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ECG permanence evaluation with QRS-complex correlation graphs

Is there a need for frequent re-enrollment in
ECG authentication

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Abstract

We see that ECG is becoming more of a viable option for biometric authentication and in some cases biometric identification and there are only a few studies related to the permanence of the ECG-signature of a person. Most of the studies we found regarding change over time were done by the medical community and looked at changes during different types of heart conditions, to be able to predict illness. We saw the need for more work performed on younger, healthy subjects, to discover if there is a change of the ECG-signature over time, that would warrant frequent reenrolments. We looked for available, reasonably priced, non-medical equipment, that would enable us to collect the biometric samples we needed. We followed several different subjects over a period of two to three months, limited by the time constraints of a thesis like this. We extracted the QRS-complex from the biometric samples we collected in each session. Then we compared the different wavelets of a subject with the other from the same subject, to discover if there were any recognisable trend in the differences between them. To do this we calculated the correlation coefficient for each comparison set and looked for whether the coefficient stayed the same or slowly got smaller over the time of the study. Our measure for permanence is the degree with which the curve slopes downward. That is horizontal curve equals perfect permanence over the time interval measured and the faster the curve sinks, the lower the permanence over the time interval measured. This is a quick visual way of inspecting whether the permanence is good enough for a given time frame and con be utilized in a company's R&D as a quick preliminary investigation, before investing heavily in a project. We discovered no sinking trend, so we concluded that based on the limited timespan, the permanence of ECG as a biometric modality is good. We recommend a similar study over a much longer period of time, maybe several years. We also concluded that a system with more or less continuous enrolment during the use of the system, will eliminate the need for long time permanence, but that it would be interesting for systems where a person might not authenticate for a long period of time, like for bank deposit boxes or voting.

Preface

I would like to thank my two outstanding supervisors Professor Patrick Bours and Professor Mohammad Derawi for good support and for giving me freedom to attack the subject matter in this thesis, in my own way. I would also like to thank both Professor Patrick Bours and Professor Christoph Busch for opening the doors to the fascinating subject of Biometrics for me, in an inspiring way. Also, a big thank you to my wife, for encouraging me to spend so much time on this project and for always being supportive. Thank you!

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Abbreviations

BIT	Beth Israel Hospital (now the Beth Israel Deaconess Medical Center)
BT	Bluetooth
CHF	Chronic Heart Failure
DNA	Deoxyribonucleic acid
DRO	Dielectric Resonator Oscillator
ECG	Electrocardiography
FFT	Fast Fourier Transform
FNMR	False Non-Match Ratio
I2C	Inter-Integrated Circuit
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
ISO	International Standardisation Organisation
IVCD	Interventricular Conduction Delay
LDV	Laser Doppler Vibrometer
MBASN	Medical Body Area Sensor Networks
MCU	Microcontroller Unit
MIT	Massachusetts Institute of Technology
NFC	Near Field Communication
PCB	Print Circuit Board
SDK	Software Development Kit

1 Introduction

1.1 Topic covered by the project

The topic covered by this project is part of the field of biometric authentication. A relatively new biometric modality is ECG biometrics, which aim to authenticate or identify a person based on the wave-pattern caused by the heart muscles work. An important characteristic of a biometric modality is that it needs to stay the same overtime, for us to be able to recognise this it and authenticate a person some time after the initial enrolment and this is called permanence. We will therefore be looking at how good the permanence is on the ECG modality and try and find a good way of expressing it.

1.2 Keywords

- Biometrics
- Authentication
- ECG
- Permanence
- QRS-complex

1.3 Problem description

If we are to use the ECG biometric modality in practical applications where different kinds of authentication and identification is needed, we need to understand the permanence of the modality much better. There has not been enough focus on the long term permanence in the earlier research in this field. There is also a need for a good way to describe the permanence to easily show how it behaves in a specific window of time, relevant to the application it is intended for in each scenario.

1.4 Justification, motivation and benefits

ECG as a biometric modality has been researched for a few years now, but is still regarded as one of the new kids on the block, compared to for example fingerprints and iris scans. This was the initial motivation for us, to look into a field where there was still need for new solutions, better solutions and where the standardisation process was not yet finished. We landed on trying to find out more about the permanence of this biometric modality and thereby also to investigate novel ways of determining said permanence. We were also motivated by looking into reasonably priced equipment for conducting biometric sample collection instead of using expensive biomedical equipment. We hope the research community and security companies performing R&D in this field can benefit from our

1.5 Research question

Main research question:
How is the permanence of ECG as a biometric modality?

Supporting research questions:

- How should we measure or calculate the permanence of ECG as a biometric modality?
- What kind of equipment can be used, with our budget?
- What can be done in the period of time available in this project?

1.6 Planned contributions

The planned contribution of this project is a better understanding of the permanence of ECG as a biometric modality. We will show whether there is a significant change in the ECG-signature of a person or not. Part of the contribution will also be the method of measuring this permanency, both calculation-wise and in regard to testing hardware.

2 Theoretical background

Biometrics is the term for metrics of specific biological or behavioural traits of living things. Related to humans it has been used for medical purposes for hundreds of years and in modern times we have started to use biometrics for authentication and identification of individuals. Authentication is the act of determining whether a claimed identity is in fact the actual identity of an individual, for example to verify if the holder of a passport is the person that the passport claims. Identification is the act of finding the identity of an individual that has not claimed an identity. An example of identification could be finding who a person in a group under surveillance is, based upon searches in databases.

The first large scale use of biometrics for these purposes was the use of fingerprints in forensic science. This emerged during the mid-1800s and was firmed up and moved into the scientific realm by Sir Francis Galton's extensive work in the 1880's and 90's classifying different traits of a fingerprint into different minutiae. Among other things he published the book Figure 2-1 Finger prints, Francis Galton, MacMillan 1892 (Wikimedia Commons)

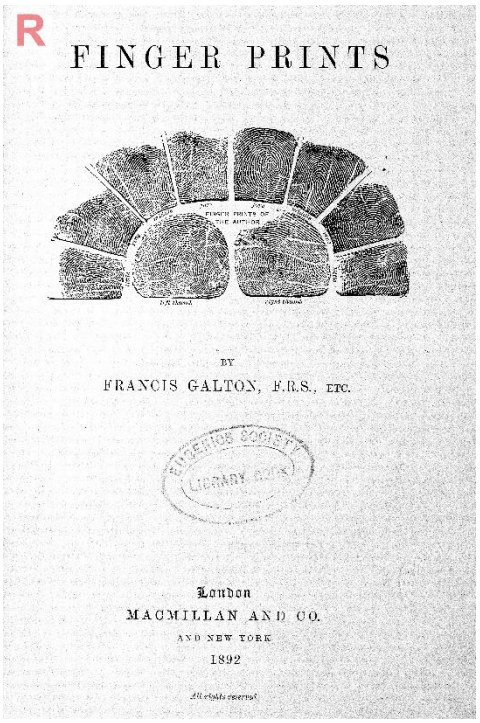


Figure 2-1 Finger prints, Francis Galton, MacMillan 1892 (Wikimedia Commons)

His way of classifying these are still used in modern forensic science, but a plethora of additional biometrics have been added to the arsenal of available modalities now used in the fields of biometric science. To mention some classical biometric modalities in use today we have in addition to fingerprints such things as DNA, iris recognition, facial recognition, vein pattern recognition and ECG recognition, that are all, more or less, constant biological identifiers of a human body.

Parallel in time to the development of fingerprint recognition, there was work done on a different category of biometrics, soft biometrics. Soft biometrics are based on traits that can categorise a person into a group, but not necessarily identify a specific individual. Types of soft biometric modalities are physical, such as skin colour, eye colour or hair colour, behavioural, such as gait, keystroke or voice and adhered human characteristics like tattoos, clothe style, or type of glasses worn. Soft biometrics is a hot topic of research and its modalities are proposed used both alone, together with other soft biometric modalities or together with “hard” biometric modalities. Since the enormous technological advances made during the past few decades have opened the possibility to fake a biometric modality in a so-called presentation attack, the research community have leaned ever more towards a liveness check and the use of more than one biometric modality, in combination, to lessen the chance of a successful presentation attack.

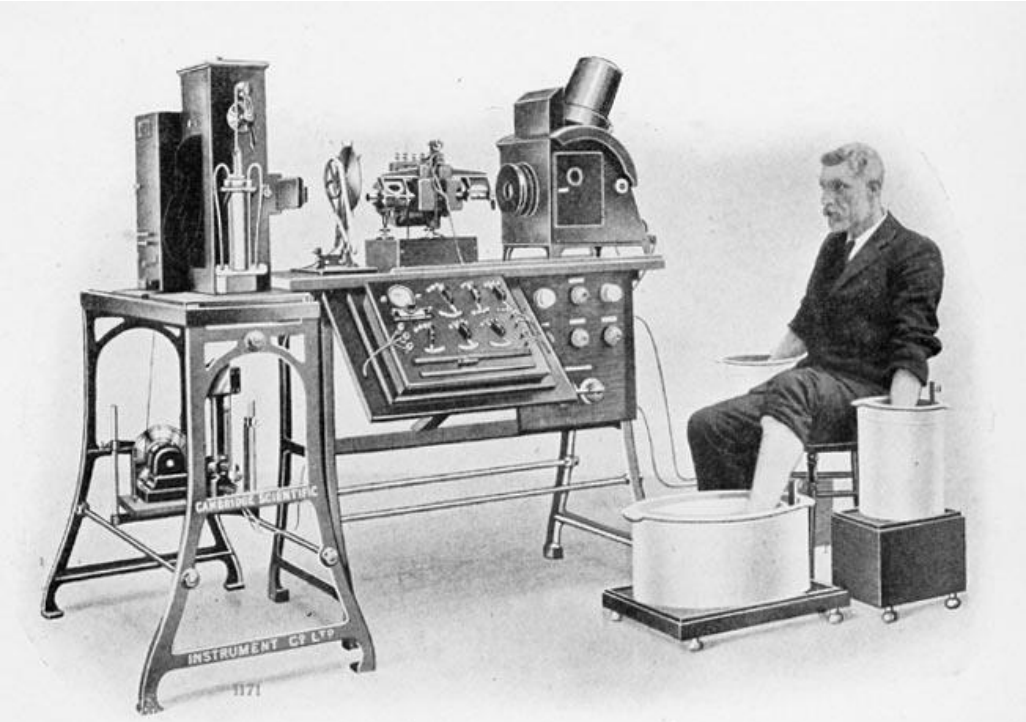
There are some generally accepted guidelines for deciding whether a possible biometric characteristic is usable for the purpose of authentication. Jain et al. writes about what they call desirable properties for biometric characteristics [1]. Universality, meaning as many people as possible should possess such a characteristic, uniqueness such that there is an extremely low or non-existent chance that two people have the same characteristic, permanence, the characteristic should not change over time, collectability, that implies that it should be easy to collect the given characteristic. They also mention the properties performance, related to different measures for accuracy, acceptability as pertaining to how willing people would be to let someone collect this characteristic from them in different situations and circumvention, meaning how easy it would be to attack a system using the specific biometric characteristic with for example a presentation attack or trick it in other ways.

2.1 Standardisation

In recent years there has been a lot of work done on trying to standardise the field of biometrics. There are several relevant ISO standards undergoing continuous work, like the ISO/IEC 2382-37 Information technology Vocabulary Part 37: Biometrics [2]. This is outlining the vocabulary to be used in the biometric field, to assist in avoiding misunderstandings and provide common ground when talking and writing about this topic. There is the main Biometric data standard ISO/IEC 19794 [3], where part 1 contains a framework for all modalities and the subsequent parts from 2 to 14 is each designated a specific modality. We expect new modalities to be added as the work on them are progressing, but as of publication of this paper, there is no chapter specifically for ECG-biometrics. Because this part is not yet ready it seemed like a natural approach to consult the ISO/IEEE 11073 Health informatics – Point of care medical device communication in general and specifically Part 10102 Nomenclature Annotated ECG [4], to fill in the blanks in ISO/IEC 19794.

2.2 ECG equipment development and medical use

ECG or Electrocardiography is the most common way of visualizing the rhythm of the heart. Wires are connected to the subject's skin to be able to register the subtle electric signals produced by the depolarizing and repolarizing of the heart muscles as it beats. The first known use of this method is from around 1872, by Alexander Muirhead, an electrical engineer working on his DSc at Bartholomew's Hospital laboratory[5] We can see one of the very early ways of connecting an ECG machine to a patient in Figure 2-2 Early ECG equipment in use on patient (Wikimedia Commons)
There were several others trying out different methods, but the first useable and sensitive ECG-machine was invented in 1901 by Willem Einthoven, from the Netherlands. He eventually ended up receiving the Nobel Prize in Medicine for his work in 1924. Einthoven was also the one to assign the letters P, Q, R, S and T to the wave form output from an ECG machine and those are still used in today's description of the waveform. We have shown an illustration of how the waveform labels are related to the different features of the signal in Figure 2-3 Sinus rhythm labels (Wikimedia Commons)



PHOTOGRAPH OF A COMPLETE ELECTROCARDIOGRAPH, SHOWING THE MANNER IN WHICH THE ELECTRODES ARE ATTACHED TO THE PATIENT, IN THIS CASE THE HANDS AND ONE FOOT BEING IMMERSED IN JARS OF SALT SOLUTION

Figure 2-2 Early ECG equipment in use on patient (Wikimedia Commons)

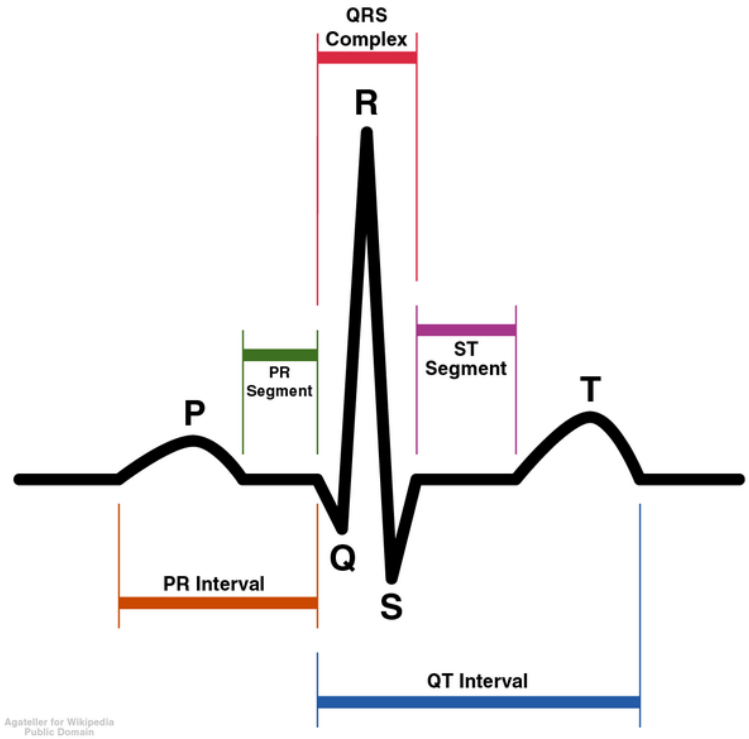


Figure 2-3 Sinus rhythm labels (Wikimedia Commons)

In the early days there were a lot of creativity involved in how to record the signals, involving, among other things mirrors, model trains and photosensitive glass plates. After a while a system with a paper strip moving with constant speed, past a pen that moved in accordance with the measured voltage, was devised. This system is still in use to record the ECG results in hospitals. In Figure 2-4 ECG-chart, 1957, we can see such a paper strip, with only one pen used.

