FACULTY OF INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING

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AUTOMATIC ECG SIGNAL QUALITY ASSESSMENT

Master's Thesis
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ABSTRACT

The quality assessment of signal has been a research topic for many years, as it is mainly related to the problem of the false alarms. Automatic quality detection/assessment and classification of signals can play a vital role in the development of robust unsupervised electrocardiogram (ECG). The development of efficient algorithms for the quality control of ECG recordings is essential to improve healthcare now. ECG signal can be intermixed with many kinds of unwanted noises. It is an important task to assess the quality of the ECG signal for further biomedical inspections. To make that happen, we made an algorithm that is efficient and uses some basic quality features to classify the ECG signals. It is a very effective way to acquire a good quality ECG signal in real-time by unskilled personnel for instance in rural areas there is not enough expertise in this field. By using this method, they can quickly know if the ECG signal is acceptable or unacceptable for further inspections. The method is used to assess the quality of the ECG signals in the training set of the Physionet/Computing in Cardiology Challenge 2011, giving a correct interpretation of the quality of the ECG signals of 93.08% which corresponded to a sensitivity of 96.53% and a specificity of 86.76%.

Keywords: Signal Classification, Electrocardiogram, ECG classification, False Alarm, Electrocardiogram quality assessment, Signal quality assessment, Electrocardiogram noise detection and classification, ECG noise.

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FOREWORD

I have had started my International Master's degree Program at the University of Oulu to become a Biomedical Engineer for my particular research interest in the biomedical field that I have discovered during my previous studies. Thanks to my parents and family, they have always been supportive and helpful with this idea and assist my decision warmly.

During my studies, I was recruited by my supervisor, Professor Tapio Seppänen, in one of his projects. It was the start of my first job ever which has been continued up to this time. A part of the project that I have been participating in was dedicated to my master thesis. This piece of research has been conducted to build an automated ECG signal quality assessment method to identify the bad parts of the ECG signal resulting from different artifacts, and finally classify the signal as acceptable or unacceptable.

During my work here at the Center for Machine Vision and Signal Analysis, I have been technically guided by Kai Noponen. Now, I would like to express my gratitude and appreciation to my examiners, advisers, and supervisor.

University supervisor: Dr. Tech. Prof. Tapio Seppänen
Second examiner: Dr. Tech. Juha Partala
Technical supervisor: M.Sc. Eng. Kai Noponen

LIST OF ABBREVIATIONS AND SYMBOLS

ECG	Electrocardiogram
ICU	Intensive care unit
ECRI	Emergency Care Research Institute
RA	Right atrium
LA	Left atrium
RA	Right ventricles
LA	Left ventricle
SA	Sinoatrial
AV	Atrioventicular
aVR	Augmented vector right
aVL	Augmented vector left
aVF	Augmented vector foot
EM	Electro-magnetic
EMI	Electromagnetic interference
EMG	Electromyogram
HR	Heart rate
HRV	Heart rate variability
AF	Atrial fibrillation
brady	bradycardia
tachy	tachycardia
mV	Millivolt
TH	Threshold
Hz	Hertz
SQA	Signal Quality Assessment
Se	Sensitivity
Pp	Positive predictivity
Np	Negative predictivity
Sp	Specificity
Ac	Accuracy
TP	True positive
TN	True negative
FP	False positive
FN	False negative
FPR	False positive rate
TPR	True positive rate
ROC	Receiver operating characteristic
DTs	Decision trees

1. INTRODUCTION

The classification of signal quality has been a research topic identified with the issue of false alarms in bedside monitors in the intensive care unit (ICU) for a long time [1]. False Electrocardiogram (ECG) arrhythmia alarms are quite frequent among the patient monitor cautions adding to "alarm fatigue" which has been recorded as one of the top technological dangers that may trade off patient medical safety in clinics or hospitals [2, 3, 4]. Right now, bedside monitors create a considerable number of potential cautions, mainly because of parameters got from electrocardiogram (ECG). The occurrence of false alerts in the ICU can be as high as 90%, as announced by many research studies. The appearance of inappropriate or false alarms could be potentially reduced by using proper signal quality intervals to adapt thresholds to the specific patient needs [1].

According to one research study [5], in 48 hours of observation total 2,184 medical alarms were counted, and the subjects were 48 critically ill patients in the intensive care unit (ICU). Hourly 45.5 medical alarms occurred per subject, and 63.8% (1,394) alarms were categorized as false alarms [5]. Clinical nurses reported that they face some problem in proper management due to a large amount of false alarm, which is an alert system used in clinics to detect false signals of a medical condition. For example, patients need urgent attention in conditions like cardiac arrest; to send a notification to the medical expert this alarm system is used. So, this is an essential part of a clinical environment for critical conditions patients. However, excessive amount of false alarm or minor situation alarm, can lead to desensitization condition found in medical experts known as alarm fatigue [6], according to the Emergency Care Research Institute (ECRI) [7] research, also they declared this alarm hazards as one of the top patient safety hazards for several consecutive years [8, 9, 10, 11]. By reducing the false alarm the patient's hazard can be reduced, that will improve the quality of the healthcare in intensive care unit (ICU), also will increase the quality of the automatic medical monitoring systems [6].

The primary objective of this thesis was to make an efficient algorithm to assess the quality of the ECG signals and to ensure that the visualization of the ECG is acceptable in quality to interpret further. In reality, for different biomedical applications, an automated quality assessment is an essential part, and it is additionally a complex task to be done [1]. So, the idea was to make an algorithm that can identify the bad parts in ECG signal resulting from common artifacts (such poor skin-electrode contact, external electrical interference and artifact resulting from patient motion) and either make up for these lacks or give direction to amending them and classify the signal as acceptable or unacceptable [12]. In developing countries, where the specialists are focused on urban clinics, this innovation can allow underserved rural populations to profit by generally difficult to reachability. It will be fundamental for therapeutic services sup-

pliers in underserved areas to end up capable in gathering high-quality ECGs, to stay away from the danger of saturating the specialist's availability. Moreover, since master elucidation may not be promptly accessible, it is vital to acquire a signal that can be verified without waiting for a specialist opinion on its quality, since it might be hard to get another ECG on one more day from a patient who may live a long way from a facility.

1.1. Background

Many investigations have been done to reduce the false cautions and handle alert fatigue issue [13, 14, 15]. It has been demonstrated that an ECG recording of low quality because of defilements with baseline wander, movement, and electrode detachment artifacts are more susceptible to producing false alerts [13, 4]. In the Computing in Cardiology Challenge 2011 they had the similar condition to the evaluation of the ECG signals [1], the objective in that challenge was to make an algorithm that can run in a cell phone and give feedback on the ECG signals. If the ECG is of sufficient quality for further interpretation, or if another ECG recording to be made [12], in this thesis the goal was more like similar, to make an efficient algorithm that can visualize the bad parts in the ECG signal and classify it as 'acceptable' or 'unacceptable.'

So, by studying all the research articles that were submitted in that event [12], we decided to implement one of them; that is we think one of the efficient one (ECG Quality Assessment for Patient Empowerment in mHealth Applications by Dieter Hayn, Bernhard Jammerbund, Günter Schreier). They developed a measure for ECG quality assessment based on a) basic signal quality properties (amplitude, spikes and constant signal portions/flat line), b) the number of crossing points in between different leads, and c) QRS-amplitude vs. noise amplitude ratio. There were two types of data set to evaluate the algorithm; at first, they had given a training data set. Later on, the algorithm checked with the test set. We also used the same test data set with our algorithm for evaluation.

1.2. Research Objectives and Contribution

The main purpose of this thesis is to develop an automated quality assessment method to identify the bad parts of the ECG signal resulting from different artifacts, and finally classify the signal as acceptable or unacceptable. So, This thesis specifically presents the following objective:

- Develop and evaluate an algorithm that automatically assesses ECG signal quality.

This thesis presents the following significant contributions:

1. Development of an ECG signal quality assessment algorithm. Because of recording poor ECG signals can provide false alarms. Thus, using automatic ECG signal quality assessment algorithm can help to identify these false alarms as they occur. This thesis describes an ECG signal quality assessment algorithm that leverages the repeatability of the PQRST complex generated by a patient's heartbeat.

2. Performance evaluation of the algorithm mentioned above using some particular datasets that are contaminated with different types of noises. Since the ECG signal quality analysis algorithm is based on the artifacts of a patient's movement or other instrumental error, it was necessary to evaluate the algorithm using ECG data containing these noises.

3. We have implemented some of the rules from the paper [16] in the algorithm in Matlab and try to classify the training dataset given in Computing in Cardiology Challenge 2011 with this algorithm and got a similar score as they [16] got with their algorithm with all rules. As this work is a part of the 'VitalSens' project, we have also tried to visualize the bad parts as described in the features of the algorithm with the 'VitalSens' data.

1.3. Structure of the Thesis

The chapters of this thesis are structured as follows:
Chapter 1 describes the introduction part that addresses ECG signal quality problem and also describes the motivation and the background information of this work. Chapter 2 describes background information on Electrocardiogram, and it's artifacts. Chapter 3 outlines the methodology employed while performing the research for this thesis; this includes descriptions of equipment and ECG databases used. Chapter 4 presents the experimental results and analysis. Chapter 5 describe the discussion part. Chapter 6 summarizes this thesis and presents recommendations for future work.

2. BASICS OF ELECTROCARDIOGRAM (ECG) AND ARTIFACTS

2.1. The ECG

ECG signal is one of the common recorded signals that are used in almost every clinical environments. Clinically-trained experts can obtain much valuable information about the condition of the patient's heart from the distinctive morphology of the ECG signal. For cardiologists, this recorded signal is used to identify different kinds of heart diseases. The ECG signal produces the electrical activity of the heart over a period using electrodes placed in prescribed locations on the skin surface. During the heart cycle, these potential differences produced, by the heart muscle contraction and expansion to pumping blood around the circulatory system. The standard ECG recordings usually were done by 12 leads setup but often 3-leads, and 5-leads are used for the easier setup procedure. Now chest band, skin patches, and monitoring garments are also being used to record ECG signals [17].

2.2. Structure and physiology of heart

There are some processing steps in the anatomy of the heart. There is a sequence in the process that can describe how the blood flows through the body. Four hollow chambers construct the heart, including two atriums (right and left atrium (RA and LA)) and two ventricles (right and left ventricles (RV and LV)). Oxygen-poor blood comes from the body is purified by them. The oxygen-poor blood from upper and lower veins of the body is guided by the superior and inferior vena cava towards the RA. By RA contraction the blood travels to RV. Then the blood goes to the lungs by the contraction of RV for the purification process by pulmonary valve and arteries. After purification, the blood sends back to the LA through pulmonary veins. Then the blood goes to LV and then to the body through arota. The cardiovascular conduction system is in charge of signaling the heart in an organized manner. Sinoatrial (SA) node is responsible for generating the electrical impulse sequence, and then it is sent through the atrioventicular (AV) node. Then the AV bundle takes the signal down to the heart septum (the margin of the RV and LV) and create the contraction of ventricles at the same time. The primary source of ECG signal and cardiac cycle production are these electrical signals. The continuation of this electrical impulse pumps the blood to the body organs by controlling the heart muscles [18].

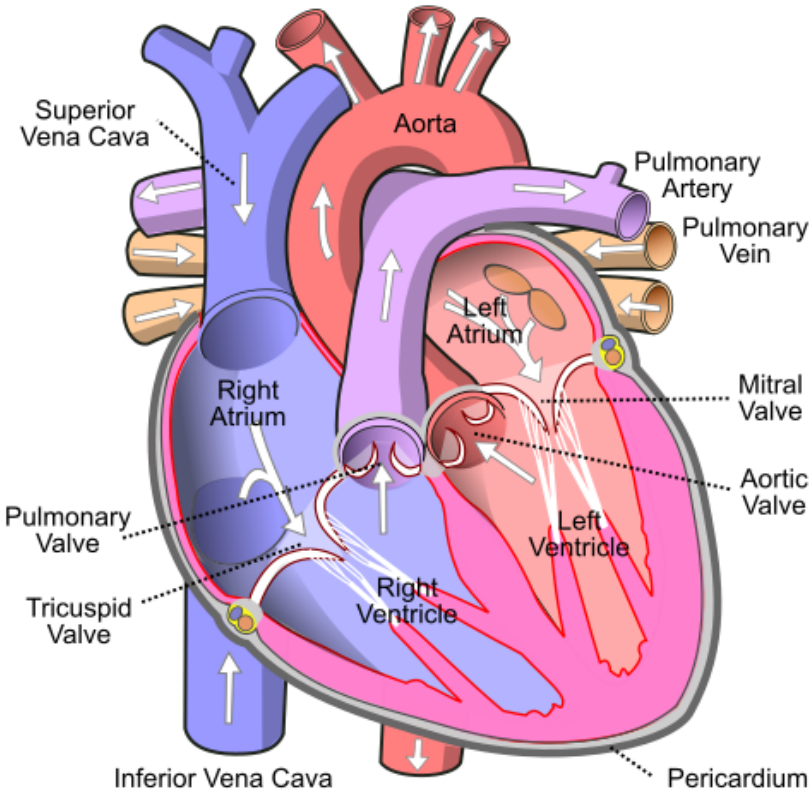


Figure 1: Physiology of heart [19]

2.3. Generation of heart beat

The graphical record of the electrical current that is generated by the depolarization and repolarization of the atria and ventricles is the ECG. The electrodes attached to the skin detect this electrical activity in the heart [20].

