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***An Algorithm Derived from the Literature to
Detect Ischemia on ECG Recordings and
Implemented by MATLAB***

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Abstract

It has been more than 100 years since Einthoven used electrocardiogram to diagnose in clinical medicine. During these years, the continuous development of ECG technology for human health and survival has made a great contribution. Electrocardiogram has also become the most important index to evaluate and diagnose the heart health condition of patients. In the processing of ECG signal analysis, the program has been developed on Matlab, based on the research of ECG processing technology. It not only can realize the ECG signal preprocessing, feature detection and analysis, but also make a simple medical report after reading the input ECG.

Firstly, based on multi-scale decomposition of ECG signal, wavelet approximation is applied to the signal and after an adaptive wavelet threshold denoising method, the original ECG signal is preprocessed.

Secondly, during feature detection of the electrocardiogram, wavelet transform method is improved in QRS complex detection. It makes use of not only wavelet coefficients, but also ECG signals to locate accurately the QRS complex. After QRS complex detection, the T wave is detected by the amplitude and the slope in certain section. This method works well for normal signals. For ST segment morphological analysis, a method is proposed. Once the ST segment analysis region is detected, the offset level, the curve type, the slope and the camber are adopted to the essential morphological features of the ST segment. Meanwhile, the classification of ST segment morphology is carried out gradually. This method can detect different shapes of the ST segment.

Finally, the ECG diagnosis of myocardial ischemia is achieved by a logical method with clinical knowledge: the logical method is like the way the physician observes the ECG recording, which is simple in principle, clear in clinical classification, effective in diagnostic realization. The evaluation of the results is measured by a confusion matrix which evaluates the precision of the algorithm in detecting ischemia in the ECG signal by some useful and common equations.

Keywords: Ischemia detection, ECG signal, feature detection, automatic diagnosis

Sommario

Sono passati più di 100 anni da quando Einthoven utilizzava l'elettrocardiogramma per le diagnosi in medicina clinica. In questi anni, il continuo sviluppo della tecnologia ECG ha dato un grande contributo per la salute e la sopravvivenza umana. L'elettrocardiogramma è anche diventato l'indice più importante per valutare e diagnosticare le condizioni di salute del cuore dei pazienti. Nel processo di analisi del segnale ECG, il programma è stato sviluppato su MATLAB, basato sulla ricerca di tecnologia di elaborazione ECG. Non solo è in grado di realizzare la preelaborazione del segnale di ECG, rilevamento ed analisi della caratteristica, ma anche di creare un semplice referto medico dopo aver letto input ECG.

In primo luogo, sulla base della decomposizione multi-scala del segnale ECG, l'approssimazione wavelet viene applicata al segnale e dopo una analisi della riduzione di rumore della soglia wavelet adattativa, il segnale ECG originale è preelaborato.

In secondo luogo, durante il rilevamento delle caratteristiche dell'elettrocardiogramma, il metodo di trasformazione delle wavelet è migliorato nel rilevamento complesso QRS. Utilizza non solo i coefficienti wavelet, ma anche i segnali ECG per localizzare accuratamente il complesso QRS. Dopo la rilevamento complessa del QRS, l'onda T viene rilevata dall'ampiezza e dalla pendenza in determinata sezione. Questo metodo funziona bene per i segnali normali. Per l'analisi morfologica del segmento ST, viene proposto un metodo. Una volta rilevata la regione di analisi del segmento ST, il livello di offset, il tipo di curva, la pendenza e la camber sono adottati per le caratteristiche morfologiche essenziali del segmento ST. Nel frattempo, la classificazione della morfologia del segmento ST viene effettuata gradualmente. Questo metodo può rilevare forme diverse del segmento ST.

Infine, la diagnosi ECG dell'ischemia miocardica è realizzata da un metodo logico con conoscenza clinica: il metodo logico è come il modo in cui il medico osserva la registrazione ECG, che è semplice in linea di principio, chiara nella classificazione clinica, efficace nella realizzazione diagnostica. La valutazione dei risultati è misurata da una matrice di confusione che valuta la precisione dell'algoritmo nel rilevare l'ischemia nel segnale ECG mediante alcune equazioni utili e comuni.

Parole chiave: rilevamento ischemia, segnale ECG, rilevamento delle caratteristiche, diagnosi automatica

1. Introduction

1.1 Description of the problem

Measuring the number of dead people per year and the reason is one of the most important means – along with gauging how diseases and injuries are affecting people – for assessing the effectiveness of a country’s health system.

Cause-of-death statistics help health authorities determine the focus of their public health actions. A country where deaths from heart diseases and diabetes rise rapidly over a period of a few years, for example, may have a strong interest in starting a vigorous programme to encourage lifestyles to help prevent these illnesses. In the other words, they could pay much attention to the common reason that will cause death, and give more budget on that prevention.

According to the fact sheets from World Health Organization, of the 56.4 million deaths worldwide in 2015, more than half (54%) were due to the top 10 causes (Figure 1). Ischemic heart disease and stroke are the world’s biggest killers, accounting for a combined 15 million deaths in 2015. These diseases have remained the leading causes of death globally in the last 15 years.

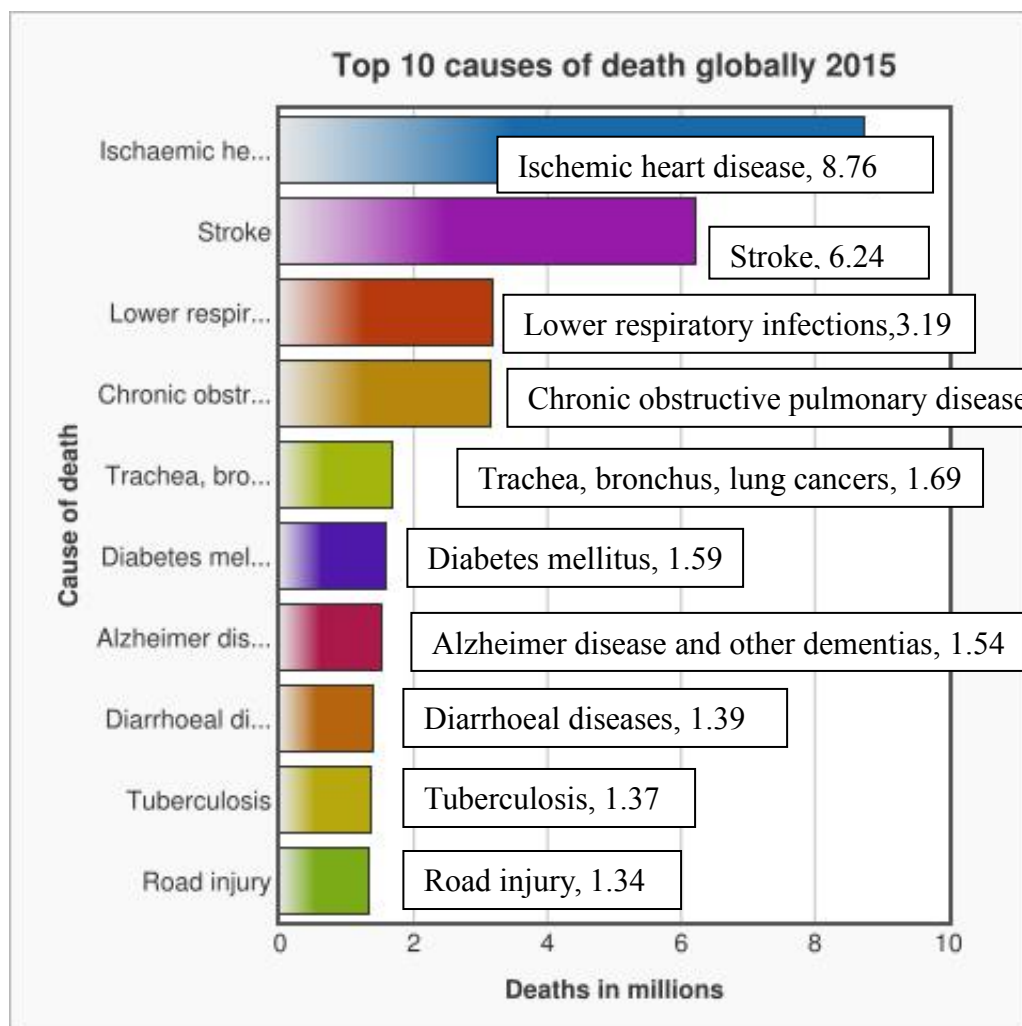


Figure 1. Top 10 causes of death globally 2015

More than half (52%) of all deaths in low-income countries in 2015 were caused by

communicable diseases, maternal causes, conditions arising during pregnancy and childbirth, and nutritional deficiencies. By contrast, less than 7% of deaths in high-income countries were due to such causes.

According to Figure 2, 3, 4 and 5, non-communicable diseases (NCDs) caused 70% of deaths globally, ranging from 37% in low-income countries to 88% in high-income countries. Through these sheets, the leading causes of NCD deaths in 2015 were absolutely is the Ischemic heart disease.

