several times. It basically leads to a fact, that both methods have their own benefits and compliment each other during data analysis.

A numerous number of works provide a variety of algorithms and methods for anomaly detection [7] [29] [31] [37]. A common procedure in many related works presumes implementing several basic steps. As a rule, anomaly detection algorithms learn models of normalities by fitting models to training sets deemed as normal. With a next step, previously unseen instances are tested by measuring their distances to the learned models, using threshold for determining anomalies[37]. Using the previously mentioned sequence we eliminate a clustering algorithm, commonly used in data mining, as it was claimed to be meaningless in our case [18].

Moreover, before initiating a detection algorithm, it is considerable to determine data representation. In many cases, this pre-step is simply eliminated and data is processed directly [21]. However, assuming a specific nature of the measured records (medical sensors, specific format), a choice of data representation might play an essential role for future analysis. A possible approach is to convert time series into a number of symbolic strings representing particular sections of the entire data sequence [17] [19]. In the paper from "ASME Transaction on Mechatronics", authors propose a novel method for anomaly detection in mechanical systems, which make use of hidden Markov model, derived from the time-series data of pertinent measurements[17]. In this particular project a concept of Symbolic dynamics is used for converting the data. More precisely, they are performing a partitioning of a compact region of the phase space and a mapping from partitioned space into the symbol alphabet, which becomes a representation of the system dynamics defined by the trajectories.

A rather alternative way of performing anomaly detection involves fuzzy rules automatic extraction[30]. An idea behind this method is the following: we split previously collected data into equal parts and extract primitive rules about the signal behavior, based on the first part. For example,

IF pulse is *High* **THEN** oximetry is *Low*

We then examine the second part of the data and register every situation which is not covered by previously formulated rules. The entire procedure is therefore reduced to implementing a sufficient automatic fuzzy rules extraction algorithm. This problem is common in data mining, and has been studied from many perspectives[30][6][9][39][23].

Among the popular approaches is a rule extraction from support vector machines [6]. Shuwei Chen, Jie Wand and Dongshu Wang are considering a general fuzzy model with m fuzzy rules of the form

IF x^1 is A_j^1 and x^2 is A_j^2 ... x^l is A_j^l **THEN** y is B_j ,

where x^i are the input variables, y is the output variable of the fuzzy system; and A_j^i and B_j are linguistic forms characterized by fuzzy membership functions. They later use a special fuzzy basis function as a kernel function for SVM and perform a step by step SVM learning procedure: (1) Assign parameters, (2) Generate fuzzy rules from SVMs (3) Create a combined fuzzy rule base. The three step procedure creates a combined fuzzy rule base whose rules are from either those generated from numerical data or linguistic rules [6].

In a similar paper [9] authors are using 3 steps procedure again. Firstly, they obtain membership degrees by projecting previously calculated SVM into the coordinate axis. With the second step fuzzy sets associated with each input attribute are constructed. And, finally, each support vector generates a fuzzy rule. The algorithm is evaluated using a benchmark classification database (Bupa Liver Disorders) [9].

Alternative methods for automatic rule extraction are based on various approaches including: ID3-based method (generating a fuzzy decision tree for a specified class)[39], separation of the input space into activation rectangles, corresponding to different output intervals [23], genetic algorithm and constrained nonlinear optimization of membership functions [28], extraction from typicality and membership partitions [35], extraction based on practical swarm optimization [25] and from a trained multi layered neural network[26].

2.4 Decision Support System in Remote Monitoring Applications

Every sophisticated monitoring system tends to provide a certain level of decision making assistance in situations when it is highly required. In our case, reasoning platform should be based on a previously examined medical experience combined into a knowledge base. Relying on this knowledge, a system will be able to make decisions about certain correlations between medical parameters and formulate responses typical for elderly people group. A universal tool, potentially capable of providing required functionality is fuzzy logic - a well known technique which has been introduced by Lotfi Zadeh in 1965 year. Originally, it received a huge amount of skepticism from the scientific society and was nearly forgotten. However, further demand in renovating and improving decision-making algorithms played an important role in rising fuzzy logic as an irreplaceable tool for applications in different areas. Ever since then, scientists have made several attempts and described several ways to use fuzzy logic in medicine [4]. Some of these projects will be briefly presented below.

A decision making process in medical area is always connected with a certain degree of uncertainty [22]. It can possibly be imprecise information, inaccurate information, missing information or conflicting information. While developing a decision making or expert system we should also account for un-

certainties in different components of such a system including uncertainty in Knowledge Base and Patient Data. As a brief example we can suggest a blood pressure variance for the patients with different health condition. Moreover, a developed healthcare system should be able to output a particular degree of an alarm in case of emergency. Assuming currently listed facts, fuzzy logic and its' versatile approach can help in dealing with previously mentioned uncertainties.

Unlike common binary logic fuzzy approach applies a special decision mechanism which can be compared to a human logic and does not have any certain restrictions or boundaries. This characteristic can be successfully used in various number of applications in medical field. The recent statistic has shown an exponential growth in number of articles describing fuzzy implementation in the very same area [4].

A project by Novruz Allahverdi surveys and summarize the most popular examples of collaboration between fuzzy logic and medicine[4]. Some of the recent applications can accomplish such sophisticated tasks as determination of the disease risk. It leads to the fact that subsequently this type of systems would serve as an advisor for a hospital personnel. More specifically, two fuzzy expert systems were developed in this particular direction. The first work contained a number of rules combined together in a fuzzy expert system (FES) in order to use laboratory or personal data and help specialists to predict a numerical value of the prostate cancer risk disease. In this study prostate specific antigen (PSA) age and prostate volume (PV) were used as system input parameters, together with prostate cancer risk serving as an output. A nearly similar approach was used for the second project, where hierarchical fuzzy expert system was designed to provide assistance in determining coronary heart disease diagnosis according to the next 10 years risk of patient. Two system resemble in definition of the input parameters. This time age, cholesterol and blood pressure were used as an input and same risk value were set as an output.

Proceeding with other examples in medical field, we should mention following projects as a demonstration of additional capabilities of the fuzzy approach [4]. They do not relate directly to the current project, however show a high usability of the chosen technique. Assuming economical and accuracy benefits of the fuzzy control scheme, a special expert system was introduced for the maintenance of the necessary conditions in the operating room. In this case heat, humidity, oxygen and particle values were considered as an input meanwhile fresh air entrance and fan circulations were used for output. An experiment with operating room prototype was held to prove feasibility of the approach. The analysis of the achieved results led to conclusion that while using an appropriate linguistic expressions and a membership functions for these expressions, fuzzy control system provides more economical, reliable and consistent solution than commonly used systems.

Another attempt to make some of the medical processes autonomous was successfully implemented and described in the very same article[4]. A serious issue, connected to drug dose determination has been addressed and tested with

fuzzy logic implementation. An amount of medical treatment given to the patient depends on various number of parameters including age, weight, sex, disease history blood segmentation etc. It can also vary from one disease to another. A series of clinical tests were performed in order to compare a reliability of the fuzzy drug determination with physician recommendations. As a result, developed system helped to shorten the treatment duration and minimize negative effects in determination process.

All the above mentioned projects make fuzzy logic and relative approaches to be a better choice. Some of the results achieved with those techniques showed a high degree of reliability, in several cases rising up to 96.55 %,94.71%,94,11% [12]. However, in our particular case (assuming continuous monitoring), correlation between main medical parameters has a complicated behavior and still requires meticulous investigation. It would be superfluous and premature to rely on incomplete knowledge while developing a monitoring system. Therefore, implementing advanced decision making algorithm using previously mentioned fuzzy logic functionality is a subsequent step. Preliminary, we make a step towards full-scale experimental research in order to clarify a nature of the correlation.

Chapter 3

System Set up

The following chapter will go step by step through each part of the developed system, including hardware devices and software involved in the development process. Everything from the initial set up to the data collection stage is covered.

3.1 Sensors

Sensors as a hardware equipment is an essential part of any monitoring device. The total amount of sensors involved in a monitoring process can be increased, providing a more sophisticated level of the analysis and enchanting data processing. Possible suggestions are discussed in Chapter 4 and 6. It was decided, however, to use a limited amount of sensors in the current project and establish a reliable connection for subsequent data transferring.

3.1.1 Accelerometer

The accelerometer sensor is an important component of the developed system as well as any other system involving patients monitoring. It provides a basic information about daily activity of the person, which can be further modified and used as one of the parameters for the analysis. Before describing the accelerometer application and usage in this particular project we consider it sufficient to mention several features of this type of sensor.

Conceptually, any accelerometer behaves as a damped mass on a spring. When the accelerometer experiences an acceleration, the mass is displaced to the point where the spring is able to accelerate the mass at the same rate as the casing. The displacement is then measured to give the acceleration.