The P wave is the voltage that is generated by atrial depolarization, the QRS complex is generated by ventricular depolarization, and T waves coincide to the repolarization process. Moreover, the effect of the atrial repolarization (Ta wave) is covered in the QRS complex because it usually happens during ventricular depolarization [20].

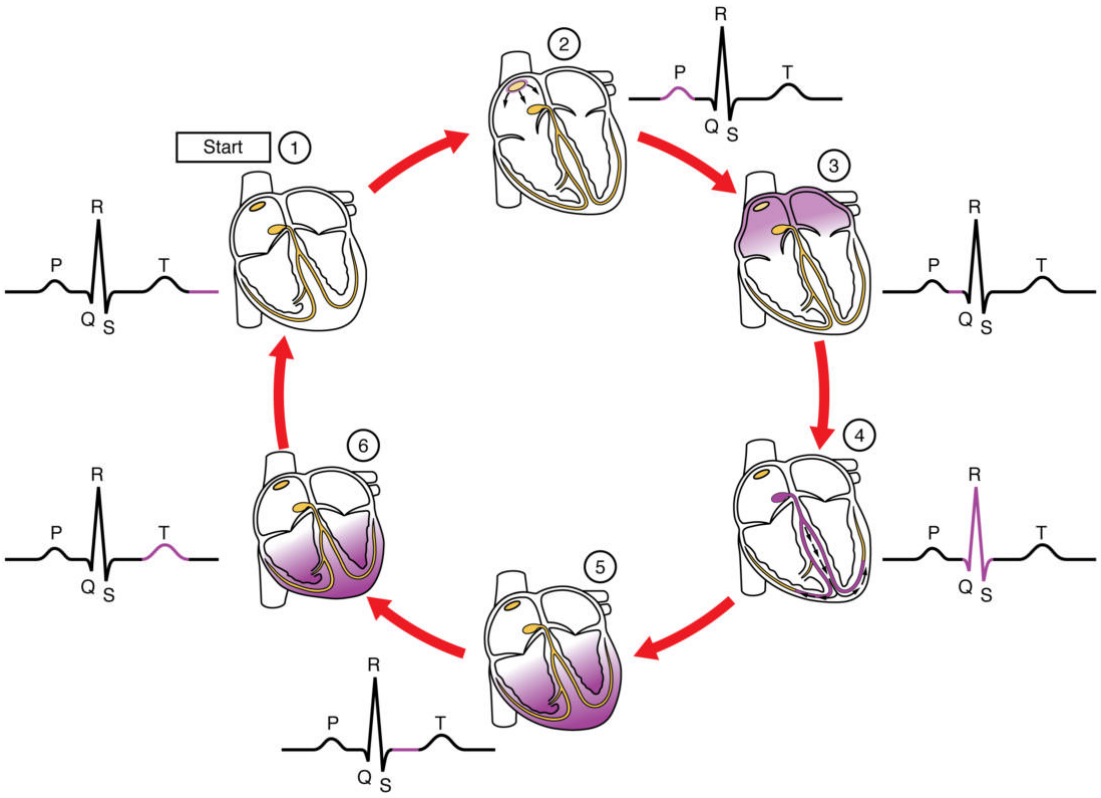


Figure 2: (1) Starting, (2) Atrial depolarization, (3) Atrial repolarization, (4) Ventricular Depolarization and (5) Ventricular repolarization [21]

2.4. ECG Morphology/Components

After detecting the electrical current by the electrodes, then it is amplified and then displayed on an oscilloscope, printed on ECG paper, or stored in memory. Generally, in a cardiac cycle, P wave occurs first, then comes the QRS complex and the T wave. The segments and intervals are the sections of the ECG waves and complexes: the PR segment, the ST segment, the TP segment, the PR interval, the QT interval, and the R-R interval. Waves and complexes are included in the intervals. When there is no electrical activity of the heart is being detected, the ECG signal is a straight or flat line at that time, which is known as the isoelectric line or baseline [20].

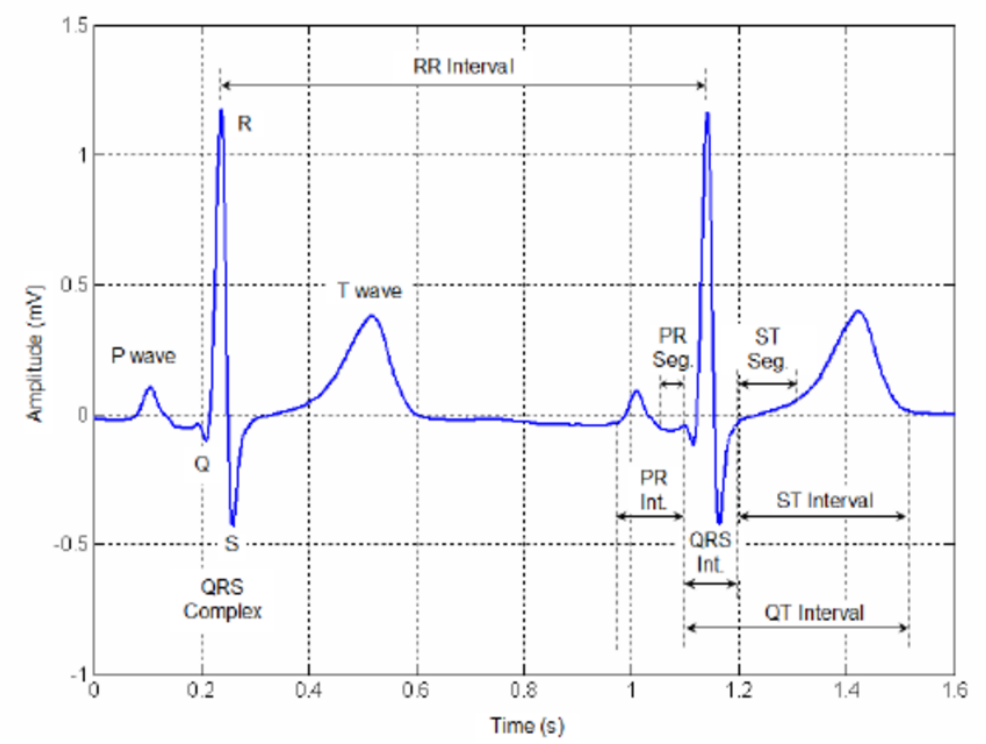
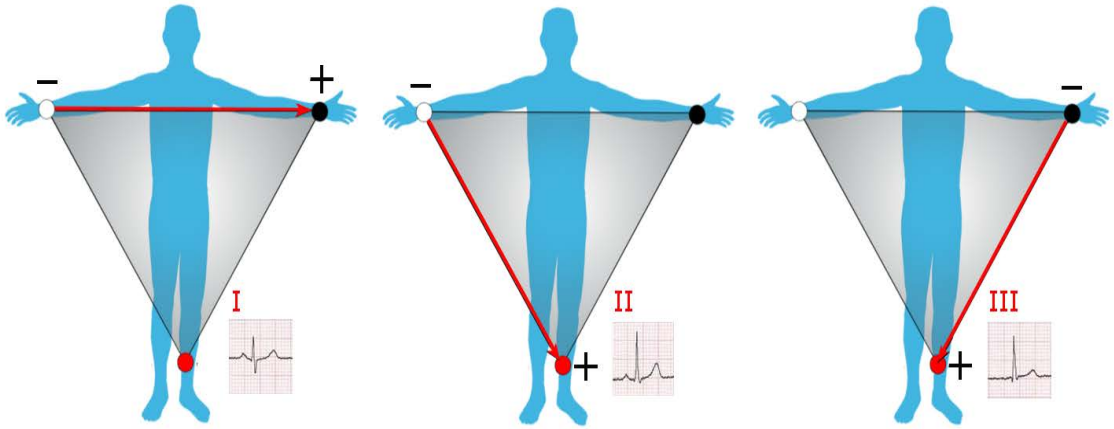


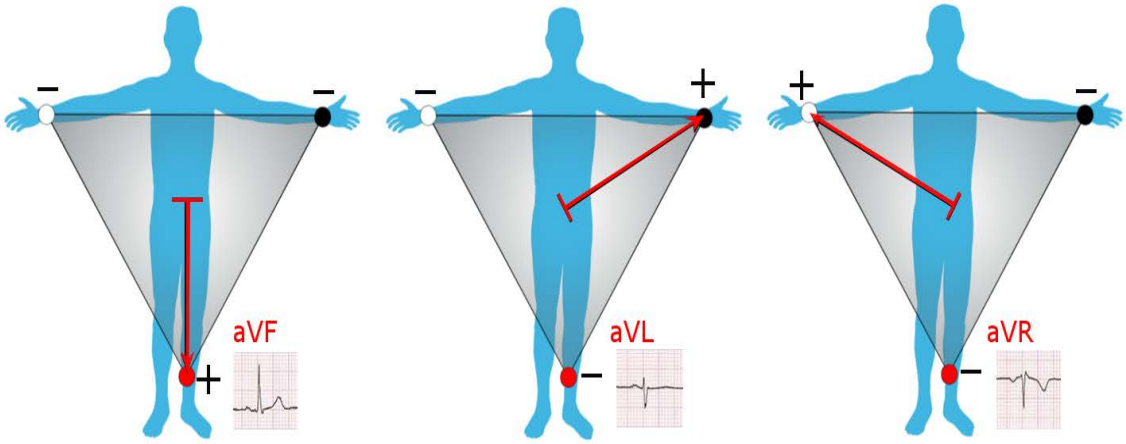
Figure 3: Components of the Electrocardiogram (ECG) [22]

2.5. Single and Multi-lead ECG

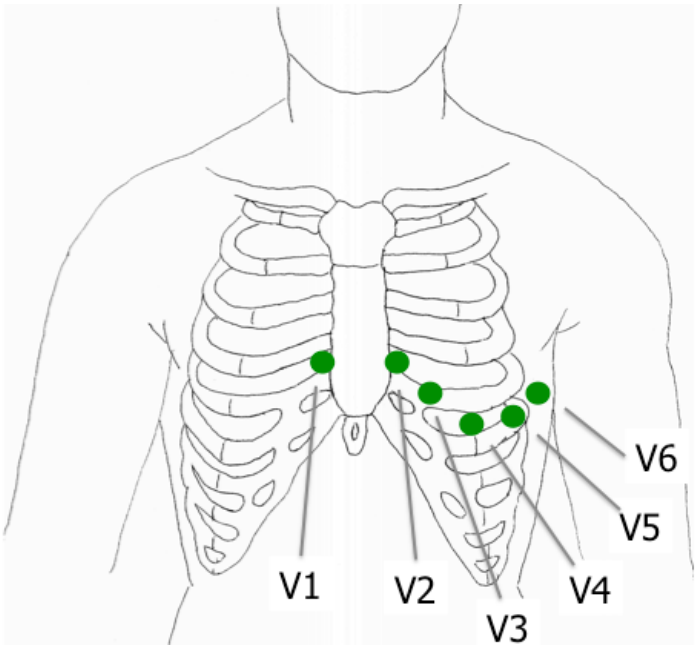
The electrical activity of the heart (ECG) that is detected by the electrodes can be done in two different ways: (1) Two discrete electrodes of opposite polarity or (2) One discrete positive electrode and a zero reference point. A bipolar lead is consist of two discrete electrodes of opposite polarity; A unipolar lead is consist of a single discrete positive electrode and a zero reference point. The positive electrode can be attached to the right or left arm, the left leg or one of a few areas on the anterior chest wall; it depends on the ECG lead. Usually, the negative electrode attached to an opposite arm or leg or to a reference point made by attaching the limb electrodes. In the hospital to get one patient's details analysis of the electrical activity of the heart, 12 separate ECG leads (12-lead ECG) setup is used to record the ECG signal. This setup (12-lead ECG) is also used in the prehospital phase of emergency care in certain advanced life support services (e.g., ICU) to diagnose acute myocardial infarction and also helps to identify particular types of heart diseases. There are three standard (bipolar) limb leads (leads I, II, and III), three augmented (unipolar) leads (leads aVR, aVL, and aVF) and six precordial (unipolar) leads (V1, V2, V3, V4, V5, V6) in a 12-lead ECG setup [20].