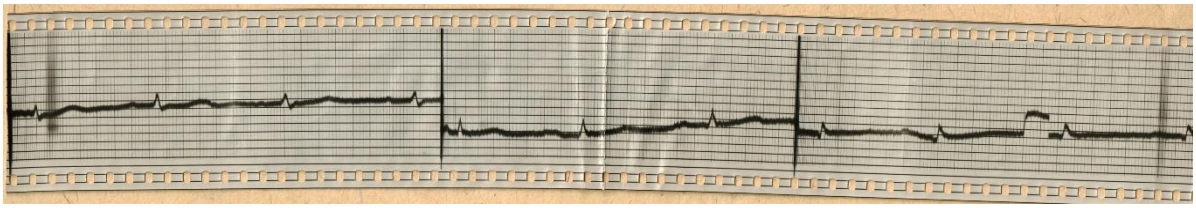


Figure 2-4 ECG-chart, 1957 (Wikimedia Commons)

Modern versions, used at hospitals are so called 12-lead ECG machines. These use 10 sensor pads to register the hearts muscles electric emissions in 12 different leads or views. We can see an example of a more modern electrocardiogram in Figure 2-5 12-lead ECG. The V1-V6 markings signify the six chest sensors in use, in addition one sensor is placed on each extremity.

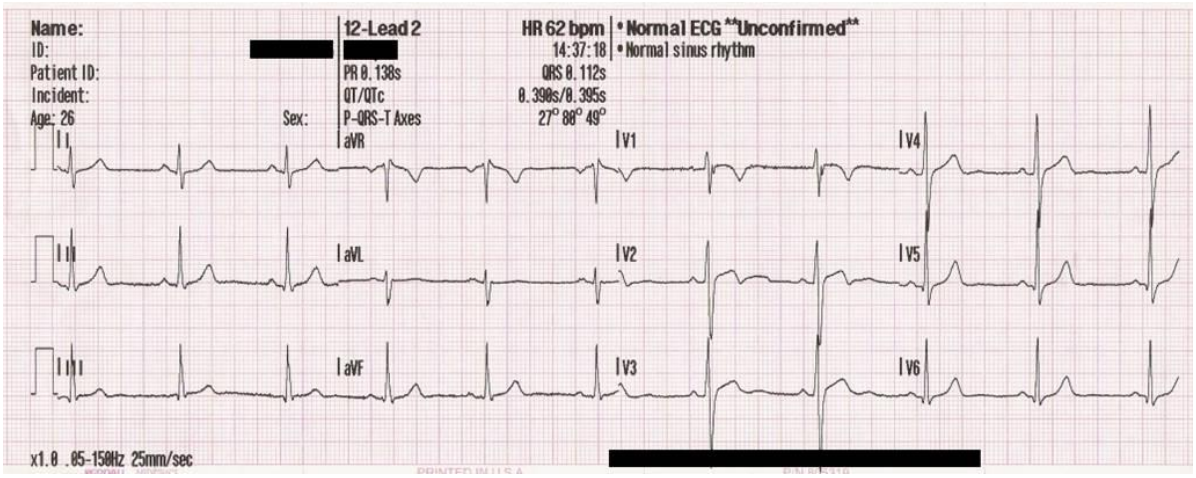


Figure 2-5 12-lead ECG (Wikimedia Commons)

The main area of use for this technology has been medical application. Through modern analyses of electrocardiograms, we can detect how the heart is performing and structural issues, such as arrhythmia (irregular heartbeat), malfunctioning heart valves. It is used for monitoring patients before, during and after operations, especially if anaesthetics are

involved. The heart is a big muscle consisting of four chambers, on top there are the left and right atrium chambers, that contract simultaneously and on the lower part we find the left and right ventricular chambers, these also contract simultaneously. The contraction also called the depolarization, of the atria, are represented by the P on the PQRST diagram Figure 2-3 Sinus rhythm labels (Wikimedia Commons), the contraction of the ventricle are represented by the QRS. The relaxation also called repolarization, of the ventricle, are represented by the T on the diagram. The relaxation of the atria are most probably hidden by the much more prominent ventricle contraction [6] . These muscle movements create a miniscule electrical current that can be measured with electrodes connected to the skin, as with the traditional biomedical equipment described, but the waveforms can also be reproduced by several other methods, like optical sensors scanning the blood flow through the veins, by doppler radars measuring the movements of the heart or even listening devices, like stethoscopes, listening to the heart work. We will get more into the different possibilities when describing our process of selecting a device for this project.

2.3 ECG for biometric authentication

The use of electrocardiography as a biometric identifier and more specifically in biometric security is a relatively new application for such data, compared to its use in the medical field. The terminology from the medical field, described in the ISO standard Health informatics — Point-of-care medical device communication ISO/IEEE 11073-10102:2014 [4] have been adopted and is used in conjunction with the security biometric terminology laid down in the ISO standard Information technology — Biometric data interchange formats ISO/IEC 19794-1:2011 [3] and the Information technology-Vocabulary Part37: Biometrics ISO/IEC 2382-37 [2]

There have been quite a few papers written on the topic of ECG as a biometric modality for authenticating a person. From 1999 up to the present day, the topic has been researched and the first commercially available products based on this technology arrived on the market in 2015. Still ECG as a method of biometric authentication is considered one of the new and not yet very common modality. It could be difficult to place ECG based authentication in the topology between soft biometrics and the more traditional “harder” modalities. Gait recognition, for example is considered a soft biometric as it is something we do and although the beating of the heart is happening involuntarily, it is still a muscle in our body doing its

work, just like our legs are when we walk. On the other hand, the signature of this muscle working is specific to each person, due to the development of the heart, based upon the specific DNA of that person, so that is a strong argument for this not being a soft biometric. Any way we chose to look at it, it could certainly be a very useful addition to other modalities as we begin to realise that we need more than one modality in a security system, to verify that one modality is not being spoofed by an attacker.

3 Related work

3.1 ECG as a biometric modality

The first studies where ECG is considered as a biometric characteristic was done by L. Biel et al. [7] in a study named “ECG Analysis: A New Approach in Human Identification” publishes in 1999. The work was done at Örebro University, Sweden. They based this work on their own data, collected with medical 12-lead equipment, with a group of 20 persons between 20 and 55 years old. They found a strong correlation between data collected from different leads and subsequently decided to concentrate their effort on the data from a smaller number of leads. They worked with a very high number of features and created a correlation matrix to be able to decide on which features had the highest correlation with other features and then again remove these, to achieve a more manageable set of features to work with. We can see an illustration of the different features they chose to use in Figure 3-1 ECG features used by L. Biel et al. [7]

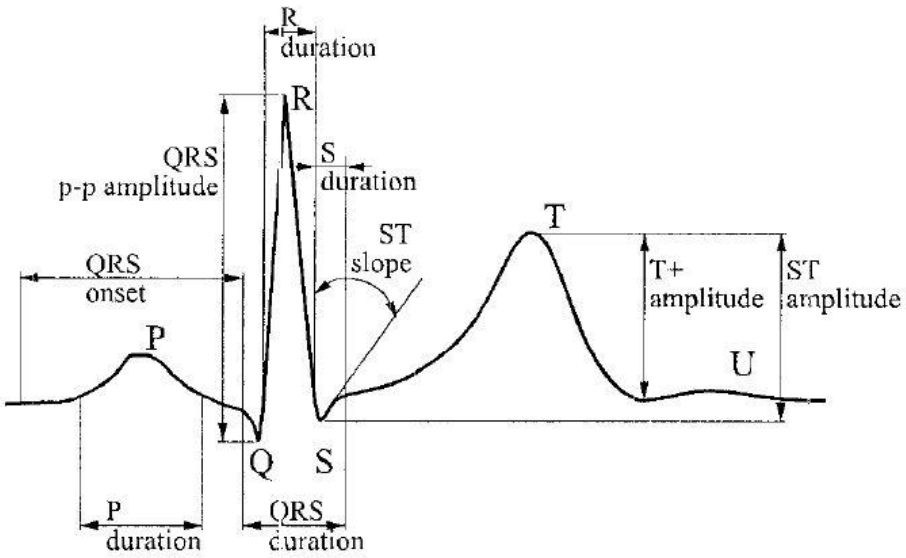


Figure 3-1 ECG features used by L. Biel et al. [7]

In the following years several papers were exploring the new biometric modality, discovering new aspects of how it could best be implemented. In 2001 M. Kyoso and A. Uchiyama [8] proposed a way of authenticating patients with the use of existing data from the patient's medical journal. They suggested using the second order derivative of the wave form to better emphasize the location of the features they wanted to extract and performed different statistical analysis on these features to find correlation of samples taken from the same subject.

The year after, T.W.Shen et al. [9] released a paper called "One-Lead ECG for Identity Verification" in which they applied two different approaches to authenticate an individual. They used both template matching, where they achieved 95% correct identity and decision-based neural network, achieving 80% correct authentication. They also combined the two methods and achieved a 100% correct rate. At this point the question of whether or not ECG data could be used for the purpose of biometric authentication, was most likely answered in a satisfactorily manner. The advance of technology in the following period resulted in a trend of miniaturisation and cost reduction of a lot of electronic equipment. The field of electro cardiology devices was affected by this trend and in 2008 J. Yao and Y. Wan [10] builds a relatively small circuit board with an instrumentation amplifier, combines it with an I/O-card and connects it to a computer running LabVIEW. All in the spirit of avoiding expensive and heavy medical equipment previously used to collect such data.

Figure 3-2 prototype PCB, Yao-Wan [10]

In 2010 M. Chen et al. [11] explore a new method for collecting ECG-data from a subject, they used a laser doppler vibrometer (LDV), to measure the vibrations of the skin from a distance, without connecting any sensors directly to the body of the person. This is a very unobtrusive method of recording data and because of that it would be worth exploring for authentication purposes in the general public. In 2015 a study was conducted by M. Derawi [12] where he introduced collecting biometric ECG samples with a small device with communicating via Bluetooth to an Android tablet. He used two sensor pads placed on the subject's chest and connected to the little box containing the ECG processing MCU and the Bluetooth radio. Derawi is employing machine learning in the recognition process and shows very promising results. Another promising study performed by D.A. Ramli et al. [13] in 2016, where they have made a prototype of a wrist band that can be used for authentication and promising results for this type of authentication are reported. The ECG biometric modality has been thought to be difficult to attack, more so than for example fingerprints or iris, since these modalities are on the outside of our body in plain view, while ECG is something inside our body. A resent piece of research by S. Eberz et al. [14] from 2017 has tried to test just how difficult it is to perform a presentation attack on the ECG biometric modality. They attack the commercially available NymiBand [15] in in three different ways. They use a hardware arbitrary waveform generator, software and a sound card and last a recorded sound file from the heart. They achieved relatively high success rates on their attacks and concluded that these results is probably representative for other ECG recording methods as well, so this could be a serious problem. Since we have these kinds of problems with the other biometric modalities as well, it does not mean we should not use this modality, but it is a wakeup call that everything can and will be attacked. There might not be any single biometric modality that can fulfil the security needs for future authentication and identification, we should probably combine two or more modalities in all such applications and ECG is a good candidate for combination with other modalities in a multi modal system. This is because of the flexibility it gives to be able to read the signals on the skin all over the body and also from a distance.

3.2 Current commercial market situation

In 2015 a company called Nymi released their product the Nymi Band [15] a tiny rubber wrist band containing a circuit that authenticates the wearer upon strapping it to ones wrist

and then becomes capable of authenticating the wearer to all sorts of other devices via near field communication (NFC). It makes it possible for companies to use as employee authentication on computers, industrial terminals, entry and exit points and for operation of equipment. It can also be used in daily life to keep one's personal smartphone, computer or car door open to the owner. There have been some demonstrations of successful attacks on these wristbands from Nymi, so they are not fool proof, but very few authentication systems are and the technology could be developed further to make them more secure or to implement them as part of several factors of authentication.

Figure 3-3 Nymi band, ECG authenticator wrist band (Nymi press kit)

Another firm that has been working with the development of ECG-authentication technology is BSecur [16]. They are developing their own algorithms for different security levels, implementing ECG-authentication as well as ECG-identification. They are working with enterprise-level customers, developing bespoke solutions for the automotive industry, airport security as well as for future payment solutions with their product HeartKey Pro and for situations where the level of needed security is a little less acute, they have HeartKey, said to be aimed at securing smart watches and smart wear.

One of the sectors where ECG authentication has been considered for some time now is the medical sector. This is an environment where often, the sensors needed to capture ECG data are already present and attached to a patient. In modern hospitals we are now talking about so

called Medical Body Area Sensor Networks (MBASNs). These are networks based on multiple wireless sensors implanted in, placed on the skin of or near the patients, to monitor different health characteristics and body functions related to illness being treated. As explained by S. Zebboudji et al. [17] these different sensors can read the ECG signal by themselves and the apply this information to conform that they are place on the same patient, the correct patient, the signals can be used to generate random keys to encrypt the data from the sensors, so that the patients' medical data are kept secure. The medical personnel can also use the authentication scheme to make sure they are in fact giving the correct medicine to the patient, since medicine mix-up can be a problem on hospitals.
Car manufacturing companies are also starting to use ECG-signals, often collected via the steering wheel from the driver's hands. So far, these implementations have been directed mostly towards the medical side of things, monitoring the driver'sheart for failure or if the driver gets sleepy. There is also some reseach into continuous authentication of the driver like the system proposed by H. Silva et al. [18] with single beat RS-T segments in real time applications.