In commercial devices, piezoelectric, piezoresistive and capacitive components are commonly used to convert the mechanical motion into an electrical signal¹. Piezoelectric accelerometers rely on piezoceramics (e.g. lead zirconate

¹Accelerometer, <http://en.wikipedia.org/wiki/Accelerometer>

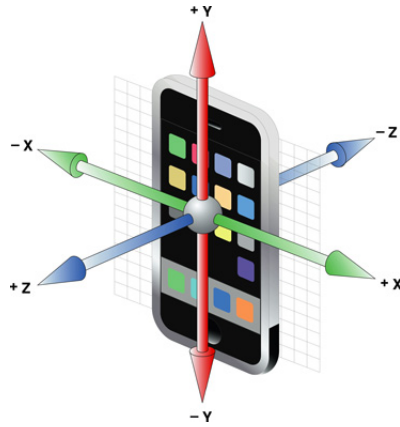


Figure 3.1: Accelerometer axes

titanate) or single crystals (e.g. quartz, tourmaline). These crystal structures become stressed by accelerative forces, which causes a voltage to be generated. Piezoresistive accelerometers are unmatched in terms of their upper frequency range, low packaged weight and high temperature range and preferred in high shock applications. Capacitive accelerometers typically use two silicon micro-machined sensing elements. Having these two micro structures next to each other, creates a certain capacitance between them. If an accelerative force moves one of the structures, then the capacitance will change. Additionally, converting some circuitry from capacitance to voltage we will be able to get a full accelerometer ². Performance of these type of sensors is superior in the low frequency range and they can be operated in servo mode to achieve high stability and linearity. Modern accelerometers are often based on small electromechanical devices (micro electro-mechanical systems or MEMS) and normally inbuilt in the latest generation of the smart phones (including the one involved in the project). In our case it can be reached by programming through the android operating system with the help of "SensorManager" class and special Sensor Activity. The simple pseudo code example is provided below:

```

SensorActivity {
    getSensorService ();
    getDefaultSensor (SensorType);

    onResume () {
        registerSensorListener (this , Accelerometer);
    }

    onPause () {
        unregisterSensorListener (this , Accelerometer);
    }
}

```

²A beginner's guide to accelerometers, <http://www.dimensionengineering.com/accelerometers.htm>


```

    }

    onSensorChanged(SensorEvent) {
    Do something if sensor is moved;
    }
}

```

Once the sensor is activated there are several methods provided by the previously mentioned class which can be used in order to measure activity. It is represented by three variables x,y,z which output device acceleration along the raw, pitch and yaw direction[33] (see Figure 3.1). First of all, we need to make sure at least one sensor is available for the measuring process. A special method "isSupported" is used for this purpose:

```

isSupported() {
    if (notSupported) {
        getSystemService(sensorService);
        List sensors = getSensorList(accelerometerType);
        supported = new Boolean(sensorsSize);
    } else {
        do nothing if sensor is supported;
    }
}
return supported;
}

```

The next step is to invoke a special "startListening" process which registers a listener and starts listening to the accelerometer callback for possible events (shaking, changing position etc.). This method also includes a configuration component where we can decide on a threshold for the changes in accelerometer and interval between shakes. It can help to react only on significant changes and simplify data collection in the next stages.

Now, any change/event, which arises while the accelerometer is in the "listening mode" will be registered and processed. It is reasonable to introduce a threshold for eliminating insignificant changes in raw/pitch/yaw values of the accelerometer. All the values below this threshold will not be considered. We can furthermore use previously detected acceleration and display it on a screen or store it in a file for further processing. Both options are implemented in our case. Possible approaches for accelerometer data processing will be described in Chapter 4.

3.1.2 Nonin Wrist Ox2

The following section is dedicated to the technical specifications of the sensor device used in this project. Description is based on a "Fingertip Oximeter Technology Specifications" document [1] and provides additional information concerning the current system features. The picture of the sensor is provided on Figure 3.2.



Figure 3.2: Nonin Wristox2 3150

All the technical specification and parameters of the Pulse Oximeter are combined into an appropriate table (see Figure ??). The most significant information in terms of the system development are Oxygen Saturation and Pulse Rate Accuracy.

| SpO₂ Accuracy (A_{rms}*) Adult/Pediatric: | SpO ₂ : 70% to 100% | | |
|---|--------------------------------|-----------|---------------|
| | No Motion | Motion | Low Perfusion |
| Reusable Sensors: | | | |
| 8000AA**, 8000AA-WO**, 8000AA-WO2: | ±2 digits | ±3 digits | ±2 digits |
| 8000J**, 8000J-WO**, 8000J-WO2: | ±3 digits | N/A | ±2 digits |
| 8000S series***: | ±2 digits | ±3 digits | ±2 digits |
| 8000Q2**: | ±3 digits | N/A | ±2 digits |
| 8000R**: | ±3 digits | N/A | ±2 digits |
| Disposable Sensors**: | | | |
| 6000CA, 6000CP, 6000CI, 7000A, 7000P, 7000I: | ±2 digits | ±3 digits | ±2 digits |
| Pulse Rate Accuracy (A_{rms}*) Adult/Pediatric: | BPM: 18-300 | 20-250 | 40-240 |
| | No Motion | Motion | Low Perfusion |
| All sensors: | ±3 digits | ±3 digits | ±3 digits |

Figure 3.3: Nonin Wristox2 3150 specification

The table is followed by bluetooth configurations including Operating Frequency and Operating Range.

Technically, Nonin Wrist Ox2 oximeter is a slave device. To connect sensor to a master device, the master device must first associate with the 3150 by inquiring for the 3150. For the initial pairing of a new host device (master) to the 3150, it is discoverable for a minimum of 2 minutes after power-on. During the discovery period, the 3150 will broadcast a friendly name to the master. The name starts with "Nonin_Medical_Inc._", followed by a 6-digit number, referred to as the PIN. The PIN is etched on the back of the 3150 enclosure.

| Bluetooth Information: | |
|-------------------------------|---|
| Bluetooth Compliance: | Version 2.0 |
| Operating Frequency: | 2.4 to 2.4835 GHz |
| Output Power: | <20dBm |
| Operating Range: | 100 meter (328 foot) radius indoors ¹ |
| Network Topology: | Point-to-point (factory default) |
| Operation: | Slave: Model 3150 |
| Antenna Type: | Internal |
| Modulation Type: | Frequency Shift Keying Frequency Hopping Spread Spectrum |
| Band Width: | 1 MHz |
| Bluetooth Profiles Supported: | Health Device Profile (HDP) Serial Port Profile (SPP) |

Figure 3.4: Nonin Wristox2 3150 bluetooth specification

To complete the pairing process once the master (host) device finds the 3150, the PIN must be provided to the master device. Once paired, the master must establish the connection to the sensor.

This particular model provides measurements in several different data formats:

- Data format 13 – provides easy spot-check measurements with the storage and forwarding of measurements.
- Data format 8 – provides real-time oximetry measurements every second.
- Data format 2 – provides real-time oximetry measurements with compressed waveform (8 bit waveform) every 1/75 of a second.
- Data format 7 – provides real-time oximetry measurements with full resolution waveform (16 bit waveform) every 1/75 of a second.

For data formats 1, 2, 7 and 8, the 3150 will not initiate the connection using the attempt to reconnect (ATR) option. If the system has only one COM port available, data format 2, 7, 8, or 13 should be used with the ATR disabled. The master device must initiate the connection by occasionally polling for the 3150. For an automatic wireless reconnection, a software should be designed to periodically poll for the 3150. If polling for the 3150 is not possible, Bluetooth connection should be started manually. Because the manual method typically requires the user to initiate the Bluetooth connection, the seek/polling method has its advantages.

The 3150 will be discoverable when not paired to an existing master. Any previous master devices should be off. Once the device pairs and establishes the Bluetooth connection with the 3150, sensor will automatically send continuous data to device as defined in Data Format Definition section later. For further details on establishing a Bluetooth wireless connection see Appendix A. A Bluetooth connection indicator becomes available on the screen, after pushing and

holding a bluetooth button. Once the Bluetooth connection is established, the 3150 receives and transmits data using the SPP protocol. Additionally, there are several settings and commands for data format and time information: (1) Set the Data Format and Activation, (2) Set Multiple Parameters, (3) Set the Date and Time in the 3150, (4) Set Bluetooth Radio timeout (power saving feature), (5) Get the Date and Time from the 3150, (6) Get the Serial Number in the 3150, (7) Get revision number.

In each case user must send a preliminary byte command string in order to select Data format, set or retrieve time. A data format is a key information for receiving, displaying and processing the sensor measurements. Thus, it is important to mention several details on it's structure. A default Serial Date Format 2 (one of the listed above) was used in development. This data format provides continuous data transmission of a 5 byte data packet sent 75 times per second. The data packet includes real-time data of: 8-bit waveform value, beat-to-beat SpO2 value, SpO2 and Pulse Rates values formatted for both recording and display purposes, status of the measurement and battery. Each particular byte represents a valid information.

Byte 1 – START BYTE:

Always set to a 01 value.

Byte 2 – STATUS BYTE:

This byte provides status information at a rate of 1/75 of second.

Range: 128 to 255

Byte 3 – PLETH BYTE:

This byte consists of an 8 bit plethsmographic waveform (pulse waveform). The pulse oximeter infra-red signal is filtered and then compressed into an 8 bit value. The compression provides good detail for low to large pulse signals. For uncompressed waveform refer to Data Format 7.

Range: 00 to 255

Byte 4 – FLOAT BYTE:

This byte is used for SpO2, Pulse Rate, and information that can be processed at a rate of 1/3 of second.

Range: 00 to 127

When the device is removed from the finger the last SpO2 and Pulse Rate reading will be reported for 10 seconds before changing to the missing data value. During this 10 second period the sensor alarm bit (SNSA) is set, indicating that the finger has been removed. This feature is useful for spot-check measurements. When SpO2 and HR cannot be computed, the system will send a missing data indicator. For missing data, the HR equals 511 and the SpO2 equals 127.

Byte 5 – CHK:

This byte is used for the checksum of bytes 1 through 4.

A concrete information on the processing of the sensor measurements can be found in Chapter 4 of the thesis.

3.2 Processing Device

The current section will go through the second part of system hardware used for the developing purposes. Several main aspects concerning technical parameters and programming Android API (Application Programming interface) will be covered and formulated according to their involvement in the process.

3.2.1 Samsung smart-phones

All the information sent by sensors (excluding accelerometer, inbuilt in phone) can be received by processing device through Bluetooth connection. Both Samsung Galaxy S and Samsung Galaxy Tab used for the actual thesis work, have a Bluetooth functionality. Thus, next step would be to get an access to this feature through the programming language, which is in our case Java. No license or special agreement is required to program previously mentioned devices, both based on an Android operating system.

Before proceeding to the next step, it is important to mention some general aspects about Bluetooth option. According to the both smart-phones manuals, Bluetooth is a short-range wireless communications technology capable of exchanging information over a distance of about 10 m without requiring a physical connection [36]. Furthermore, we do not need to line up the devices to beam information with Bluetooth. If devices are within the range of one another, any information exchange between them is possible even if they are located in different rooms. However, we should always ensure that sharing and receiving data is performed with devices that are trusted and properly secured. If there are obstacles between the devices, the operating distance may be reduced. Moreover, some devices, especially those that are not tested or approved by Bluetooth SIG³, may be incompatible with the involved device.