(a) The standard (bipolar) limb leads I, II, and III [23]



(b) The augmented (unipolar) leads aVR, aVL, and aVF [23]



(c) Precordial (unipolar) leads [24]

Figure 4: ECG leads placement

In this thesis, we will concentrate on 12-lead ECG & 3-lead ECG. This algorithm also can be applied in a single channel of an ECG signal. The single channel, limb lead II ECG is commonly used in the prehospital phase of emergency care when monitoring the heart for arrhythmias. In lead II ECG, signal's diagnostic features can be observed entirely. However, the patient's movements or other interference can still affect easily to decrease the accuracy because the amplitude range is in the millivolt, which is relatively small [20].

2.6. Noise in ECG

Noise is present in all signals. In ECG signals there are also some noises that originate from different kinds of sources. There are five main types of noise in ECG signal: Powerline interference, Electrode contact noise, Electromyographic noise, Motion artifacts and Instrumentation noise [20].

Each type of noise is discussed here. The figure (5) is an example of an ECG signal with a low noise level that has a normal sinus rhythm.

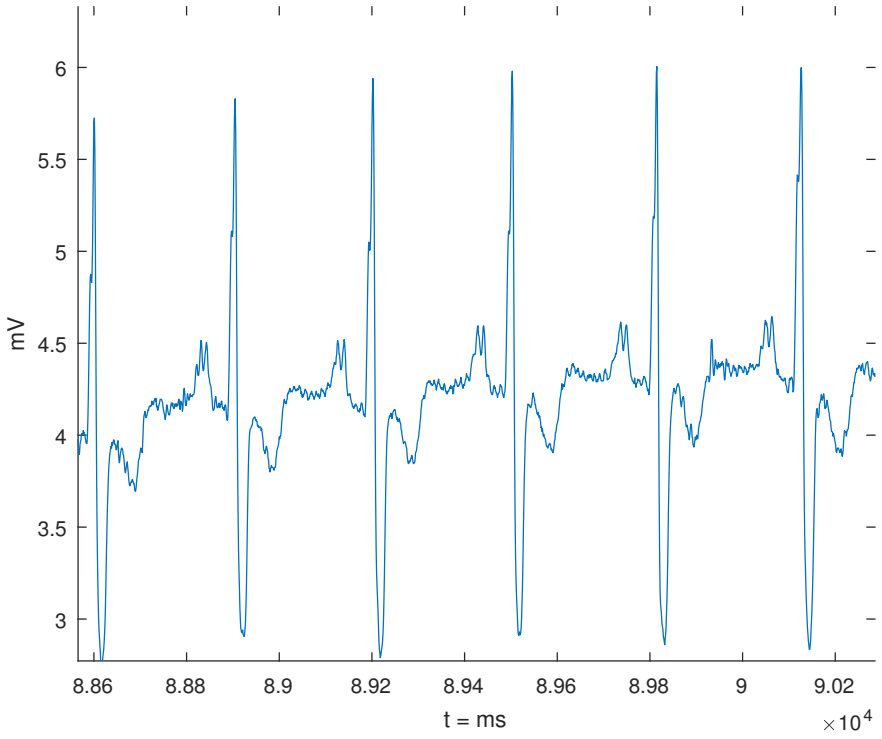


Figure 5: ECG signal with a low noise level [25]

2.6.1. Powerline interference

The leading cause behind the powerline interference noise in signals is because of the fault in the medical instruments or because of the experimental environment where there is Electro-magnetic (EM) waves[20], for example in ECG signals. Cables carrying ECG signals from the experiment room to the monitoring equipment are responsive to the electromagnetic interference (EMI) of power frequency (50 Hz or 60 Hz) by omnipresent supply lines and plugs so much that sometimes the ECG signal is masked by this type of noise [26]. So, power line interference removal is the initial step in all ECG signal processing [27]. The powerline interference can corrupt the signal of interest [20]. Also, the usage of differential amplifiers with high common mode rejection ratio is essential [20].

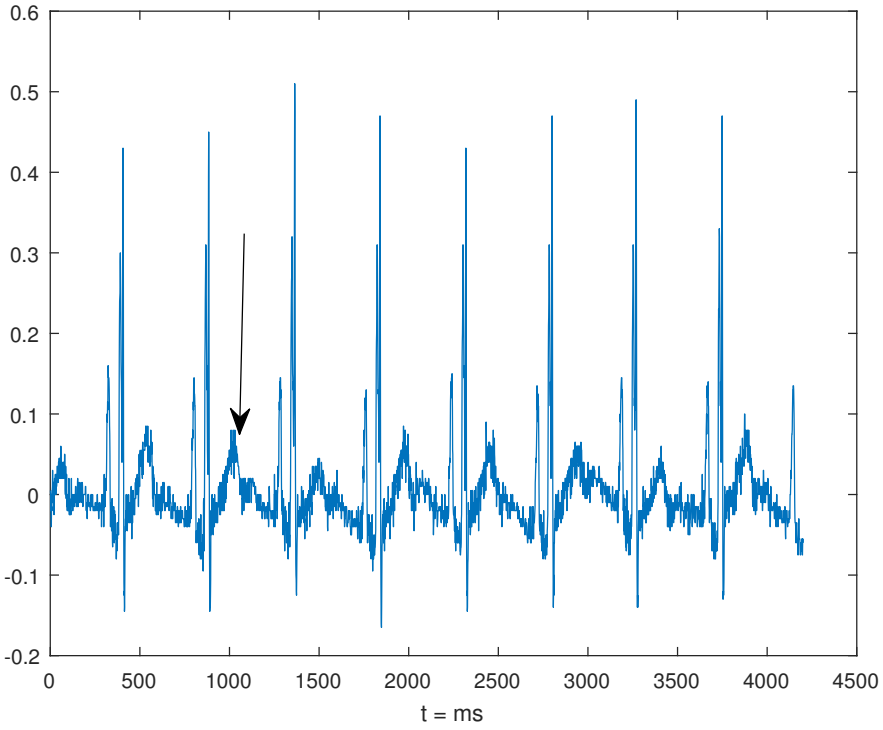


Figure 6: ECG signal with powerline interference

2.6.2. Electrode contact noise

Electrode contact noise is represented by a sinusoidal drift of the baseline of the ECG signal [20]. The main reasons behind baseline wandering are changing electrode-skin impedance, movements, and breathing of the patients [27]. This kind of noise is present in the ECG signal, while it is recorded during exercise, also during ambulatory and Holter monitoring [27]. Usually, the frequency range of baseline wander is less than 1.0 Hz, but it can be wider during exercise [27].

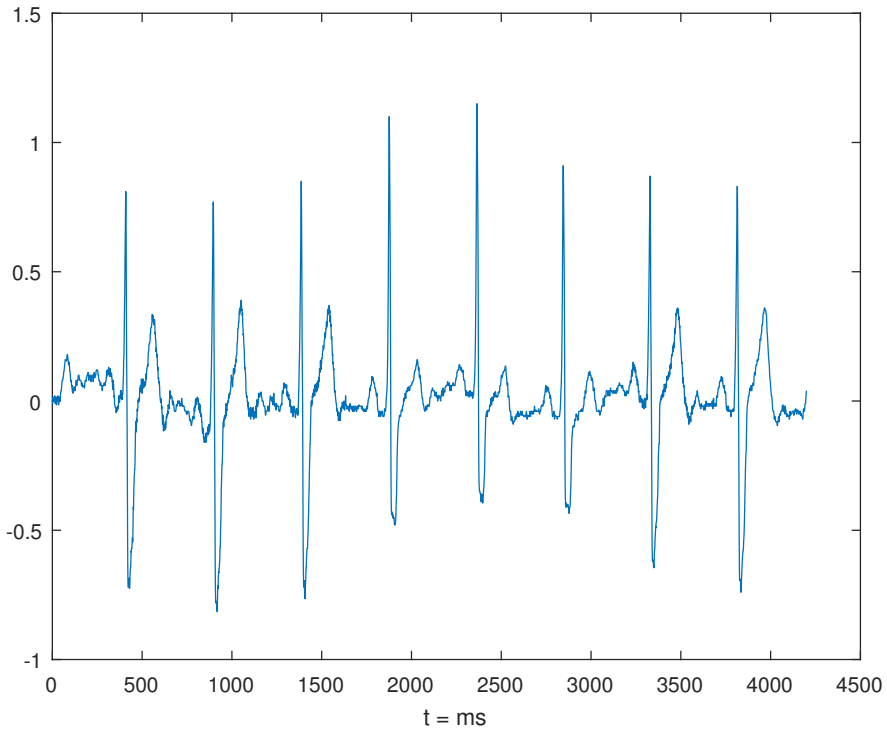


Figure 7: ECG signal with baseline wandering

2.6.3. Electromyographic noise

The generation of electromyogram (EMG) is from the electrical activity of the muscle; the range of the electrical signal is microvolt [20, 28]. During the ECG recording if the patient coughs or squirms then EMG noise will be generated in the ECG signal [20]. Portions of the ECG signal can be interfered and corrupted by EMG noise which can create difficulties in processing or analyzing the ECG data [28]. This kind of phys-

iological interference can be minimized by proper guidance and patient self-control. However, this may not apply to infants, children and older patients [20].

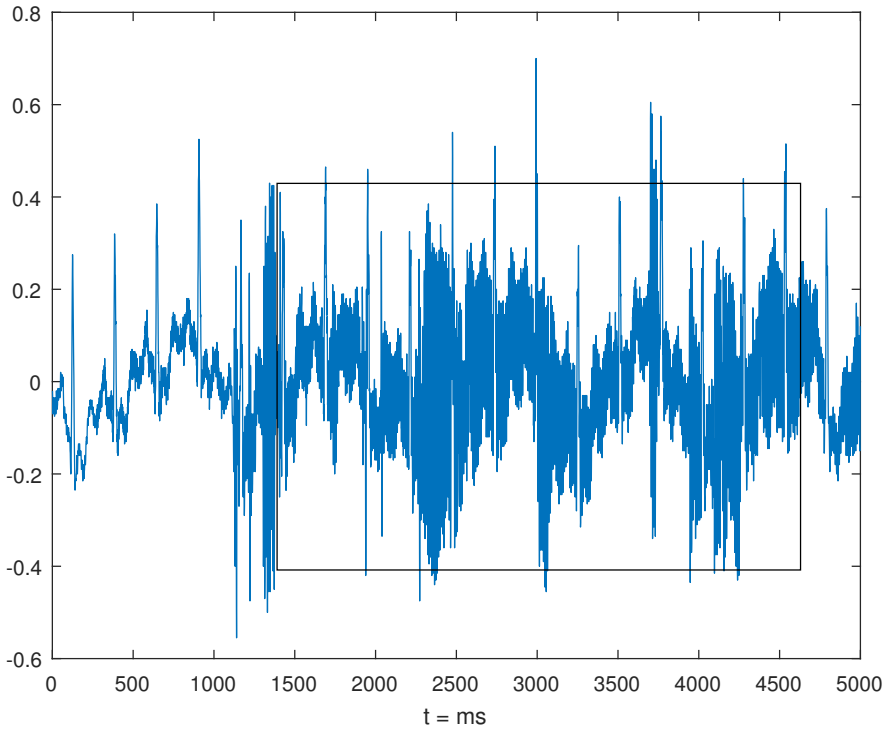


Figure 8: ECG signal with EMG noise

2.6.4. Motion artifacts

Motion artifact mainly can cause if the ECG signal recorded during the exercise of the patient [29]. Also, a patient lying on a hospital bed can make sudden movements: move a hand swiftly, turn on the bed or coughing can produce motion artifacts. In mobile ECG recordings, motion artifacts represent the most problematic source of the noise. These artifacts are potentials that are superimposed onto the ECG signal. It can be challenging to assess the ECG signal in this situation. Motion artifacts from electrodes are generated by disturbing the electrode/electrolyte equilibrium potential. An artifact which is generated from the skin is produced by the deformation of the skin under the electrode by changing the skin potential.