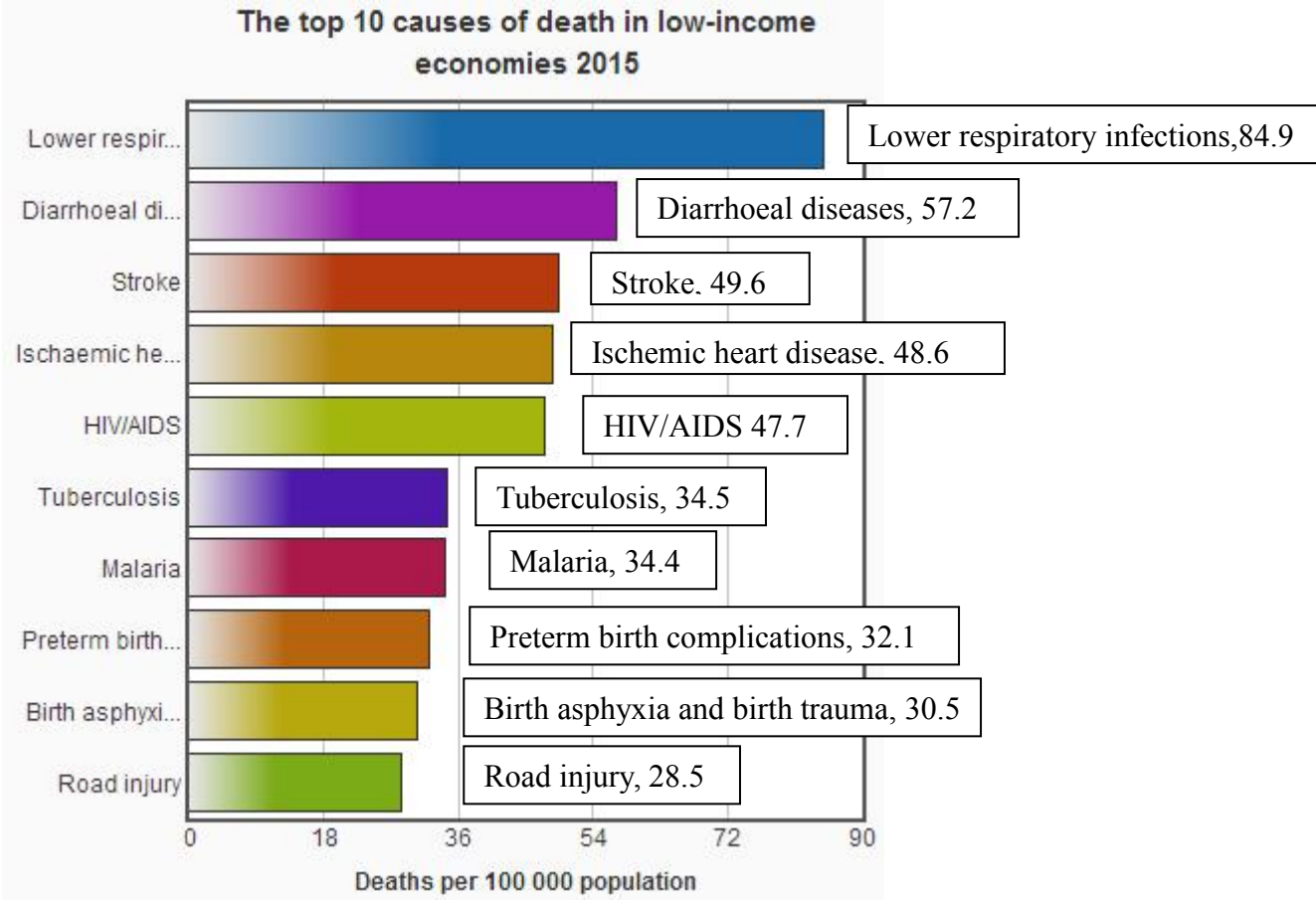


Figure 2. The top 10 causes of death in low-income economies 2015

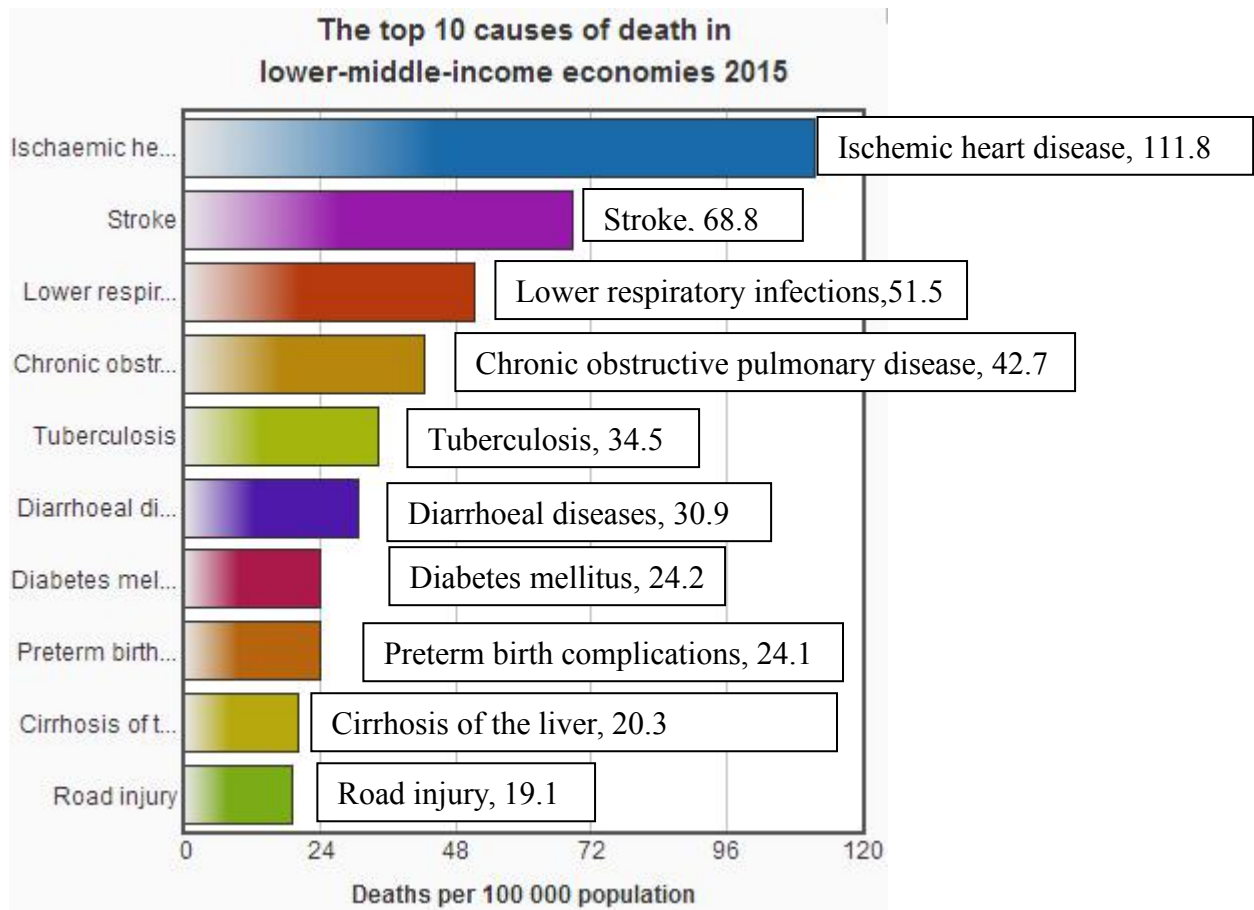


Figure 3. The top 10 causes of death in lower-middle-income economies 2015

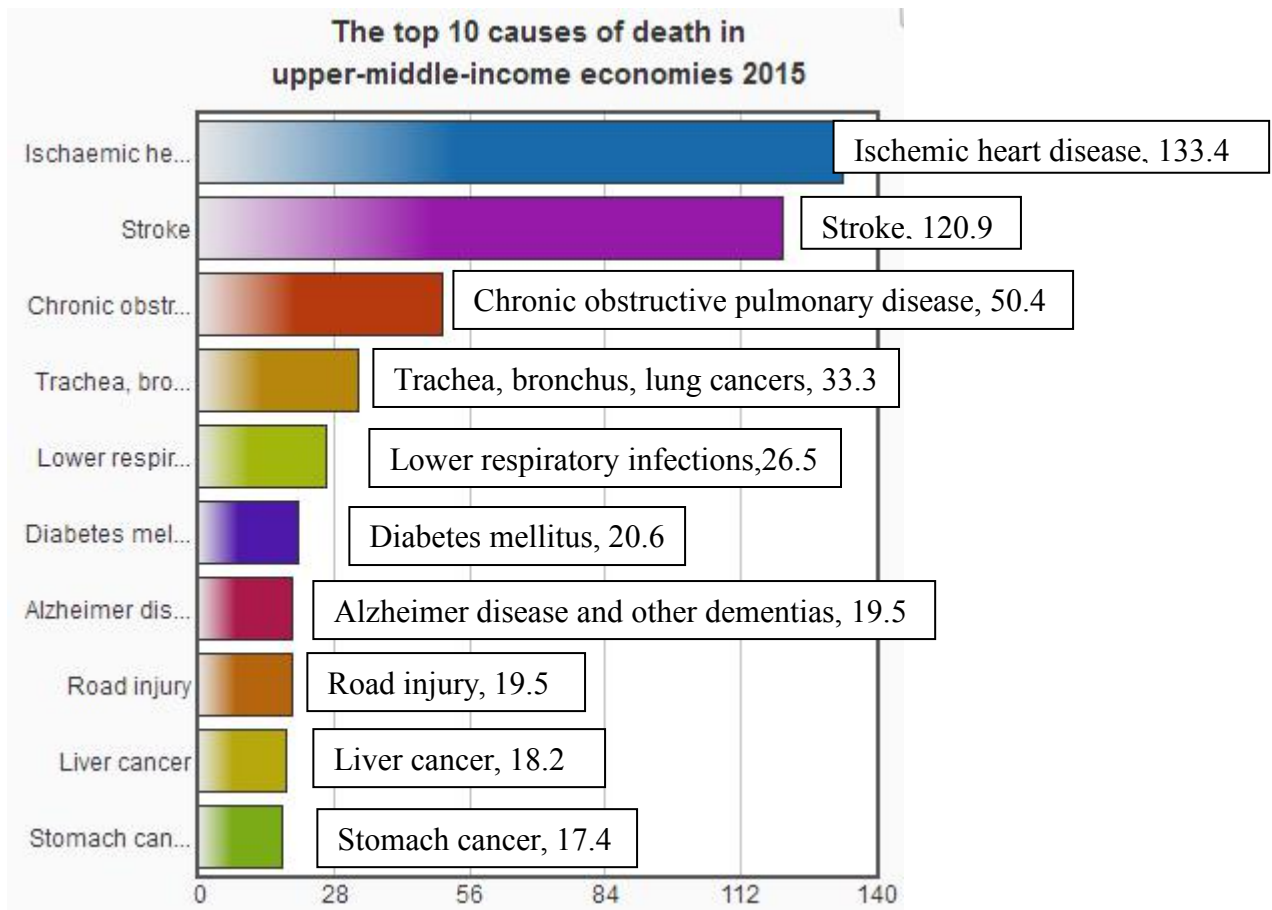


Figure 4. The top 10 causes of death in upper-middle-income economies 2015

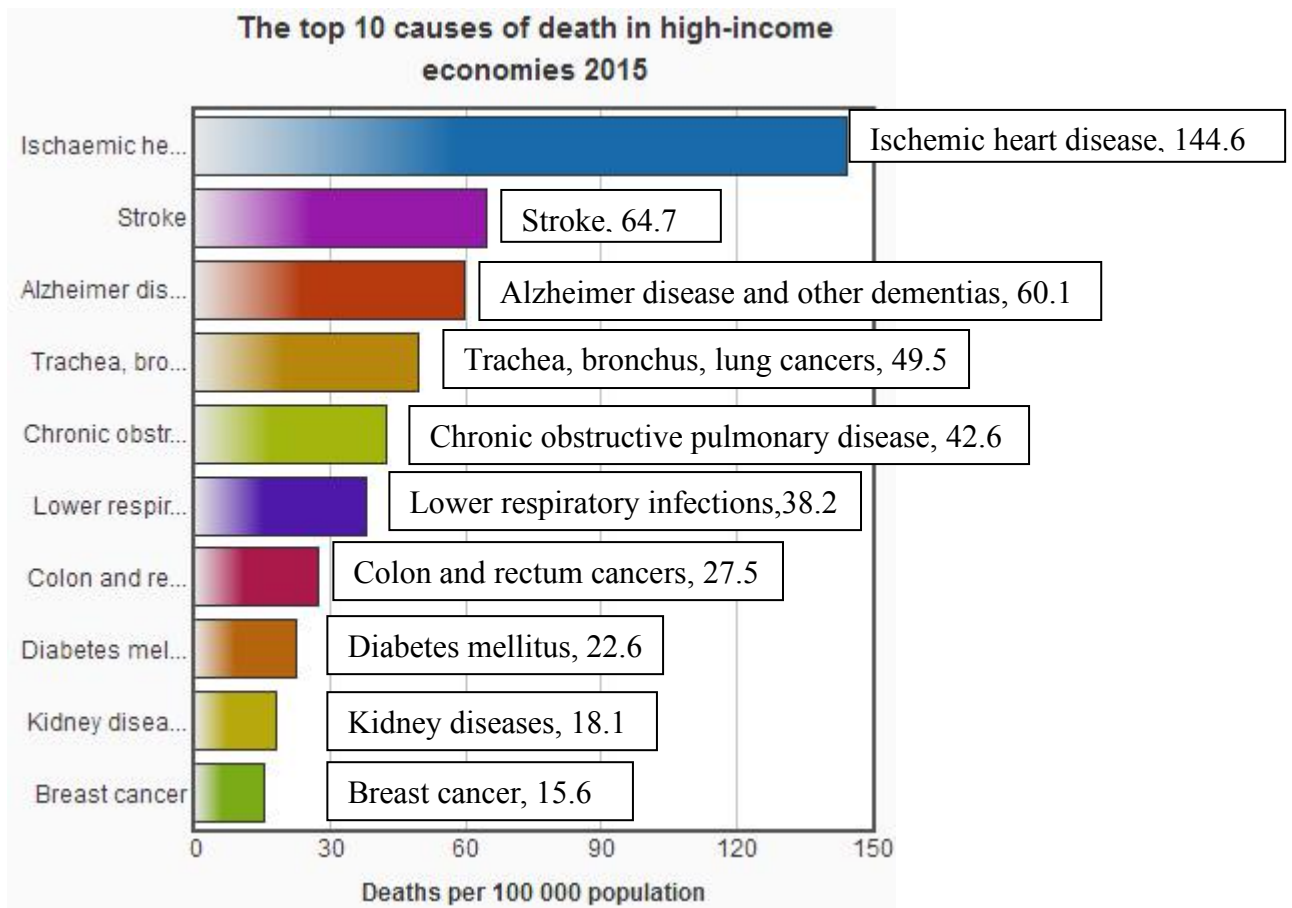
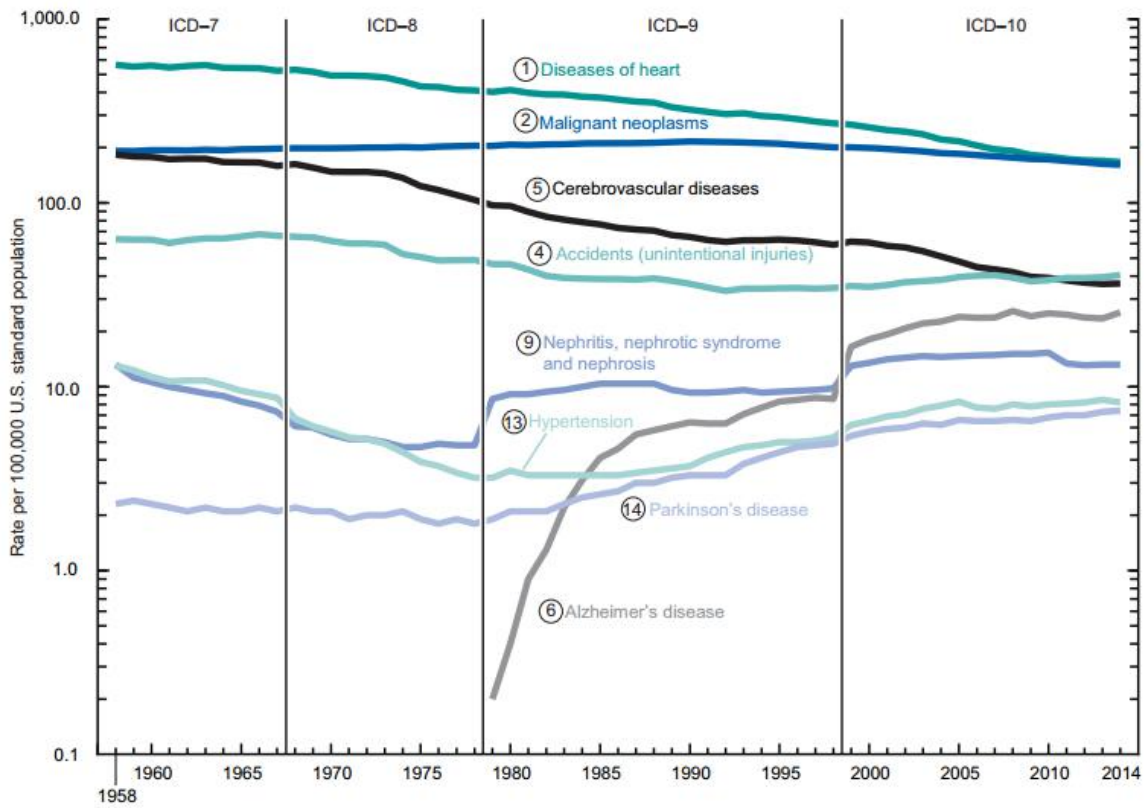


Figure 5. The top 10 causes of death in high-income economies 2015

In addition, according to the report from American Heart association and National Vital Statistics Report (Figure 6), heart disease, which refers to several types of heart conditions, is No.1 leading cause of death for both men and women. In the United States, that's 1 in every 4 die from heart disease, someone has a heart attack every 42 seconds. Each minute, someone in the United States dies from a heart disease-related event. Coronary heart disease is the most common, worst type of Cardiovascular disease (CVD) which is a class of diseases that involve the heart or blood vessels, killing about 800,937 people in 2013 (Figure 7).



NOTES: ICD is the International Classification of Diseases. Circled numbers indicate ranking of conditions as leading causes of death in 2014. SOURCE: NCHS, National Vital Statistics System, Mortality.

Figure 6. Age-adjusted death rates for selected leading causes of death: United States, 1958-2014

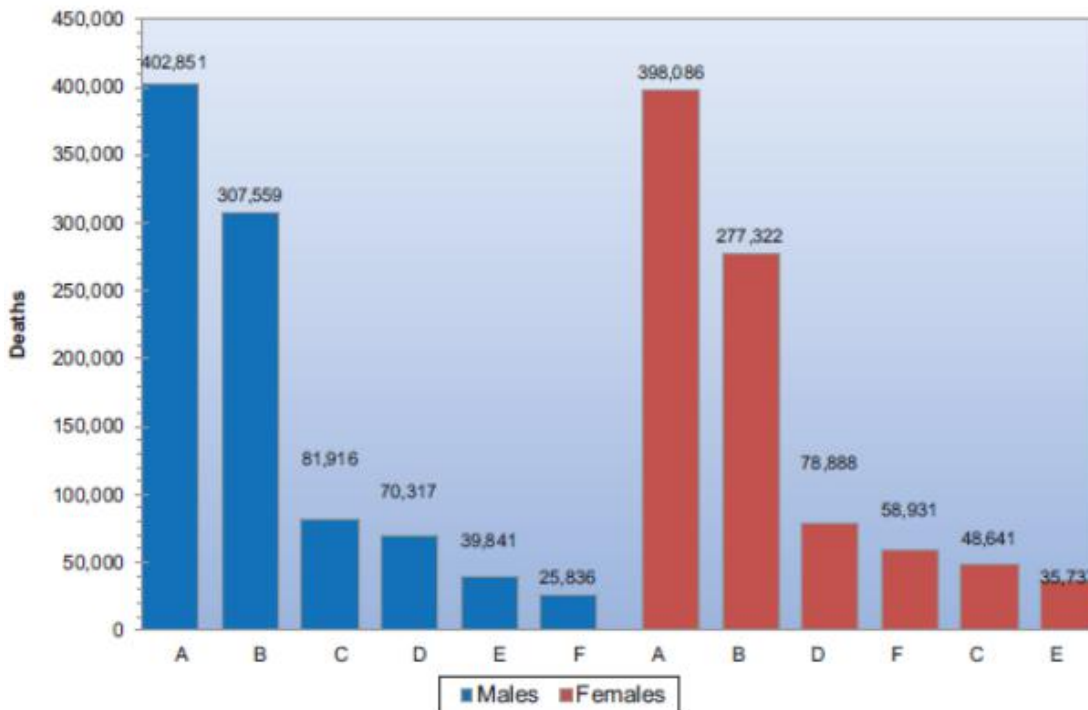


Figure 7. CVD and other major causes of death (United States: 2013, Source: NCHS and NHLBI). A indicates CVD; B, cancer; C, accidents; D, CLRD; E, diabetes; and F, Alzheimer's disease

1.2 Arrhythmia and ischemia

One of the most common causes of CVD morbidity and mortality is ischemic heart disease (IHD). IHD occurs when the heart's blood supply is blocked due to the buildup of fatty substances and cholesterol in the coronary arteries, causing their free-flowing passages to narrow. Such blockages inhibit oxygen and nutrient supplies to the heart muscles, hampering the functioning of the heart. Eventually, the affected heart dies, resulting in a heart attack. Myocardial ischemia is an intermediate condition in coronary artery disease during which the heart tissue is slowly or suddenly starved of oxygen and other nutrients. Eventually, the affected heart tissue will die and when blood flow is completely blocked to the heart, ischemia can lead to a heart attack. Additionally, acute myocardial infarction (AMI) is the total occlusion of a major coronary artery with a complete lack of oxygen and nutrients leading to cardiac muscle necrosis. Ischemia can be silent or symptomatic. According to the American Heart Association, a large numbers of Americans may have ischemic episodes without knowing it, it means at high risk of having a heart attack with no prior warning.