Other than Bluetooth option, there are more technical parameters possessed by Samsung Galaxy S, making it sufficient enough to be involved in monitoring system and subsequent data analysis. The parameters within our scope are memory (capacity) and operating frequency. The Samsung Galaxy S has the S5PC110 processor. This processor combines a 45 nm 1 GHz ARM Cortex-A8 based CPU core with a PowerVR SGX 540 GPU made by Imagination Technologies which supports OpenGL ES 1.1/2.0 and is capable of up to 20

³Special Interest Group, <http://www.bluetooth.com/Pages/About-Us.aspx>

million triangles per second. The CPU core, code-named "Hummingbird", was co-developed by Samsung and Intrinsity.

In terms of memory, the Samsung Galaxy S has 512 MB of dedicated LPDDR2 RAM (Mobile DDR) and 16-32 MB of OneDRAM. Some variants also come with either 8GB or 16GB of OneNAND memory combined in a package-on-package stack with the processor. An external microSD card slot supports up to 32GB of additional storage memory ⁴. Additionally, the smart-phones used for programming runs on Android 2.1 (a.k.a. "Eclair") operating system.

3.2.2 Application development

It was decided to use Eclipse programming environment for development as one of the most sufficient and user friendly. All the communications between processing device and sensors are implemented through the application interface. A special application was designed and successfully ran for this particular purpose. The first step and a one of the main goals of this program was to establish a reliable connection. Once connection is initialized and running, it is important to maintain a signal in order to provide consistent interaction. In other words, we want to continuously store all the data received from the sensor in the phone memory and any kind of interruption would negatively affect the quality of the future analysis. A special android project was created, based on the Eclipse software in order to use all the available classes of android development environment. A project consists of two main "activities" and one special "service" which is responsible for a consistent data transmission. We consider it important to highlight main parts of these programming components in the following description.

Firstly, we want to ensure the Bluetooth option is available and enabled on the device before we start any kind of operations [27]. Two simple commands perform a system check for both previously mentioned cases and can be executed with the following pseudo code:

```
//check if bluetooth is supported
if (BluetoothAdapter(notSupported)) {
    printOut(''Bluetooth is not available'');
    finish();
    return;
}
```

and

```
//check if bluetooth is enabled
if (BluetoothAdapter(notEnabled)) {
    BluetoothAdapter = ActionRequestEnable;
}
```

The last command sends a request to enable bluetooth on the operating device in case this option is currently disabled. Once bluetooth function is switched on,

⁴Samsung Galaxy, http://en.wikipedia.org/wiki/Samsung_Galaxy_S

we can proceed to the next step. An advanced user interface was not among the highest priorities of this project, however, several options are available within the main application screen depicted below.

It is important to store some basic patients personal information, which will be further used in data processing part. So, as it is shown on Figure 3.5, every user can type in and save his/her age and weight in the corresponding field. The number will be later written to a special file and ready to be extracted for processing.

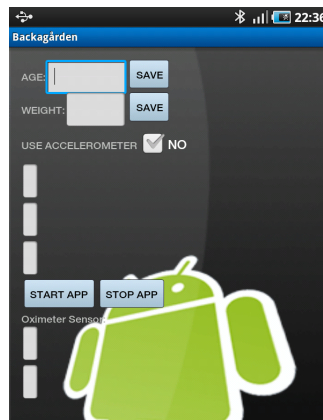


Figure 3.5: Application main screen

Next option allows user to get an access to accelerometer sensor through the android API. This part was described more specifically in Section 3.1.1 of this thesis. A data storing procedure is performed again. This time a special file, representing accelerometer along three axis is created and updated continuously. Current numbers are displayed on a screen and match the values stored to the device memory. You can read more about data format in Section 3.2.3 of the current chapter.

After accelerometer is set up and running, we can proceed to the main part, where connection between a sensor and android phone needs to be established. A "START APP" button will initiate a second main activity, which provides user with a list of paired devices and opportunity to search for new ones (see Figure 3.6).

In order to create a connection between application and a remote device (sensor in our case), we must implement either server-side or client-side mechanisms, because one device must open a server socket and the other one must initiate the connection (using the server device's MAC address to initiate a connection). The server and client are considered connected to each other when they each have a connected BluetoothSocket on the same RFCOMM channel. At this point, each device can obtain input and output streams and data trans-

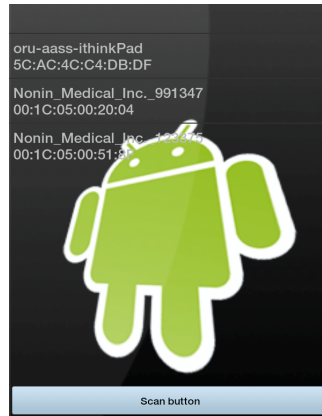


Figure 3.6: Device list menu

fer can begin. We are interested in client-side option.

So, in order to initiate a connection with a sensor (a device holding an open server socket), we should first obtain a `BluetoothDevice` object that represents the remote device. After that we use the `BluetoothDevice` to acquire a `BluetoothSocket` and initiate the connection. This part of the mechanism is implemented in a "BluetoothService" section of the program.

After device is chosen and bluetooth connection service is running, application will automatically return to a main screen and we can now observe measurements below the "Oximeter sensor" section on a display. A step by step tutorial on starting sensor readings is provided in a special manual (see Appendix A) written for the Backagården personnel.

3.2.3 Data collection

Once the system is set up properly and the main application has been started on the testing device, it is possible to start data collection for the subsequent analysis. Two possible categories of the data that can be processed are represented by two different scenarios. Firstly, we perform testing with the healthy person, who is unlikely to have any kind of abnormalities and moreover any kind of chronic diseases. A second data set is expected to come from preliminary selected patients, who agreed to participate in the experimental part of the current research. The experimental part is described in details further below forming Chapter 5 of the thesis. The process implies receiving, storing and analyzing the data extracted from the measuring devices. All the information is sent via Bluetooth channel establishing "mobile phone - sensor" communication.

processing device. Each measurement is retrieved from a different source and represented by four separate files:

- sensors.txt (pulse rate and oxymetry)
- activity.txt (raw, pitch, yaw from accelerometer)
- age.txt (user input)
- weight.txt (user input)

The first two files have a particular format and consist of three separate column vectors, including a special time vector.

```
20110519T175925 82 96
20110519T175927 82 97
20110519T175929 82 96
20110519T175931 82 96
```

This information is intended to simplify and at the same moment significantly improve further analysis of the data. Having access to the time makes it easier to register every particular change and follow the input flow as it is shown on Figure 3.7.

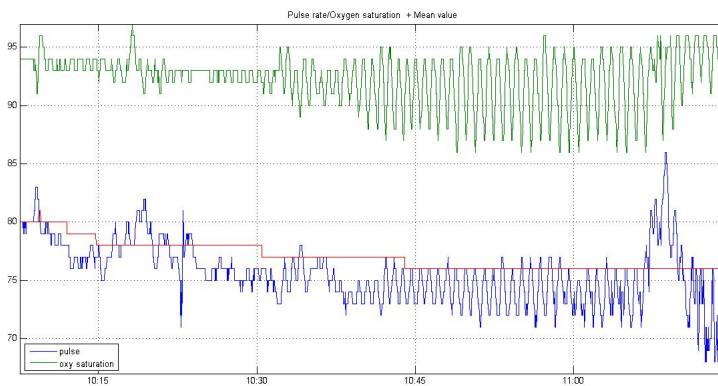


Figure 3.7: Data sample plot

The entire concept of Chapter 3 was based on several goals announced in the introduction part of the thesis. Firstly, it was required to establish a reliable connection between sensor and processing device, which is impossible without considering key aspects of sensor technical specification such as data format and operating modes. Secondly, we provide general information on data collection procedure, which is summarized in Table 3.1 above. Moreover, Table 5.3

Table 3.1: Floating Mean

| | | Test I | Test II | Test III |
|-------------------|---------------|--------|---------|----------|
| Pulse, BMP | <i>min</i> | 33 | 56 | 22 |
| | <i>max</i> | 126 | 114 | 126 |
| | <i>f</i> loat | 79,5 | 85 | 74 |
| Oxygen, % | <i>min</i> | 81 | 80 | 81 |
| | <i>max</i> | 100 | 100 | 100 |
| | <i>f</i> loat | 90,5 | 90 | 90,5 |

from Section 5.2 contains detailed information about data transfer, including data loss in percentage. These measurements are sent and retrieved in a particular format (see a cutout of measurements above), developed for this particular application. It was designed to cover all the details and provide user with an easy interface for a sensor - device communication. The very same application carries out a data collection procedure.

Chapter 4

Data Processing

Following set up of the developed system, we proceed with the analysis, applied for collected measurements: (1) change point detection, (2) anomaly detection, (3) activity correlation. Each item is responsible for particular function and represents different level of analysis. The first technique detects and registers every unexpected *sudden* drop/jump during the monitoring process. The next method, anomaly detection is aiming on detecting and highlighting unusual patterns in the signal that might represent extra interest for a medical specialist. Both algorithms are complementary and serve as a pre-step towards the on-line monitoring system. Ideally, after change point is detected we should add other parameters and perform correlation analysis. As it was discussed in Chapter 2 fuzzy logic can be used in this case to combine medical parameters and perform a certain level of reasoning about patients health conditions. However, as it was previously mentioned, particular qualities of the correlation are not thoroughly verified when it comes to continuous datasets. Therefore it is essential to conduct a series of experiments involving patients from different age groups and with various diagnosis. After collecting this data we can apply the above mentioned techniques to examine the nature of the correlation between medical parameters involved in the monitoring. This will help to enhance the final reasoning algorithm and avoid triggering an alarm when it is not necessary. Finally, as a separate part of the correlation analysis, we consider accelerometer data and examine how it can complement and improve reasoning algorithm.