On the other hand, it is difficult to minimize motion artifact by design which is produced by interference from the electrical field. The amplitudes range of motion

artifact could be several millivolts. Motion artifact has the same frequency spectrum as ECG signals, and the shape of it can be very similar to ECG events [30].

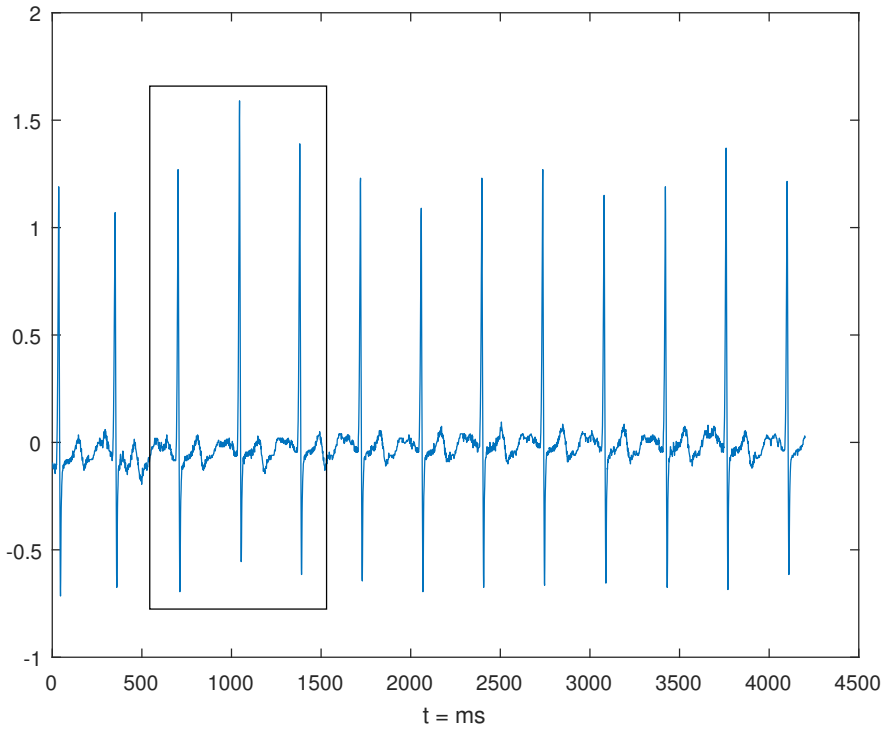


Figure 9: ECG signal with motion artifact

2.6.5. Instrumentation noise

The electrical instruments that are used in ECG recordings can also create noise. The primary source of this type of noise is electrode probes, signal processor/amplifier, cables and analog to digital converter. We usually cannot get rid of this noise unless using high-quality instruments and be very careful while designing the circuit. Resistor thermal noise which is also known as Johnson noise is one type of electrical noise. Because of the random fluctuations of the electrons for the thermal agitation make this type of noise. The power spectrum is given as

$$\bar{V}^2 n = 4kTR \tag{1}$$

Where k is the Boltzmann's constant, T is the temperature, and R is the resistance. By this equation, we can say that the resistor thermal noise is white for all frequencies. However, if the frequency is larger than 100 Hz, then the power spectrum starts to drop off. There is another important type of noise named flicker noise in ECG recordings because of its low frequency. The actual reason of this type of noise is not clear yet, but there is one widely accepted theory related to this type of noise that is the reason of this noise is caused by the energy traps which happens between the interfaces of two materials. It is believed that the charge carriers get randomly trapped/released and create flicker noise. Flicker noise results would be highly noticeable at the electrodes since the amplitude of the detected signal is in millivolts range [31].

2.7. ECG Signal Quality Considerations

The quality of the signal depends on the application of it. One possible approach to defining ECG quality is the following:

• Basic ECG quality: Can identify the R-peaks. In this case, we can extract a reliable HR and also some types of arrhythmias and information of HRV.

• Diagnostic ECG quality: identifiable p (if present), QRS and T waveforms. This form of ECG signal can be used for clinical diagnosis of more critical conditions like myocardial ischemia and coronary heart disease.

In the first type of ECG signal there can be some presence of noise; the quality feature is less strict in this case. We may still get a reliable HR from it. For example with baseline wandering in the ECG signal, which is generated from the motion artifacts, it is possible to get reliable HR from it. The data that is obtained from any wearable health devices contain more noise; in this case, the basic quality of the signal is sufficient.

It is not common that diagnostic applications from the ECG signal are used when the patients are in some motion unless the wearable device is intended to identify some abnormality, for example, Atrial Fibrillation (AF). In this situation, it is a clear indication of the arrhythmia if the P-wave is absence. So, it is the most important thing to identify the absence of P-wave in the presence of motion artifact [17].

2.8. ECG Signal Quality Assessment

Research shows that existing ECG recording systems sometimes produce unreliable or inaccurate ECG measurements, which is the main reason to get the high amount of false alarm in healthcare because of the noisy ECG signal [14, 15, 4, 32]. Frequently generation of false alarms is not only a disturbance to the medical experts or clinicians

and also to the patients, but it can also lead to a misdiagnosis of cardiac arrhythmias [4, 32]. Currently used ECG signal detection and recognition algorithms are still suffering from getting high rates of false alarms because these algorithms cannot distinguish between the ECG artifacts, noises, and the real ECG morphology. SO, it is a mandatory task to assess the quality of the ECG signal & filtering the signal with specific features related to the noise or artifact to reduce the false alarm.

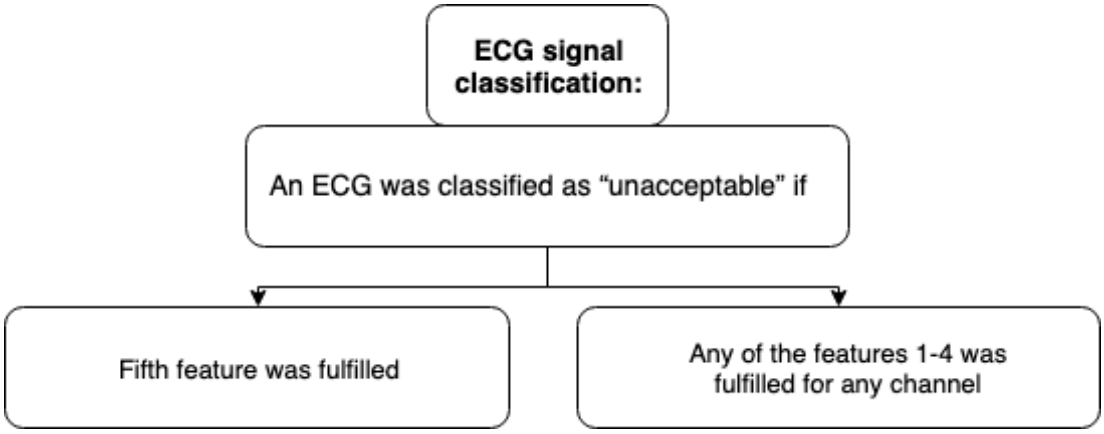
The issue of high false arrhythmia event alarm and heart-rate alarm rates highly impact the usability of real-time ECG monitoring systems. Because of the two main reasons: first, Noises and artifacts in the isoelectric line of the ECG signal are falsely detected as normal beats or abnormal beats; and Second, severely contaminated ECG beats are misclassified due to the inaccurate measurements of necessary ECG feature parameters. Therefore, many approaches have been taken to handle the problem of high false alarm rate due to the noises and artifacts: 1) ECG denoising based strategy to suppress the noises and artifacts in the ECG recordings and 2) Signal quality index (SQI) based strategy to assess the clinical acceptability of the recorded ECG signals [14, 15, 4, 32]. In this thesis, we focused on the Signal quality features based strategy to assess the quality of the signal.

3. METHODS

3.1. Signal Quality Features

In this chapter ECG signal quality assessment methodologies are explained. We have implemented an algorithm to develop a measure for ECG quality assessment based on a) basic signal quality properties (amplitude, spikes, and constant signal portions/flatline), b) the number of crossing points between different leads. These are the essential quality of an ECG signal to be assessed [16]. Every single channel of ECG was analyzed utilizing four features that are based on a fixed set of Boolean rules that combine knowledge from the data based on if it fulfills or not certain basic features concerning the fundamental signal properties.

The first feature is based on Signal amplitude, the Second feature is based on Spike detection of the signal, the Third feature is based on Zero line detection of the signal, the Fourth one is the combination of the previous three criteria (Total length of the remaining signal), the Fifth quality feature is based on the number of lead overlapping in the ECG signal [16] and the sixth quality feature is based on the energy of the signal [1]. These features are developed for a specific duration (i.e.10-seconds) ECG signals and the ECG sampled at 500 Hz. The final ECG signal classification is shown below:



3.1.1. Amplitude of the signal

The first signal quality feature is based on an essential signal characteristic, which is the signal amplitude. In this feature, we have selected a standard amplitude (i.e., +-2mV for the ECG signal) threshold to detect the ’bad’ portion of the ECG signal. So,

if the feature detected ‘bad’ portion is higher than 40 percent of the ECG signal, then the feature will be fulfilled [16]. That is the signal amplitude considered as the bad portion which is higher than +-2 mV (see Fig. 10).

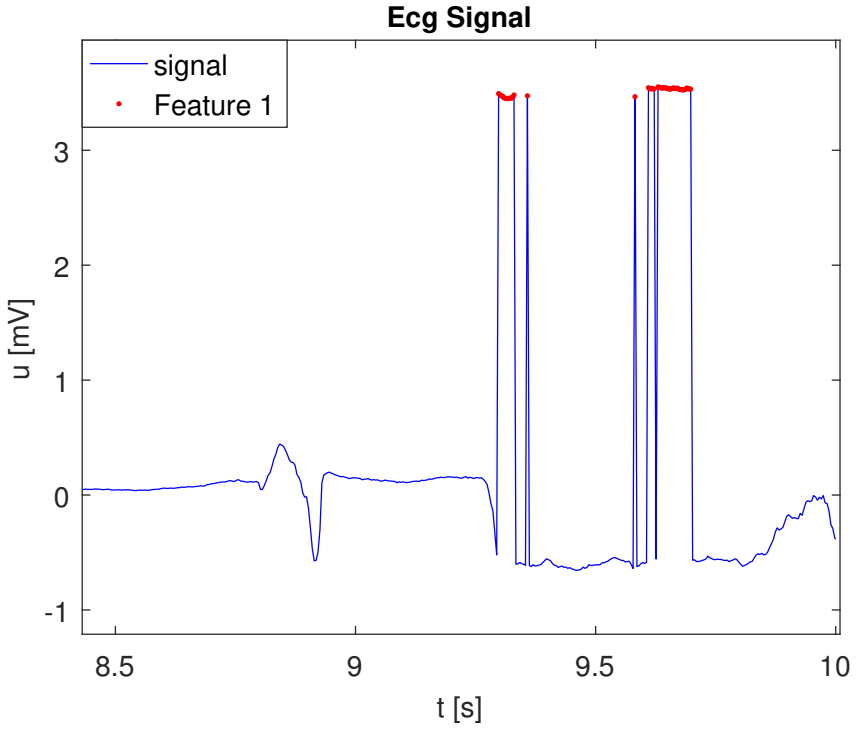


Figure 10: The red portions of the signal marked as bad parts by feature one of the algorithm as it crossed +2 mV.

3.1.2. First derivative of the signal

The second signal quality feature is based on the first derivation of the signal. By calculating this, we can detect the signal portions which are situated near to the signal spikes. These portions will be detected if the first derivation of the signal is higher than 0.2 mV/sample (see Fig. 11) and the feature will be fulfilled if the portion is higher than 40 percent of the analyzed signal [16].