Chest pain called angina pectoris is the characteristic pain of IHD, also of Symptomatic ischemia. It is caused by atherosclerosis leading to stenosis (partial occlusion) of one or more coronary arteries. The American Heart Association estimates that nearly seven million Americans have angina pectoris, which occurs more frequently in women than in men.

An arrhythmia is an abnormal heart rhythm. It may feel like fluttering or a brief pause. Some are so brief, like a premature beat, a temporary pause that it doesn't affect greatly on your overall heart rhythm. But if arrhythmia last longer, it can cause the heart rate to be too slow, too fast or erratic. Some arrhythmias don't cause any symptoms, may be completely harmless. Others can make you feel lightheaded or dizzy, may be life-threatening. There are two basic types: One is the heart rate is too slow, called Bradycardia — less than 60 beats/minute. The other is the heart rate is too fast, called Tachycardia — more than 100 beats/minute. Many things can lead to, or cause, an arrhythmia, such as coronary artery disease(blocked arteries in your heart), a heart attack that's occurring right now or Scarring of heart tissue from a prior heart attack, changes to your heart's structure, high blood pressure and so on.

1.3 The ECG signal

The surrounding heart tissue and body fluids can be conductive, so the human body can be seen as a long, wide, thick three-dimensional volume of the conductor, the heart is like a power supply. The sum of the changes in myocardial potential can be transmitted and reflected to the body surface. There are potential differences among many points on the body surface, there are also no potential differences between each other. This point is the key basis for the ECG applications.

The ECG application has been more than 100 years of history. At the end of the 19th century, firstly, people found that the animal's heart beat accompanied by weak electrical activity, and later gradually realized that the human body has a similar change. In 1903, the Dutch Wilhelm Einthoven recorded the first electrocardiogram with string currents. At that time it is referred to as EKG, which is from German Elektrokardiogramm. In 1905 the formal application of electrocardiogram technology was used in the clinic. In 1942, in the United States, a group of scholars led by Wilson presented six cardiac leads in the American Journal of Cardiology. In the same year, Goldberger improved and completed the 12-lead ECG, which has been used ever since.

The Electrocardiogram (ECG), the recording of the electrical activity of the heart over

time easily recorded using noninvasive electrodes on the chest or limbs, is used to measure the heart's electrical conduction system. It is for the detection of arrhythmia, ventricular atrial hypertrophy, myocardial infarction, myocardial ischemia and others related to the heart disease. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. Then, the waveform is for measuring the rate and regularity of heartbeats, as well as the position and size of the chambers, the presence of any damage to the heart, and effects of drugs or devices used to regulate the heart.

The ECG as an indirect method [1] is the most commonly used clinical detection to diagnose myocardial ischemia and myocardial infarction. Around 70% heart attacks can be detected through the ECG, the remaining 30% is because of different reasons, like multiple or small infarction. Its correct interpretation, particularly in the emergency department, is always the basis for immediate therapeutic interventions and/or subsequent diagnostic tests. As we know, early diagnosis of acute heart attacks, within 1 hour of the onset of symptoms, is crucial part to determine whether the treatment will be succeed or not.

A typical ECG tracing of the cardiac cycle (heartbeat) comprises a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECG signals because it is hidden by the T wave and upcoming new P wave. The ECG signal change that occurs in association with acute ischemia and infarction includes the large T wave, referred to as hyperacute T wave change, ST segment elevation and/or depression, the change in the QRS complex, and inverted T wave. Then diagnosing ischemia normally main depends on the ST segment change, even if the abnormal T wave also has the meaning for diagnosis, however, there is not much information provided by the T wave and less experience on it.

A typical normal ECG tracing is shown in Figure 8.

1) The P wave: a small semi-circular wave is at the beginning of the ECG waveform, reflecting the left and right atrial depolarization process of electrical excitement. The first half is mainly from the right atrium, the latter half is mainly from the left atrium. A good place to look at P waves is in II, where the P shouldn't be more than 2.5mm tall, and 0.11 seconds in duration.

2) The QRS complex: after the P wave, there is a sharp narrow, large wave, which is often composed of several waves. The QRS complex reflects the left and right ventricular depolarization process of electrical excitement. An initial downwards deflection is a Q, any negative deflection after this is an S. An upward deflection is an R. Depending on the patient and the lead, the QRS complex may be in multiple forms. Generally, upper case is for main wave, lower case is for smaller waves. The width of the QRS complex represents the duration of all ventricular myocardium excitement. The normal one is not more than 0.11s.

3) The T wave: At the end of the QRS complex, there is a low-blunt and wide wave called the T wave, which reflects ventricular recovery or repolarization. In the R wave based ECG, T wave amplitude should not be less than 1/10 of the R wave.

4) The U wave: in the some leads, after the T wave there is a wave with the same direction of the T wave, known as the U wave, the general amplitude is not more than 0.3mv, which probably reflects the potential change after the excitement. Anyway, it is still In the discussion.

5) The PR interval (PR segment): it extends from the P wave to the beginning of the QRS complex, representing the excitement from the atrium to the ventricle. It is an important indicator to measure the relationship between the atria and ventricle, generally between 0.12 ~ 0.20s. This duration will increase with age. Moreover, it is often used as the baseline to measure the ST segment offset.

6) The ST segment: it is from the end of the QRS complex to the beginning of the T wave, which represents the slow phase of ventricular repolarization. The ST segment usually merges smoothly and imperceptibly with the T wave. The normal ST segment is close to the baseline, ST segment elevation not exceed 0.3mv in V3, V4 lead, otherwise, no more than 0.10mv. Then, ST segment depression is not more than 0.10mv.

7) The QT interval: from the beginning of the Q wave to the end of the T wave. It represents the duration of the ventricular depolarization and repolarization, generally around 0.30 ~ 0.47s, affected greatly by the heart rate.

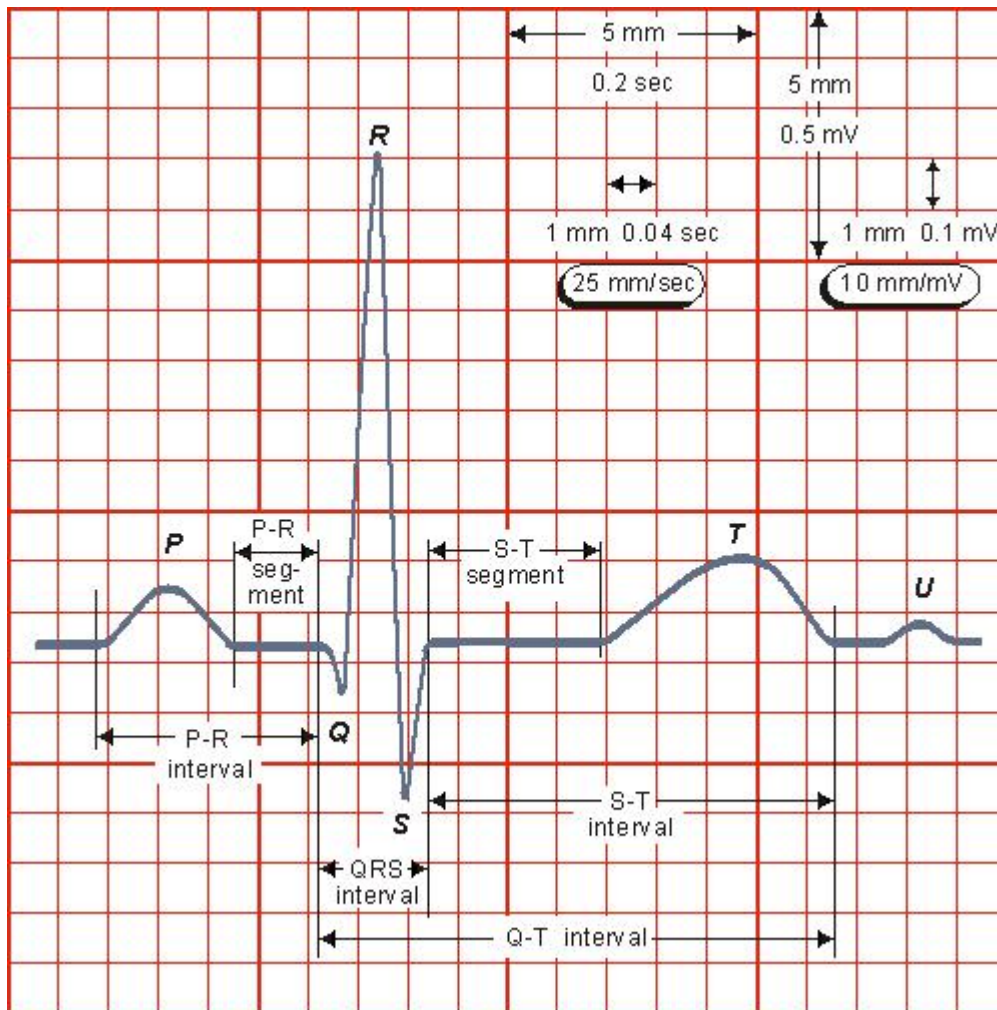


Figure 8. A typical normal ECG tracing

1.4 Research relevance

After we are clear that CVDs are one of the most important diseases that threaten human life, and IHD is the single largest cause of death in the developed countries and is one of the main contributors to the disease burden in developing countries. Myocardial ischemia (MI) is the main symptom during its occurrence and development. Continuous and severe myocardial ischemia will lead to myocardial infarction. Early detection and intervention has a great impact on the prognosis. The timely and accurate detection of myocardial ischemia is critical to the treatment of patients.

In recent years, myocardial ischemia detection method has developed rapidly, mainly

coronary angiography, myocardial radionuclide imaging, myocardial magnetic resonance imaging, echocardiography, 64 rows of CT, and electrocardiogram detection. Among them, ECG detection with low prices, non-invasive and easy operation becomes the most commonly used and basic method in myocardial ischemic detection. Because of the long-term detection of electrocardiogram, it is beneficial to evaluate myocardial ischemia in daily life especially for the diagnosis and evaluation of asymptomatic myocardial ischemia [2]. Therefore, the relevant scholars follow this topic which is one of the hot spots in the electrocardiogram research field.

The ECG is the main basis method to diagnose CVDs, the characteristic analysis has become a hot topic in the medical profession, particularly the ECG helps experts easily quickly and accurately know the patient's condition. With the development of network technology and multimedia technology, the data structure is getting more complex, and there is a popular tendency that the computer is used to complete that intelligent data collection, storage, management, processing and transmission. The traditional ECG analysis is done by the physician, The physician make a diagnosis based on the patient's ECG waveform and other auxiliary information. But sometimes the physician has to face thousands of heartbeat data, obviously, the number of physicians is limited with great pressure, in such circumstances, the development of the intelligent computer application, automatic ECG analysis, can save them much time and labour, which can definitely improve the above situation, so as to assist physicians to make accurate and efficient diagnoses, reduce misdiagnoses and missed diagnoses

Importantly, automatic analysis helps to detect real diseases, real emergency situations from false alarms. To improve health and reduce preventable deaths, the faster detect diseases, the sooner save patients' lives. Therefore, the goal of this tesina is to develop a program in MATLAB to automatically analyze the ECG signal and diagnose ischemia preliminarily through ST segment and T wave morphology classification, based on reviewing research of the current state of the art. The program not only can realize the ECG signal denoising, feature detection and analysis, but also make a simply medical report about ischemia with medical knowledge after reading the input ECG.

1.5 Tesina outline

The main research work and structure of this tesina are as follows.

Chapter 2 describes the state of the art of the QRS, the ST segment and the T wave analysis involved in the diagnosis of myocardial ischemia.

Chapter 3 describes the main noise distribution in the ECG signal, the basic knowledge of wavelet transform and the denoising principle, to select the appropriate wavelet function and threshold to denoise the original ECG signal is to get the ECG signal after denoising.

Chapter 4 describes the essential knowledge of extracting characteristics from ECG signals. Extremum point and the boundary detection, or wavelet transform method can be used to detect the QRS complex, the local transform algorithm or wavelet transform method can be used to detect the T wave. In this tesina, wavelet transform method is selected to locate the QRS complex, the T wave. First of all, the improved method based on the modulus maxima pair is used for R peak detection, then Q peak and S peak detection, the QRS onset and offset are detected based on R peak location. Then, the T wave is detected effectively by removing the QRS complex on the basis of QRS complex detection. What's more, morphological analysis of the T wave was made. For ST segment morphological analysis, a method is proposed. The 4 morphological features of the ST segment, the offset level, the

curve type, the slope and the camber, are used as identified criteria. Meanwhile, the morphological classification of the ST segment is carried out gradually.

In Chapter 5, according to the feature analysis combined with clinical knowledge, the ECG diagnosis of myocardial ischemia is achieved by logical method: the logical method describes the way the physician observes the ECG recording, which is simple in principle and clear in clinical classification.

Chapter 6 summarizes the work and the existing problems of this tesina, and puts forward the future research work according to the ideas and drawbacks occurred in the research.

2. State of the Art

With the development of computer technologies, the ECG automatic analysis has become a hot topic in the field of biological signal processing, and the function has been enhanced, which not only can analyze the heart rate, but also extract the feature value, and finally classify and diagnose various heart diseases. It plays an important role in the prevention and diagnosis of some heart diseases. However, the ECG automatic analysis is still a minority in practical clinical application. The main reason is that automatic analysis algorithm is difficult to meet requirements of clinical diagnosis when dealing with special waves of all kinds of diseases. So improving the accuracy of automatic analysis algorithm still has a long way to go.

There is no accepted uniform standard for ECG detection of myocardial ischemia as yet, but the clinical physician mainly examines the morphological changes of the ST segment and the T wave when diagnosing myocardial ischemia with the electrocardiogram. Therefore, ST segment change and T wave change are the most common characteristics in the detection of myocardial ischemia. However, QRS complex detection is directly related to the acquisition of R-R interval, that is, the accuracy of heart rate calculation. Then generally, only after the QRS complex is determined, it is easy to correctly locate the T wave and ST segment in the ECG signal.

2.1 Research on QRS complex detection

Currently, QRS complex detection usually is divided into 2 parts, the hardware method and the software method. The hardware method is mainly based on the difference of the frequency characteristics among the QRS complex, other waveforms and noise [3]. The software methods are as follows: the PT algorithm [4] can be used to detect the location and the QRS complex coverage, and a special digital bandpass filter is to eliminate the wrong detection in the ECG waveform. The differential threshold method [5, 6] is to compute the sum of the forward difference and the backward difference of the ECG signal, get a bimodal signal, and highlight the R wave of the original signal, finally by choosing the appropriate threshold to locate the R wave. This method is simple and fast, but the efficiency of R wave detection is not good. After the Hilbert transformation [7] of the original signal, the envelope of the signal can be computed by the function of the original signal and the transformed one, and the QRS complex can be located by analyzing the envelope signal, but it is susceptible to the noise. Wavelet transform [8 - 10] can be used to weaken other waves and highlight characteristics of the QRS complex, and get a good QRS complex detection rate. Neural network algorithm [11] is to train, learn and classify the input signal. For all kinds of waves, it has a good detection rate, but the appropriate training algorithm is in demand, mostly for non-linear prediction. There are also variable threshold methods [12], difference operation method [13], adaptive threshold method [14], master-slave coordinated QRS detection method [15], template matching method [16] and so on.

2.2 Research on ST segment detection

The ST segment is normally parallel to the equipotential line or has a slight upper and lower shift. For myocardial ischemia, the ST segment can be elevated or depressed, and the corresponding changes in various forms can occur.