4.1 Change Point Detection

The first part of data processing in the developed system is focused on a change point detection procedure. Ideally, we consider on-line monitoring of the patient, which normally should be maintained on a regular” continuous basis. However, if processing is performed on the phone, it is superfluous to analyze situations when nothing wrong is happening to the patient and all the parameters are within a normal range. It might unnecessary sophisticate the process

and affect memory consumption. Thus, there is no use in full-scale analysis unless *one of the parameters is significantly off the normal range or/and abrupt drop/jump is detected*. The first case can be easily controlled by thresholding of the input signal (pulse rate or oxygen saturation). However, in the second situation we require more sophisticated analysis. At the same time, apart from on-line, there is a high demand in off-line processing of the data, where change point detection can also be effective. It will register every abrupt change in the signal and give a better perspective on a patient's health profile. The algorithm, described in Chapter 2 [2] is sufficient to be applied for the on-line monitoring, however, prediction of the data distribution is not among the goals of this thesis.

Another alternative would be calculating a mean value every time step after a new observation is received. Normally, all the measurements vary within a certain range represented by a green line on Figure 4.1. Every time next pulse measurement jumps/drops significantly from this line, we register this point and mark it as a danger point as it might be potentially dangerous for a patient. The whole process consists of several steps followed by a plotting command. We should, firstly, load the file and split the parameters into three categories: time, pulse and oxygen saturation. The next step excludes all "corrupted" measurements and replace them with the previous value in a sequence to calculate accurate mean value:

$$\bar{x} = \frac{1}{n} * \sum_{i=1}^n x_i$$

, where n is a number of measurements and x_i is a current measurement. We then compare each received measurement with this mean and detect change points throughout the signal. Once the next point is registered we reset this number and start calculating from zero. It allows us to update a mean value and split data into different segments throughout the signal.

A zoomed-in part of the parameter variations on Figure 4.1 demonstrates a danger point detection process. We can observe two sectors where pulse measurement first drops and then jumps beyond the normal range. Both cases are detected and marked as a change/danger point. The green line represents the mean value of the pulse signal and is used as a main criteria for abnormality. Oxygen saturation is depicted with a red line and (in case of on-line reasoning) is addressed after danger point has been detected, initiating correlation analysis.

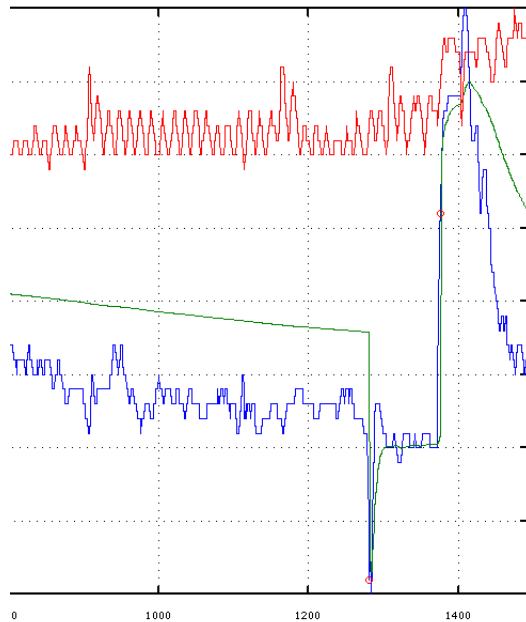


Figure 4.1: Change point detection

The pseudo code for selected algorithm is presented below:

```
(in Java)
-READ FROM FILE
(in C++)
WHILE(x(i))
  IF (incoming signal is corrupted)
    replace(x(i), x(i-1))
    mean(xi)
  IF (x(i)} > threshold or x(i) < threshold)
    x(i) is a danger_point
    add(oximetry, activity, age, weight)
    fuzzyCorrelation (pulse, oximetry, activity, age, weight)
    alarmLevel()
END WHILE
(in Java)
-SEND INFORMATION
```

After performing a change point detection on collected data, we are able to provide a summary of results for a subsequent analysis by medical specialists (see Table 5.3 in Chapter 5). However, we can also make one extra step towards the on-line monitoring system and create a simulation model. This model will serve as a testing platform before transferring the above mentioned algorithms

directly to the processing device. It can also perform analysis for the collected data and tests with different types of input. It is essential to confirm reliability of the system before the on-line analysis take place on a real device. A scheme of the simulation model on Figure 4.2 contains different medical parameters and personal data as an input, processing block which is performing change point detection and a fuzzy logic block.

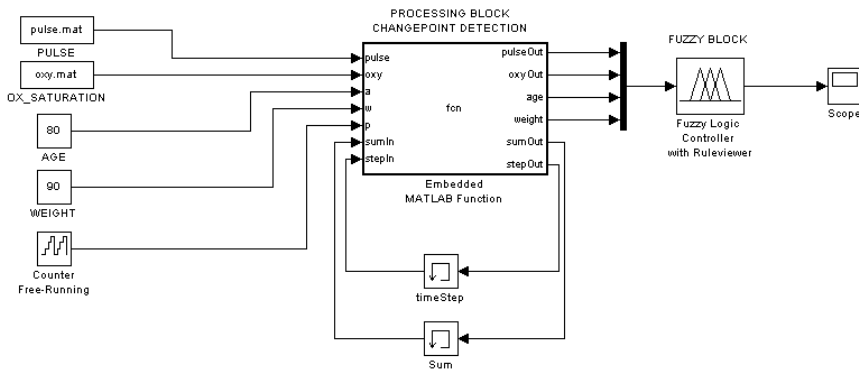


Figure 4.2: Signal Processing Scheme

After change/danger point is detected, the system should perform decision making algorithm based on a fuzzy logic block. It can be implemented by attaching the rest of the parameters and executing correlation analysis with fuzzy logic rules. However, it is still unclear how the collected measurements should be processed in terms of correlation. The large amount of continuous data has not been thoroughly explored yet and the nature of correlation is not verified. Therefore, we concentrate our attention on the off-line processing and consider the on-line reasoning options as a future work, which will be discussed in Chapter 6.

4.2 Anomaly Detection

The next step towards complete correlation analysis in the off-line mode implies anomaly detection procedure. It is intended to complement change point detection and has several main distinctions discussed in Section 2.3.2 of Chapter 2. Here, our aim is to search through the whole data set and find pieces of data which are the most unusual and rare. In many cases, these anomalies can be a reason for an emergency situation, and thus should be registered and highlighted for a further medical investigation. This problem has been ad-

dressed previously which resulted in a wide choice of algorithms to implement [7][31][29]. However, a particular approach involving Symbolic Aggregate Approximation of the signal has proved its efficiency when compared to other methods[16]. It can be applied for a medical data and significantly reduces computational demands when it comes to processing of large datasets. We describe the algorithm and analyze its performance in the next section.

Anomaly Detection with SAX

As previously mentioned, we are looking for a simple and straight forward technique which would help to find and highlight the most unusual parts of the data sequence. Assuming the amount of measurements we collect, it is highly required to employ the algorithm which can significantly simplify data processing without reducing accuracy. A Symbolic Aggregate Approximation (SAX) is a relatively novel technique, developed and described by Eamonn Keogh, Jessica Lin and Ada Fu in their article "HOT SAX: Finding the most Unusual Time Series Subsequences: Algorithms and Application"[16]. It was previously tested on a medical data including anomaly detection in Electrocardiogram and change detection in patient monitoring[17].

The first step in SAX implementation is data conversion. We need to transform a numeric data into a symbolic format. This procedure is subdivided into following parts: with the first step we represent a given time series with a length n in a w -dimensional space where every element is calculated with a special equation:

$$C = \frac{w}{n} \sum_{j=\frac{n}{w}(i+1)+1}^{\frac{n}{w}i} C_j$$

, in other words we divide data into w equally sized "frames", calculate a mean value of the data within each frame and form a vector C consisting of these values[16]. This form of data representation is also known as Piecewise Aggregate Approximation (PAA).

With a next step we apply further transformation to obtain a discrete signal [16]. Tests on more than 50 datasets showed that normalized subsequences have highly Gaussian distribution [11]. Thus, it is possible to determine the "breakpoints" that will produce equal-sized areas under Gaussian curve. So, after we obtained a PAA of time series, all coefficients that are below the smallest breakpoint are mapped to symbol "a", all coefficients greater or equal than the smallest breakpoint are mapped to symbol "b", etc. The Figure 4.3 below depicts the algorithm results.

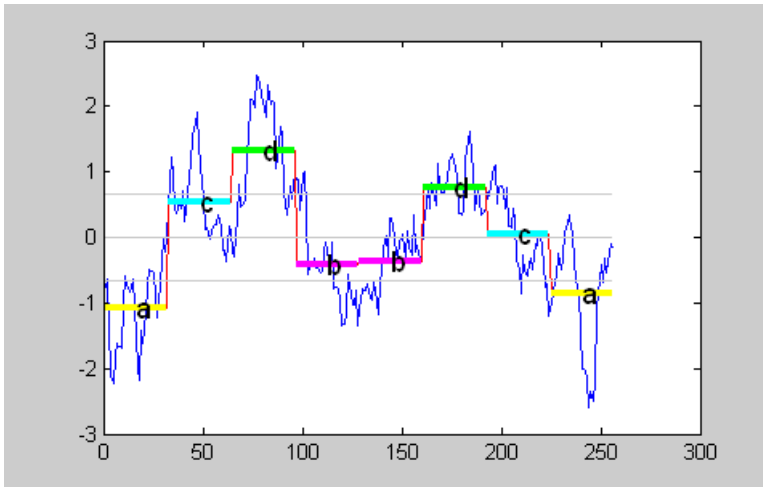


Figure 4.3: A sample signal after mapping

Once a signal has been transformed to a symbolic representation, we can now perform anomaly detection. The brute force algorithm can be implied as an algorithm for finding discords. We simply take each possible subsequence obtained after transformation and find the distance to the nearest non-self match. The subsequence with the greatest distance is obviously a discord. The pseudo code of the method is shown below.

```

1  Function [dist, loc]= Brute_Force(T, n)
2  best_so_far_dist = 0
3  best_so_far_loc = NaN
4
5  For p = 1 to |T| - n + 1                               // Begin Outer Loop
6  nearest_neighbor_dist = infinity
7  For q = 1 to |T| - n + 1                               // Begin Inner Loop
8  IF |p - q| ≥ n                                         // non-self match?
9  IF Dist([tp, ..., tp+n-1], [tq, ..., tq+n-1]) < nearest_neighbor_dist
10 nearest_neighbor_dist = Dist([tp, ..., tp+n-1], [tq, ..., tq+n-1])
11 End
12 End                                                    // End non-self match test
13 End                                                    // End Inner Loop
14 IF nearest_neighbor_dist > best_so_far_dist
15 best_so_far_dist = nearest_neighbor_dist
16 best_so_far_loc = p
17 End
18 End                                                    // End Outer Loop
19 Return[ best_so_far_dist, best_so_far_loc ]