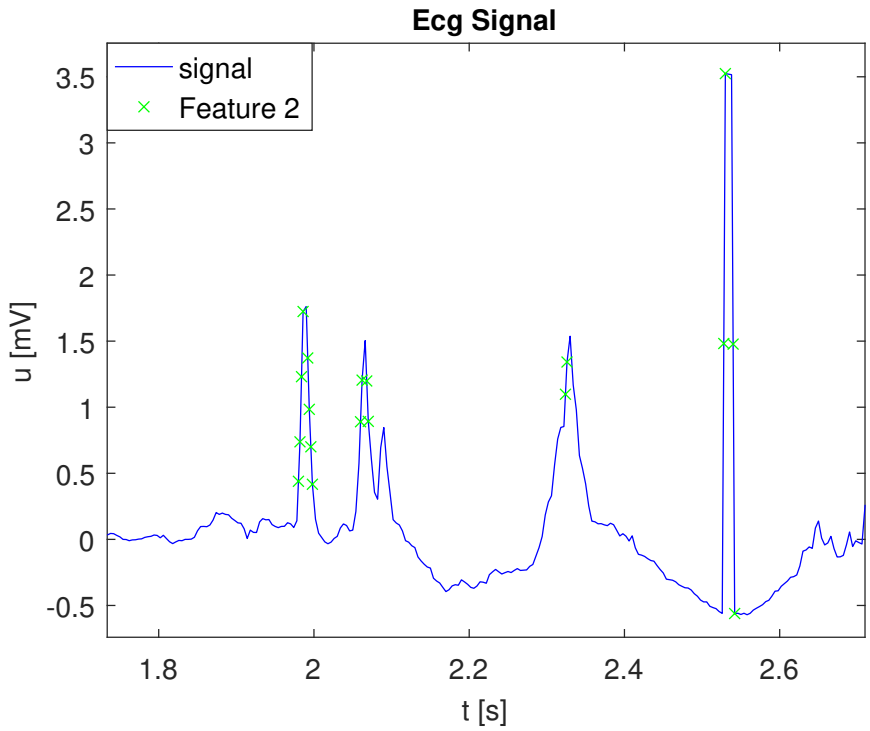


Figure 11: The portion of samples that is close to spikes is detected with green cross marks as it satisfy feature 2 (i.e., part of samples arranged near to spikes that are the first derivative of the signal is greater than 0.2 mV/sample).

3.1.3. Samples with same amplitudes

The third signal quality feature is based on having the same amplitudes with their previous sample (see Fig. 12) in the signal. This criterion will be fulfilled if these portions of the signal are higher than 80 percent of the total signal. By using this feature, we can detect the zero line portions and also entirely overpowered portions [16].

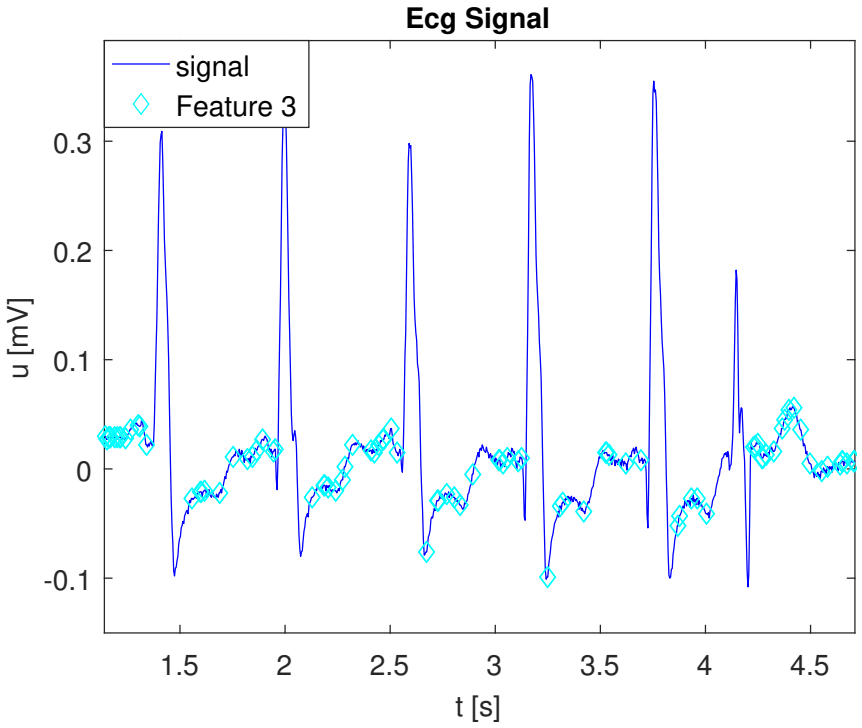


Figure 12: The portion of samples that is having the same amplitudes with their previous sample detected with blue marks as it satisfies the third quality feature (i.e., having the equal amplitudes with their previous sample in the signal, if these portions of the signal are higher than 80 percent of the total signal).

3.1.4. Combination of previous features

The fourth feature is the combination of the previous three features. We considered the percentage of the signal portions that are detected as 'bad' by the first three features as the fourth feature. So, if the percentage of these 'bad' portions of the signal is higher than 68.5 percent, then the fourth feature will be fulfilled [16].

3.1.5. Overlapping of the ECG leads

The fifth feature is based on the overlapping of the leads in a paper ECG. Analyzing the ECG signal in this situation is difficult. So, we have plotted the signal as one lead underneath the other to see the overlapping (see Fig. 13) of the leads. When a lead overlapped with other leads it is not just so difficult to analyze the drifting lead; also it is quite difficult to analyze others sometimes. So, in this feature, we have counted how many times a lead crosses any other leads. If the number of this situation goes higher than 49, then the ECG signal will be classified as 'Unacceptable' [16].

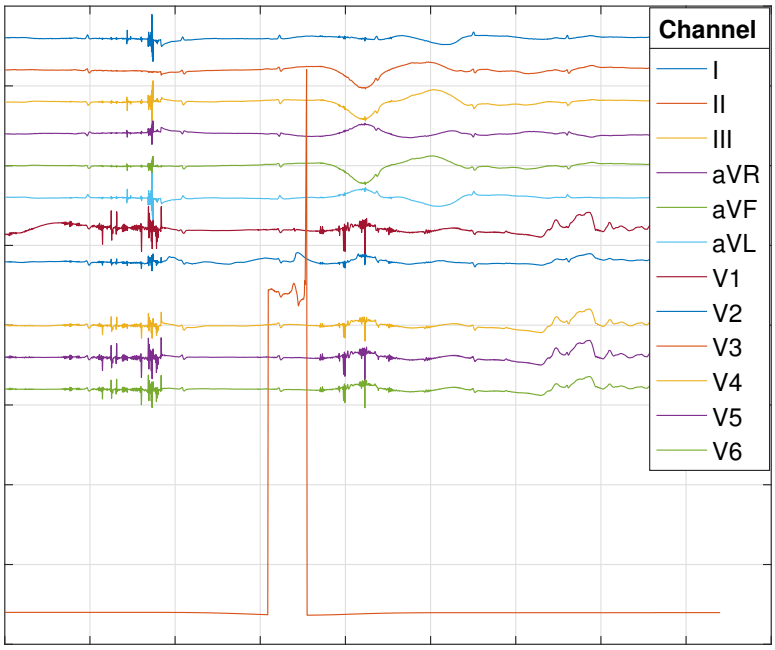


Figure 13: ECG representation plotting one lead underneath the other illustrating the effect of drifting leads (V3) on the quality of the plot. If any lead overlap with any other leads more than 49 times, then the signal will be classified as unacceptable by the fourth quality feature.

3.1.6. Energy ratio of the signal

To identify the noise content in the ECG signal frequency-domain method uses spectral features analysis. It separates the signal contents in two different frequency bands, i.e., low-frequency noise band (0–0.5 Hz) and high-frequency noise band (45–250 Hz) by using simple spectral features calculated in the 0.5-40 Hz band of the signal. By computing different parameters such as the signal-to-noise power ratios and the power in each frequency band, the complete feature space is obtained for each channel, both on the entire signal and 2.5 seconds segments of the signal [1].

3.2. Material

Training data Set-A is used of the PhysioNet/Computing in Cardiology Challenge 2011 [25, 33] to verify the algorithm. It contains 1000 recordings with quality labeled for reference either as acceptable (773 of 1000) or unacceptable (225 of 1000). Cases without a label are considered to be of indeterminate quality (2 of 1000). For our aims and purposes, the uncertain records are removed from the learning dataset. In our experiments we avoided the initial 800 ms of the signals as they have also done

the same methodology in the PhysioNet challenge 2011, due to a few ECGs indicated transient beginning characteristics [16]. This dataset contains standard 12-lead ECG recordings with 10-second duration acquired with conventional ECG equipment. Each ECG lead is sampled at 500 Hz with 16-bit resolution and the bandwidth from 0.05 Hz to 100 Hz [34].

The 'VitalSens' dataset, which is measured by research partner in India in the 'VitalSens' project and the data collection has been given ethical permission by the local authorities. There are 19 subjects in this dataset; the duration of each recorded ECG is 6 hours and the sampling rate of 125 Hz. ECG signals included with motion artifacts and missing data. All the subjects were cardiac disease patients; most of them were arrested by atrial fibrillation, bradycardia and tachycardia heart diseases.

4. EXPERIMENTAL RESULTS AND ANALYSIS

In this chapter, we elaborate the conducted experiments and the results obtained using the methods.

4.1. Performance evaluation metrics

The performance of the ECG signal quality assessment method is evaluated using the five benchmark performance metrics such as sensitivity (Se), positive predictivity (Pp), negative predictivity (Np), specificity (Sp) and accuracy (Ac) [35], which are defined as,

$$Se = \frac{TP}{TP + FN}, Sp = \frac{TN}{TN + FP} \tag{2}$$

$$Pp = \frac{TP}{TP + Fp}, Np = \frac{TN}{TN + FN} \tag{3}$$

$$Ac = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Where the true positive (TP) indicates the number of correctly identified unacceptable or noisy ECG signals by the ECG signal quality assessment method, the false negative (FN) indicates the number of poor quality of ECG signals which are identified as the acceptable signal quality by the method, the true negative (TN) indicates the number of correctly identified acceptable ECG signals and the false positive (FP) indicates the number of acceptable ECG quality signals which are identified as unacceptable quality signals by the ECG signal quality assessment method [35].

4.2. Experiment Results

This algorithm classified 188 out of 998 ECGs of the trainings-set (set a) as “not acceptable.” The remaining signals were classified as “acceptable.” The portion of correctly classified ECGs was 92.6% with the training-set using the threshold of the first quality feature +-2 mV. Then we also applied the algorithm with some different thresholds in these criteria if the results differ a bit. The algorithm classified 186 out of 998 ECGs of the trainings-set (set a) as “not acceptable” for the threshold 2.5 mV and 185 with threshold 3 mV in quality feature-1. The accuracy was respectively 92.68% and 92.58% (See table 1). As we can see by selecting a higher threshold, the accuracy is going down. Therefore, we tried with some thresholds lower than 2 mV. For 1.8 mV

and 1.5 mV we got the same accuracy but with 1 mV we have got the highest accuracy that is 93.08% (See table 1). Then we applied some threshold less than 1 mV for the feature-1, by using 0.8 mV and 0.5 mV we got the accuracy 92.48% and 92.58% respectively (See table 1).

Table 1: Performance Metrics For Different Thresholds for Quality Feature 1 (Signal Amplitude). The Value of All Performance Matrices Increases by Decreasing The Value of The Threshold of Quality Feature 1.

Thresholds (mV)	Accuracy	Sensitivity (TPR)	Specificity (FPR)
0.5	92.58%	94%	84%
0.8	92.48%	94%	86%
1	93.08%	96.53%	86.76%
1.5	92.68%	95.8%	83.9%
1.8	92.68%	95.33%	82.13%
2	92.69%	95.33%	82.13%
2.5	92.69%	95.09%	81.25%
3	92.58%	94.97%	80.77%

The values of the Sensitivity (TPR) and Specificity (FPR) changes not so much (as all the points are so close to each other) by varying the threshold of the first quality feature, we can see that by the points in the ROC curve (see Fig.14). We also checked the performance of the of the first three principle quality feature separately with the same dataset (training dataset a), by using only the first quality feature we got accuracy 89.98%, sensitivity 90% and specificity 64% (See table 2). For the second feature we got accuracy 78.45%, sensitivity 78% and specificity 50% (See table 2). And for the third quality feature we got accuracy 90.98%, sensitivity 91% and specificity 66% (See table 2).

Table 2: Performance Metrics of each feature with fixed thresholds.