Measuring the shift level is one of the most important elements in the analysis of ST segment change. There is no uniform standard for measuring the shift level at which point to

measure the offset level. The methods of measuring the ST segment shift level are frequently used including J + X method [17], R + X method [17], window search method [17] and the turning point detection method [18] and so on. J + X method and the R + X method are used to measure the ST segment offset at X (ms) after the J point or the R peak, The precision of X selection in this method basically determines the accuracy of detection point. Window search method is to select a search window in the ST segment, in this window to search its lowest or highest point as a measurement point. The turning point detection is to get the turning point between the ST segment and the T wave, usually the starting point of the T wave, as the measurement point of the ST segment offset.

The analysis of ST segment morphology also has very important significance. ST segment morphological changes often vary from diseases, not only help to analyze the reasons for ST segment change, but also to provide more accurate bases for ECG diagnoses. Then, there are a few researches on the effective morphological recognition of the ST segment.

Skordalakis et al. proposed a ST segment morphological recognition algorithm in 1986 [19]. But its essence is to determine the endpoint of the ST segment by function regression, which does not involve the concrete analysis of ST segment morphology. Function regression [20] is to adopt the principle of digital fitting to identify and classify the signal, and the polynomial function is often used to fit the signal by the least squares. Sometimes, exponential function is also used [21]. But due to the variety of ECG signal, it is very difficult to fit well, and its reality is poor. The slope method [22], a combination of the slope and the function regression [23] are used in the ST segment morphological recognition as well, and the combination method are found to achieve the relative good effect, which is simple and quick, also can meet the real-time system. But it has big limitation. First of all, the calculation of the slope is affected by the noise, this method can achieve better results in the case of large signal-to-noise ratio. Secondly, the method is greatly affected by the accuracy of the feature point, especially the J point.

Jeong et al. [24, 25] proposed four slope method, which was to divide the ST-T segment, easier to locate part, according to a certain rule into four segments, then complete the classification of ST segment morphology through slopes of four segments. In addition, some scholars put forward secondary curve fitting the ST segment, and analyzed ST segment morphology [26], while it was easy to be affected by the noise and with a large computational quantity.

Shen Zhao et al. [27] computed the end direction and waveform of the ST segment by wavelet and morphological method, and applied the change trend of the ST segment to the detection of myocardial ischemia.

Kwok et al. [28] used PCA method to extract main characteristic components of single heart beat in the ECG signal, and used it as the input signal to realize the recognition of various ST segment depression by LVQ Neural network. LIU Hai-long et al. [29] directly used the signal at 150ms backwards the R wave as the input signal, and adopted RBF neural network to realize ST segment morphological recognition. The ST morphological analysis based on neural network has good fault-tolerant ability, but this kind of method needs a large number of training samples to be modeled. It is tedious and difficult to be implemented with large computational capacity, and it is easy to be disturbed by the noise. Moreover, it cannot properly recognize the new pattern which has not appeared in training samples.

On account of the variety of the ST-T segment, its detection is far less mature than the QRS complex detection, and it is difficult to have a method that can both has universality and accuracy.

2.3 Research on T wave detection

Due to the low frequency component of the T wave, much noise, and the variety of the T wave morphology, it is inevitable that some threshold detection methods [30 - 33] used in time domain are false detection and missed detection. Some more robust methods of T wave detection have been developed. Based on principal component analysis [34], T waves were detected by multi-lead signals. Yu et al. [35] used the genetic algorithm to obtain the approximate value of the global optimal solution, and took it as the initial value of the neural network to obtain the exact value of the global optimal solution. However, this method does not consider the diversity of the T wave morphology comprehensively.

Considering the diversity of T wave morphology, the improved wavelet transform detection method [36, 37] establishes a corresponding relationship between T wave morphology and the modulus maxima pair, and it can detect T wave more comprehensively, but it is prone to false and missed detection of abnormal T wave.

Vila et al. [38] established a mathematical model of the T wave, and then finished T wave detection and classification according to that model. But it is very difficult to detect the T wave by using mathematical template because of noise interference and T wave morphological change. In fact, so far, T wave detection is still a difficult problem in the field of ECG signal processing. Wang Yun-He et al. [39] used support vector machines (SVM) to achieve T wave classification. Hadjem et al. [40] designed an abnormal T wave detection algorithm based on classifier integration. Firstly, they detected the QRS onset and the T wave endpoint, then extracted the morphological features of the QT segment, finally integrated decision tree, support vector machine and logistic regression classifier to judge whether the T wave is abnormal.

Bernardo et al. [41] used the computer model to analyze T wave changes with heart rate. Zhang Qinghua et al. [42] proposed a real-time effective algorithm for the T wave endpoint, which is related to the area covered by the T wave, but it required good T wave morphological classification. Other methods of T wave endpoint detection are not only dependent on the threshold, such as based on area [43, 44], template matching [45], wavelet transform [46, 47], curvature [48], statistical pattern recognition (KNN) [49] and so on. Among them, template matching, statistical pattern recognition are both more computational, time-consuming methods.

3. Signal Preprocessing

Since the ECG signal is relatively weak with mV, collected ECG signal is usually with much noise, causing the signal distortion and blur, which greatly affects the correctness of the signal analysis results. Therefore, ECG signal preprocessing is significant to the automatic diagnosing recognition. Frequency range of the normal ECG signal is mainly around 0.0 ~ 100Hz, about 90% of the ECG signal spectrum energy concentrated in 0.25 ~ 45Hz [77]. During the ECG signal acquisition and A/D conversion process, ECG signals are inevitably interfered by various kinds of noise, mainly including powerline interference, electromyographical (EMG) interference and baseline drift [50, 51].

This Section describes how the signal is processed: the noise of the signal is removed (Section 3.1); then by the wavelet transform the signal is preprocessed (Sections 3.2 and 3.3); the signal is filtered by removing its baseline (Section 3.4) and the interference from the electric network (Section 3.5).

3.1 Noise contained in ECG waveform

3.1.1 Baseline drift

In general, using the body surface paste electrode to collect the ECG signal, so there is such a contact resistance between the electrode and the skin. However, changes in space position of the electrodes in contact with the skin caused by respiratory movement, temperature drift of the amplifier, postural activity and other factors will lead to ECG baseline drift and amplitude fluctuations, even may also lead to serious ECG distortion in severe cases (Figure 9). Frequency of the baseline drift is generally considered to be less than 0.5 Hz, low frequency interference, which is similar to the characteristic of the ST segment. In fact, it is difficult to completely suppress such noise on the hardware, so baseline drift is mainly removed by the software.

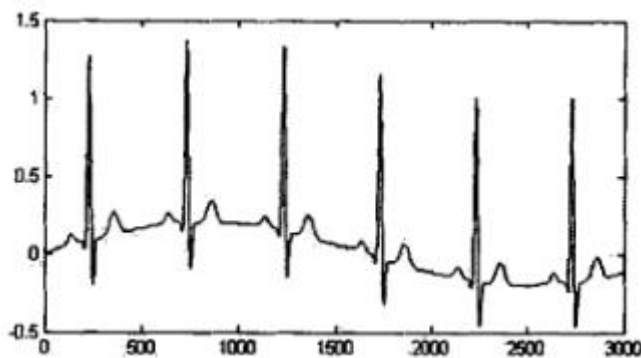


Figure 9. The ECG signal with baseline drift

3.1.2 Powerline interference

ECG detection box usually uses AC power supply, there is a power circuit system around it, no wonder it will introduce powerline interference that affects the ECG analysis (Figure 10). Filtering out the powerline interference is a necessary step in ECG signal preprocessing. The frequency band of the powerline interference is narrow, generally 50Hz ~ 60Hz, high frequency interference. The task of removing powerline interference is to remove the signal in this band.

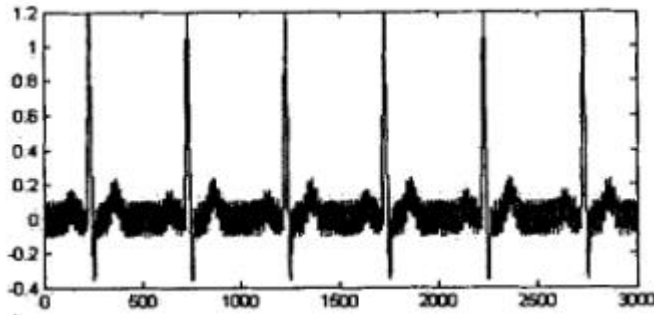


Figure 10. The ECG signal mixed with powerline interference

3.1.3 EMG interference

In the human epidermis, there is a typical skin potential of 30mV. When the skin is stretched, the skin potential drops to about 25mV that means the electrical noise produced by the muscle contraction in the ECG signal. Therefore, when human muscle contraction and relaxation happen, EMG interference, high-frequency interference, will exist (Figure 11). The frequency range of this interference is very wide, about 30-2000Hz.

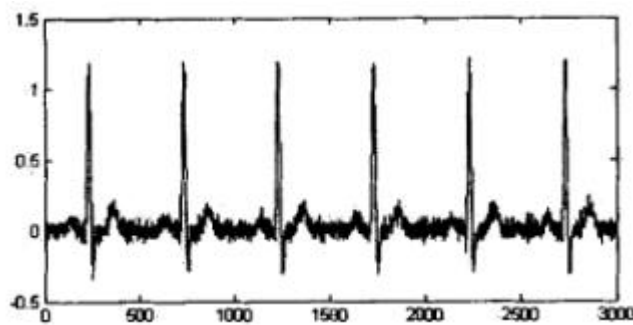


Figure 11. The ECG signal with EMG interference

3.2 Wavelet transform introduction

Since 1822, Fourier transform (FT) is a kind of effective analytical method which is widely used in signal processing field. However, FT is a analytical method only in frequency domain, which means the resolution in frequency domain is the highest, but the weakest in time domain. That is to say, FT is a reflection of the complete characteristics the whole time in frequency domain, but not with the capability of getting frequency information in the local time period. That will make each signal point mutation on the time axis will affect the whole frequency domain. In order to solve this problem, Short Time Fourier Transform (STFT) is developed. Although it can realize the signal analysis in time domain, but still cannot accomplish effective analysis of the abrupt and non-stationary signals.

For the purpose of realizing the effective analysis of the abrupt non-stationary signal, the wavelet transform comes into being, which not only inherits the advantages of Fourier transform, but also compensates for the shortage. It has been widely used in many fields, such as signal denoising, image compression, feature extraction, edge detection and so on. The main idea of wavelet transform is extension and translation, and make the time signal into the linear superposition of the wavelet function group, which has better time-frequency localization and multi-resolution characteristics. So it can effectively distinguish the abrupt

part and the noise part in different decomposition levels, and realize signal preprocessing. Therefore, the wavelet transform is applied to the ECG signal preprocessing and feature extraction, and satisfactory results are obtained.

Owing to the multi-resolution characteristic, wavelet transform can decompose the signal at different scales, which means it decomposes the mixed signals into different frequency bands, so wavelet transform can produce good results in the ECG signal denoising. In the original ECG signal waveform, the useful parts and the noise parts have different frequencies, so the wavelet coefficients have various characteristics at different scales in the wavelet transform. After the wavelet transform, for useful parts, the energy of its mutation points (singularities) is mainly concentrated in a few sparse, larger wavelet coefficients with larger amplitude that are also modulus maxima at each scale. Besides, for the noise part, it is still white noise after wavelet transform, and the wavelet coefficients are irrelevant and widely distributed on the time axis of each scale with small amplitudes. Finally, taking advantage of this type of characteristic that decomposition coefficients of useful signal are different from and noise's ones is to realize the ECG signal preprocessing. The ECG signal denoising process by wavelet transform is actually the process of signal decomposition and reconstruction. The main idea is shown in Figure 12.

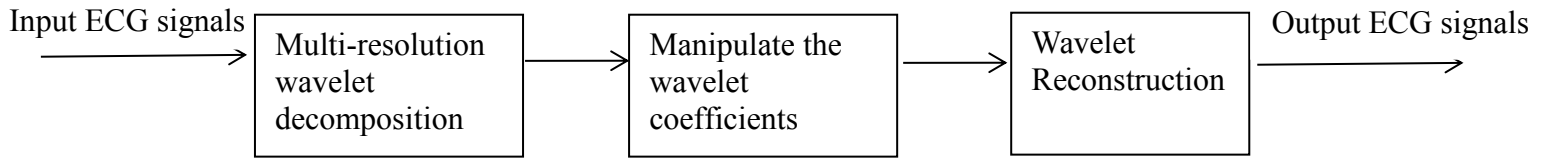


Figure 12. The flowchart of ECG signal preprocessing

3.3 The principle of wavelet transform

In this tesina, wavelet transform is used for the ECG signal preprocessing. First of all, there are some important theories that need to be introduced.

3.3.1 Wavelet Transform definition

There is a basic function

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-b}{a}\right) \quad (3.1)$$

Where a, b are constants, $a > 0$.

Obviously, $\varphi_{a,b}(t)$ is obtained after $\varphi(t)$ shifts firstly and stretches later, if a, b are constantly changing, a set of functions $\varphi_{a,b}(t)$ can be obtained. If a square integratable signal $x(t)$ is given, the wavelet transform of $x(t)$ is defined as:

$$WT_x(a,b) = \frac{1}{\sqrt{a}} \int x(t) \varphi\left(\frac{t-b}{a}\right) dt = \int x(t) \varphi_{a,b}(t) dt = \langle x(t), \varphi_{a,b}(t) \rangle \quad (3.2)$$

Where b indicates the time shift, a, the scaling factor, $\varphi(t)$, mother wavelet function, $\varphi_{a,b}(t)$, wavelet basis function.

WT can be seen as the inner product of $x(t)$ and a set of wavelet basis functions.

3.3.2 Discrete wavelet transform (DWT)

In practice, the signal is always discrete, and DWT is a kind of wavelet transform with a , b and t are discrete values. The space V_j is defined by the orthogonal basis $\phi(a^{-j}t - k)$, and $P_j x(t)$ is the projection of $x(t)$ in the space V_j . The space W_j is formed by the orthogonal basis $\psi(2^{-j}t - k)$ and $D_j x(t)$ is the projection of $x(t)$ in the space W_j

$$P_j x(t) = \sum_{k=-\infty}^{\infty} a_j(k) \phi_{j,k}(t) \quad (3.3)$$

$$a_j(k) = \langle x(t), \phi_{j,k}(t) \rangle \quad (3.4)$$

$$D_j x(t) = \sum_{k=-\infty}^{\infty} d_j(k) \psi_{j,k}(t) \quad (3.5)$$

$$d_j(k) = \langle x(t), \psi_{j,k}(t) \rangle \quad (3.6)$$

$$P_{j-1} x(t) = P_j x(t) + D_j x(t) \quad (3.7)$$

If we define the band $(0 \sim \pi)$ of the signal $x(n)$ to the space V_0 , it is divided into two subspace after the first decomposition, a low-frequency band $V_1 (0 \sim \frac{\pi}{2})$ and a high frequency band $W_1 (\frac{\pi}{2} \sim \pi)$. According to this method V_1 further will be divided into two parts, one is low-frequency band space $V_2 (0 \sim \frac{\pi}{4})$, another is high-frequency band space $W_2 (\frac{\pi}{4} \sim \frac{\pi}{2})$. According to the above method, continue to decompose, at the end, the frequency band decomposition of the signal can be realized, as shown in Figure 13.