```

Figure 4.4: Brute force algorithm

However, in spite of the obvious simplicity and straight forward implementation of the current procedure, there is one significant drawback: it has $O(m^2)$ time complexity, which makes it non-applicable in case of large datasets. In order to improve the algorithm and reduce complexity, the previous code (Figure 4.4) was modified into a new version, depicted on Figure 4.5.


```

1  Function [dist, loc] = Heuristic_Search(T, n, Outer, Inner)
2  best_so_far_dist = 0
3  best_so_far_loc = NaN
4
5  For Each p in T ordered by heuristic Outer // Begin Outer Loop
6  nearest_neighbor_dist = infinity
7  For Each q in T ordered by heuristic Inner // Begin Inner Loop
8  IF |p - q| ≥ n // non-self match?
9  IF Dist([tp, ..., tp+n-1], [tq, ..., tq+n-1]) < best_so_far_dist
10 Break // Break out of Inner Loop
11 End
12 IF Dist([tp, ..., tp+n-1], [tq, ..., tq+n-1]) < nearest_neighbor_dist
13 nearest_neighbor_dist = Dist([tp, ..., tp+n-1], [tq, ..., tq+n-1])
14 End
15 End // End non-self match test
16 End // End Inner Loop
17 IF nearest_neighbor_dist > best_so_far_dist
18 best_so_far_dist = nearest_neighbor_dist
19 best_so_far_loc = p
20 End
21 End // End Outer Loop
22 Return[ best_so_far_dist, best_so_far_loc ]

```

Figure 4.5: Modified brute force algorithm

The main distinction from the earlier method is based on the way we order and search the discord. This becomes possible due to the following observations:

- In the inner loop we don't actually need to find the true nearest neighbor to the current candidate. As soon as we find any subsequence that is closer to the current candidate than the *best_so_far*, we can abandon the instance of the inner loop, safe in the knowledge that the current candidate not be the time series discord.
- The utility of the above optimization depends on the order in which the outer loop considers the candidates for the discord, and the order which the inner loop visits the other subsequences in its attempt to find a sequence that will allow an early abandon of the inner loop[16].

Unlike the standard brute force algorithm, the modified version is able to break the searching loop much earlier without going through the entire dataset. At the same time, a symbolic representation of the dataset can help to define a particular order for the algorithm which will significantly reduce computational time. With the introduced improvements we are able to achieve functionality which will only requires $O(m)$ time.

Table 4.1: Brute force vs. SAX

| Number of samples (duration) | Brute force | SAX |
|------------------------------|-------------|----------|
| 1000 (45 min) | 15.6 sec | 3.7 sec |
| 5000 (3 h.) | 7 min | 17.5 sec |
| 10000 (6 h.) | 28 min | 35.7 sec |

A number of tests with different amount of data, combined in Table 4.1 demonstrate a change in the processing time mentioned before. We can obviously see the direct advantage of using a modified version of the brute force algorithm. It becomes even more essential in our case assuming the final perspective of on-line monitoring, huge amount of data and limited computational power of the processing device. The obtained result of SAX anomaly detection is illustrated on Figure 4.6.

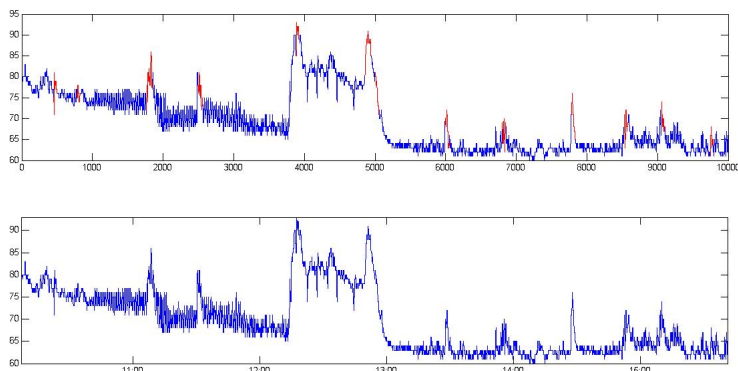


Figure 4.6: Anomaly detection with SAX results

We use a subplot where the first plot represents a particular section from the dataset with detected anomalies and the second graph corresponds to a pulse variation withing the same period of time. This representation makes it easier to register the time when anomaly has been detected. It will be useful while creating patients personal health profile in future work.

Another important issue concerns signal correlation. A concrete answer on pulse/oxygen saturation/activity interrelation should be done after collecting a moderately large database of measurements. This process presumes a tight collaboration with physiologists and other specialists. However, our aim on this stage of the project is to provide a reasonable assistance in a future research. Thus we consider it useful to make an addition to anomaly detection procedure and calculate correlation coefficients between pulse and oxygen saturation for anomaly sections. Whenever discord is detected, we can check a correlation value of the corresponding index, register signals behavior and follow the tendency throughout the entire dataset. A special sliding window is used for this particular purpose which goes through the time series and applies a Matlab function giving a coefficient as an output. What we have in the end is a number between 0 and 1 showing the strength of relation between two parameters. The bigger this number the more one signal proportional to another. In case

this value is negative, pulse and oxygen saturation are inversely proportional to each other. We provide more results of the processing with SAX in Chapter 5 of the thesis.

4.3 Activity Correlation

An important part of the signal processing is a correlation with the third parameter representing a patients activity during the monitoring time. In some situations, person's position or current movement can be a crucial factor in a decision making algorithm. This issue has been a subject of recent research within continuous supervision of the health state problem[40].

This particular data, as it was previously mentioned in Chapter 3 comes directly from the inbuilt accelerometer in the smart-phone device and is stored in the internal memory of the phone in a special format, consisting of four columns. Repeating the case with pulse and activity, first column is an exact time of the measurement. The next three columns are representing x, y, and z values respectively of the phone's acceleration.

This data can potentially provide us with patients posture information and allow to perform a motion detection. It has a potential to improve the analysis of the monitoring system. According to the research in the Berlin Technical University[40] a general approach is basically to distinguish between high and low activity, whereas low activity also is divided into passivity and marginal activity e.g. caused by slow posture changes during sleep. In order to understand the term activity, a special equation is used for calculating an empirically developed activity measure *Act*:

$$Act = E[|v_a^2 - E[v_a^2]|]; v_a = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

Feature extraction and then classification are executed whenever this value rises above a threshold for a certain frame of accelerometer data.

Another examples is a fall detection routine which warns a user every time a fall is detected[41]. The main steps of this functionality are depicted below:

1. Filter data to remove accelerometer offset
2. Look for high acceleration value
3. If found check for high delta acceleration in previous 3 seconds, else return step 1
4. If found check for change in device orientation over next 10 seconds, else return to step 1
5. Declare that a fall has occurred, use change in orientation to determine fall type

6. Issue Alert with time, fall type, mote id

After adding orientation of the accelerometer sensor in relation to the ground data is further tested with the algorithm described and a fall is detected.

However, at this point, the initial problem is to examine the correlation between the accelerometer data and a pulse variation. A first step is to match a particular change in activity to a medical data and vice versa. For this particular purpose we present both parameters along the time axis. Now, after performing a fall or any other motion detection we can observe the precise time of the event and correlate this event to a concrete change in a pulse or oxygen saturation.

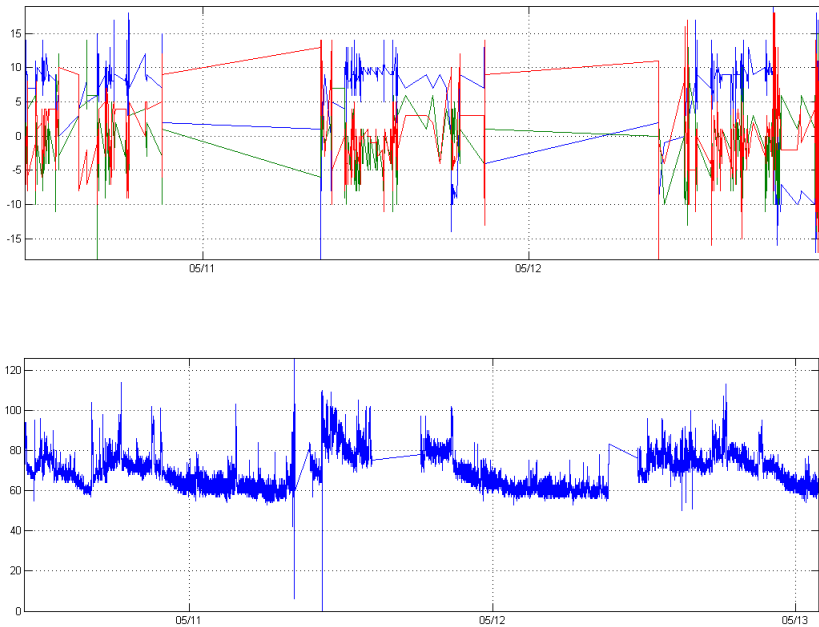


Figure 4.7: Pulse variation and acceleration measurements vs. time

All the straight lines on the activity (first) graph (see Figure 4.7) are showing zero activity level during the night or rest time. They correspond to a low pulse rate values. The process of correlation should be entirely supervised by a medical specialists in order to prepare a reliable background for a future advanced analysis, which can further improve level of the on-line monitoring and reasoning.