Feature	Accuracy	Sensitivity (TPR)	Specificity (FPR)
Feature 1	89.98%	90%	64%
Feature 2	78.45%	78%	50%
Feature 3	90.98%	91%	66%

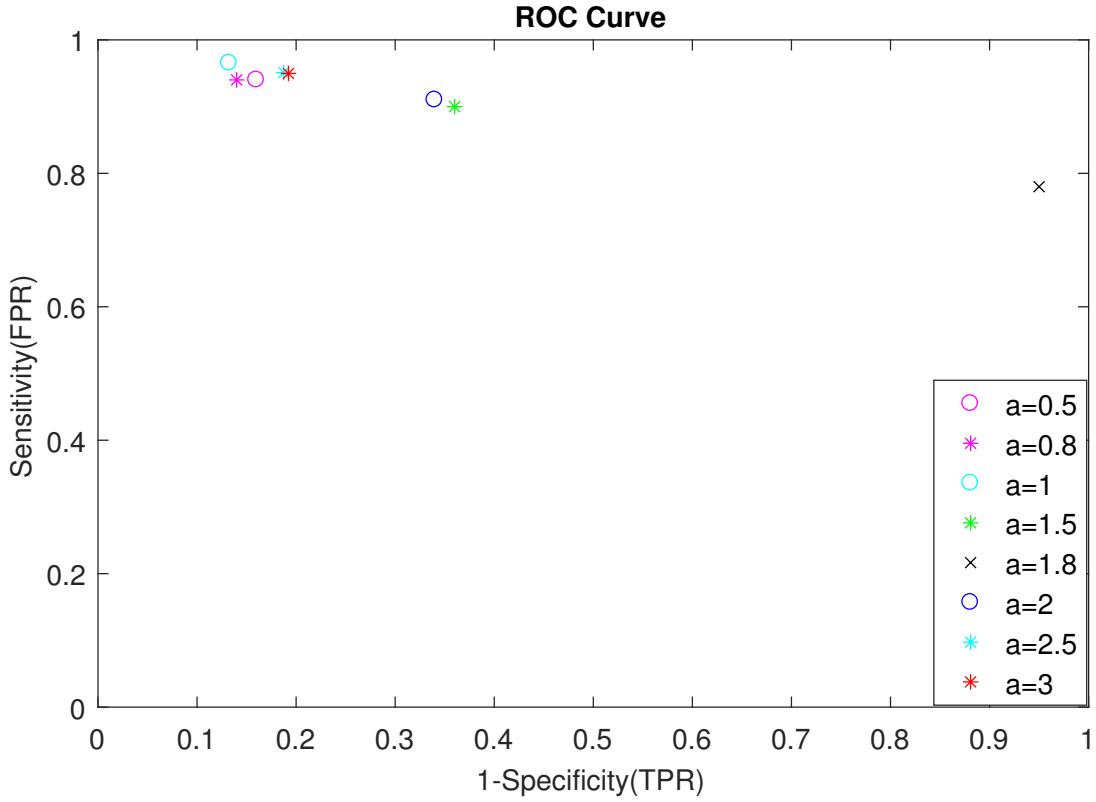


Figure 14: Points of the ROC curve with different thresholds for quality feature 1, we can see the difference in the performance of the algorithm by changing the threshold of quality feature 1.

The energy ratio of the signal feature correctly classified 86.7% of the ECG signals (see Fig. 16). We combined this quality feature with the previous features and got the highest accuracy of 92.98% (See table 3).

Table 3: Performance Metrics of the energy ratio feature with the algorithm using different thresholds. Here, Threshold 1 is the ratio and threshold 2 is No. of bad signal leads.

Threshold 1	Threshold 2	Accuracy	Sensitivity (TPR)	Specificity (FPR)
0.6	7	92.28%	95%	84%
0.8	6	78.45%	94%	87%
0.8	8	92.98%	94%	88%
0.8	9	90.08%	93%	88%

We can see in Figure 15, the performance of the algorithm with a different threshold for the ECG quality feature 1(signal amplitude) and quality feature 2 (first derivative of the signal). For the threshold 0.5 (signal amplitude in mV) of first ECG quality feature, we used a range of threshold (i.e., 0.1, 0.15, 0.2, 0.25, 0.3) for the quality feature 2, the highest accuracy achieved with this combination of the thresholds is 92.58%. For

the thresholds 0.8 of the first quality feature with the range of second quality feature thresholds, the highest accuracy of 92.48%, which is less than previously achieved accuracy. Then for the thresholds 1 of the first quality feature with the range of second quality feature thresholds, the highest accuracy of 92.48%, which is the highest achieved accuracy 93.08% with this algorithm. Then using thresholds 1.5 for the first quality feature with the range of different thresholds of quality feature 2, highest accuracy achieved is 92.68%, which is less than previously achieved accuracy. Then with the thresholds 2 for the first quality feature with the range of different thresholds of quality feature 2, highest accuracy achieved is 92.69%. Also, finally with the thresholds 2.5 for the first quality feature with the range of different thresholds of quality feature 2, highest accuracy achieved is 92.58%, which is less than previously achieved accuracy.

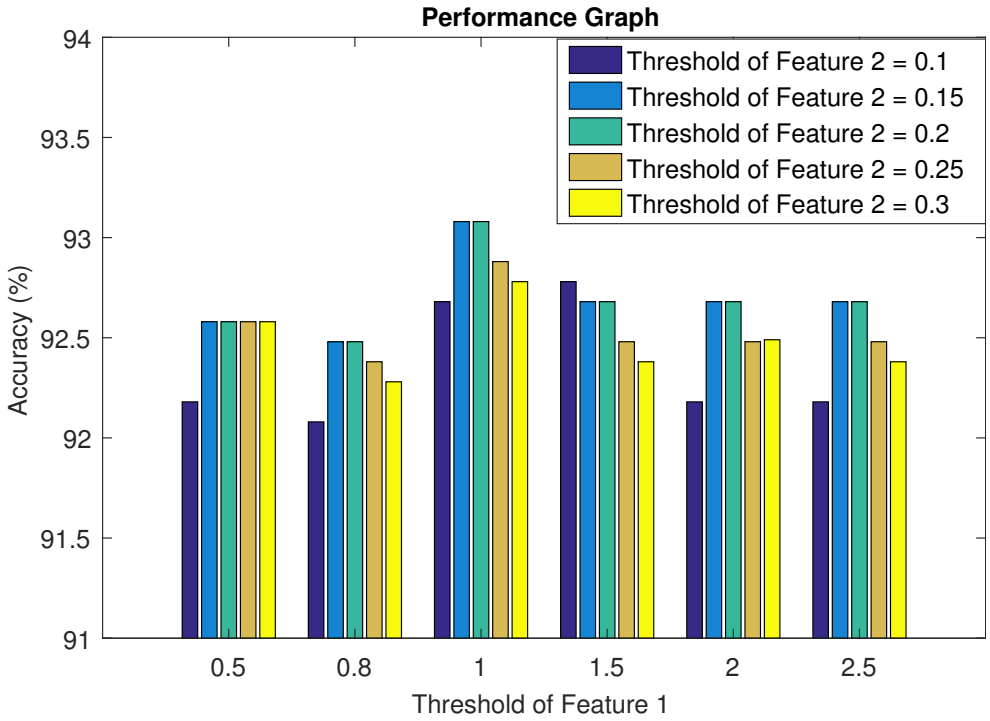


Figure 15: Performance Graph of the algorithm using different thresholds in Feature 1 & Feature 2.

In Figure 16 we can see, the performance of the algorithm with a different threshold for the energy ratio of the signal quality feature threshold 1(i.e., energy ratio of the filtered signal) with the range (i.e., 4,5,6) of the second threshold (No. of leads over the threshold). For the threshold 0.5 (ratio of the filtered signal) for the first threshold, we used a range of values (i.e., 0.1, 0.15, 0.2, 0.25, 0.3) for the second threshold, the highest accuracy achieved with this combination of the thresholds is 85.87%. For the value 0.6 of threshold 1 with the range of values for the second thresholds, the

highest accuracy of 86.67%, which is the highest achieved accuracy by this quality feature. Then for the value 0.7 of threshold 1 with the range of values for the second thresholds, the highest accuracy of 86.37%, which is less than the previously achieved accuracy. Finally for the value 0.8 of threshold 1 with the range of values for the second thresholds, the highest accuracy of 86.37%, which is the same as the previously achieved accuracy.

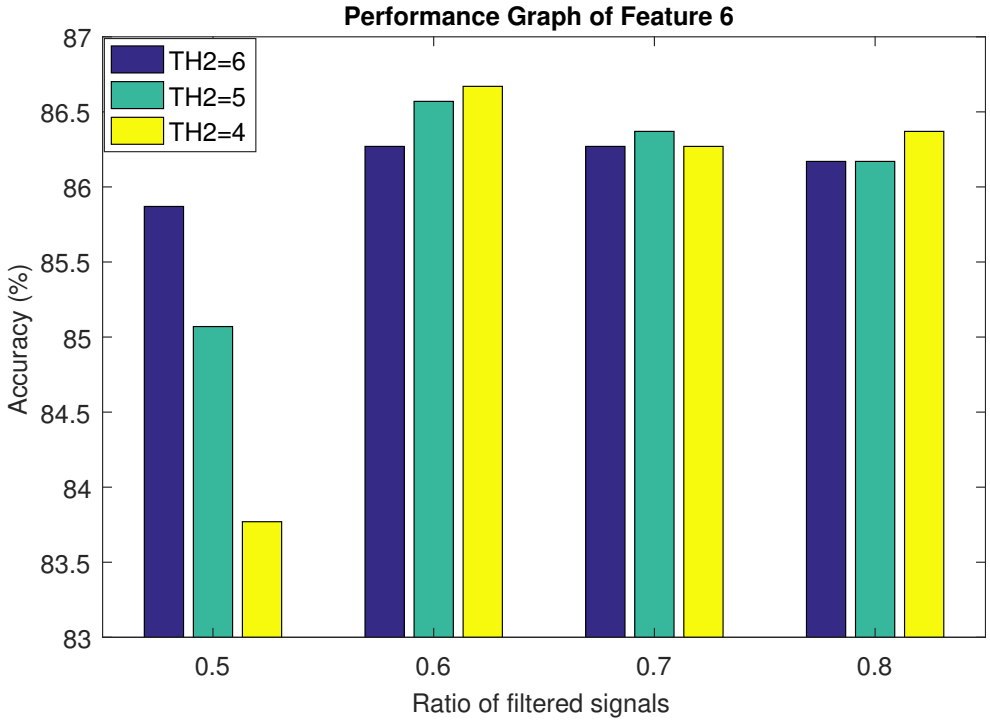


Figure 16: Performance graph of Energy ratio of the signal quality feature.

In figure 17 and the figure 18 we can see the effects of the algorithm visually with the physionet training data set-a. The first signal in figure 17 is classified as 'acceptable' by the algorithm, where a very small portion of unwanted artifacts detected by the different quality features of the algorithm. Red portions are detected by the first quality feature (signal amplitude), and green cross marks are detected by the second quality feature (first derivative of the signal) of the algorithm. Now in figure 18 which is classified as 'unacceptable' by the algorithm, we can see a large portion of red (feature 1) and green (feature 2) marks in the signal.