3.3 Related work specific to permanence of the ECG-modality

When it comes to the specific study of the change of QRS-complex morphology over time, we have not been able to find a lot of work from the biometric realm. So first we will look at some related work from the medical field. Different types of heart failure and other cardiovascular disease will cause abnormal heart rhythm and hence several distinct changes in the QRS-complex. One such sign of a worsening condition is interventricular conduction delay (IVCD) also known as QRS-widening, as shown by Shamim et al. [19] in their paper Intraventricular conduction delay: a prognostic marker in chronic heart failure, where they followed 241 patients and found that together with blood oxygen level, the prolongation of the PR-interval and of the QRS-interval could be used to successfully predict chronic heart failure (CHF). Encouraged by these findings Shamim et al. [20] enlisted 112 elderly people with heart conditions and continued down the same path in the study "Incremental changes in QRS duration in serial ECGs over time identify high risk elderly patients with heart failure". This is an example of following the changing form of the QRS-complex over time, to see if there is gradual change. They concluded that the most prevalent change in the ECG-data of the patients before adverse events was the duration of the QRS adding that none of the other

measured intervals were significant on their own. These studies are conducted with elderly subjects with known heart conditions without any younger heathier groups of control subjects, so we cannot draw any conclusions as to whether any part of the change is simply due to passing of time, nor do they address all the specific properties that would be relevant to be able to authenticate a subject by their QRS-complex. However, they pointed us in the direction of what we believe is the most important part of the entire PQRST-wave-form, when it comes to changes over time.

Another important issue when considering using ECG-authentication is changes to the signals temporarily or permanent over short or long term, related to the use of drugs. When considering the method for patient authentication at hospitals, it should be considered whether the patient is medicated with drugs that could possibly influence ECG-data. This has been studied by M. Wolzt et al. [21] when it comes to cardiovascular drugs and they found that some drugs had an effect on the QRS duration. There could be many non-cardiovascular related drugs that also influences the ECG-wave form. If considering the authentication method for other purposes in society, the effect of both drugs for medical use and for recreational use, should be factored in as a possible source of false negatives.

Now to the work done in the biometric authentication realm, regarding the permanence of the ECG modality. H. Silva et al. [22] did a study on ECG signals captured from fingers, using dry Ag/AgCl electrodes. Testing the performance, they also looked at the permanence as a parameter. Their conclusion, based on some data minutes apart and some months apart are that it seems promising for the permanence of the signals. R.D.Labati et al. [23] did a permanence analysis for 24 hour continuous authentication in 2013, which is very relevant to our study. They also use the QRS-complex since they found it is the most stable component of the ECG signal. QRS-cross-correlation is used to remove outliers, giving us the idea to use a standard correlation coefficient to measure the permanence. Their study concentrated on a public dataset with 24 hours of data and they are discussing the modality for use in continuous authentication systems. Since there is not a need for long term permanence in such systems our angle is a bit different, but this is the paper we think is closest to addressing the same topic we have done. We have also considered methods developed for biometric permanence in general, and a contributor in this field as recent as in 2017 is J. Harvey et al. [24] which have developed a system for calculating the permanence of a biometric modality and defined it as the change in false non-match ratio (FNMR). They also propose a method for robust calculation that will can isolate the difference in signals from session to session. This was a very interesting paper for our purpose and we considered using some of their

methods, but in the end we decided to rather work with the basic wavelet to find permanence instead of enrolment and FNMR calculations.

4 Selection of ECG capturing device

4.1 Test environment

At the beginning of the project a broad spectrum of different ECG devices was considered. Even though this part was not the main focus of this project, we spent quite a bit of time and effort going through what we found available on the market, of ECG devices that were simple and low cost. This was to gain some knowledge of and to display this since things are moving very quickly, because of all the smart devices on the market. We wanted to find a device that was relatively low cost, easy to operate while still maintaining a reasonable level of quality on the data captured. We wanted to go through the different technological classes of sensors, like contact electrodes, light based and doppler radar based.First, we acquired the devices we wanted to consider using from different online suppliers. Then we set up a testing environment with an oscilloscope, an arbitrary function generator, a programmable lab power supply among other things, as shown below in Figure 4-1 Testing environment.

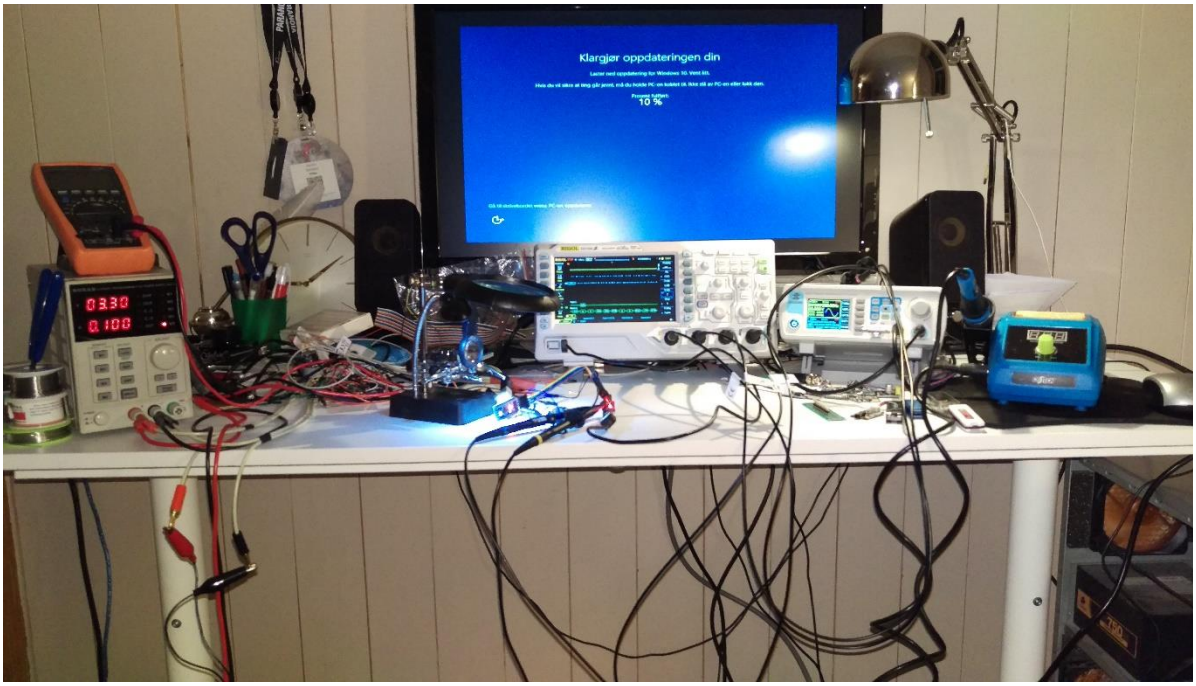


Figure 4-1 Testing environment

This environment gave us the possibility to scrutinize the raw ECG-signals directly from the devices, to filter these in real-time and to decode the I2C-communication between the devices

and the Arduino as we can see done in Figure 4-2 I2C decoding on oscilloscope

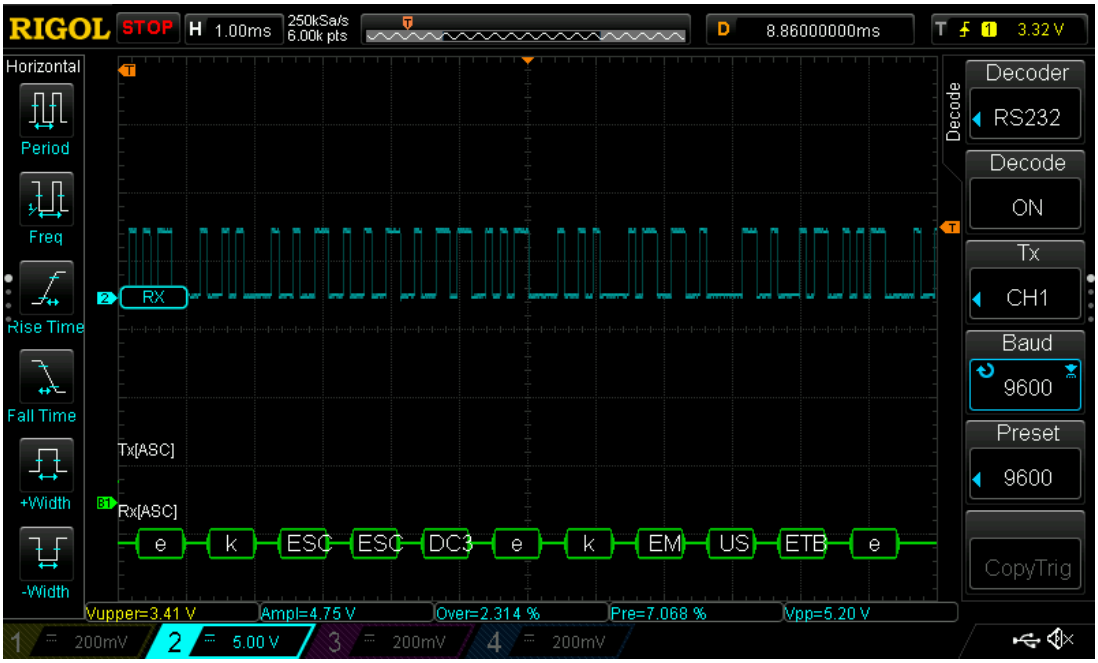


Figure 4-2 I2C decoding on oscilloscope

We were also able to perform real-time Fast Fourier Transform (FFT) to look at the signals in the frequency domain, to easier locate spectrum specific noise problems. We did not however, have access to a spectrum analyser in the frequency ranges of the radar transducers (5 GHz to 25 GHz), so the consideration of those were limited to the output signals from the device terminals and not based upon directly viewing the reflected radar signals. This would only have served a limited purpose anyway, since the onboard chip calculates the difference between transmit and receive frequencies to produce the doppler resultant.The main categories of sensors are the traditional medical signal from disposable patches placed on the body, the newer optical sensors relying on light to penetrate the skin and being recorded as it is reflected from the blood vessel and the latest a non-contact system utilising doppler radar sensors that read the movement of the heart directly. The devices we tested were either bare sensors/break out board style devices relying on connection to an external microcontroller unit (MCU) or development units, so no units for commercial use was considered in this elimination process, however, the MCUs from NeuroSky and Analog Devices are incredibly tiny and are meant to be incorporated in modern day commercial devices such as heart rate monitoring exercise watches or armbands. The sensors without onboard data transmission

was tested connected to either an Arduino Mini Pro, an oscilloscope as in Figure 4-3 ECG-signal monitoring on oscilloscope, or both.

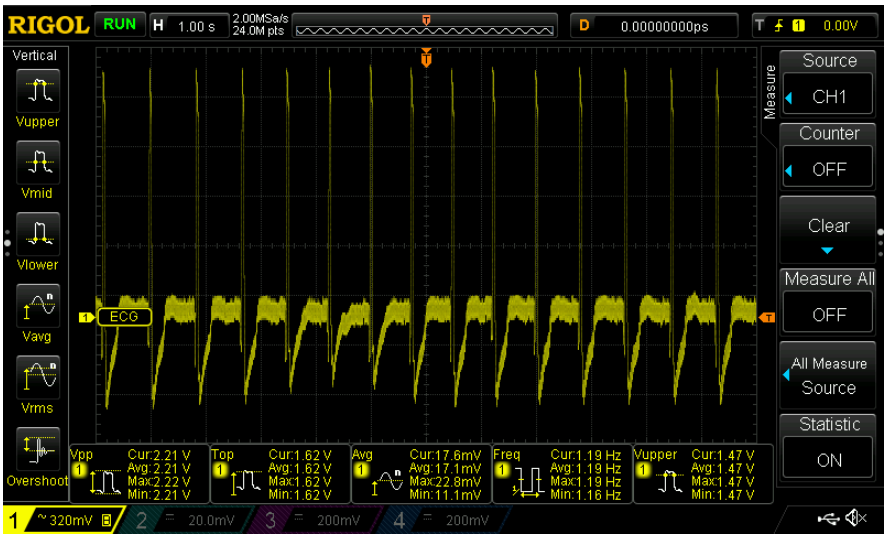


Figure 4-3 ECG-signal monitoring on oscilloscope

Using an oscilloscope, it was easy to assess the sensor without the need to write any source code. With just the turning of a few nobs and pushing of a few buttons we would try to apply such things as notch filters as seen in Figure 4-4 Filtering ECG on Oscilloscope, to reduce noise from nearby AC current conductors if the onboard filters for this was either not built in to the sensor filtering and most of this AC mains noise is probably picked up in the wires between the different components anyway.

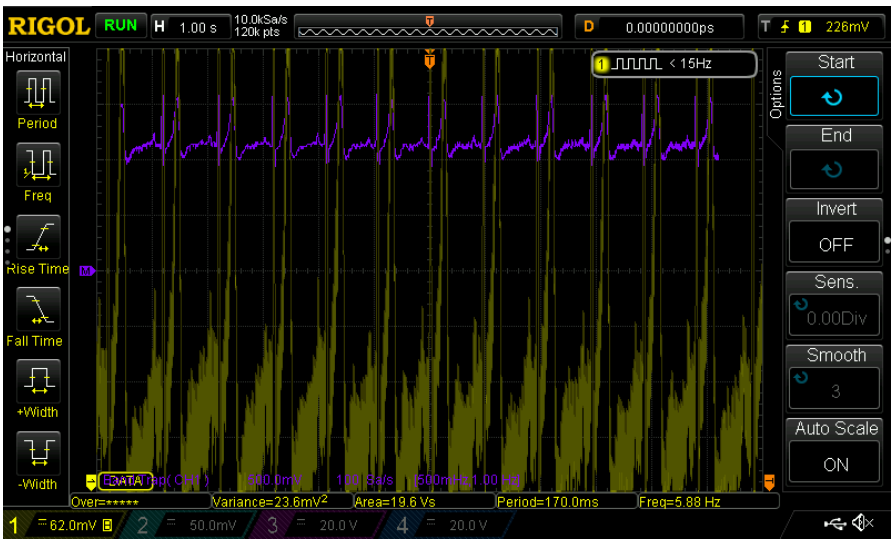


Figure 4-4 Filtering ECG on Oscilloscope

4.2 ECG capturing devices

BMD101 from NeuroSky [25] is a very popular chip for many manufacturers of smaller portable devices for ECG-monitoring. Many of the available devices use wrist or fingertip attached sensors.