Chapter 5

Patient Trials

A close collaboration with medical facilities is an important step in creating a reliable monitoring system. Assuming a lack of knowledge, concerning the correlation of medical signals, it is reasonable to conduct a long term experimental procedure. We should run continuous tests in order to collect enough data from different types of patients, with different health conditions and from different age groups. This will help to take into account every particular detail and combine a universal set of rules for a reasoning mechanism of the system. As a first step, we decided to conduct a short term experiments in order to evaluate systems reliability and discover its weak points to simplify future development. The following chapter represents a short profile information of the patients involved in the trials and results for the data analysis described in Chapter 4.

5.1 Target group

There are two main groups of potential users for the developed system which were in focus during experimental part. The first group includes a person with normal health parameters, who has no chronic disease. The data, received from this target group will help to compare results with the second and more important one. The second group includes two persons from a medical facility named Backagården in Örebro, Sweden. These people were chosen by the personnel and agreed to participate in the experiment after preliminary consultations. A special step-by-step tutorial was issued and handed out to nursing personnel, who had consistent access to a patient and was able to provide any kind of assistance if needed (see Appendix A).

The whole experimental part was conducted in the Backagården medical center for elderly people (vårdcentral) and involved collaboration between center's authorities, nursing personnel and previously chosen patients. The format of the experiment was discussed and approved on a meeting beforehand. Data collection was performed with one patient at a time letting him wear a device

for three days without any break and more importantly during the night time. Keeping experiment in this particular way was supposed to launch a platform for further testing and create an unique opportunity to monitor and subsequently register any kind of sleeping disorders. Moreover, a chosen person was able to maintain his normal level of activity during the day according to a schedule, which includes taking a long promenade, taking a meal and even cycling. In case of strong demand for any unacceptable for sensor functionality activity (e.g. taking a shower, other medical testing), the system can be easily paused and launched again after necessary action is finished. No data will be lost in this situation and measurements will be written to the same file.

The following section describes a health profile of the patients involved in the experiment and data processing results for each of the cases. It is important to mention, that both patients had different health profiles which gave experimental part more coverage. All the information is published after preliminary agreement of the patient.

5.2 Results

Healthy Person

A first stage of the experimental part is processing of the data, received from a relatively healthy person. An experiment was conducted for two days and two nights and no significant problems were encountered during this period. No data was lost or corrupted, a sensor and a phone were maintained and charged in case of low battery indication. A graphical result is plotted in figures below.

We initially applied a change point detection mechanism (see Figure 5.1, second plot) to check when the signal dropped or jumped during the monitoring process. And the second part of analysis performed the anomaly detection, implemented using the HOT SAX method (see Section 4.2). Anomaly detection results for a healthy person are presented in the same graph.

We consider it more illustrative to present this data as an activity subplot (see Figure 5.2) for this particular case and compare pulse variation to a data received from accelerometer. In many occasions, change in a pulse variation was caused by a significant change in activity which can be detected from the graph. We can also relate any event to a particular time, which improves a level of analysis.

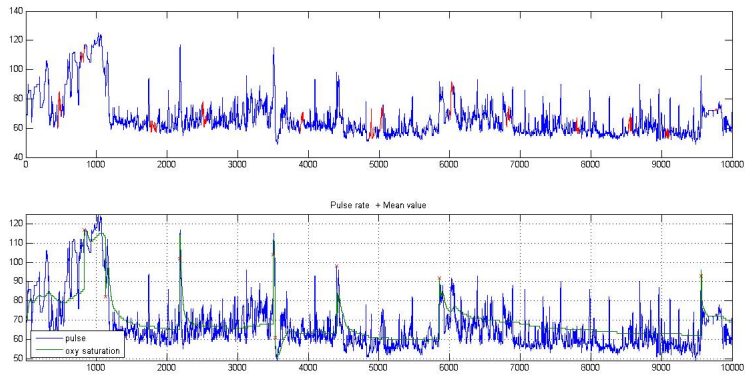


Figure 5.1: Test III results (Healthy Person)

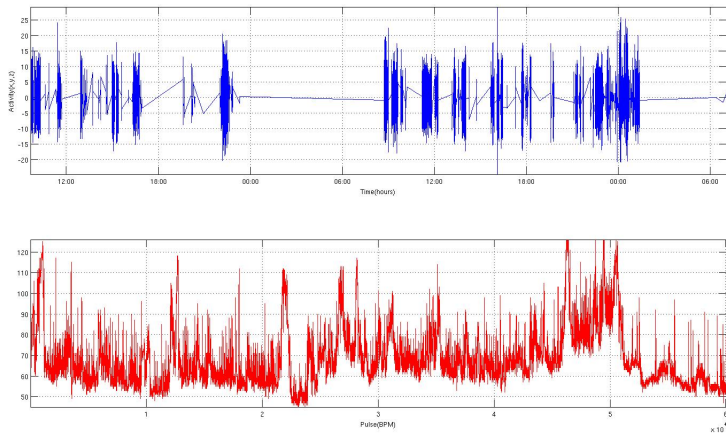


Figure 5.2: Test III results, anomaly detection

In this case, and for the rest of the plotting, red sections on the graph (Figure 5.2) are representing areas of interest or situations, which would require further medical investigation. The depicted plot is a small section cut from the whole dataset to demonstrate an algorithm performance within several hours of monitoring.

Patient I

Table 5.1: Personal information (Patient I)

| | |
|-------------------------|---|
| <i>Birth year (Age)</i> | 1924 (87 years) |
| <i>Diagnoses</i> | Dementia(non-specified), Hypertension, Kidney insufficiency, Hypothyreosis, Depression, Falling tendency |
| <i>Hospital care</i> | Admitted to hospital one time during the last 10 years; latest March 2010, two days in the Dept. of Surgery at the University Hospital Örebro |

During the next part of the experiment system was launched on the first patient from Backagården medical center (see Table 5.1). We were expecting several challenges to appear during this stage, therefore it was considered as a pilot test and was supposed to uncover all the weak points of the system. The most important issue refers to the level of collaboration with medical personnel. None of the patients is capable of dealing with any kind of advanced technical equipment, which makes it crucial for nursing staff to be around. In a worst case scenario we have three situations that interrupt a consistently running monitoring system:

- a sensor runs out of battery
- a smart-phone runs out of batteries
- a patient takes off or displace a sensor thimble

Even though, the first two points are highly related to each other, all three situations require same measures and approach. If personnel checks a system and launch a data collection process every time it was interrupted, we will be able to minimize the loss of the data to nearly zero. Normally, all three situations are unlikely to emerge more than once or twice a day. So, if a system is checked within the day several times we avoid a data loss significantly. Another approach is to set a sensor in a special mode which sends a particular command to a phone and warns a user about low battery condition. The same procedure can be done with a smart-phone. In case of sensors thimble displacement, the

operation should be repeated again. If a relatively young person is being monitored, these issues are unlikely to cause any problems. A user can pause or stop a system for a short period of time and then launch it again when it is necessary. In Figure 5.3 and Figure 5.4 we can observe plotted data of the first patient:

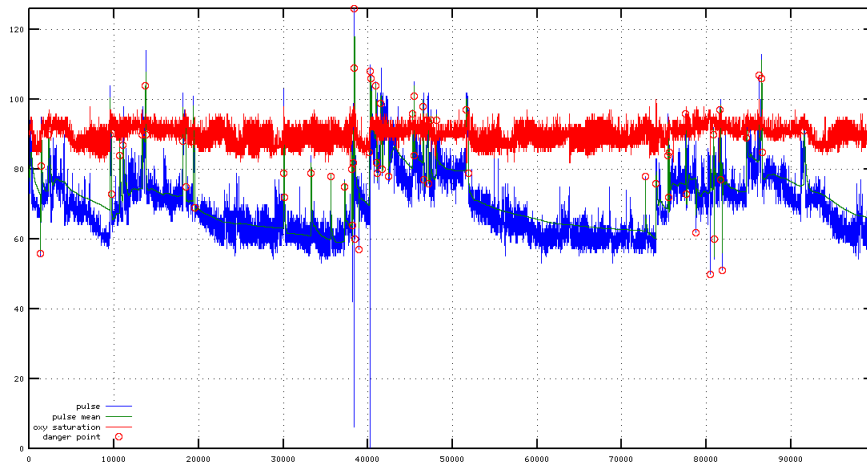


Figure 5.3: Patient I result

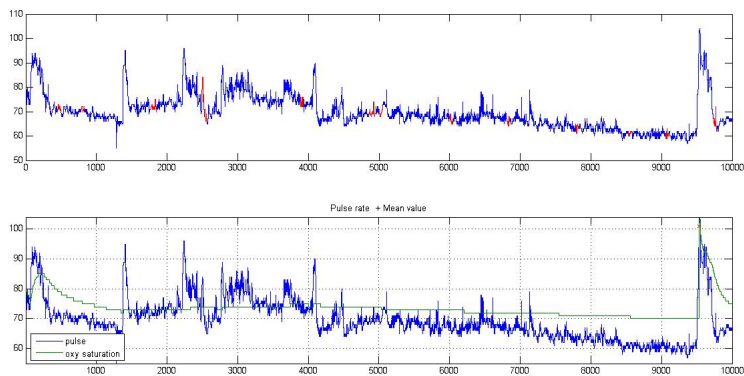


Figure 5.4: Patient I result, anomaly detection

Patient II

Table 5.2: Personal information (Patient II)

| | |
|-------------------------|---|
| <i>Birth year (Age)</i> | 1937 (74 years) |
| <i>Diagnoses</i> | Dementia (vascular), Diabets mellitus, Pituitary tumor (prolactinoma), Gait problems; walker, Polyneuropathy with pain in legs, Depression |
| <i>Hospital care</i> | Admitted to hospital four times during the last 10 years; latest November 2006, four days in the Dept. of Surgery at the University Hospital Örebro |

Assuming the health profile of the second patient, presented in Table 5.2, an essential addition to the system could be made. A special blood sugar rate sensor would help to introduce another vital parameter and improve the level of analysis. Additionally, a group meeting was held before starting a second part of the experiment, which helped to improve the monitoring process significantly and make it more robust. A test was initiated for two day and two nights and differed from the first one with a low number of interruption. A system was stopped only for a short period of time (several seconds) in order to change sensor battery. That allowed us to receive a stable output and simplified a processing of the data. A pulse and oximetry variation of the second patient are depicted on the figure below.