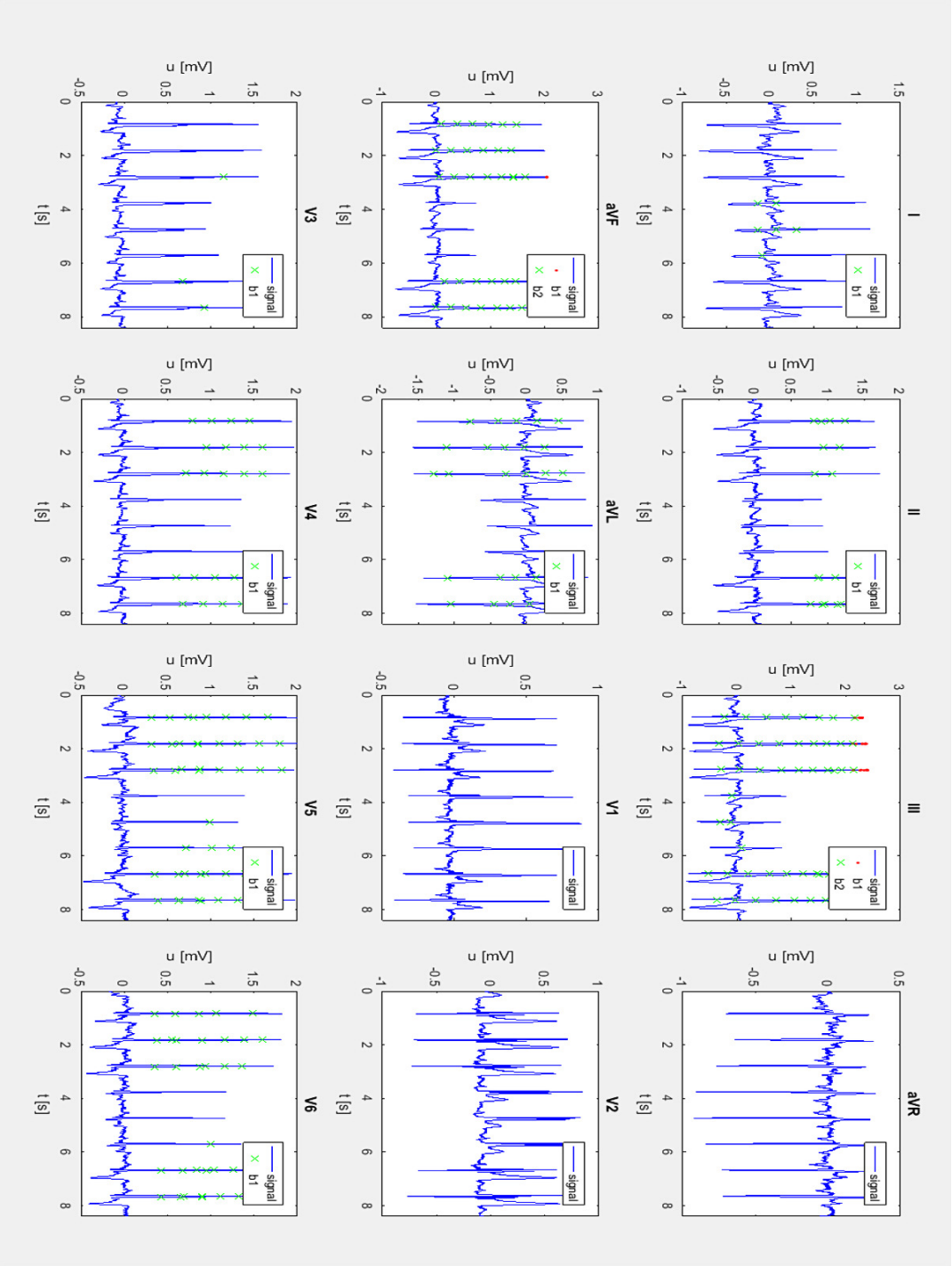


Figure 17: Visualization of the Physionet training data (acceptable/good quality signal) with the algorithm.

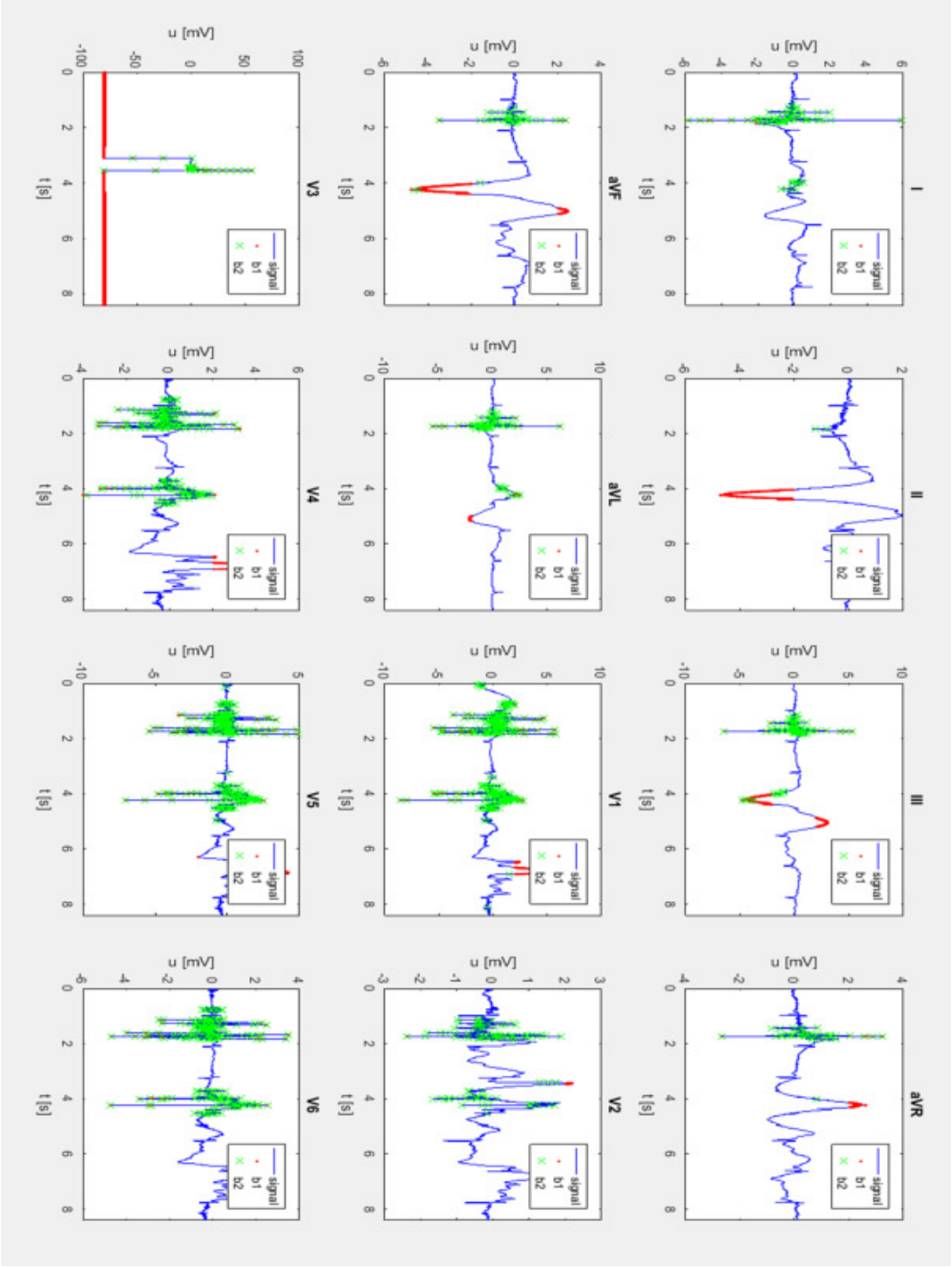


Figure 18: Visualization of the Physionet training data (Unacceptable/bad quality signal) with the algorithm.

As this thesis work was a part of the 'VitalSens' project, we have used the algorithm to visualize the bad parts of the 'VitalSens' ECG data (see Fig. 19 & 20). In figure 19, we can see sky-blue marks in the signal which is detected by the quality feature 3 (samples with same amplitudes).

And In figure 20, we can see the portions detected by different quality feature of the algorithm; red portions are detected by the quality feature 1 (signal amplitude), green cross marks are detected by the quality feature 2 (first derivative of the signal) and sky-blue marks are detected by the quality feature 3 (samples with same amplitude).

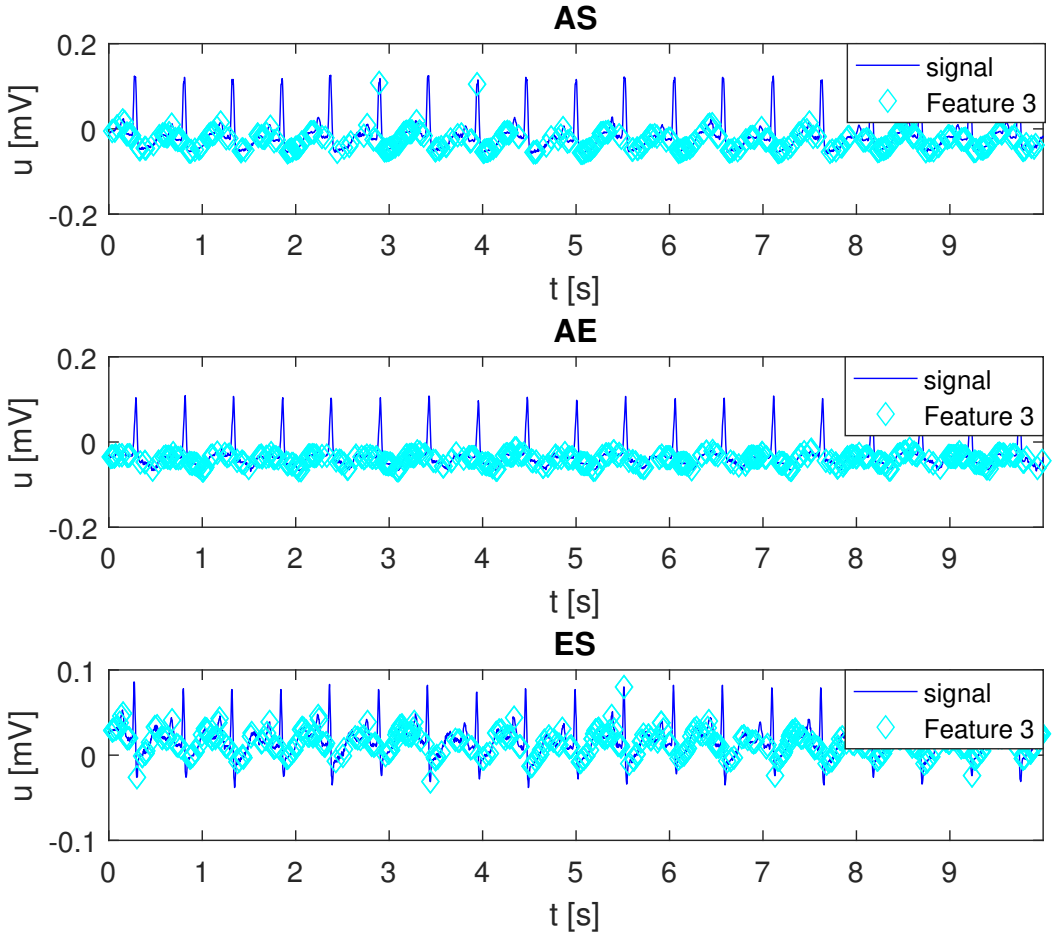


Figure 19: Visualization of the 'VitalSens' data (good quality) with the algorithm.

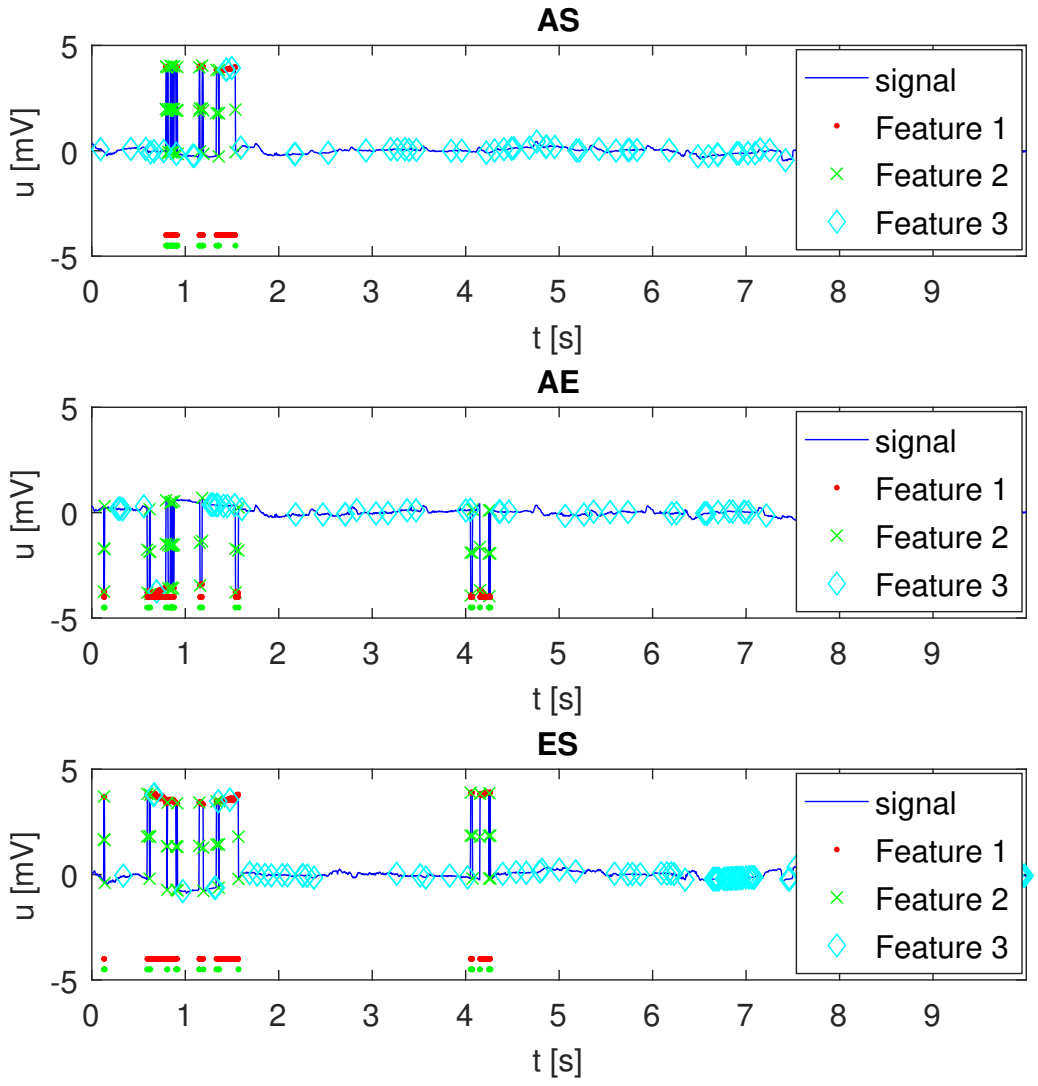


Figure 20: Visualization of the 'VitalSens' data (bad quality) with the algorithm.