Sichiray Bluetooth ECG device with BMD101 [25] is a device with two leads, where the electrode pads are connected directly to the PCB, avoiding any wires and it features a built in Bluetooth communication device and rechargeable battery. These features ensure that the device can autonomously acquire ECG data and transmit the data to an external device for storage and monitoring in a completely wireless manner. After some trial we found that there was less noise in the signal and that the signal contained better waveforms the closer to the heart we mounted the sensors. In Figure 4-5 Sichiray ECG Bluetooth (BT) device we can see the small BMD101 chip on the right-hand side of the battery, hidden under opaque glue.

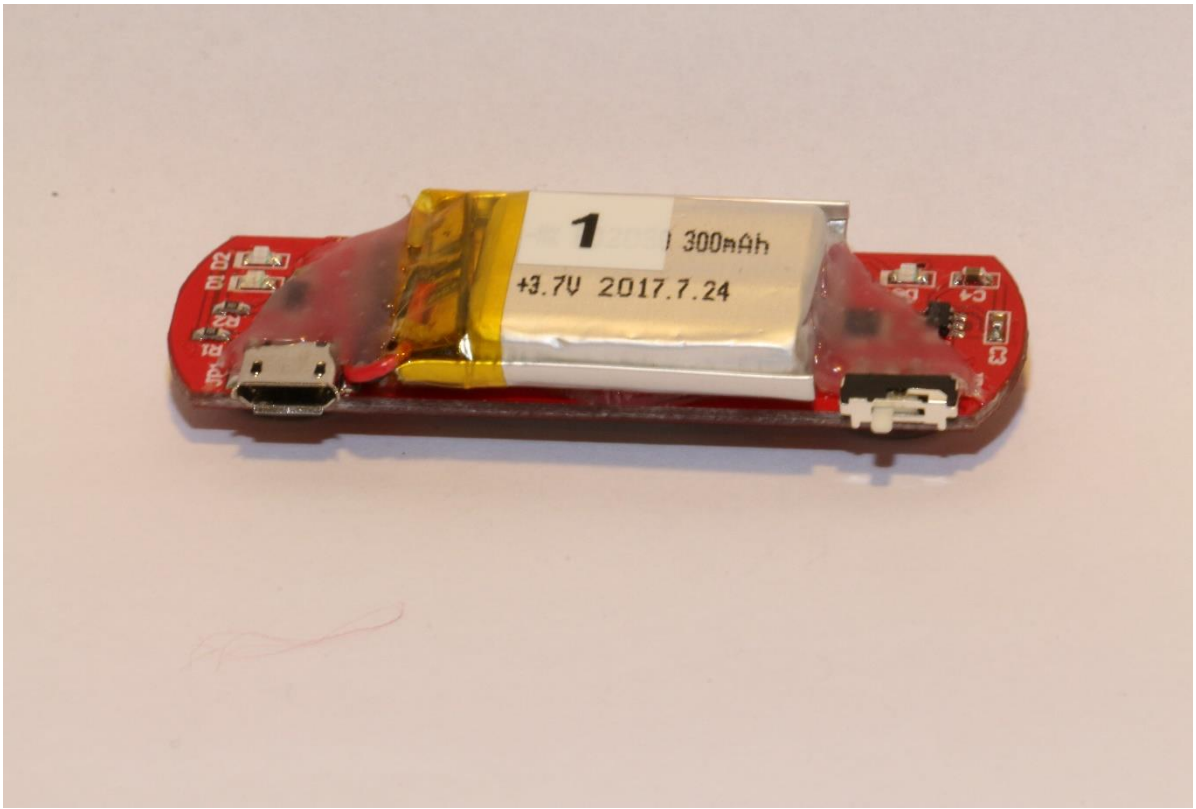


Figure 4-5 Sichiray ECG Bluetooth (BT) device

On the bottom side of the device, as seen in Figure 4-6 Sichiray BT ECG device backside. Blue communication PCB with ESP8266-module and connectors for disposable ECG-pads. The entire device measures only 65mm x 20 mm x 12 mm and weighs in at about 10 grams, so it is an extremely compact, lightweight and convenient package for research and development. Because of the chip from NeuroSky it can be used with their software development kit (SDK). We used part of the example software installed on a computer to communicate with the device and record the data it transmitted.

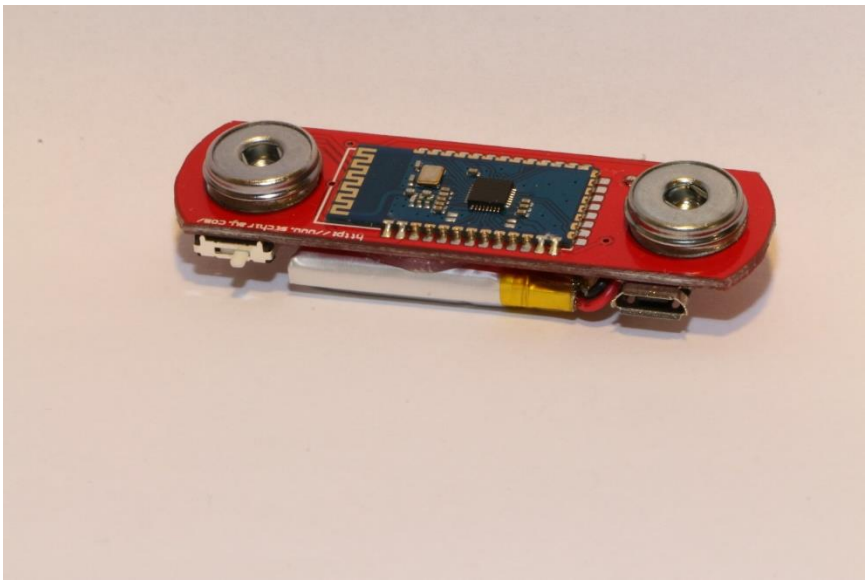


Figure 4-6 Sichiray BT ECG device backside. Blue communication PCB with ESP8266-module and connectors for disposable ECG-pads.

HB100 MC420S microwave module 10.525GHz [26] is a X-Band Mono-static DRO Doppler transceiver front-end module. We can see the device in Figure 4-7 HB100 MC420S microwave module 10.525GHz with metal cover and in Figure 4-8 HB100 MC420S back side with PCB-antennae patches visible as four small squares. The theory is that the doppler shift effect when something is moving relative to the sensor will create a reflected signal with a frequency higher than the transmitted signal if the item is moving towards the sensor and a reflected signal with a lower frequency than the one transmitted if the item is moving away from the sensor. We were able to detect motion in this way with the sensor, but not on the needed scale to accurately detect the microscopic movements of the chest, to record the QRS-complex. We wanted to check this to see if it would be possible to repeat the method of D.Obeid et al [27] or M. Chen et al [11] with much more reasonably priced equipment than used by these. We have not categorically ruled out the possibility of using this type of sensor

to collect ECG data in this test, but concluded that if possible, it would take a lot more work on the side of connected amplifier and noise filter circuits to reach that goal and that would be outside the scope of our work here, which was to briefly assess a set of sensors to find the one most suitable for our purpose of collecting ECG data to study the possible QRS template ageing.

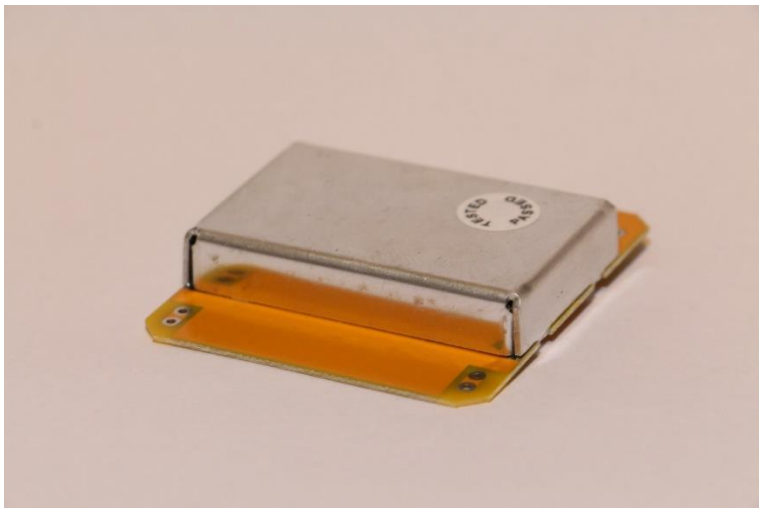


Figure 4-7 HB100 MC420S microwave module 10.525GHz with metal cover

Figure 4-8 HB100 MC420S back side with PCB-antennae patches visible as four small squares.

CDM324 CW microwave human body module 24GHz Radar inductive switch sensor is based on the CDM324 chip made by Infineon Technologies. We also wanted to test a Radar doppler device operating in the K-band, so we acquired this 24 GHz device that you can see in Figure 4-9 CDM324 CW microwave human body module 24GHz, and in Figure 4-10

CDM324 CW microwave human body module 24GHz, back side with PCB-antennae patches visible. This frequency is becoming more popular in the sensors in today's IoT devices and we used it to double check our results from the X-band device above. The results were pretty much the same and we decided against going any further with radar based devices in this work. We were only measuring the output signal of the transceiver in our tests, because of limited measuring equipment. We were using a 100 MHz Oscilloscope with some limited FFT-capabilities and if we were to register the Radar signals reflected directly we would need a very high-grade spectrum analyser covering the X or even K-band area.

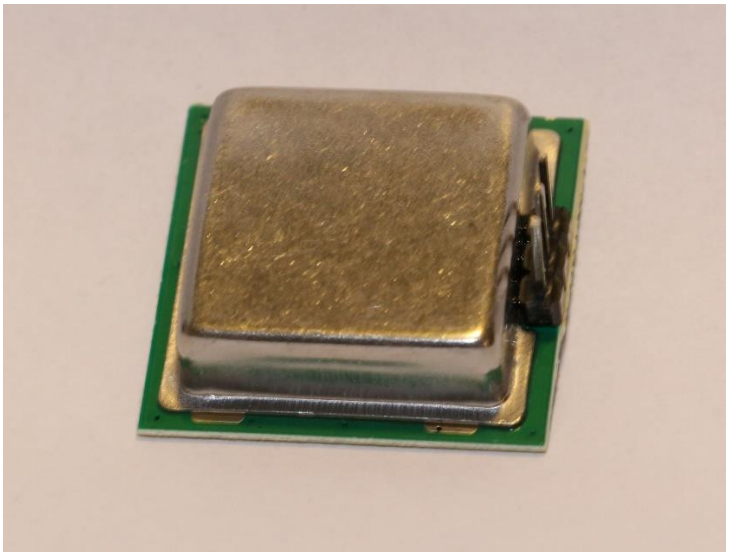


Figure 4-9 CDM324 CW microwave human body module 24GHz

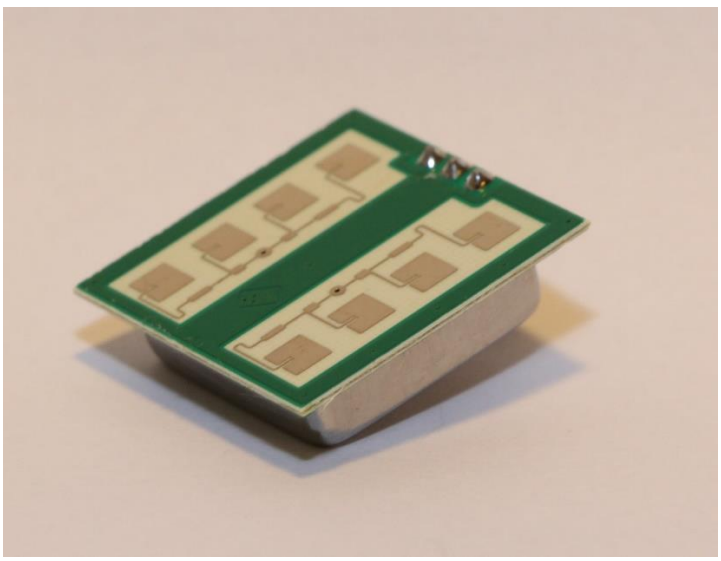


Figure 4-10 CDM324 CW microwave human body module 24GHz, back side with PCB-antennae patches visible.

We also wanted to see whether a different antenna would make any difference and found a 5.8 GHz module with a needle point antenna. It was said to have a switching transducer and a range of about 6-7m. We didn't have any more luck with this type and put inexpensive radar modules aside, to more thoroughly investigate the traditional wired, disposable electrode pad devices. In Figure 4-11 5.8GHz Microwave Radar Sensor. Antenna type Aerial Needle 5.8G 6-7m we can see the antenna protruding from the print circuit board (PCB) at an angle of 90 degrees, contrary to the other microwave devices like for example Figure 4-10 CDM324 CW microwave human body module 24GHz, back side with PCB-antennae patches visible.

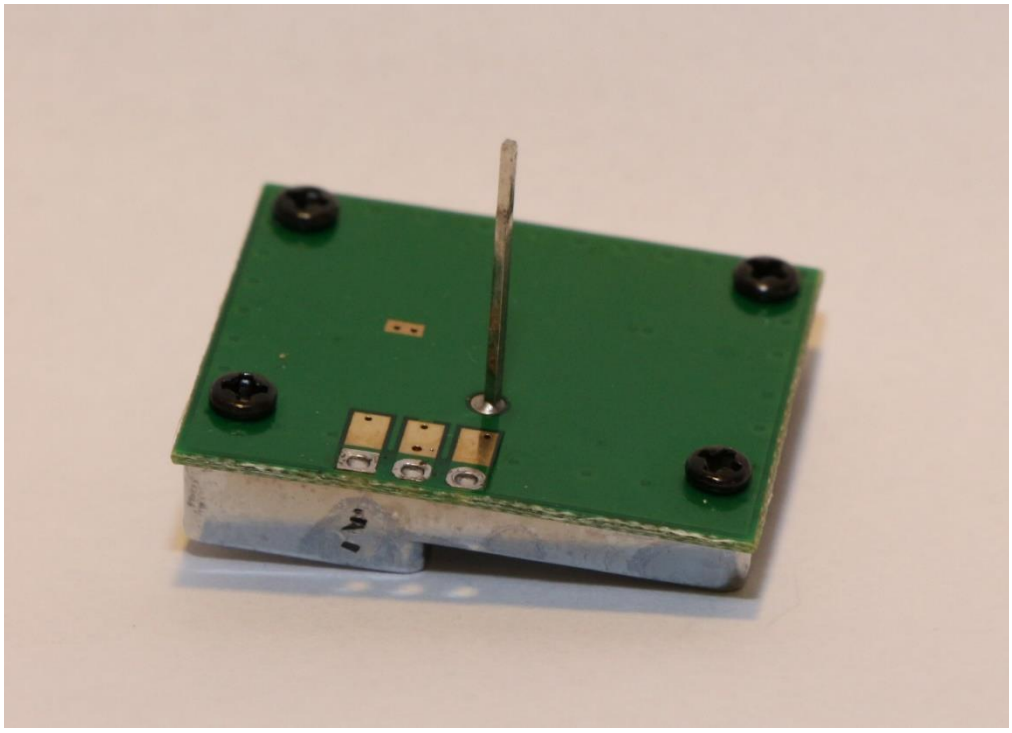


Figure 4-11 5.8GHz Microwave Radar Sensor. Antenna type Aerial Needle 5.8G 6-7m

DFRobot Gravity: Analog Heart Rate Monitor Sensor (ECG) For Arduino [28] with AD8232 [29] chip was a good candidate. It is a reasonably priced device utilizing the AD8232 chip from Analog Devices [29]. This device is meant as a development board slash maker board but the onboard MCU is built to be incorporated in commercial products. The MCU contains signal amplifiers and filters in a package measuring only 4 by 4 mm. The device uses three electrode patches, two on the chest and one on the stomach or leg.
On 25in the centre of the PCB, the power-in/data out on the right side and a connector for three wires for electrodes on the left side.