A difference in the health profile of the second patient reflected in a final result which can be observed in Figure 5.5 and Figure 5.6. The pulse value is varying within a wider range and danger points are detected more frequently. A next figure is representing results from anomaly detection part where the unusual sections are again highlighted with red. We use a subplot in order to show a change point detection performance on the same data sector. This will help to analyze the performance of both algorithms and compare results.

All the further professional derivation based on the presented graphical results are to be made by medical specialists. At this point, algorithms applied for measurements are tend to simplify processing of the data in terms of future medical investigation. However, we are able to provide a general overview of the system performance and summarize the main analyzed parameters.

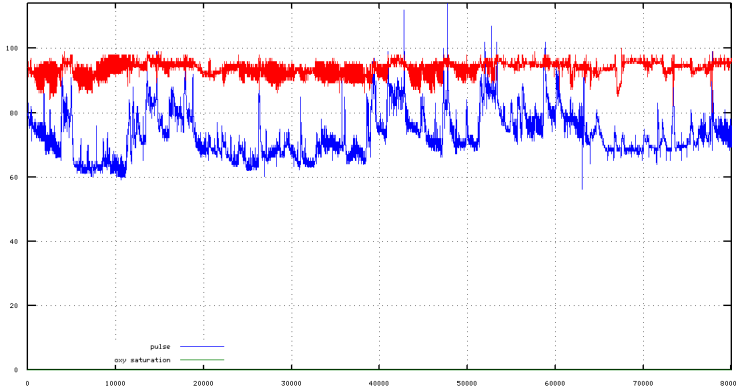


Figure 5.5: Test II results

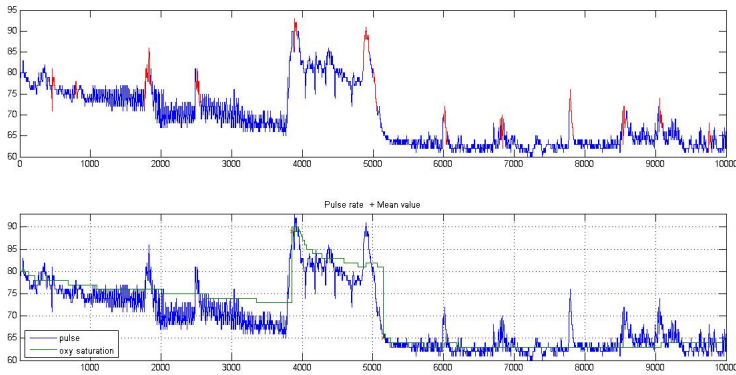


Figure 5.6: Test II results, anomaly detection

Overview

In order to summarize the performance of the system we combined a table of the most essential parameters (see Table 5.3) including percent of data loss during experiment and number of danger points detected for each case.

Moreover, it is possible to make several important observations based on the data processing results presented above. The subplot of the anomaly and change point detection can prove the complementary character of both methods as it was claimed in Chapter 2 and Chapter 4. The same section of the signal was processed with different approaches and results do not replicate each other. In other words, the detected anomaly section does not necessarily

Table 5.3: Summary

| | 1st Patient | 2nd Patient | Healthy person |
|------------------------|-------------|-------------|----------------|
| <i>duration, hours</i> | 63 | 45 | 45 |
| <i>data loss, %</i> | 9,5 | 2,2 | 1,1 |
| <i>danger points</i> | 20 | 23 | 10 |

contain a change point and vice versa. On the cutout in Figure 5.7 we consider the same period of time, processed first by change point detection method and later by anomaly detection algorithm. In the first case all the detected points are

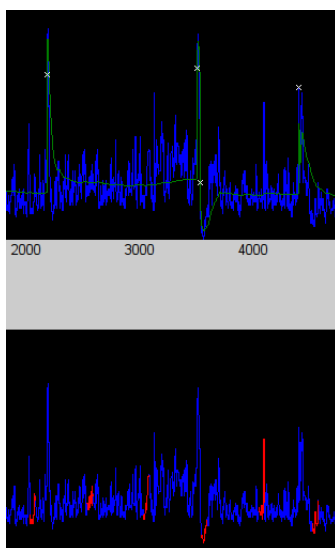


Figure 5.7: Change point detection vs. anomaly detection cutout

corresponding to an abrupt drop/jump in the signal and should be registered for further investigation. However, this information is not enough if we want to see a typical signal behavior for the current patient. Therefore, we should add an anomaly detection procedure and find the most unusual patterns in the dataset.

Furthermore, one of the possible SAX algorithm outputs is the exact index of the registered anomaly. We can use this index to check a corresponding correlation coefficient. As a result we determine behavior of the measured parameters within anomaly section which will help to combine a patients health profile in the future development. The coefficient can vary between 0 and 1 corresponding to the low and high correlation respectively. The bigger the coefficient the more proportional two signals are. If this number takes a negative

value, proportionality is inverse. A table below provides a summary of the correlation coefficients corresponding to particular anomaly sections in the signal represented by an index.

Table 5.4: Correlation coefficient data

| Patient I | | Patient II | |
|--------------------------------|----------------------|--------------------------------|----------------------|
| <i>correlation coefficient</i> | <i>anomaly index</i> | <i>correlation coefficient</i> | <i>anomaly index</i> |
| -0.2 | 38 | -0.7 | 9 |
| -0.5 | 515 | 0.04 | 527 |
| -0.2 | 1032 | -0.9 | 1014 |
| -0.6 | 1541 | -0.8 | 1513 |
| -0.4 | 2009 | -0.8 | 2022 |
| -0.5 | 2544 | -0.6 | 2541 |
| 0.4 | 3020 | -0.9 | 3045 |
| -0.4 | 3550 | -0.5 | 3529 |
| -0.3 | 4031 | -0.2 | 4030 |
| -0.5 | 4515 | -0.5 | 4505 |

Every index in the table corresponds to a particular time period in the dataset and therefore, it is possible to determine, which type of correlations is more typical for each patient and compare this values on different time sections.

Finally, it is important to mention that a variable number of situations might occur during the monitoring process and data collection. They depend on patients health condition and more importantly on the number of chronic disease that he or she has. This fact makes it harder to implement a unique and universal decision-making algorithm which can cover all possible scenarios. However, processing algorithms, described above can provide a unique information for detecting these situations and help to create a combination of rules for sufficient and reliable decision making algorithm.

Chapter 6

Conclusion

Following the latest United Nation statistic database covering developed countries, we can predict a rapid growth in elderly section of the population. This circumstance will inevitably lead to a high demand in advanced health care technologies, which will replace special centers for elderly people and minimize a cost of their maintenance. Motivated by this fact we make a first step towards the development of sophisticated monitoring system, including tracking patient's vital health parameters on a distance. The latest achievement on a smart phone market provided an opportunity to integrate a sensor, measuring pulse and oxygen saturation with android based smart phone device in order to execute a patients monitoring procedure.

This work consisted of three main parts, including smart-phone/sensor connection, data collection and data processing. All three parts were successfully implemented and resulted in a stable and sufficient system, which was tested in an experimental part of the work. Here are the most important points pursued during the research:

- a special application for sensor/smart-phone communication was designed which is capable of: connection with Nonin Wristox2 3150, data transfer, acceleration tracking, user input, data storage. All the data is stored in corresponding files and can be subsequently written/extracted for further analysis. It can be also sent directly to the hospital personnel for a full graphical output.
- an ability to continuously monitor patient's vital health conditions instead of the discrete measurements. In many cases doctors are more interested in a consistent tracking of the patient instead of spot checking. It mainly concerns the night time, when discrete measuring are rather complicated.
- a collection of the data representing two main health parameters of the patients and subsequent analysis of the measurements based on the data processing techniques. The main purpose is to provide a medical special-

ist with the basic information about the health profile of the monitored person.

Based on objectives introduced in the beginning of the thesis we can formulate conclusion and contributions of the presented work. We were able to combine the latest mobile technology together with medical equipment and design a robust system for health condition monitoring. Our next aim was to apply data processing algorithms (change point detection, anomaly detection) as a first step towards sophisticated monitoring system. Both employed techniques are complementary and tend to assist specialists in particular medical analysis. Moreover, a theoretical research was conducted in terms of fuzzy logic applications for developed system in the future. As we are not able now to create a reasonable decision making algorithm (due to the lack of professional knowledge), it was decided to combine a simulation model to demonstrate a possible concept of the future system. This issue, as a part of possible improvements is covered in the following section.

6.0.1 Future work

Fuzzy Inference System

A vital step for the processing part is to connect a fuzzy logic block to a monitoring process. As it was previously mentioned, correlation analysis involve a large number of experiments and could potentially take a lot of time. Until this part of analysis is complete we can only imply intuitively combined fuzzy rules, which are obviously not accurate enough. However, we can provide a theoretical framework for future practical implementation. In the Chapter 2 of the report, we discussed different example of application in medical area based on fuzzy approach. In the following section we will provide the main structure of the Fuzzy Inference System for the monitoring device including specific rules, membership functions and possible input/output. A Matlab software was chosen as a main developing platform for this part of the project. A scheme on Figure 6.1 demonstrates a structure of the fuzzy block:

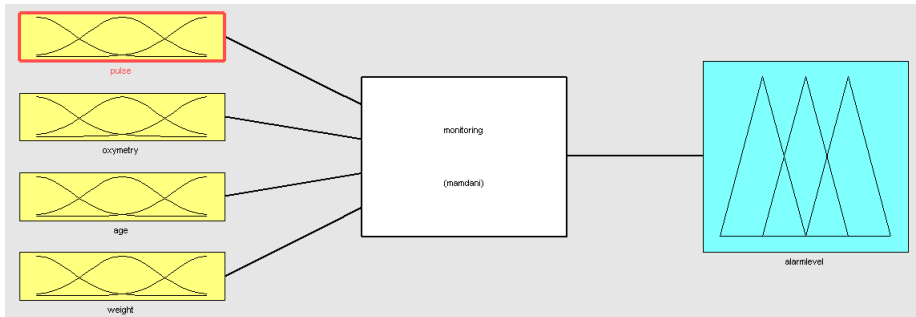


Figure 6.1: Fuzzy Inference System

There are several issues which require particular consideration. The correlation between three major parameters, involved in the processing algorithm is still unknown, therefore, at this point we are only able to cover basic scenarios. We used this approach to create a simple model and simulate a system behavior using real data sets. Despite the correlation part, there are also some minor particularities that are needed to be covered. For instance, a pulse variation is decreasing during the life for every person according to the following formula:

$$\text{MaxPulse} = 220\text{BPM} - \text{Age}$$

Therefore, it is reasonable to tune some of the criteria described below, to match a certain age .