5. DISCUSSION

The performance of the algorithms has been evaluated by using the same data set that is used in the Computing in Cardiology Challenge 2011. We could consider that such algorithms are a valuable tool for ECG recordings done by untrained personnel or patients themselves in rural areas or where less expertise is available. We expect that the algorithm would be advantageous to get the desired ECG data for further biomedical procedures.

The algorithm is extraordinarily compact and fast from a particular algorithm from the paper [16] by Dieter Hayn et al. we followed where both classification accuracy and computation time were relevant. We got nearly the same results with a reduced set of rules as in the paper [16] by Dieter Hayn et al. they have used more rules. Based on the data that we have tested with this algorithm, it was fast; it took only around 7 minutes to run and check the 1000 ECG data (Physionet 2011 training dataset A). That is it takes less than 1s (exactly 0.42s) to check one 10s long ECG signal. In a real-life scenario, computation times up to real-time (e.g., 0.42 s computation time per 10 s ECG) would probably be sufficient for giving feedback to the person recording the ECG [16].

In this algorithm the fixed number of Boolean rules logic limit the scope of the work, here we used some criteria with some fixed threshold to classify the ECG signals. So, this algorithm would be more efficient with the fixed kind of ECG signals as we fixed the threshold in the algorithm to classify. For different kinds of ECG signals, we have to change the thresholds manually. For better result, in future machine learning method can be applied to fix the threshold for different subject needs automatically.

Decision trees (DTs) have been successfully utilized for regression and classification assignments. Effortlessness when applying DTs, interpretability, the capacity to handle lost attributes also the characteristic of being non-parametric are considered as first preferences of DTs [18]. Using this algorithm, they [18] got 90.4% accuracy in CinC challenge 2011, for that case we did not use that algorithm.

6. CONCLUSION

It is quite difficult to assess the quality of the signal during the recording of the ECG signal, although it can be achievable and can be helpful to non-specialist and patients. The method for classifying the quality of ECGs presented in this thesis is a compact, simple and a general approach to the problem of automatically identifying trustworthy ECG signals for further biomedical inspections. We got the scores those are marginally near to the scores they [16] got by using the same type of ECG signal quality features in the PhysioNet competition [16].

The achieved training accuracies of 93.08% indicate the accurate classification of noisy ECGs is possible, although the accuracy might not seem so impressive, but the paper [16] we have followed got 93.33% accuracy and got the 1st place in one of the events in CinC challenge 2011. The accuracy of the algorithm Varies for different types of ECG data that is collected with different types of ECG measuring equipment. We can change the threshold of the rule/rules like the signal amplitude related rule here in this algorithm to get better accuracy for different ECG signal data sets. So, this an efficient way to assess different types of ECG data with this simple algorithm.

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8. APPENDICES

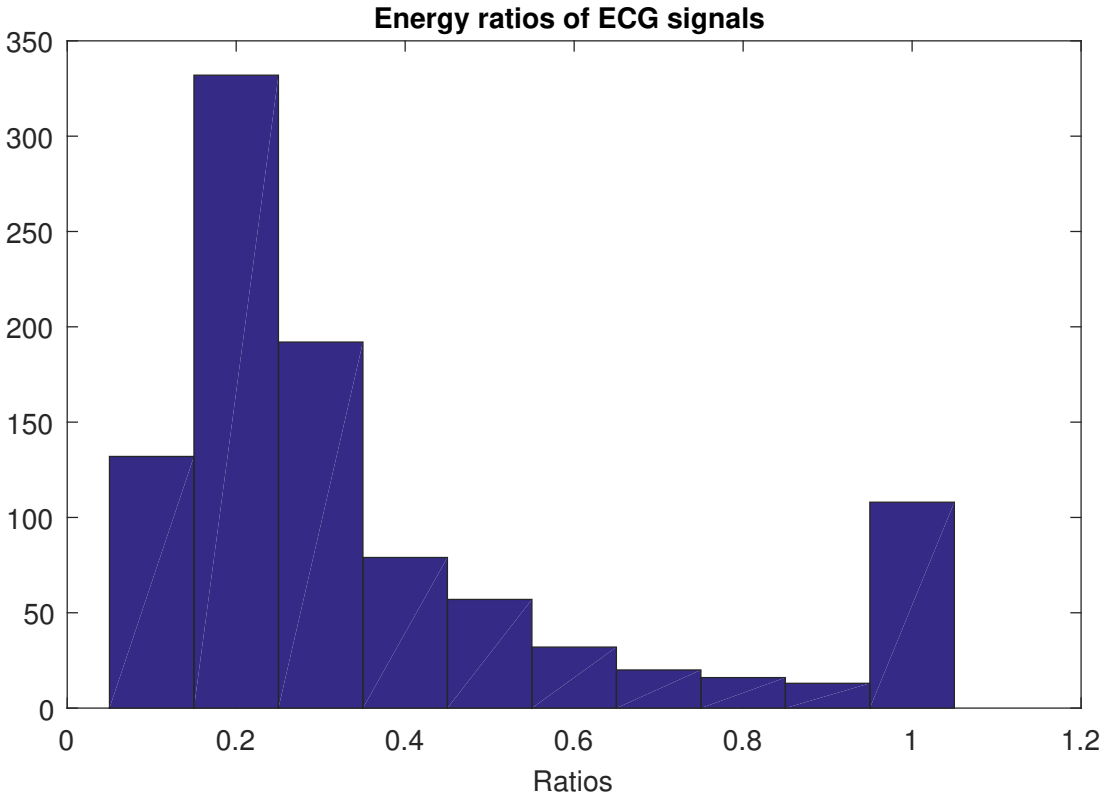

Figure 21: Energy ratio of all Physionet training data (Set-A) signals.

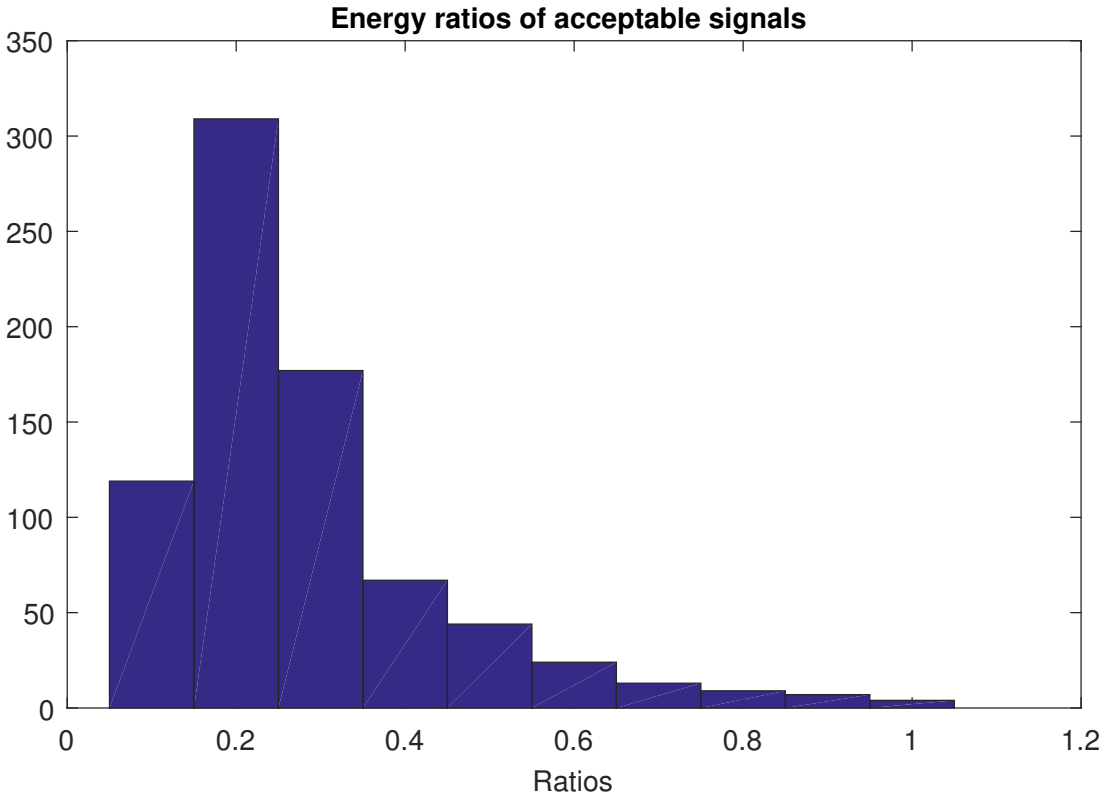

Figure 22: Energy ratio of Physionet training data (Set-A) acceptable signals. We can see that most of the acceptable signal's energy ratios are less than 0.8.

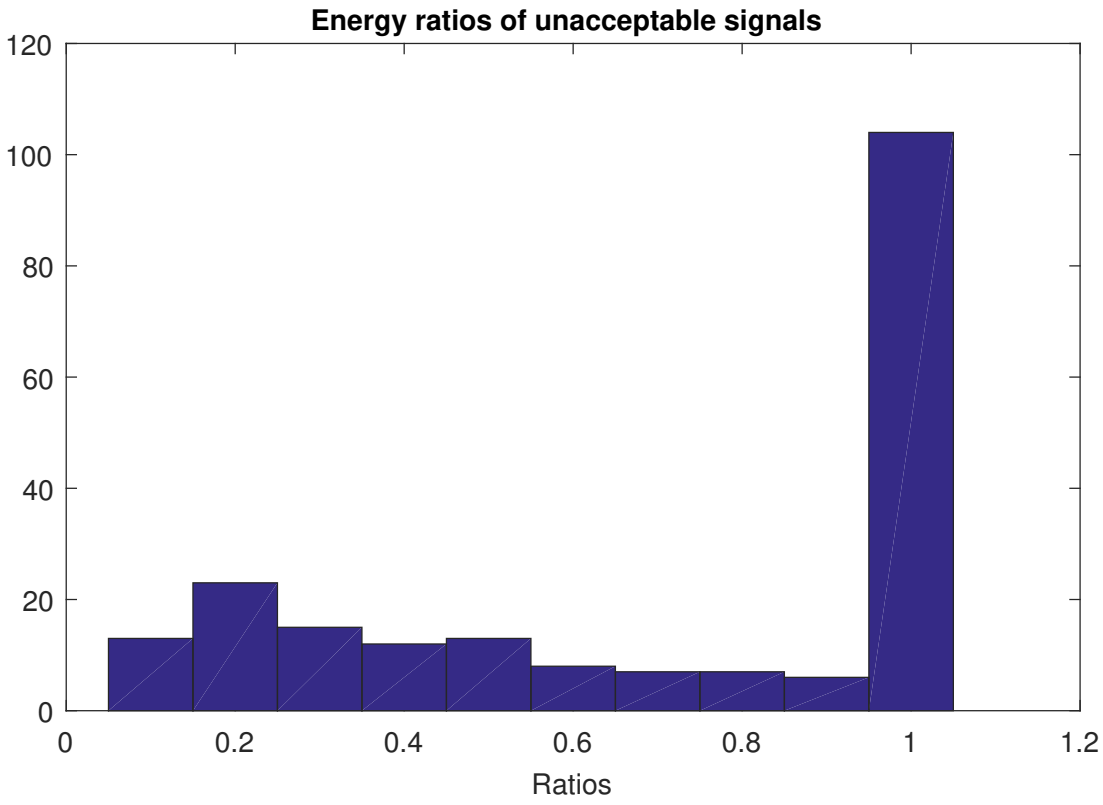

Figure 23: Energy ratio of Physionet training data (Set-A) unacceptable signals. We can see that most of the unacceptable signal's energy ratios are greater than 0.8 or equal to 1.