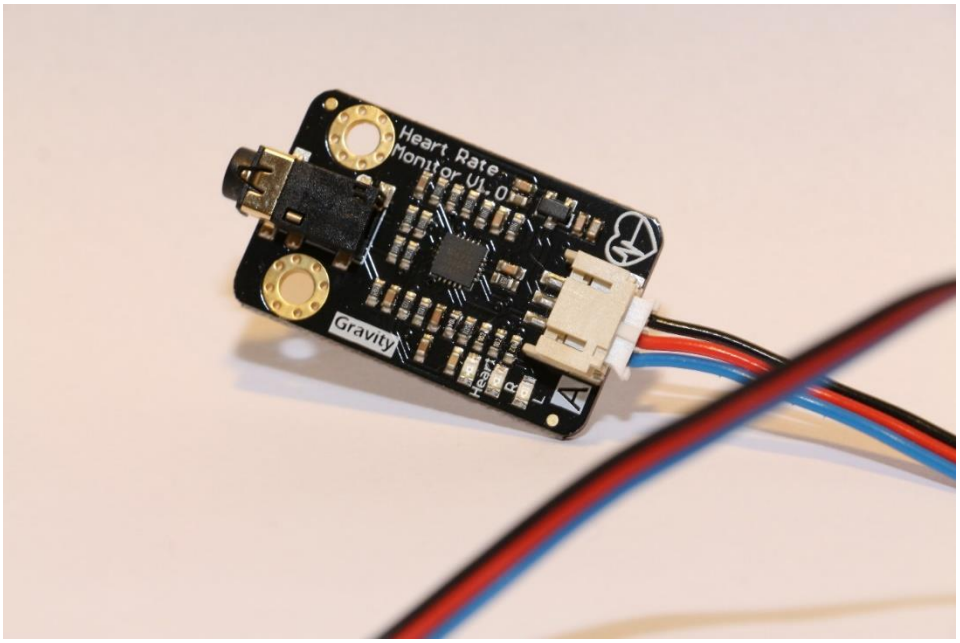


Figure 4-12 DFRobot Gravity with AD8232 chip

This device was tested with an Arduino Mini Pro and here is an example of the signal after transfer from the Arduino to the serial plotter on a computer 25

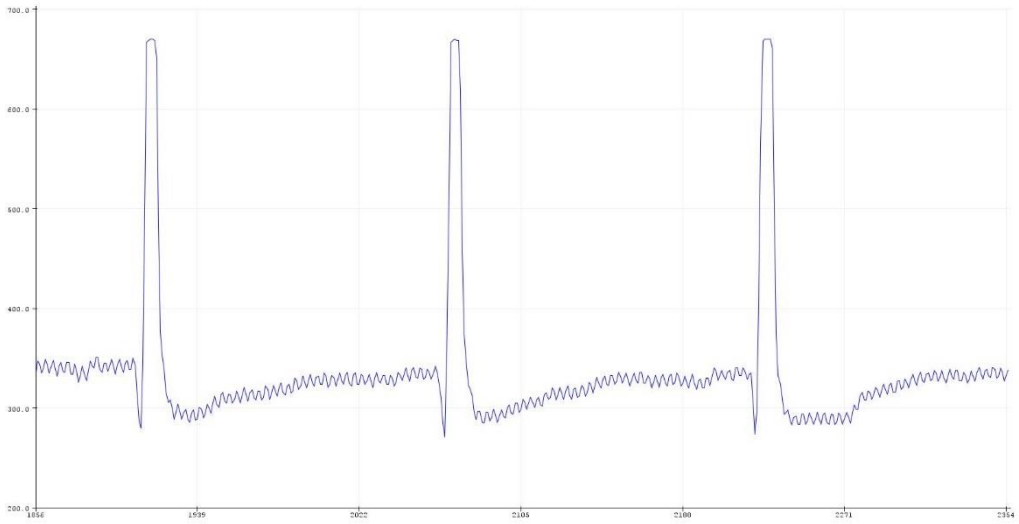


Figure 4-13 Arduino ECG output from DFRobot device plotted on computer

It seems that the signals are lacking good filtration of AC- 50 HZ noise and with this setup there is a lot of wires both from the electrodes to the DFRobot-device and on to the Arduino as seen in Figure 4-14 DFRobot device connected to Arduino Mini Pro and electrodes.

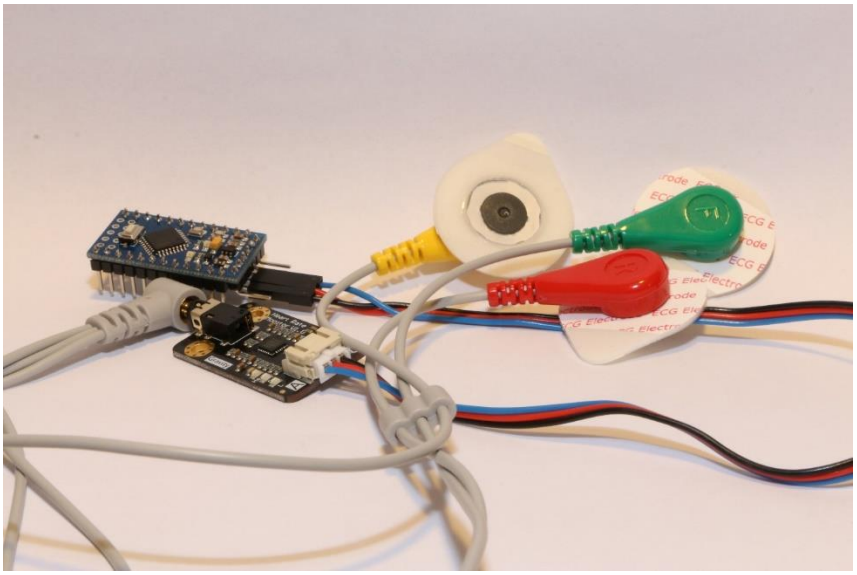


Figure 4-14 DFRobot device connected to Arduino Mini Pro and electrodes

These wires pick up such noise and this is not ideal, but it should be a relatively simple task to apply further slot filtering around 50 Hz to remove this noise. We tried with a slot filter when monitoring the device directly on the oscilloscope and managed to remove most of this noise, but not all. This is not a deal breaker though, because the noise can be removed during analysis in MATLAB as well.

Keyestudio AD8232 ECG Measurement Heart Monitor Sensor Module for Arduino [30] is, as the name suggests, using the same ECG chip as the device from DFRobot and this is also built for connection to an Arduino MCU to enable easy implementation of code for makers. The tiny footprint of the chipcanbe seen in the centre of Figure 4-15 Keystudio AD8232 ECG Measurement Heart Monitor Sensor Module for Arduino

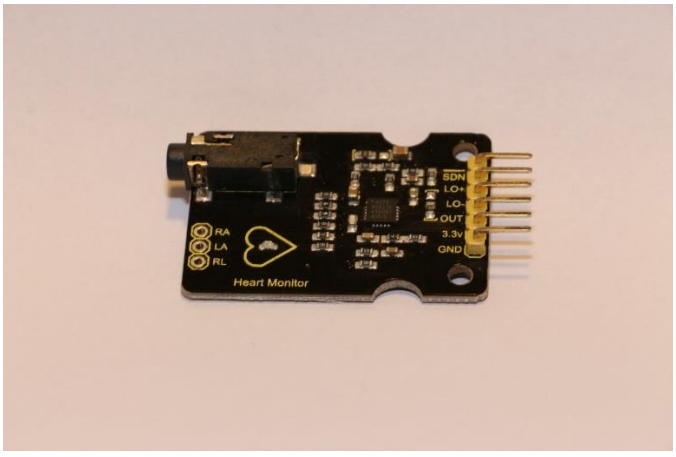


Figure 4-15 Keystudio AD8232 ECG Measurement Heart Monitor Sensor Module for Arduino

The output as seen in Figure 4-16 Arduino ECG output from Keystudio device plotted on computer, is heavily affected by the AC mains 50 Hz noise.

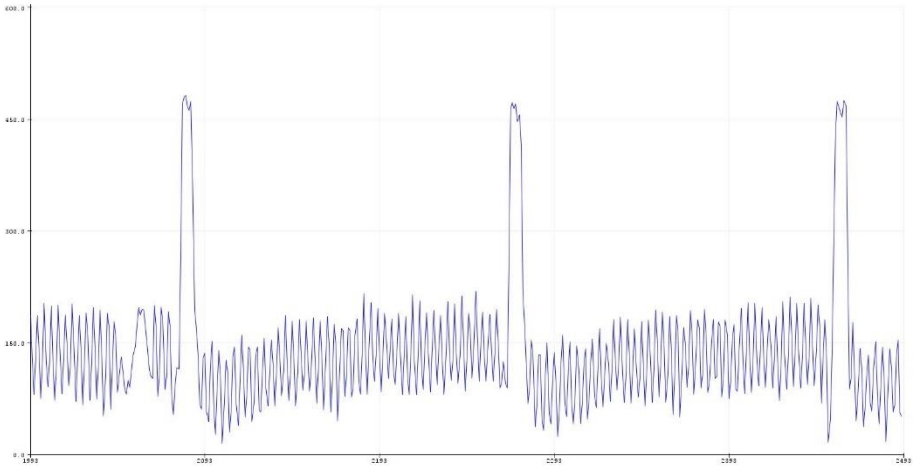


Figure 4-16 Arduino ECG output from Keystudio device plotted on computer

We briefly looked at another kind of device, that is becoming popular because of the easy and unobtrusive way it collects data. It is usually used on the tip of a finger, but can also read data from other parts of the body. It utilizes light to scan the bloodstream through the skin of the subject. One of the resent breakout boards for use with MCUs like the Arduino is the MAX30100-series, seen in the centreFigure 4-17 MAX30102 sensor (centre) on break out board of the PCB in

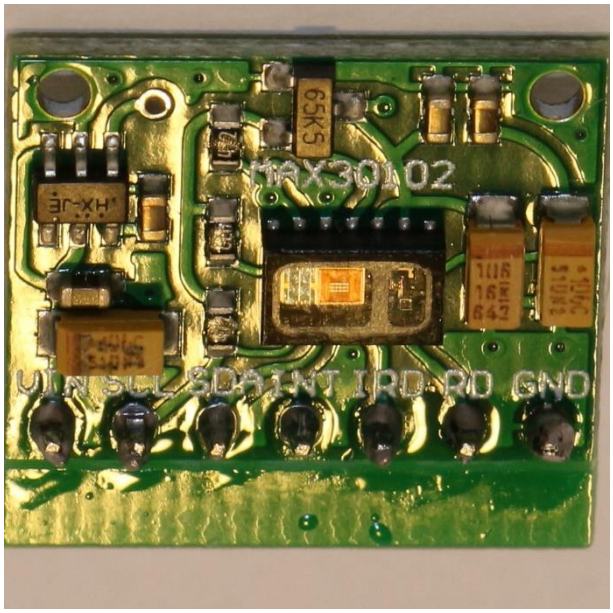


Figure 4-17 MAX30102 sensor (centre) on break out board

where the MAX30100/MAX30102 contain Red/IR LEDs while the MAX30101 has Red/Green/IR LEDs imbedded. The sensor itself is incredibly tiny and covered by glass as we can see between the two large holes in Figure 4-18 MAX30100, sensor side. The centre distance between the two holes on the 30100-board is only 9 mm, so this sensor can easily be built into small smart devices like workout wristbands and such. We found it to be a bit more prone to noise than the device from Sichiray, but this is probably only due to our test setup, with wires to an Arduino. Built into a device without loose wires connected, in a production device, we think this is a great way to unobtrusively collect ECG biometric samples.

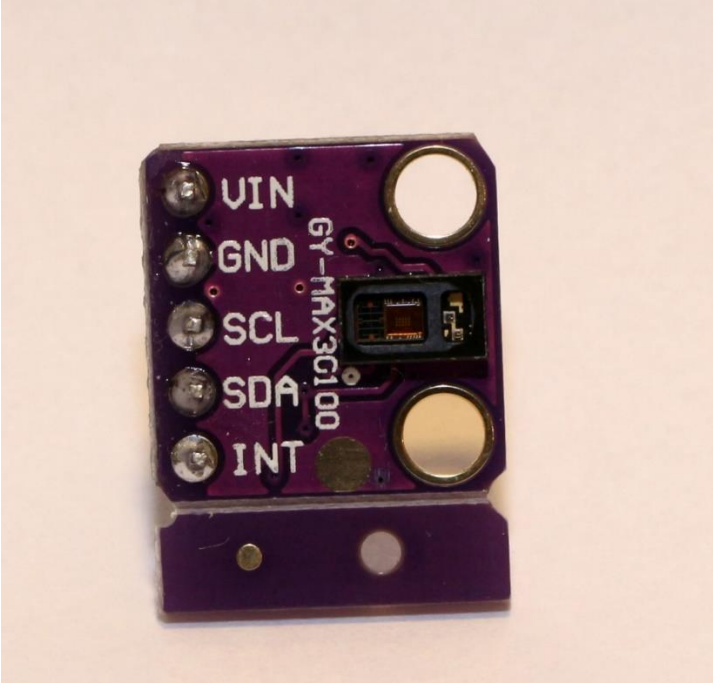


Figure 4-18 MAX30100, sensor side.