Normally, fuzzy logic is applied, immediately after a danger point or anomaly is detected. We include all four signal channels (oxygen saturation, activity, weight, age) to a process and perform a correlation analysis between each of them. All the channels are now active and sending parameters to a fuzzy logic section. Each parameter can vary within a certain range (e.g. pulse: 30-220 beats per minute(BMP)). In the next step, an input value is processed by a predefined membership function, which outputs a degree of fuzziness for this input. The shape of the membership function can vary depending on purposes of the current task and should correspond to a parameter involved in a process. We applied different functions for every parameter: pulse, oxygen saturation and activity. Pulse is represented by sigmoid

$$f(x, a, c) = \frac{1}{1 + e^{-a(x-c)}}$$

and gaussian curves

$$f(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}}$$

A pulse range is intuitively divided” into three categories: low, normal, high. It can normally vary between 50 and 100 beats per minute which is reflected

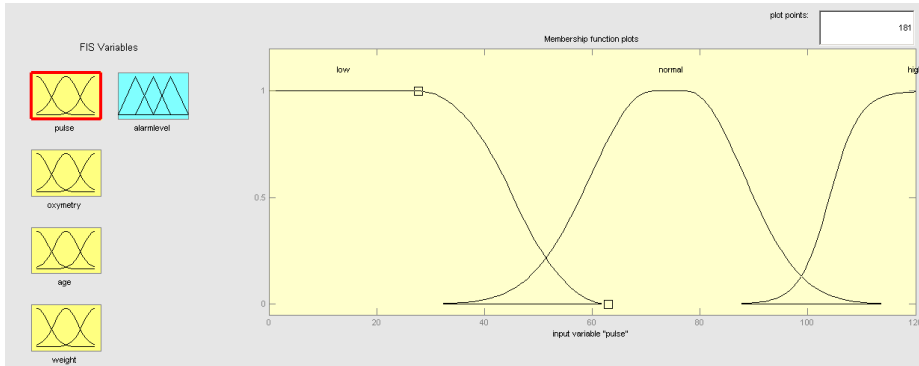


Figure 6.2: Pulse Range and Membership functions

in the function shape and indicates a normal range(see Figure 6.2). If it drops down to less than 50 BPM or jumps over 100 BMP, it occurs in low and high category respectively. Every new parameter is mapped to a value between 0 and 1 according to its membership function curve and to which part of the range it belongs. A similar process is conducted for the oxygen saturation value. It is represented by sigmoid membership function with the following shape on Figure 6.3:

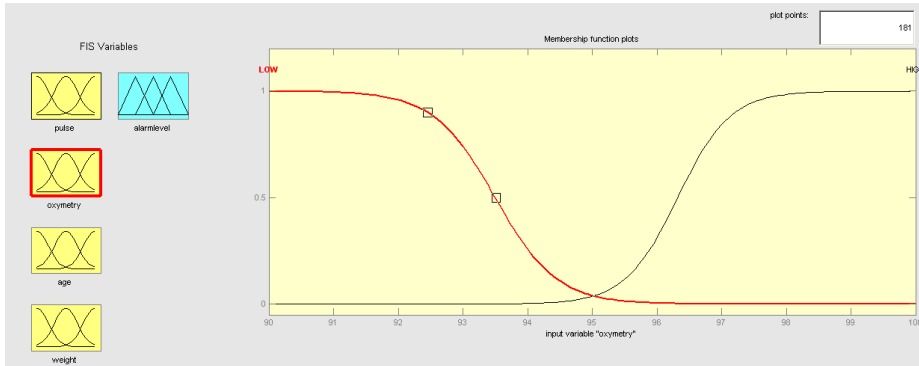


Figure 6.3: Oxygen saturation Range and Membership functions

The whole process can be represented in a three-steps diagram on Figure 6.4:

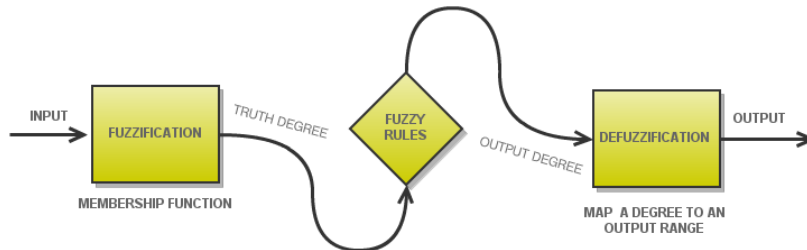


Figure 6.4: Fuzzy Logic Diagram

An extensive co-operation with medical specialist is essential to complete this particular part of the work. A reliable experience, based on medical recordings and several years of studies is an irreplaceable ground while creating membership functions or tuning the range of the parameters. Moreover, it can be used in order to combine approximate fuzzy rules which would subsequently decide on patient condition during the monitoring process. An example of the rule looks like the following:

IF pulse is High AND oximetry is Low AND activity is Low AND age is Old OR weight is Overweight THEN alarmlevel Danger

An output from the rules block is "defuzzified" and represents an alarm/emergency degree for a currently monitored patient. It varies within a certain range between 1 and 100 percent corresponding to a low and high emergency situation respectively. The information gained from the correlation analysis part of the thesis will help to enhance the level of fuzzy rules and create a reliable system for patients health monitoring in the future.

General Improvements

Every electronic system requires a consistent energy supply and therefore can be autonomous to a certain extend. As it was described in a "Patient trials" part of the thesis, we can start losing data once the sensor is discharged and breaks

a bluetooth connection with a smart-phone. There are two possible improvements of this issue, which can be combined in a single and effective solution. As we previously mentioned, a collaboration with a nursing personnel can help to avoid breaking a connection and save as much data as possible. Checking a sensor display once in a while, changing battery of the sensor once in two days, charging a phone and re-running an application if needed will lead to a consistent monitoring process without data loss. Additionally, we can program a processing device to warn a user every time a phone accumulator or a sensor battery is close to be discharged. If a warning signal is indicated, personnel can act appropriately to fix a problem and run an application again.

Another improvement refers to a processing of the accelerometer data. There are several ways to analyze and benefit from this information, which we previously discussed in Chapter 4 of the thesis. One way is to calculate an average value for activity and consider it as an additional parameter for the fuzzy inference system. In this case we can determine whether a person has for example high, medium or low activity by the moment a danger point has occurred. However, there are more approaches to activity processing. By introducing several machine learning techniques, we can classify activity into several categories, including sitting, walking, falling, running down or up the stairs. This will additionally improve the level of the analysis as we can further correlate this data with sensor measurements.

The whole range of improvements lies in a medical area. On the initial stage of the system development, we provide a platform, which will be subsequently analyzed and improved in terms of medical sufficiency. In other words there are many more ways to look at the received data than discussed in this paper. It depends on a particular medical application and areas, where this system is used. Moreover, we can include additional measuring devices which will increase the number of processed parameters. One of the examples related to an experimental part of the thesis is a blood sugar rate sensor for people with a diabetes diagnosis.

The last, but not least improvement is an integration with an intelligent home environment, or so called "smart homes". As a part of this environment, monitoring system could be an extremely important feature, serving for the benefit of the humans health and convenience in everyday life. By integration we imply a data exchange and possible treatment from the system (reminder to take pills, advice to have a rest and etc.).

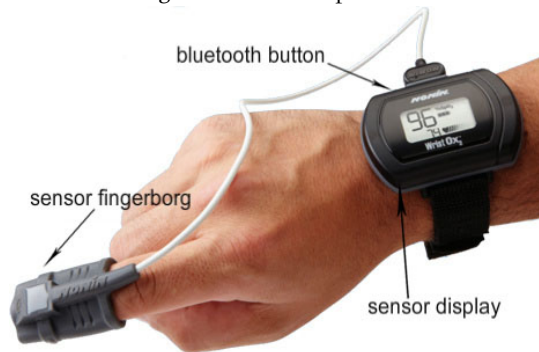
Appendix A

Application Userguide

A.1 Step 1: Sensor Set Up

Place a sensor on a non-operating hand of the patient. Wrap a display belt around the wrist and fix a measuring thimble on a fingertip. A sensor thimble should cover fingertip but not go beyond the hole. See a picture below for more details.

Figure A.1: Sensor position



Once a sensor is set properly, it might take several seconds to start reading the measurements. Wait for relevant numbers on the screen. Before proceeding to a next step, press and hold a Bluetooth button (see Figure 1) to activate bluetooth function.

A.2 Step 2: Start an Application

Take a phone and unblock device if it is blocked by pressing a button like it showed on a figure below

Figure A.2: Phone block



Find on a screen and click an icon named "Backagården" (below a google bar, next to "SoftAlarm").

A.3 Step 3: Connect to Sensor

After entering an application you will see a screen representing connection interface. Main objects within our scope:

- "use accelerometer" checkbox
- "start app" button

check in "use accelerometer" checkbox



click on "start app" button.

You will now proceed to a new screen



choose "Nonin_Medical_Inc._123375"

You will now return to a main screen



wait until relevant numbers appear below "Oximeter Sensor"



block the phone (block button, see Step 1)

OBS!

In case of interruption or system fail. Take off the sensor until the display is blank and repeat Step 1-3 again.

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