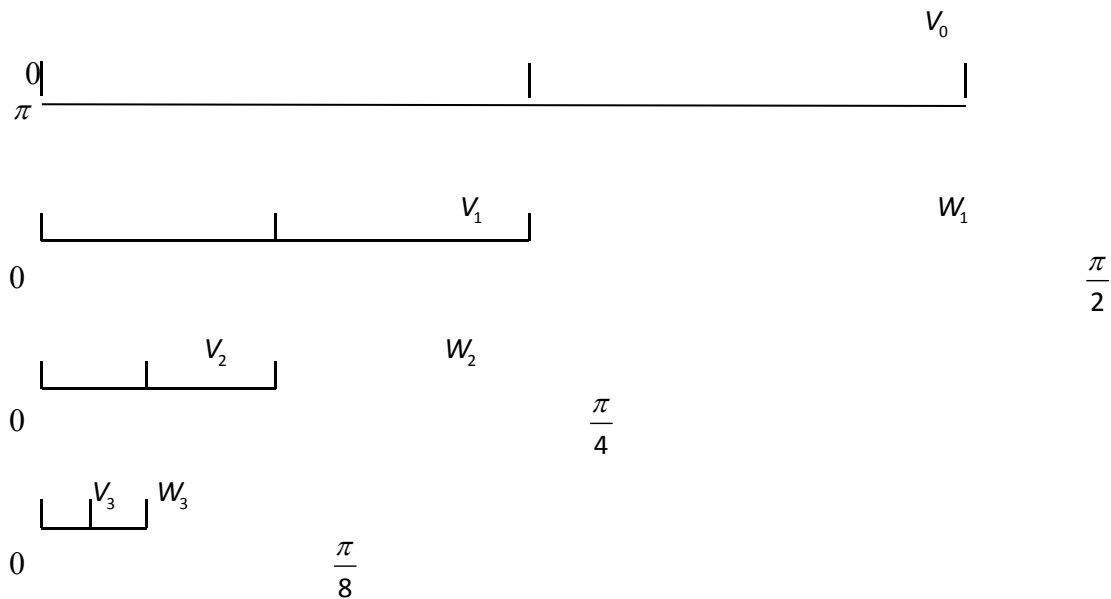


Figure 13. Signal band decomposition

The discrete wavelet transform primarily has the following characteristics:

1) The constant Q property of each high-pass space W_j and the low-pass space V_j , that is, time-bandwidth product is independent of the scale factor.

2) The consistency of filter at all levels. The filter is designed on the grounds of the normalized frequency, so the low-pass filter H_0 and high-pass filter H_1 at all levels use the same filter bank, which not only embodies the consistency in the tree-structured filter bank, but also embodies the characteristics of the frequency band decomposition.

3.3.3 Mallat algorithm

A breakthrough result of the discrete wavelet transform is the fast algorithm--Mallat algorithm, which is proposed by S. Mallat on the basis of multi-resolution in 1989 [78].

3.3.3.1 Decomposition algorithm

$$\begin{cases} A_0[f(t)] = f(t) \\ A_j[f(t)] = \sum_k H(2t - k)A_{j-1}[f(t)] \\ D_j[f(t)] = \sum_k G(2t - k)A_{j-1}[f(t)] \end{cases} \quad (3.8)$$

Where t indicates a discrete time sequence, $t = 1, 2, \dots, N$; $f(t)$ indicates the original signal; j indicates the layer, $j = 1, 2, \dots, j, j = \log_2 N$; H, G indicate wavelet decomposition filters in time domain, namely filter coefficients. For signal $f(t)$, A_j indicates the approximate part of the layer j , the low-frequency part of the wavelet coefficient, and D_j indicates the detail part of the layer j , the high-frequency part of the wavelet coefficient.

The meaning of the formula (3.8): assuming that the detected discrete signal $f(t)$ is A_0 , making the convolution of the wavelet appropriation coefficients A_{j-1} at scale 2^{j-1} (layer $j-1$) and decomposition filter H , the approximate portion of the signal $f(t)$ at scale 2^j (layer j), the low-frequency portion of the wavelet coefficients A_j is obtained through the convolution result alternately sampling. Similarly, Making the convolution of the wavelet appropriation coefficients A_{j-1} at scale 2^{j-1} (layer $j-1$) and decomposition filter G , the detail portion of the signal $f(t)$ at scale 2^j (layer j), the high-frequency portion of the wavelet coefficients D_j is obtained through the convolution result alternately sampling. By decomposition, at each scale 2^j , the signal $f(t)$ is decomposed into approximation coefficients A_j (low-frequency) and the detail coefficients D_j (high-frequency). The process is shown in Figure 14.

3.3.3.2 Reconstruction algorithm

$$A_j[f(t)] = 2 \left\{ \sum_k h(t - 2k)A_{j+1}[f(t)] + \sum_k g(t - 2k)D_{j+1}[f(t)] \right\} \quad (3.9)$$

Where j indicates the layer of decomposition, if the depth of decomposition is $J, j = J-1, J-2, \dots, 1, 0$; h, g indicate wavelet reconstruction filters in time domain, namely filter coefficients.

The meaning of the formula (3.9): The convolution of reconstruction filter h and the wavelet appropriation coefficients A_{j+1} at scale 2^{j+1} (layer $j+1$) which is after zero insertion, the convolution of reconstruction filter g and the wavelet detail coefficients D_{j+1} at scale 2^{j+1} (layer $j+1$) which is after zero insertion, the low-frequency portion of the wavelet coefficients A_j is obtained through the sum of them. Then after continuous repetition, the reconstruction

signal can be obtained until scale 2^0 . The process is shown in Figure 15.

What's more,

$$\begin{cases} H(n) = h(-n) \\ G(n) = g(-n) \\ g(n) = (-1)^{1-n} h(1-n) \end{cases}$$

(3.10)

Mallat algorithm can decompose the signal into approximation signal and detail signal of different levels, then analyze and process them to reconstruct new coefficients. That is the general process to preprocess signal through filtering, denoising signal.

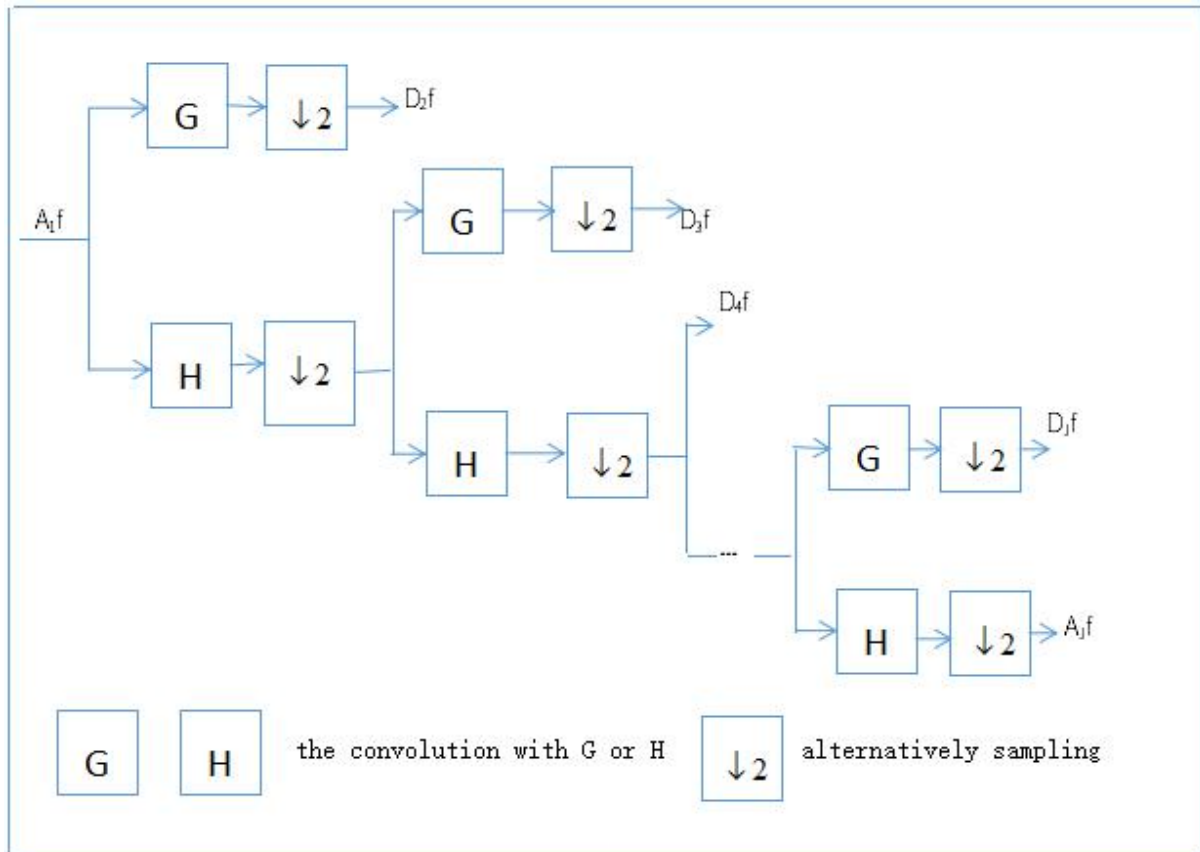


Figure 14. The flow chart of Mallat decomposition algorithm

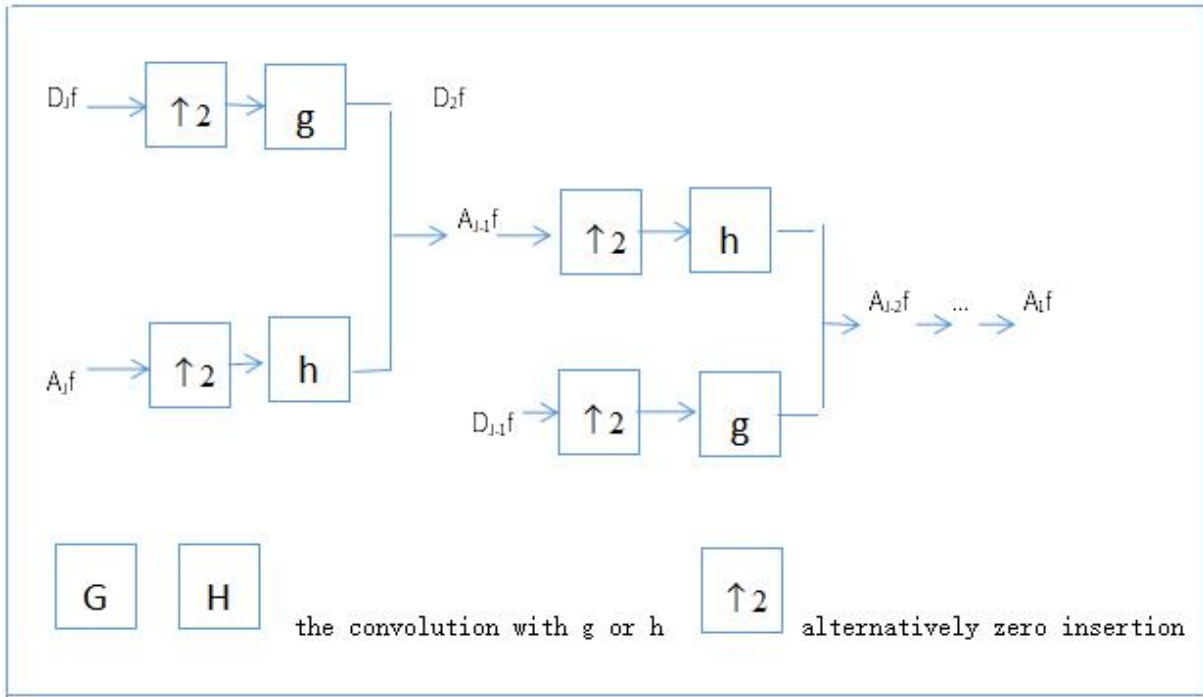


Figure 15. The flow chart of Mallat reconstruction algorithm

3.4 Correcting baseline drift

For removal methods of baseline drift, there are chiefly median filtering methods [52, 53], neural network based adaptive matched filter [54], combining method based on interpolation, extraction and linear filter [55], adaptive method [56], cubic spline method [57, 58], wavelet transform [45, 46] and so on.

The effect of the median filtering method is closely related to the width of the filter window. If the filter window is too narrow, the fitting baseline still contains more high-frequency components, which leads to the ECG signal distortion; if the filter window is too wide, it will not only influence the filtering effect, but also result in increasing computational complexity. Cubic spline method is based on the correct recognition of the band feature points and the slow variation of the baseline drift, which can degrade the performance seriously if the waveform recognition is inaccurate or the baseline drift has a high frequency. Wavelet transform has a good time-frequency resolution. For baseline drift which is mostly less than 0.5Hz caused by respiration, as long as removing the wavelet coefficients at the corresponding scale, and then making the wavelet reconstruction, the problem will be smoothly solved.

Based on the comprehensive basic principle and algorithm of wavelet transform, it found that the decomposition of the original signal at different layers corresponds to signal components of different frequency bands, and Mallat algorithm can conveniently realize the wavelet decomposition and reconstruction of the signal.

A noisy one-dimensional signal model is as follows:

$$X[n] = f[n] + W[n] \tag{3.11}$$

Where $X[n]$, $f[n]$ and $W[n]$ indicates respectively the signal with noise, the useful signal, the noise. Making wavelet decomposition of the signal, then processing the wavelet

coefficients and wavelet reconstruction to the signal can achieve the purpose of denoising signal. That is, the process is to suppress the useless part and restores the useful part of the signal.

The specific steps of eliminating the baseline drift by wavelet transform are as follows:

1) The ECG signal used in this tesina is S (250Hz), and the frequency of the baseline interference is mainly low frequency (<0.5Hz), so the ECG original signal is decomposed into 8 layers successively(MATLAB wavedec function, the wavelet is db6). Then the corresponding detail coefficients (high-frequency component, highpass, CD) and approximation coefficients (low-frequency component, lowpass, CA) are obtained.

The reason for choosing wavelet function db6 is that, through theoretical analysis and experimental comparison, the discrete wavelet Haar makes the detail signal and the approximation signal both discontinuous, and the baseline drift is continuous, thus the reconstructed signal cannot completely eliminate the baseline drift and damage partial detail information. The approximation signal obtained by bior3.1 decomposition is continuous, but it produces a new baseline drift due to the high frequency components which are not included in the baseline drift. For rbio3.1, the approximation signal does not have any similarity with the baseline drift, and the result of the reconstructed signal also completely loses the information of the ECG signal. For these three kinds of wavelet, the satisfactory approximation signal can not be obtained even though changing the decomposition level, so that no favorable effect of removing the baseline drift can be obtained. In conclusion, db6 is one of the wavelet functions that can better meet the requirements. There are scaling function, wavelet function for db6 in Figure 16.