4.3 Disposable ECG Electrode selection

We considered a few different types of disposable ECG electrodes for the collection of biometric data as shown in Figure 4-19 A selection of disposable electrodes considered. We wanted to get electrodes with low noise and good contact, to minimise the noise added to the data and the electrode pad small enough to not overlap each other when connected to the ECG-monitor, since this distance is fixed at 45 mm between the centre of the two electrodes on the ECG-monitor we chose to use.

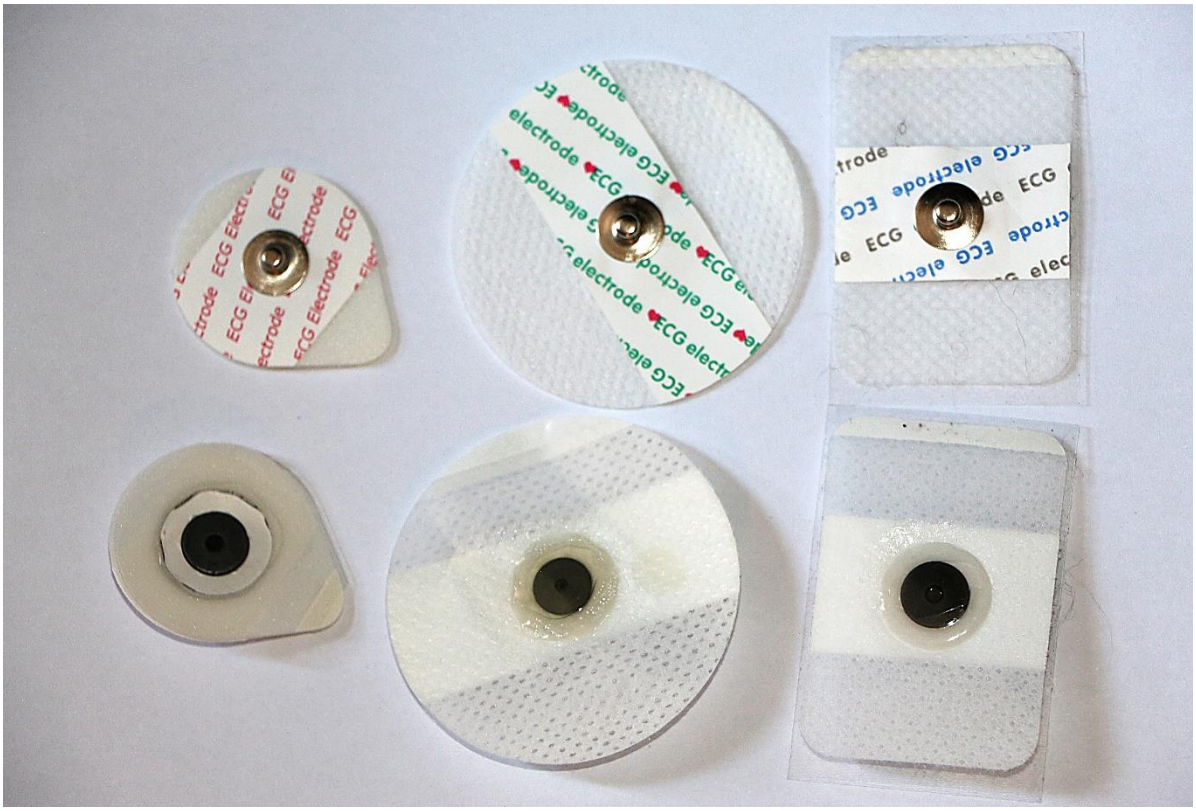


Figure 4-19 A selection of disposable electrodes considered.

We also chose to use the same type of electrode for all sessions, to avoid different type of electrodes to be a factor, when examining the data. We ended up choosing self-adhesive Ag/AgCl pads of 34 mm x 48 mm, model JK-1(A) made by Shanghai Junkang Medical Supplies LTD, shown in Figure 4-20 Disposable ECG electrode JK-1(A), used to collect all the data in this project This was not the smallest electrodes, but because of the rectangular form they still provided enough space between them and provided a bit more secure contact than the smallest round ones.

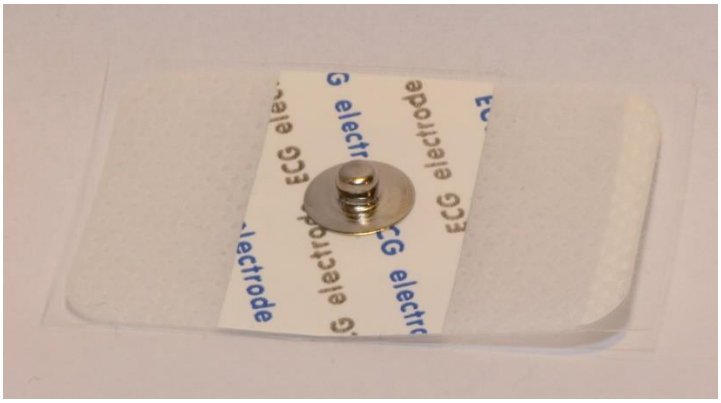


Figure 4-20 Disposable ECG electrode JK-1(A), used to collect all the data in this project

The main technical indicators of these electrodes are:

1. AC impedance: ≤ 3KΩ
2. DC offset voltage: ≤ 100mV
3. Content noise: ≥ 150uVp-P
4. Simulated defibrillation recovery performance: five seconds after each discharge, the electrode pair the voltage value is less than or equal to 100mV
5. Tolerance of the bias current: The electrode continuously acts on the 400nA DC current for 4 hours. During the entire period of operation, the voltage across the pair of electrodes changes by ≤100mV

Used on the Sichiray device and connected to the subject's chest on the left side as seen in Figure 4-21 ECG device attached to the chest of a test subject.

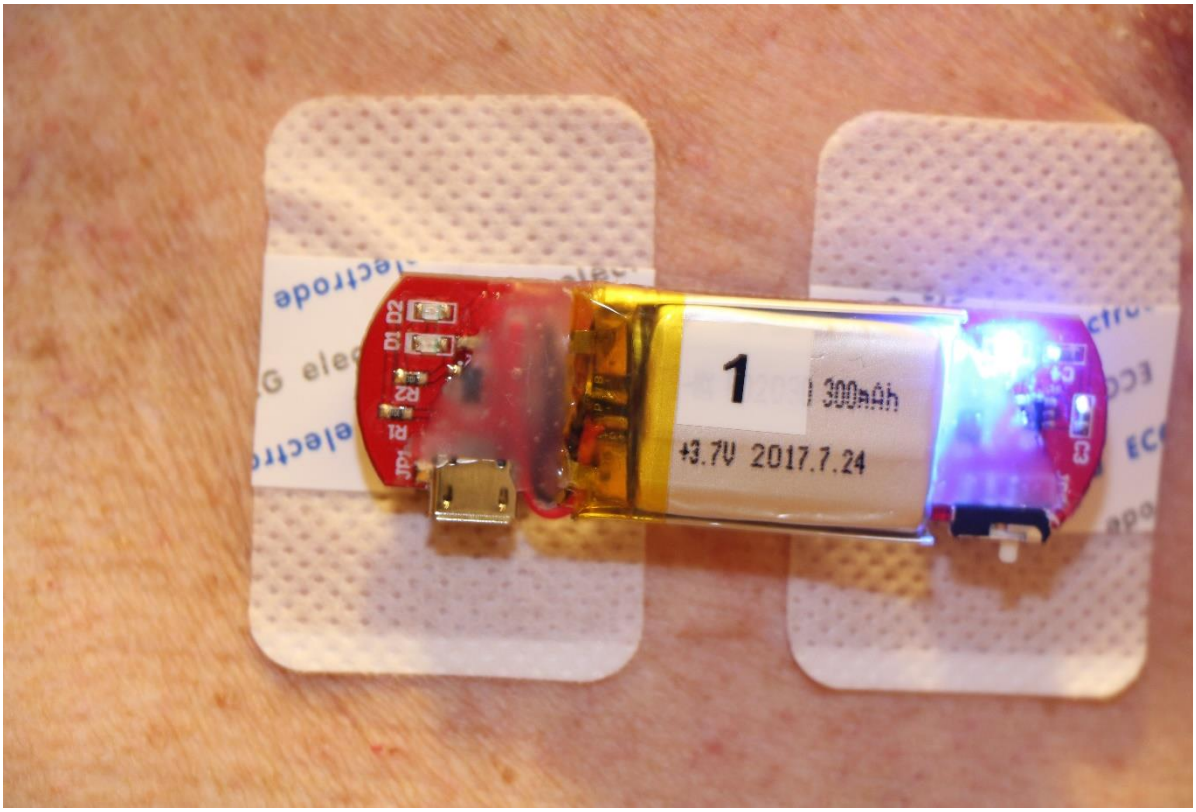


Figure 4-21 ECG device attached to the chest of a test subject.

5 Metodology

5.1 Initial considerations

There are several different methods of extracting minutiae from raw ECG-data. We can use the wave forms directly in the time domain and record the rise and fall of the signal over time, like duration and amplitude of the separate elements P, Q, R, S and T, we can use Fourier Transforms (FFT) to translate the raw data from the time domain into the frequency domain and extract minutia based upon the slight changes in frequency specific to each subject. It is up to the system designer of any system to decide a method for minutia extraction to construct a biometric template to use in authentication and this means that there are endless ways of doing this and so an endless number of possibilities. Most of these template vectors does not in any way accurately represent the exact nature of the wave form it is extracted from, so you would not be able to reproduce the entire wave form from a template where only some but not all features the raw data is chosen. We found that for our purpose of finding whether the signal changes in a person, over time, we would need to consider the wave form itself and not a generically generated minutia template. This lead us to try an approach where we calculate the cross-correlation between processed QRS wavelet representations, between the first session and several subsequent sessions with the same subject. We realise that this method is not a perfect measure of the permanence of the modality, as it is prone to be affected by differences in which the data were collected. We have made sure the circumstances were as close as possible to each other in all data collection sessions, but it would not be correct to use this measure to indicate significant change in the QRS-complex of a person form one session to the next. We are looking for a gradual change between several sessions, were the average change is pointing in one direction. This would of course be easier to do with a lot more data over a much longer period of time, more about that in the chapter about future work, but we had to conclude based on the data that were available to us.

5.2 Research subjects

We chose six healthy male subjects under 50 years of age. None of the subjects with known heart conditions. Because most of the data collected by others are collected for research in the

medical sector, naturally the test subjects often have different kinds of heart conditions. For our purpose healthy subjects with a relatively young heart would help us avoid changes to the ECG signals caused by a progressing illness. Of course, heart conditions are something that would have to be taken into consideration when using this biometric modality in a production environment authentication system.

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5.3 Data collection

The subjects had only done normal walking around in the period before collection of biometric data. We placed the subject on a chair and they were instructed to sit still and relax during the data collection session, each lasting between one and three minutes. Some subjects were more easily available than others so we have a varying number of sessions depending on which subjects were available when we were collecting data. All the sessions for one subject is separated in time. We started in the beginning of March and ended the data collection in the middle of May 2018, leaving a span in time of more than two months for some of the subjects. During data collection the ECG-monitor is connected to the left side of the chest with two standard medical self-adhesive Ag/AgCl electrode pads of 34 mm x 48 mm, JK-1(A) made by Shanghai Junkang Medical Supplies LTD. The output from the device on the subject is sent via Bluetooth to a computer where we ran a piece of example software provided in NeuroSky's SDK. Here we monitored the signal live on the screen as seen in Figure 5-1 Screenshot of capturing software during data collection.

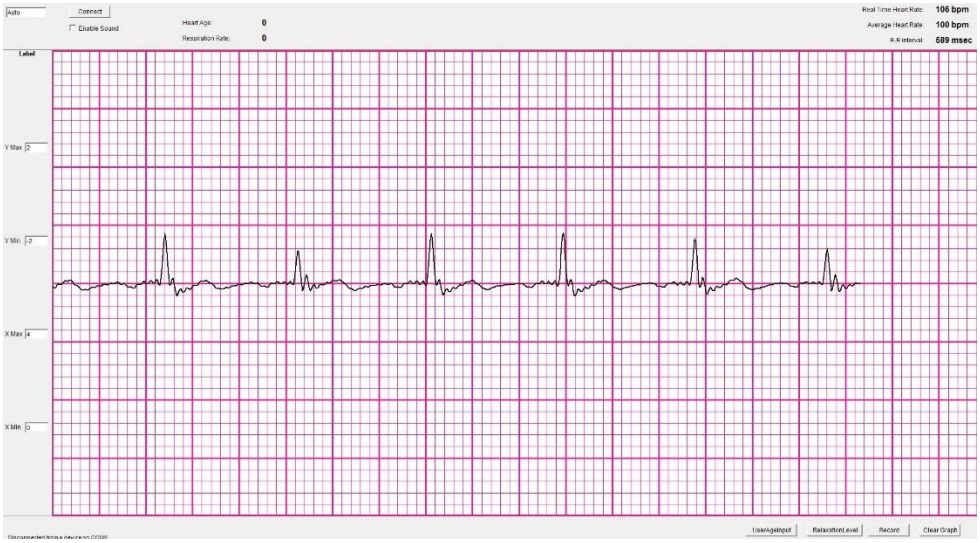

Figure 5-1 Screenshot of capturing software during data collection

The software saves a number of parameters in two different files. We were only interested in one single column in one of these files and so we wrote a script in MATLAB to extract this column and store it for further analysis. We can see the datafiles before and after extraction in Figure 5-2 Device file on the left and data after extraction on the right-hand side. The data we stripped away was the timestamps and average heartrate over 4 seconds and 30 seconds.