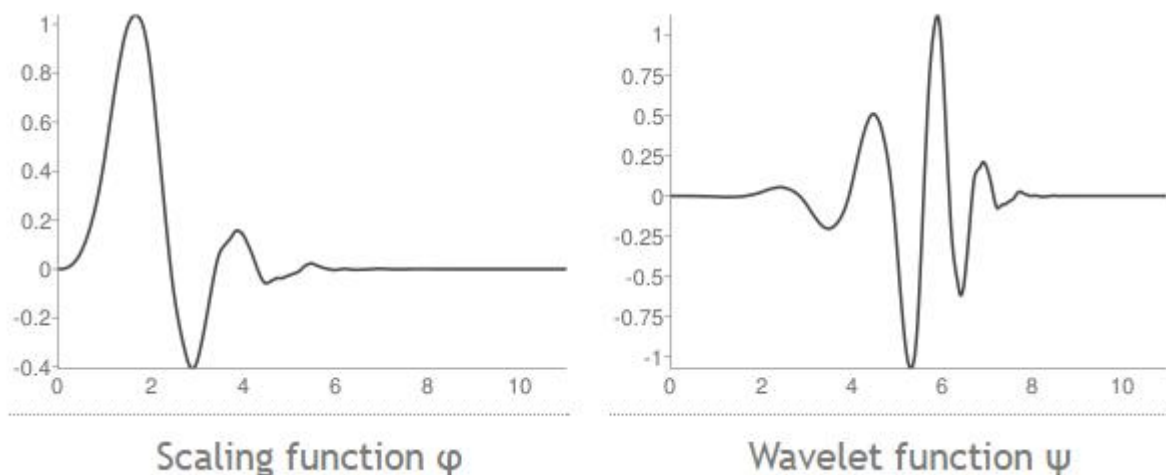


Figure 16. db6: Scaling function, Wavelet function

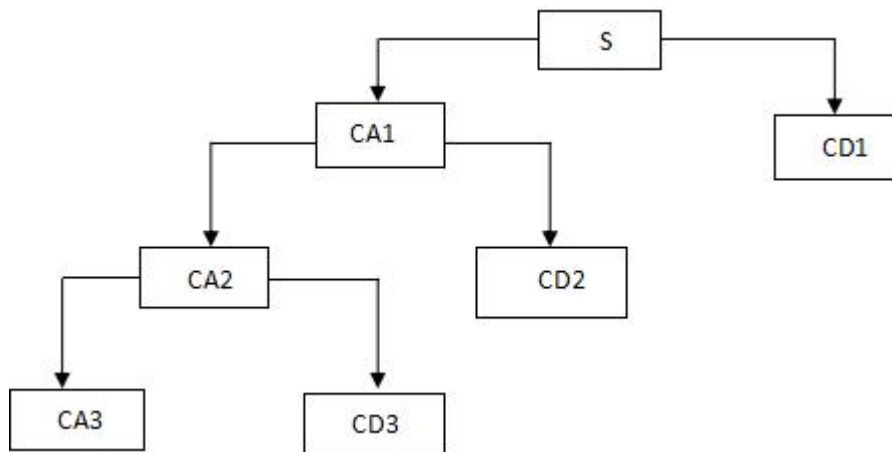


Figure 17. Three-layer wavelet decomposition example

As shown in Figure 17., S is the ECG signal with 250Hz (that is, the sampling rate), the most recoverable frequency is 125Hz, then S is decomposed into CA1: 0 ~ 62.5Hz, CD1: 62.5 ~ 125Hz. CA1 continues to be decomposed into CA2: 0 ~ 31.25Hz and CD2: 31.25 ~ 62.5Hz. And so on, until CA8: 0 ~ 0.4883Hz, CD8: 0.4883 ~ 0.9766Hz.

2) The frequency range of CA8 is basically consistent with the range of baseline drift. Hence, the corresponding signal is set to 0 to eliminate the information of baseline drift.

3) Finally, according to the 8th layer low frequency coefficient and high frequency coefficients of the 1st to the 8th layer, one-dimensional reconstruction is performed, the wavelet reconstruction. Finally, the corrected ECG waveform is obtained. This method eliminates the baseline drift, the DC component introduced in the measurement is removed as well.

3.5 Removal of powerline and EMG interference

A useful signal is usually a low frequency signal or a relatively smooth one. Since EMG interference and powerline interference in the ECG signal are considered as zero mean Gaussian white noise with higher frequency relative the ECG signal, they can be solved by removing high-frequency noise. Because a single cut-off frequency filter is hard to meet the needs of various circumstances, many scholars have put forward a variety of methods. Through the corresponding operation of discrete digital signal processing, the digital filter[61, 62] changes the signal spectrum. The Gaussian filter (LPF) [63] obtains the high signal-to-noise ratio smoothing signal by using the Gaussian function to make convolution. What's more, there are nonlinear filtering methods based on average filtering [64], adaptive filter, wavelet threshold denoising [65] and so on.

3.5.1 The principle of wavelet threshold denoising

In view of the favorable characteristics of wavelet transform, it is better to use wavelet threshold denoising to remove powerline and EMG interference.

Wavelet threshold denoising is to compress the signal according to a certain preset threshold, and then reconstruct the signal with the compressed coefficient to reach the aim of noise elimination. So far the most widely used are hard-thresholding method and soft-thresholding method.

T indicates the threshold, W_T , the signal after processing with the threshold. Soft-thresholding method:

$$W_T = \begin{cases} \text{sign}(W)(|W| - T), & |W| \geq T \\ 0, & |W| < T \end{cases} \quad (3.12)$$

Hard-thresholding method:

$$W_T = \begin{cases} W, & |W| \geq T \\ 0, & |W| < T \end{cases} \quad (3.13)$$

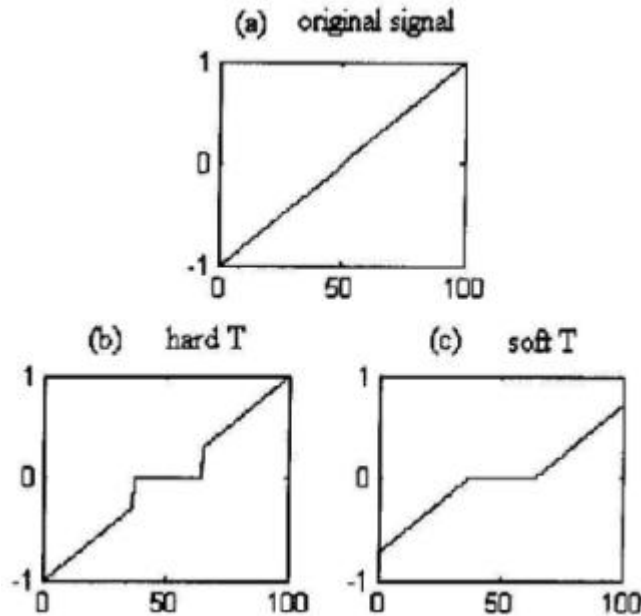


Figure 18. (a) The original signal, (b) The signal with hard-thresholding method, (c) The signal with soft-thresholding method

It is shown in Figure 18 that hard-thresholding method corresponds to the simplest processing way that is more risky, while the threshold method is more risky. Soft-thresholding method reduces the noise by slightly reducing the amplitude of all coefficients with less risk and strong mathematical characteristics.

One of the most critical problems is to estimate the noise level of the signal when threshold denoising is performed. Recently, several estimation methods have been proposed for wavelet denoising:

1) Rigrsure: a threshold selection rule based on Stein's Unbiased Estimate of Risk (SURE, quadratic loss function). One gets an estimate of the risk for a particular threshold value (t). Minimizing the risks in (t) gives a selection of the threshold value.

2) Sqtwolog: global or fixed thresholding denoising method uses a fixed-form threshold to get better denoising performance. The threshold value is $\sigma\sqrt{2\ln(n)}$, n is the length of the noisy signal, σ is Median Absolute Deviation(MAD).

3) Heursure: combination of Rigrsure and global thresholding method is the optimal threshold selection of the predictive variables. As a result, if the signal to noise ratio is very small, the SURE estimate is very noisy. In such case, fixed form threshold of Sqtwolog method gives better threshold estimation

4) Minimax thresholding method: this method finds threshold using minimax principle. It uses a fixed threshold to yield minimax performance for mean square error against an ideal procedure. The Minimax principle is used in statistics to design estimators. Since the de-noised signal can be assimilated to the estimator of the unknown regression function, the minimax estimator is the option that realizes the minimum, over a given set of functions of the maximum Mean Square Error (MSE). This procedure finds optimal thresholds [66].

In general, because powerline and EMG interference contain a large number of high-frequency components, the wavelet adaptive threshold is used to eliminate them simultaneously. The above analysis shows that in order to ensure that ECG signal characteristics are not damaged, soft-thresholding method must be used to remove the noise. Rigrsure and Minimax thresholding method are both conservative (only some coefficients are set to zero), so it is impossible to obtain better filtering effect when little high-frequency information of the signal is in the noise range. Others are more effective in removing noise, although the R peak has a small attenuation, it does not affect the follow-up work. It is found that using Heursure is slightly better than Sqtwolog, so Heursure is adopted. For the wavelet function, db6 is used continuously.

Since the main components of the signal are concentrated in the frequency bands below 45Hz. Therefore, signal of the 1st layer detail coefficient (high-frequency coefficient) is set to zero. Then using Sqtwolog, soft-thresholding method, db6 wavelet function to denoise CD2. Lastly, after the wavelet reconstruction, denoising signal can be obtained.

At last, Figure 19 is the comparison diagram that using the above methods to remove baseline drift and high-frequency noise, it can be seen that after preprocessing, the ECG waveform is more smooth than the original one. Furthermore, the oscillation has been basically eliminated, and the waveform is not obviously distorted, which preferably reflects the main information of the original ECG signal.

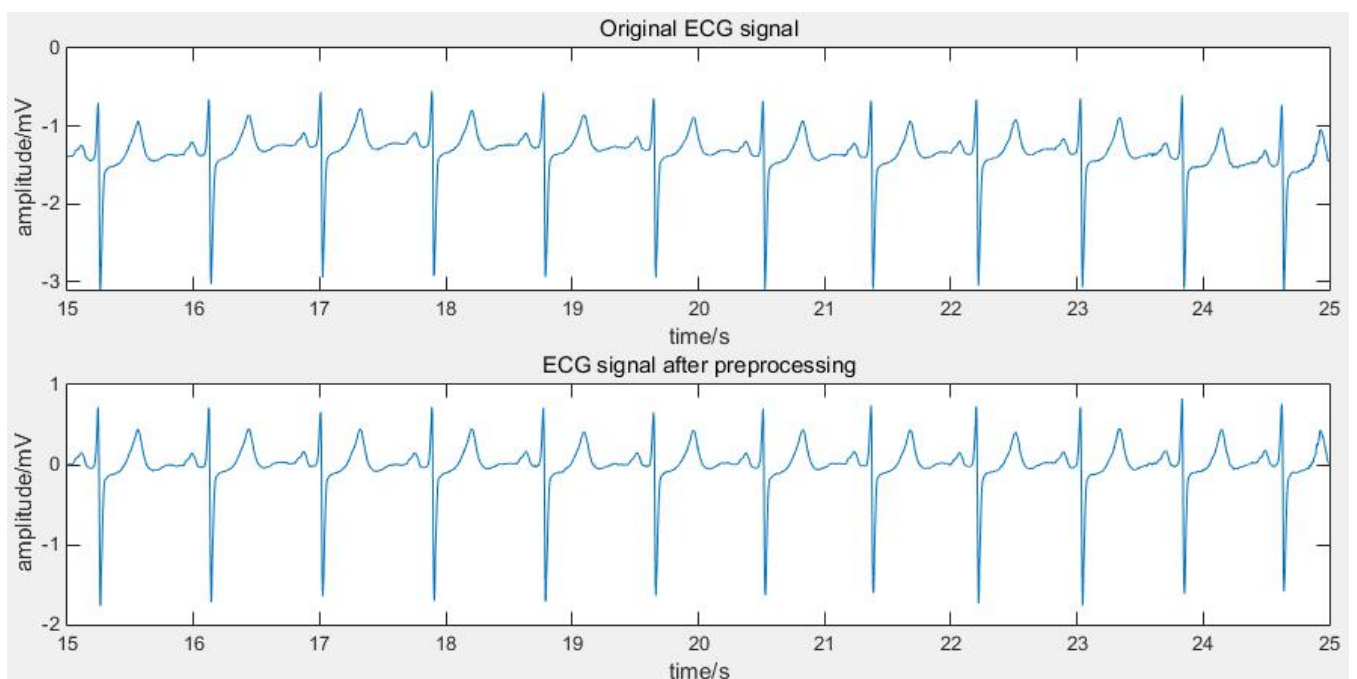


Figure 19. Sample e0106 in European ST-T Database: the original ECG signal and the denoised ECG signal

4. ECG Feature Detection

In the process of ECG signal analysis, first step is usually filtering the ECG signal, then detecting waveform, and the correlative parameters of waveform are calculated. Eventually, they are combined with pathological knowledge to determine the variation of the ECG signal, thus automatically diagnosing myocardial ischemia. Consequently, the waveform detection, that is, the accuracy and reliability of feature extraction, the waveform detection, will directly affect diagnostic results. The ECG signal has been preprocessed before, this section will mainly accomplish QRS complex detection, ST segment morphological detection, T wave location and morphological detection.

Generally speaking, compared with the ECG signal features of the same cardiac cycle, the QRS complex has the most obvious one, and the location of the R wave with high amplitude is the key to calculate the heart rate and detect the characteristics of the ST segment, thus distinguishing between normal and abnormal shape. Hence, universally, QRS complex detection is the first step in ECG feature extraction. Then other waves or segments are located on the basis of the R wave.

This Section describes how the features of the signal are detected: the QRS complex is detected (Section 4.1); the T wave is detected (Section 4.2); then the ST segment is detected (Section 4.3).

4.1 QRS complex detection

4.1.1 Extremum point detection and the boundary detection for QRS complex detection

4.1.1.1 R peak detection and QRS onset detection

At a matter of fact, in the ECG signal, peak points of P, Q, R wave must be extreme points, but not necessarily the maximum. if we determine extremum points in all sample points before we detect the characteristic points of the ECG signal, only the extreme points are analyzed to avoid searching all sample points. This can save time and reduce the cumbersome process. The main idea is to determine all extremum points in the sample by the appropriate threshold, then the R wave is detected in extremum points in response to the situation. After that, the Q wave can be detected forwards, and the S wave is detected backwards. The flow chart is shown in Figure 20.

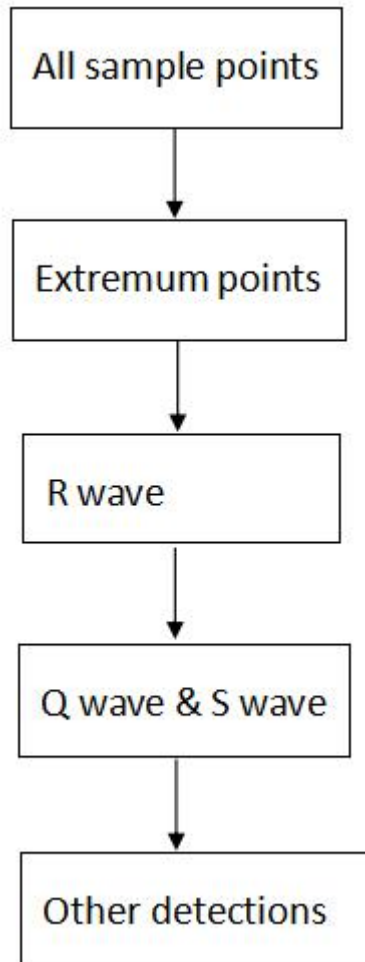


Figure 20. The flow chart of extremum point detection for the QRS complex

According to the characteristic of the normal ECG, the R peak is the most prominent:

- 1) Maximum amplitude
- 2) The most sharp waveform

Therefore, the R peak is determined by the maximum of the amplitude or the minimum of the second derivative. Then, the R peak can be determined by the average of 5 maximum values. After R peak detection, QRS onset and offset detection are carried out by using the boundary detection algorithm. First of all, the R wave is the center of the detection, the R peak is R1. In the window [R1-100ms, R1-40ms], Searching for a flat interval of 20ms and the slope of the signal is less than or equal to 25. The rightmost point of the interval is the QRS onset.

4.1.1.2 Q peak detection and S peak detection

For the Q peak detection and S peak detection, the process is as follows:

- 1) Determine the search period 1: for a normal EDG, QRS complex is between 0.04 ~ 0.11s , so the search period 1 is defined as 20 sampling points. In the search period 1, the minimum before the R peak is Q₁, the minimum after the R peak is S₁.

- 2) Determine the search period 2: that is 80 sampling points. Similarly, in the search period 2, the minimum before the R peak is Q₂, the minimum after the R peak is S₂.

3) Determine the Q peak position.

$$MV_{qq} = V_{q1} + T_v \quad (4.1)$$

Where MV_{qq} indicates the maximum between Q_1 and Q_2 , V_{q1} is the amplitude of Q_1 , $T_v = 0.18\text{mv}$, which is based on a large number of experiments.

$$V_{q2} > V_{q1} \quad (4.2)$$

Where V_{q1} and V_{q2} are the amplitudes of Q_1 and Q_2 respectively.

The process is as shown in Figure 21.

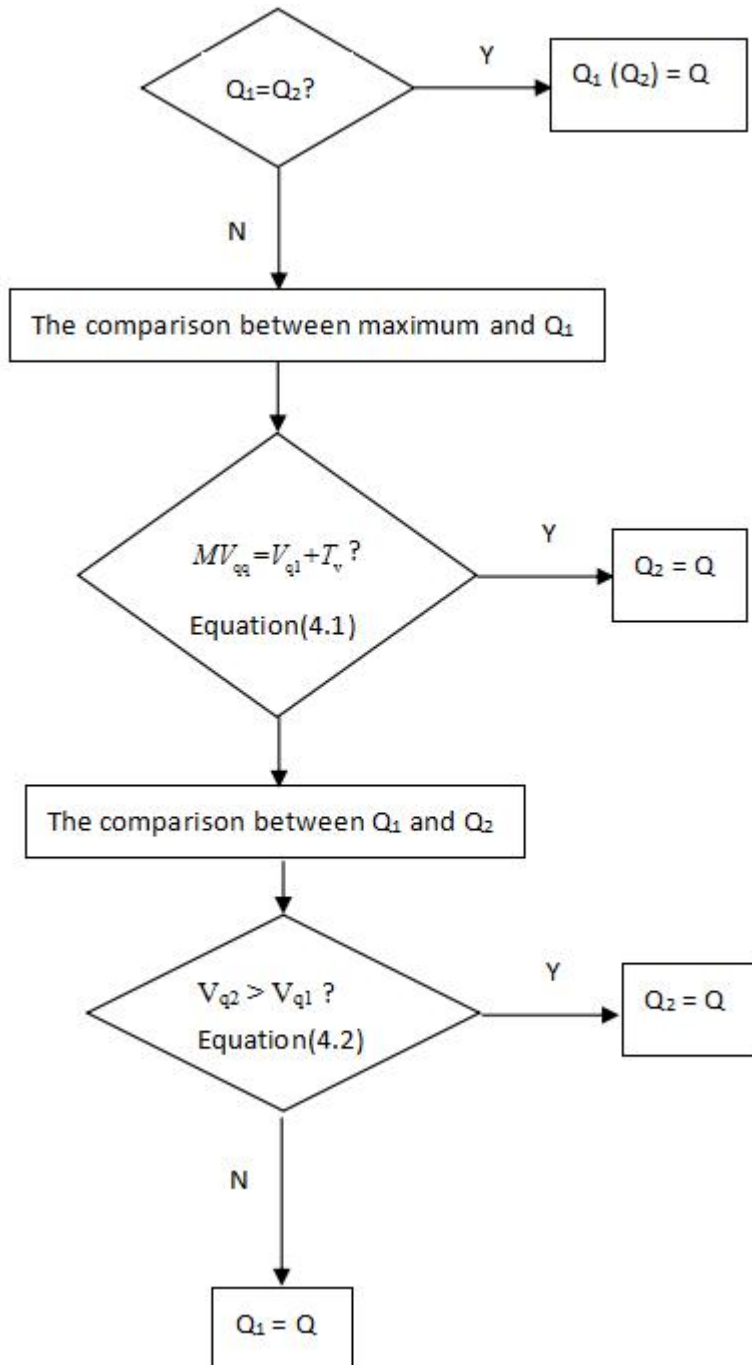


Figure 21. Specific flow chart for Q peak detection by extremum point detection

4) Determine the location of the S peak. If S_1 is equal to S_2 , then $S_1 (S_2)$ is the S peak. If

equation (4.3) is established, S_1 is the S peak, otherwise, S_2 is the S peak.

$$V_{s2} > V_{s1} \quad (4.3)$$

Where V_{s1} and V_{s2} are the amplitudes of S_1 and S_2 respectively.

The final example result of QRS complex detection is shown in the following figure (Figure 20).

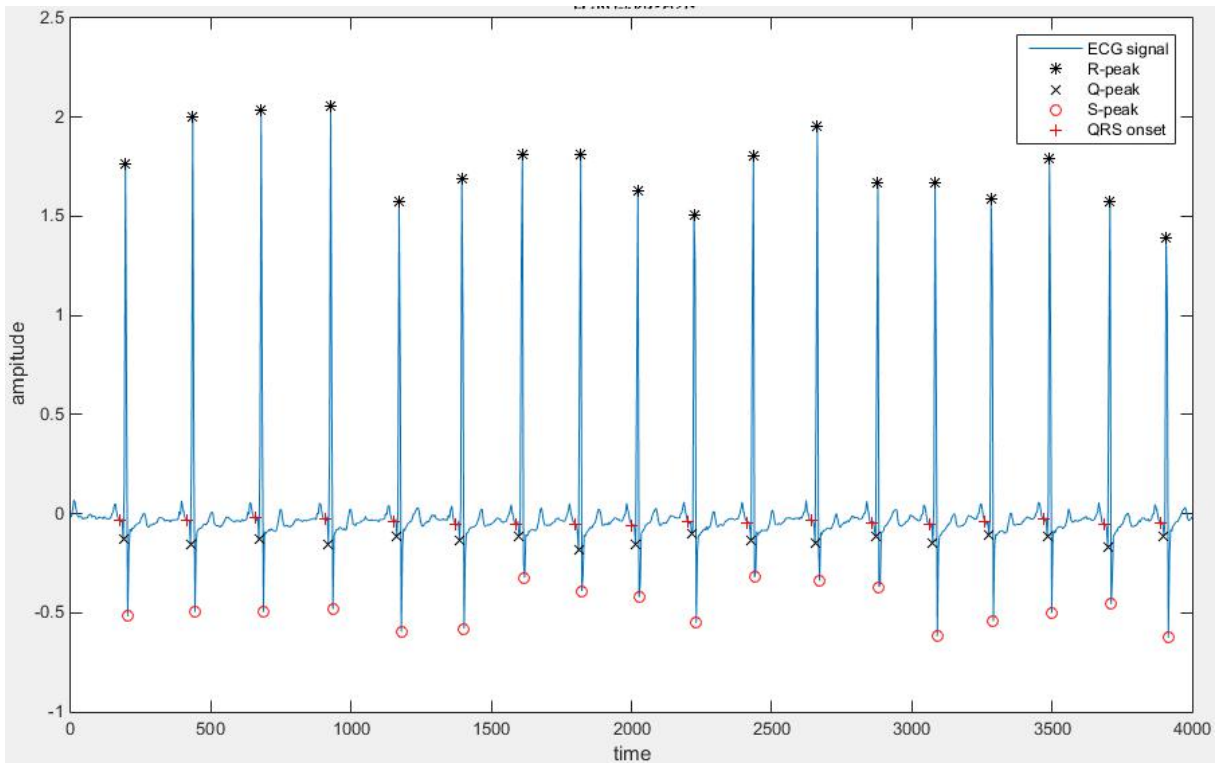


Figure 20. Sample e0127 in European ST-T Database: QRS complex detection by extremum point detection and the boundary detection

Because the extremum point detection needs to use the appropriate threshold value to determine all the extremum points in the sample, this method is too sensitive to singularities, if there is a super large value, the threshold will increase a lot, resulting in failure of QRS complex detection, which means the large T wave may be considered to be a R wave, or a slightly smaller R wave is missed. Because in the terms of the ECG signal, after the extraction of extremum points, there are two main types can be confused with the R wave, one is the large T wave, the other is the notch appeared on the R wave. The missed or wrong detection of the R peak will definitely influence subsequent detection of the ST segment and the T wave. So the improved method is to use multi-scale wavelet transform to detect the QRS complex, which has a good detection rate for most kinds of the abnormal QRS complex. It can accurately distinguish various waves, and also detect the P wave and the T wave.

4.1.2 The singularity of wavelet detection

In the signal, irregular mutations and singular points often contain more important information, which is one of important features of the signal. As described in section 3.2, Fourier transform is the main method to study singularity of the function. However, Fourier transform lacks spatial locality, that is to say, it is hard to determine the location and

distribution of singularities in space. Wavelet analysis has the property of spatial locality, so it is more effective to analyze the singularity, the location and the degree of singularities by using wavelet analysis.

For the singularity, it is necessary to give a precise quantitative description of the regularity for the signal $f(t)$. Lipschitz exponent can be used to measure the regularity of a signal. If f is at v point and Lipschitz $\alpha < 1$, then f is not differentiable at v point and α depicts its singular type.

Mallat and others have shown that when f is at v point, the local Lipschitz regularity is dependent on the decay of $|Wf(u,s)|$ at fine scales, which is the neighborhood of v . Measuring this asymptotic decay is equivalent to focusing the fine structure of a signal with a scale tending to zero. It is unnecessary to measure the decay directly in the time-scale plane (u, s) . In practice, the decay of $|Wf(u,s)|$ can be controlled by its local maxima, then using modulus maxima to represent them.

At a certain scale s_0 , if there is a point (u_0, s_0) makes $\frac{\partial Wf(u_0, s_0)}{\partial y} = 0$. Then the point (u_0, s_0) is the local extremum, and there is a modulus extremum on $\frac{\partial Wf(u_0, s_0)}{\partial y}$ when $u = u_0$.

If there is $|Wf(u, s_0)| \leq |Wf(u_0, s_0)|$, when any point u in the neighborhood of u_0 , then the point (u_0, s_0) is the modulus maximum for wavelet transform. The connection of all of them is called a modulus maximum line.

If and only if there is a wavelet maximum sequence $(u_p, s_p)_{p \in \mathbb{N}}$ converges to v at fine scales, that is,

$$\begin{cases} \lim_{p \rightarrow +\infty} u_p = v \\ \lim_{p \rightarrow +\infty} s_p = 0 \end{cases} \quad (4.4)$$

Then f is singular at point v . The result ensures that all singularities can be detected by searching abscissa values that make modulus maxima converge at fine scales. In order to better understand the significance of these maxima, the wavelet transform is written into a multi-scale differential operator. If the wavelet ψ with compact support has the n vanishing moments, it can be proved that wavelet transform is equivalent to a n -order multi-scale differential operator, which is a function θ with compact support set, so that

$$\psi(t) = (-1)^n \frac{d^n \theta(t)}{dt^n} \quad (4.5)$$

$$\text{Then } Wf(u, s) = s^n \frac{d^n}{du^n} (f * \bar{\theta}_s)(u) \quad (4.6)$$

$$\text{Where } \bar{\theta}_s(t) = s^{-1/2} \theta(-t/s)$$

If the wavelet has only the one vanishing moment, the wavelet modulus maximum is the maximum of the first derivative after f is smoothed with $\bar{\theta}_s$. If the wavelet has two vanishing moments, the modulus maximum corresponds to the high-order curvature. If $Wf(u,s)$ has no modulus maximum at fine scales, then f must be local regular.

4.1.3 Wavelet transform for QRS complex detection

4.1.3.1 Wavelet function selection

The Gaussian function can be used to construct a wavelet series, and any order derivative of Gaussian function is an infinite smooth wavelet, and the n^{th} derivative has n vanishing moments. Therefore, using modulus maxima of the signal $f(t)$ by wavelet transform, the singularity of $f(t)$ can be detected until the $(n-1)^{\text{th}}$ derivative. Through the above analysis, there is a QRS complex randomly extracted from sample e0106 in European ST-T Database, using the first derivative and the second derivative of Gaussian function as wavelet function respectively to transform it, and the comparison result is shown in Figure 21.

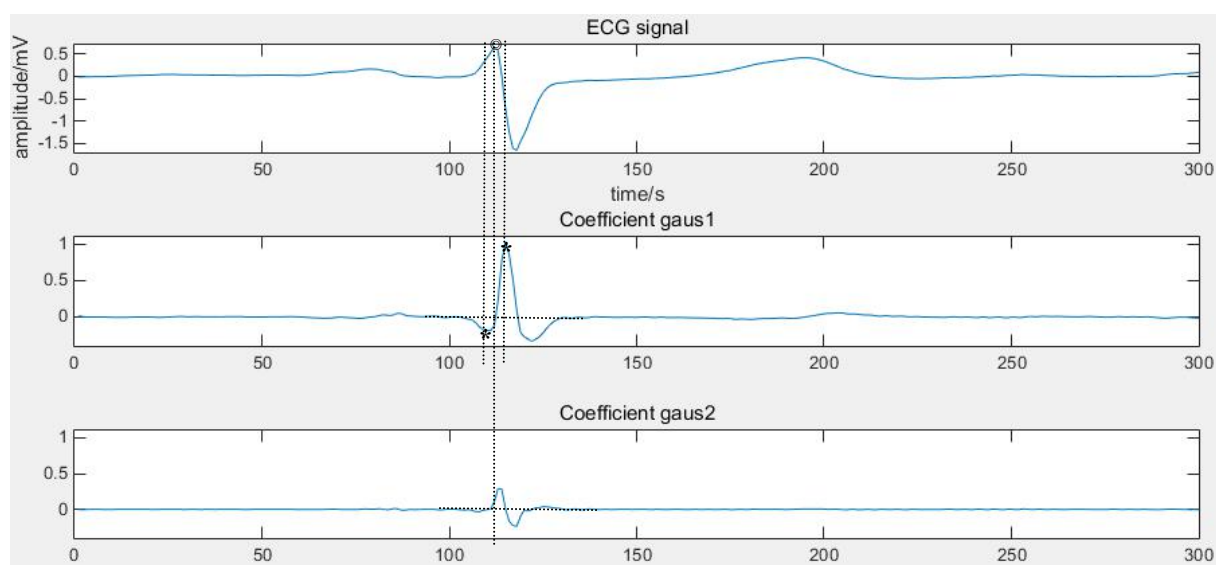


Figure 21. Using coefficient gaus1 and gaus2 to make wavelet transform in the ECG signal

All singularities of the signal $f(t)$ are located along the modulus maximum line at the scale-time space when the scale tends to zero. That is, the smaller the scale, the closer the singularity and the modulus maximum position. So in Figure 21, the modulus maximum corresponding to the singularity at scale 1 is selected. This QRS complex is a common one with a upward R peak. For the sake of facilitating comparison, the coordinates of coefficient gaus1 and coefficient gaus2 are identical. It can be seen that the results of the wavelet transform in the ECG signal using the first derivative and the second derivative of Gaussian function as the wavelet function are consistent with the previous analysis. Therefore, the peak position can be obtained by finding the zero crossing on the signal with gaus1 wavelet transform, or finding the extremum on the signal with gaus2 wavelet transform. Here the difference between the two wavelet functions for determining the peak position need to be compared.

It can be seen from Figure 21, compared with coefficient gaus2, coefficient gaus1 is more sensitive to the mutation of the signal, and its modulus maxima pair is sharper than the extremum in coefficient gaus2, which is convenient to be detected. Meanwhile, the noise will make the waveform with the wavelet coefficients near the modulus maximum have a certain oscillation, so it is very difficult for coefficient gaus2 to select a uniform threshold to determine whether the local extremum is the required modulus maximum. If the local extremum is filtered individually, the workload is greatly increased. For coefficient gaus1,

this contradiction is much smaller. Moreover, the modulus maxima pair has more constraints on itself, in other words, it is necessary to ensure it with inverse amplitudes. This can greatly improve the accuracy of detection. Therefore, the wavelet gaus1 is used to detect the QRS complex in the ECG signal.

4.1.3.2 Peak detection of the QRS complex

In the aspect of ECG feature extraction, it is feasible to locate mutation by using the modulus maxima pair of continuous wavelet transform. In the existing peak detection and calibration, the wavelet function is more of the first differential wavelet. After the wavelet decomposition of the ECG signal, various signal parts can be found at different scales to correspond with a pair of modulus maxima. Since in the continuous wavelet transform, the modulus maxima pair, a positive one and a negative one, corresponds to the singularity (mutation). The singularity position can be determined by searching zero crossings between the modulus maxima pair. The core strategy of the detection algorithm is to search the zero crossing between the modulus maxima pair at a certain scale or some scales. The R wave corresponds to a modulus maxima pair at each scale, and zero crossing between them is its peak position, R peak.