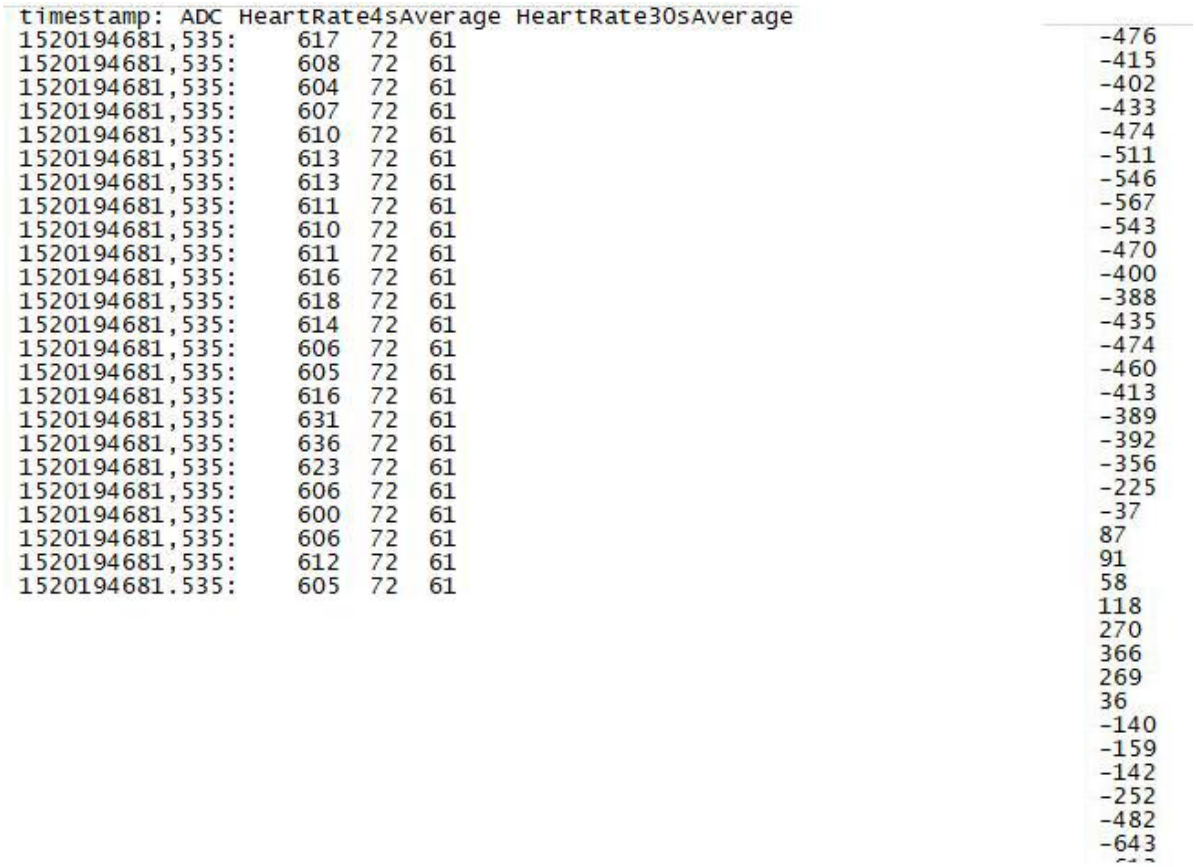

Figure 5-2 Device file on the left and data after extraction on the right-hand side

5.4 Signal processing for QRS detection

Although the capturing device onboard chip (NeuroSky BMD101) has some built in noise reduction filters, noise is always inherent and because of circumstances around connecting electrodes properly to the research subjects, subject movement and other things, artefacts will be embedded in the signal recorded and transmitted for storage. Because of this we need good

algorithms to be able to detect and extract the QRS-complex in the signal. There has been done a lot of research on signal detection and manipulation in many different areas of electronics and signal research, but as it is there is a very good specialized solution for this task. As described earlier in this thesis massive amounts of work has been done on ECG in the medical sector and it is in this body of work we find the excellent 1985 paper from J.Pan and W.J.Tompkins 'A Real-Time QRS Detection Algorithm' [31] . They developed a method that they found correctly detected 99.3 percent of the QRS complexes when applied on data from the MIT/BIH database. Though there are several other algorithms in use for this purpose we found that this was exactly what we were looking for, to pre-process our data in this project.

They devised a set of steps that we will describe our implementation of here:

First we have the raw data from the capturing device as seen in Figure 5-3 output from ECG data capturing device (from [32])

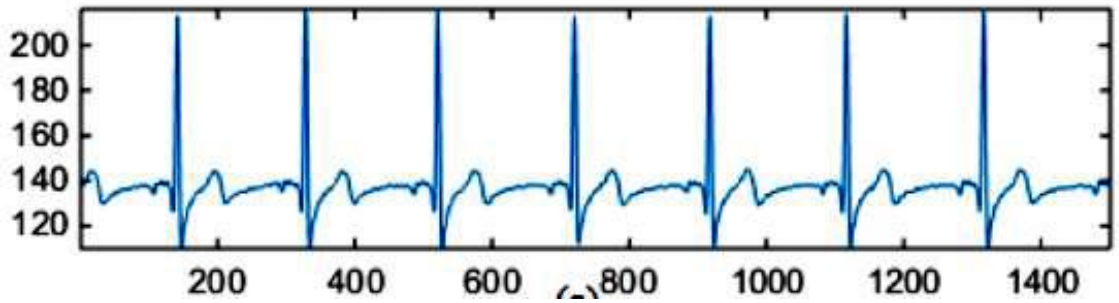

Figure 5-3 output from ECG data capturing device (from [32])

First, we apply a bandpass filter constructed of one low pass and one high pass filter. We set the low pass filter to slope off at an attenuation of 3 dB from 35 Hz and 40 dB from 45 Hz. The high pass filter we sloped off at the same rates from 5 Hz and 3 Hz, leaving us with a bandpass filter, passing the frequencies between 5 Hz and 35 Hz with full strength. This is where we find the frequencies of the actual ECG signal (approximately 8 Hz to 18 Hz) and it properly removes the largest factor of noise at 50 Hz (60 Hz in some countries) emanating from the mains frequency, among other high and low frequency noise sources.

Then We differentiate the signal (X(n)-X(n-1)) ending up with the slope characteristics of the signal. There might be R-peaks with a spiky character because of noise, making it difficult to pick the correct R-peak point, but the slope characteristics of the ECG-signal will be the same as illustrated in Figure 5-4 ECG signal after bandpass and differentiation (from [32])

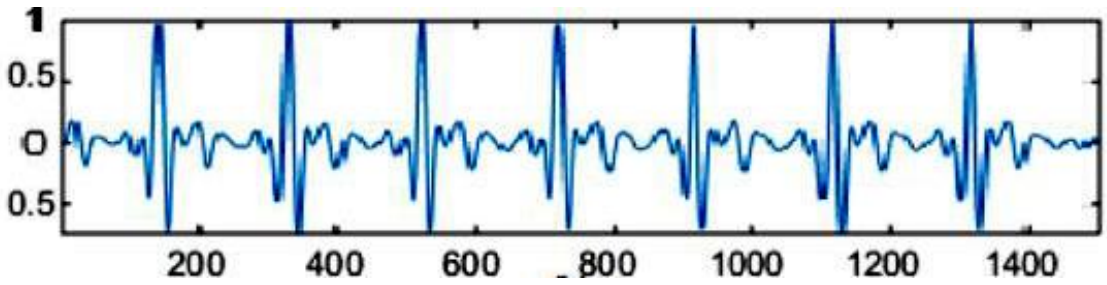

Figure 5-4 ECG signal after bandpass and differentiation (from [32])

The next step is squaring the differentiated signal and in that way amplifying the stronger ECG signal a lot more than the much weaker noise signal. The R wave will now be consisting of two strong positive peaks, with a point between them with amplitude of zero. That zero is the R-peak as seen in Figure 5-5 ECG signal squared (from [32])

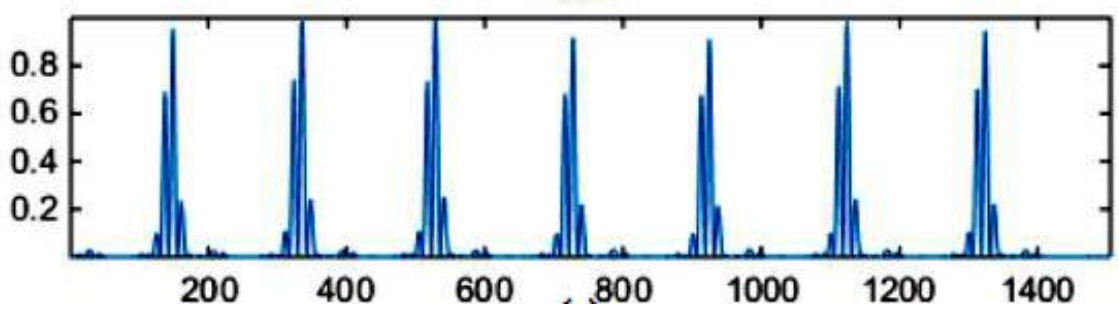

Figure 5-5 ECG signal squared (from [32])

Now we apply a so called moving average via integration. This is a very good noise filter for the time domain (not so much for the frequency domain). The size of the integration window is important here, if it is too large it will merge the QRS-complex with the T-wave and if it is too small it might end up dividing the QRS-complex into more than one peak. We have chosen a window of 60 ms, which seems to work very well. Then we apply a threshold value that is variable. We take the maximum R-peak amplitude in a window of two seconds (to be sure to have at least one QRS-complex) and divide it by three. This variable threshold is floating securely over the remaining noise, while dropping adequately to still register the lower R-peaks if the signal strength drops. Threshold adjustment method is a bit of a simplification of the original method outlined in the Pan-Tompkins paper [31], but it seems to work just fine. Based on the R-peaks circled in Figure 5-6 ECG signal integrated for R-peak detection (from [32]) we can extract the QRS-complexes from the session.

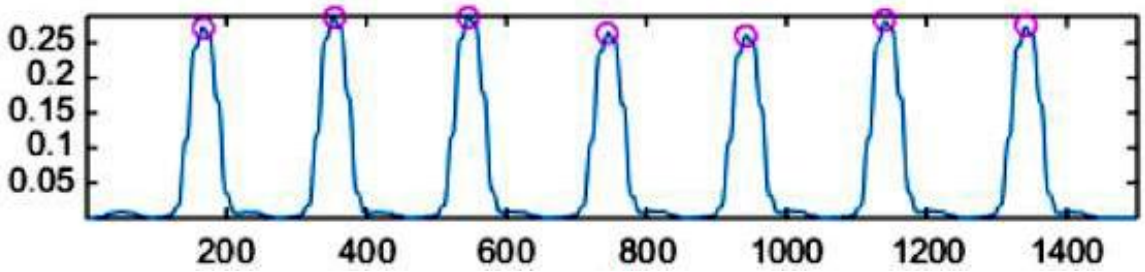

Figure 5-6 ECG signal integrated for R-peak detection (from [32])

6 Analysis

6.1 Preliminary visual data inspection

After carefully selecting a device to collect the data and recruiting a few subjects that we would be able to follow over a period of time, arranging sessions at several occasions during this period it was time to start analysing the collected data. We have plotted some examples of the QRS-complexes from a good session with varying level in MATLAB as seen in Figure 6-1 QRS-complexes from one good session, where we can see that the waveforms are neatly aligned, but with varying signal strength, this is not a big problem.

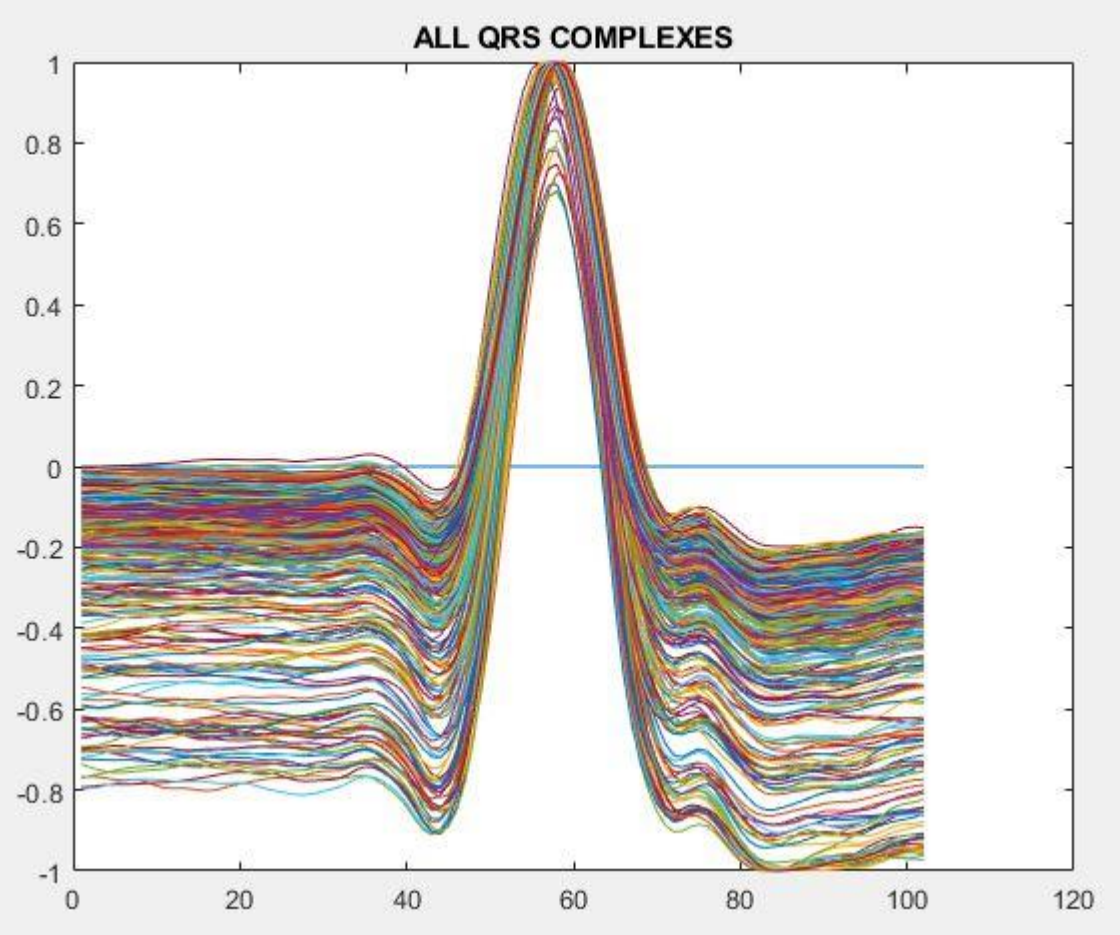

Figure 6-1 QRS-complexes from one good session

With a subject that had relaxed beforehand and was sitting completely still, we got sessions with where all the QRS-complexes were practically identical over the time of the session, like in Figure 6-1 QRS-complexes from one good session, this would not be a probable situation

for capturing authentication data in a real-life application, but one could possibly, by repeated enrolment sessions under very controlled conditions, get access to such data sets. We have plotted an example in Figure 6-2 QRS-complexes from very uniform session.

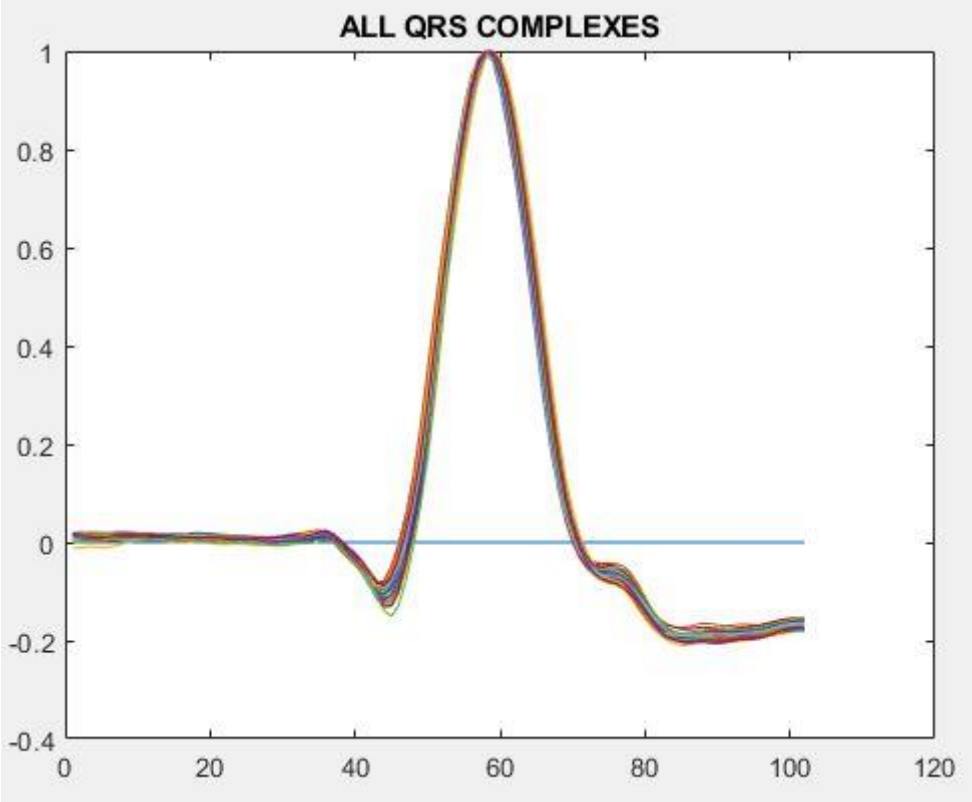

Figure 6-2 QRS-complexes from very uniform session

This would be easy to match with a session of similar quality, but some sessions have change in pulse, movement and possibly changing contact conditions in the electrode pad. This is probably avoidable during enrolment if one has good equipment and a lot of time, but for capturing data to authenticate a person in real life situations, one would have to overcome the fact that we only have access to limited duration of far from perfect data. Anyhow we had the data captured and started to look at the files in MATLAB. We first plotted the data as shown above and found that we had a few sessions where the ECG signal seemed reversed. We knew from the equipment testing earlier on that this happens when the capturing device is turned upside down, effectively switching the left electrode to the right side and vice versa. We had tried during the collection of the biometric samples to make sure that this was done right by attaching a sticker with “1” on the device to be able to easily detect if it was upside down. We must have missed it a couple of times due to the device being under a shirt during

the capturing session. We decided to just exclude these, since there were only a couple of files reversed.

6.2 Pre-processing discoveries

The data was sometimes noisy and the amplitude of the pulse varied from session to session so we thought it would be necessary to create more than one wave form average from the sessions that had a lot of variation and probably exclude the sessions with the worst quality. After some trial and error, we decided against using more than one average from a session and found the Pan-Tompkins [31] method of signal processing, described in the methodology chapter. To overcome some of the effects of varying signal quality we also decided to concentrate our studies on the strongest part of the PQRST, namely the QRS-complex only. After testing a method of clustering to isolate what we believed to be outliers, we found that the QRS-complexes in the less stable sessions were actually good. The problem was artefacts imposed upon the signal due to less than perfect collection conditions. It could be glitches caused by electrode contact problems or muscle movement in the subjects. We therefore decided to just detect the artefacts and throw them out. To do this we differentiated the ECG signal and then counted the number of zero crossings and if there were more than five, we threw it out as an artefact. To extract one single representative QRS wavelet from the multitude available in the data from a capturing session, would be a bit random. We chose to build an average that would be more representative for the entire session. We have used a weighted average method we devised for this purpose. Much of the problem with averaging lies in the remaining signal noise and we thought about the method we had already used in the more general noise reduction earlier, counting the number of zero crossings on the differentiated signal. We decided to use a similar way of assigning a weight. Each separate QRS-complex in the entire session is assigned a weight from a set of three:

$$w[0.6, 0.3, 0.1]$$

We could easily add more weights or different weight values, but stayed with simple in this round. We also needed to assign each weight to a specific number of zero crossings and have proposed 0.6 for less than 7, 0.3 for 7 to 9, and 0.1 for 10 and up. We have tweaked these values to suit our need and with a different capturing device they can easily be changed.

6.3 Comparing QRS-complexes

As described before we chose to avoid the path of extracting minutia from the biometric data and simply look at the correlation between the separate average waveforms we have calculated for each session. This was to avoid operations on results that were based on a subjective choice of minutia and calculations on these, removing them one step away from what we really wanted to study, namely the changes in the waveform and not the changes in specific minutia.

There is an enormous amount of approaches to calculating the difference between two waveforms and no specific answer to which is the best way of doing it, but through looking at some relevant methods we decided to compare the extracted QRS-complex waveform form the initial session, with each of the following sessions to get a comparison over time looking like:

(1:1, 1:2, 1:3, 1:4, …., 1:n)

To be able to properly compare the entire wavelets, we chose to calculate the cross-correlation coefficient between the two sessions in each pair, to illustrate if there is a sinking trend in the correlation or if it was just small random changes up and down. The reasoning behind it being that if the correlation coefficient is steadily sinking from session to session that is a measure of low permanence and if the correlation coefficient stays more or less the same over time, the permanence is very high. We calculated the correlation coefficient of the two compared clusters in MATLAB, using their built-in function corrcoef

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i - \mu_A}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right)$$

We then plotted the coefficients of the compared sessions for a person on a graph (perfect similarity gives a coefficient of 1.0. We can see on the curve in Figure 6-3 Correlation coefficient graph, subject 4 (6 sessions), that the coefficient is high and does not seem to be sinking over the time calculated for.

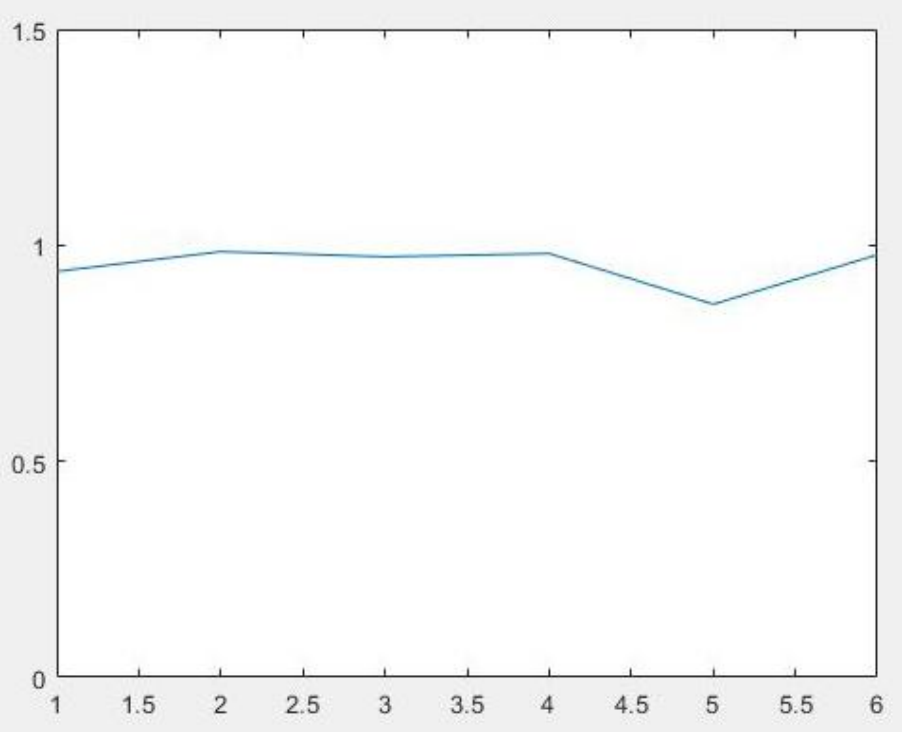

Figure 6-3 Correlation coefficient graph, subject 4 (6 sessions)

Looking at a comparison of the sessions from subject 1, where we have 15 good sessions to compare in Figure 6-4 Subject 1, 15 sessions compared, we can see there are the occasional dip in the curve, but no significant reduction over the period.

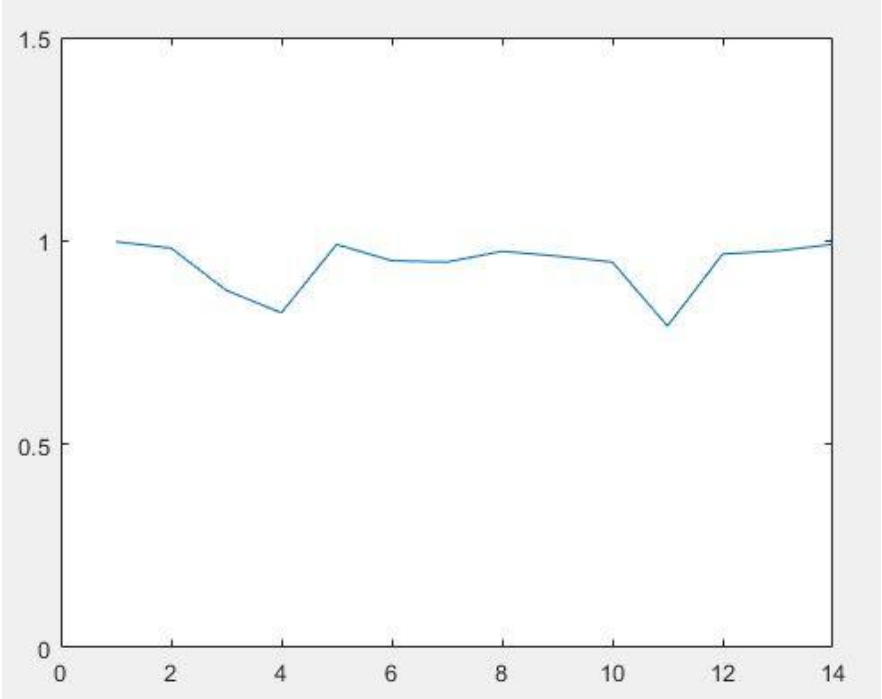

Figure 6-4 Subject 1, 15 sessions compared

This was a very common result, we cannot detect a sinking correlation and must conclude that the permanence of the biometric modality ECG is very good over the time period that we have collected biometric samples. Within the tolerances we can see on the permanence here, there would be no real problem to recommend a given development project, to continue with this modality, within the approximately same time constraints between enrolments. We can see some dips in the curves where the correlation is lower, but this is random and probably just due to the fact that we got more noise and artefacts and lower QRS amplitudes in some sessions. This was partly due to contact issues between the skin and the disposable ECG electrodes and partly because of movement in the subjects.

7 Discussion/conclusion

We see that ECG is becoming more of a viable option for biometric authentication and in some cases biometric identification and there are only a few studies related to the permanence of the ECG-signature of a person. Most of the studies we found regarding permanence of the ECG-modality, were done by the medical community and looked at changes during different types of heart conditions, to be able to predict illness. We saw the need for more work performed on younger, healthy subjects, to discover if there is a change of the ECG-signature over time, that would warrant frequent reenrolments. We looked for available, reasonably priced, non-medical equipment, that would enable us to collect the biometric samples we needed. A go-to source in the study of ECG-data in a general sense and for comparison data has been the MIT-BIH Arrhythmia Database [33] since its initial release in 1980. This is data collected during a period of seven years from 1972 to 1979, and it can be seen referenced in a lot of papers on the subject. There are also several other large public datasets available and we considered using one of these datasets initially to test code in MATLAB, but found that the testing could easily be performed with our own ECG-data. We could most likely have gotten a much better view of the permanence of the ECG biometric modality, by just performing our calculations on some of those datasets, but a large part of the task we set out to perform here, were finding a reasonably prized device to collect this kind of data and then actually collect our own biometric samples with those devices, to prove that this is research that can be done with non-medical tools on a low budget.

We followed several different subjects over a period of two to three months, limited by the time constraints of a thesis like this. We extracted the QRS-complex only, from the biometric samples we collected in each session and then extracted a QRS-template from each session. We compare the different templates of a subject with the other templates of the same subject to discover if there were any recognisable trend in the differences between them and draw a curve of the cross correlation. This is a quick visual way of inspecting whether the permanence is good enough for a given time frame and con be utilized in a company’s R&D as a quick preliminary investigation, before investing heavily in a project.

8 Future work

This study relies on data sets collected during a relatively short period of time, due to the nature of a mater thesis project. What we set out to determine was whether a system authenticating a subject with the use of an ECG profile, needed to repeat the enrolment process after some time has passed. A study with data of the same subjects collected over a much longer period of time, would have provided an even more reliable conclusion, as to whether the QRS-complex of one individual stays the same over time. We can only conclude based on the time period of the study. If we could follow a larger group over several years, where some of the subjects develop heart conditions during the study, one could see whether any part of the wave form stays the same, and can be used to authenticate a subject, even if other parts of the waveform changes.

Ideally, we would follow a group of individuals from childhood to old age, to be able to map the entire lifespan of several people and see if there is a pattern to the changes that would enable us to age adjust a template to be able to be able to authenticate a person that enrolled many years ago. This would be useful both to avoid the need for frequent reenrolment and as an additional biometric trait to authenticate criminals that has changed identity a long time ago.

We discovered no such trend, so we concluded that based on the limited timespan, the permanence of ECG as a biometric modality is good. We recommend a similar study over a much longer period of time, maybe several years. We also concluded that a system with more or less continuous enrolment during the use of the system, will eliminate the need for this information, but that it would be interesting for systems where a person might not authenticate for a long period of time.

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