Then, based on these, some strategies are put forward to improve the detection, also making a time shift correction between the peak position and zero crossing of the modulus maxima pair, but it is still unable to accurately locate the peak point. In this thesis, the first derivative of Gaussian function, which belongs to the first differential wavelet as well, is used as the wavelet function. Then the zero crossing in the ECG signal with wavelet transform corresponds to the peak position. However, in this thesis, the method of peak detection has further improved that can be used to locate the peak accurately.

The specific process of R peak detection is: making wavelet transform in the ECG signal at scale 1, in which the wavelet function is the first derivative of Gaussian function. Detection of the modulus minimax pair with zero crossing property is made on it, each detection of such the modulus minimax pair means that the ECG signal has a peak within the interval. Then, the local extremum, the peak position, is searched in the interval which is determined by each modulus minimax pair. Furthermore, because the Q wave and the S wave are the mutation with smaller amplitude in the ECG signal, also can be detected by wavelet transform with the signal mutation characteristic. According to the R peak, it is reasonable to forward and backward search for the Q peak and the S peak in the ECG signal. As shown in Figure 21, "*" indicates the modulus minimax pair with zero crossing property, the interval between the leftmost and the rightmost line is the scope where the R peak exists, and "O" is the R peak detected in that scope.

The optimization of this method is not to directly find the zero crossing of the modulus minimax pair, but only to use it to determine the range of the peak, then return to the ECG signal to search the peak. Completely taking advantage of time domain information from wavelet transform, that can avoid the time shift between the peak position and the zero crossing of the modulus maxima pair, which greatly improves the accuracy of peak detection.

4.1.3.3 QRS onset and offset detection

In general, the method of QRS onset and offset detection is basically the slope threshold detection. This method is forward and backward respectively to search the point with the slope close to zero using the R peak, the Q peak or the S peak as the center, that is, the location is determined as the QRS onset and the QRS offset once the curve changes into a horizontal line. The method is not ideal to realize in programming, and the result of detection

is susceptible to be interfered [67].

In this tesina, the QRS onset and offset are determined by combining the information of the ECG signal and the signal with wavelet transform. For the signal with coefficient $gaus1$, the mutation is also expressed as a modulus maximum, while in the slowly changing part of the signal it is approximate to a straight line. Therefore, the starting and ending position of the mutation on the signal with wavelet coefficient can correspond to the starting and ending position of mutation in the ECG signal, and the detection of the starting and ending position on the signal with wavelet coefficient is much easier and the noise has a very limited influence on it. Even if the starting and ending position of the mutation on the signal with wavelet coefficient has a small shift to the real position in the ECG signal, considering that the estimation of the QRS onset and offset cannot be precise, the shift within this small range is permissible. So in this tesina, using the information on wavelet transform and the ECG signal together to determine the QRS onset and offset is an effective method.

The specific method is that with the peak detected in the core, looking for the point with amplitude and slope successive searched forward and backward both close to zero, and checking whether the value of the ECG signal at that point is close to the baseline, then the search is stopped and the point is determined to be the QRS onset or the QRS offset.

Although there are some problems in the feature extraction of ECG signals by wavelet transform, compared with other methods, it still has many obvious advantages with the appropriate wavelet, threshold and transformation scales. Adopting the modulus maxima pair of wavelet transform can not only accurately locate the R wave position, but also avoid the influence of the large T wave. Besides, the method still can realize R wave detection under the influence of the variable-shaped R wave and the strong noise.

The example result is shown in Figure 22.

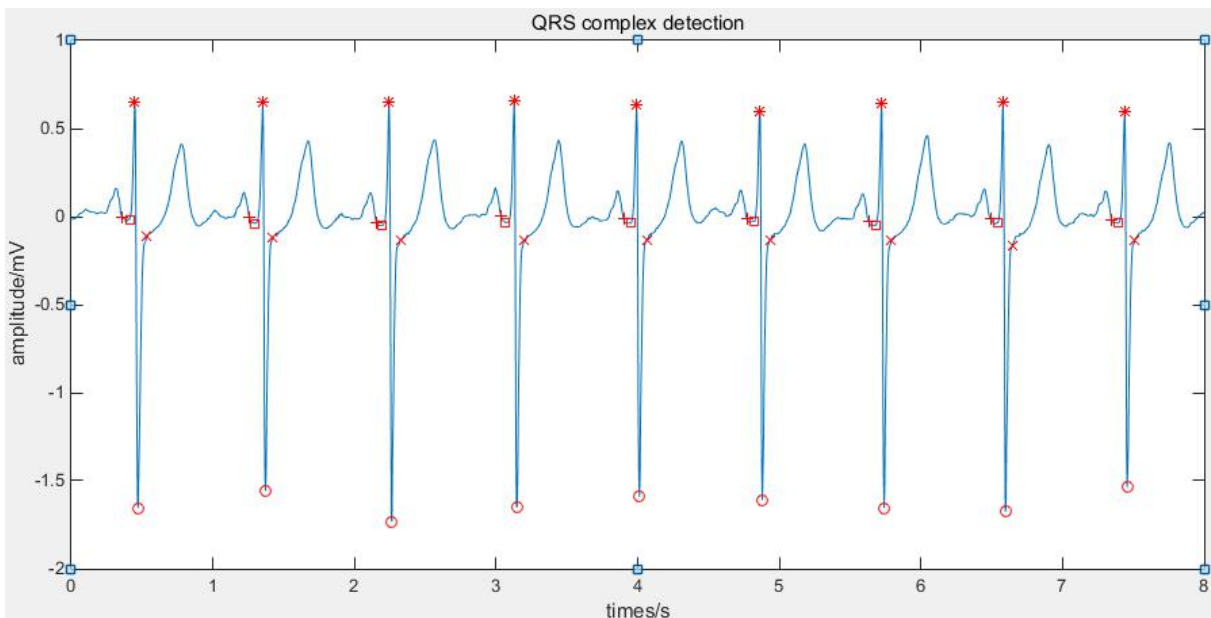


Figure 22. Sample e0106 in European ST-T Database: QRS complex detection by wavelet transform, where ‘*’ indicates the R peak, ‘o’, the S peak, ‘square’, the Q peak, ‘+’, the QRS onset, ‘x’, the QRS offset

4.2 T wave detection

Besides the QRS complex, the T wave is another important part in the ECG signal. T wave localization and morphological type recognition are essential indicators for myocardial ischemic diagnosis. Moreover, the ST segment is in front of the T wave, as one of the essential diagnostic indicators of myocardial ischemia, and accurate T wave detection is directly related to the ST segment. But compared to the QRS complex, the T wave with low frequency has smaller amplitude and morphological diversity, which makes it difficult to locate the starting point and the endpoint. In a word, T wave detection is still a problem that is not well solved.

The normal T wave, blunt and accounted for a longer time, slowly rises from baseline and then descends rapidly, forming a longer front, and shorter back waveform. T wave direction is often consistent with the main wave direction of the QRS complex. According to clinical statistics, the common T wave morphology are as follows, as shown in Figure 23, the positive wave, the inverted wave, the biphasic wave (positive/negative or negative/positive), the bimodal wave (positive/positive or negative/negative) [69]. Besides, not all kinds of abnormal T waves belongs to ischemia, just the hyperacute T wave and the deep inverted T wave, almost symmetrical with the R wave, are both the significant kinds in ECG manifestations of myocardial ischemia. This part will be discussed in detail in Section 5.3.

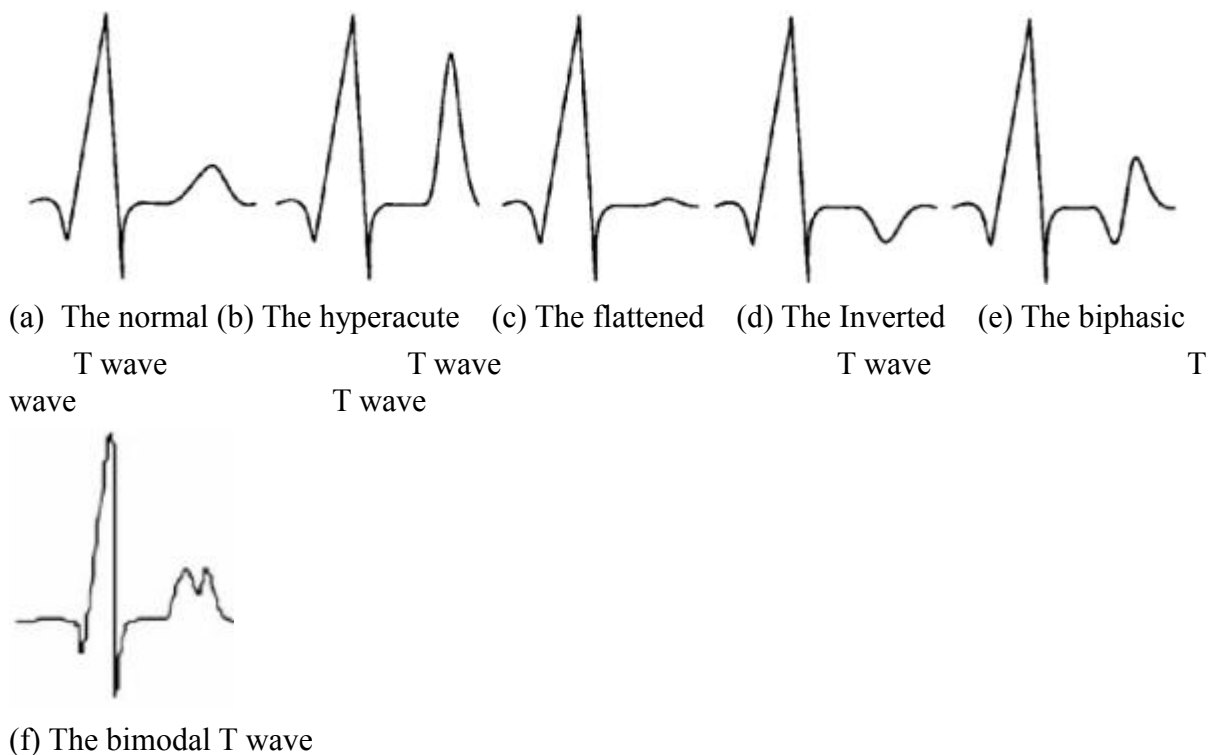


Figure 23. 6 most common kinds of T wave morphology: (a) is the normal T wave, the others are abnormal T waves, but only the (b) hyperacute T wave and the (d) deep inverted T wave are both ECG manifestations of myocardial ischemia. The other abnormal shapes of the T wave are ECG manifestations of suspected myocardial ischemia.

4.2.1 The local transform algorithm

T wave is usually detected by difference threshold arithmetic or slope method, but these methods are susceptible to high-frequency noise interference. In this section, the local

transformation is used to detect the T peak, the basic idea is to connect the starting point and the endpoint of the detection area as a straight line, then to compute the distance between the each signal point in the region and the point on this straight line corresponding to that signal point, and the extremum of the distance is the slope mutation in the detection area.

Firstly, adopting the QT empirical formula (4.7), the position of the T wave endpoint can be estimated,

$$T_{end} = Q_{on} + 0.55\sqrt{R - R} \quad (4.7)$$

Where T_{end} indicates the time corresponding to T wave endpoint, and Q_{on} indicates the time for the QRS complex onset, and the R-R indicates the interval between the current heart beat point to the previous heart beat point.

The local transform detection area is from backward the S peak at 40ms to the T wave endpoint, and the point with maximum difference is used as the T peak.

The specific steps are as follows:

1) Draw a straight line from backward the S peak at 40ms to the T wave endpoint, and the equation of the straight line is obtained:

$$y(n) = x(S_{peak}) + (n - S_{peak}) \frac{x(T_{peak}) - x(S_{peak})}{T_{peak} - S_{peak}} \quad (4.8)$$

2) The corresponding local transformation equation is:

$$D(n) = |x(n) - y(n)| \quad (4.9)$$

Where $x(n)$ is the signal amplitude at abscissa n in the detection area, S_1 and T_{peak} are the horizontal axis of the point from backward the S peak at 40ms and the T peak respectively.

Taking the extremum point of $D(n)$, the point with the maximum distance from the fitting line, is to obtain the T peak.

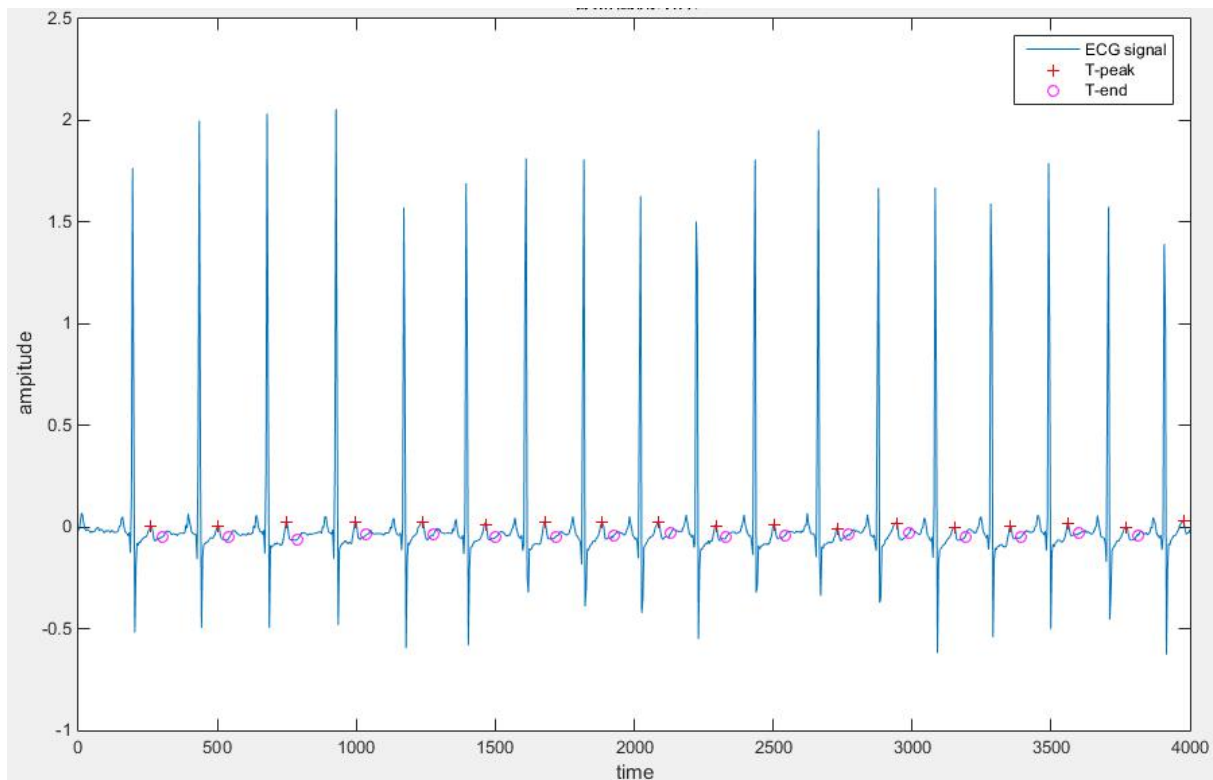


Figure 23. Sample e0127 in European ST-T Database: the T peak detection and the endpoint detection by the local transform algorithm

As shown in Figure 23, in normal case it performs well. However, because local transformation algorithm are done in the whole signal band, T wave characteristics are not obvious, which leads to inaccurate detection, wrong and missed detection. So in this tesina, a simple improved method is proposed, which is similar to the above-mentioned QRS complex detection, makes T wave characteristics are prominent and the effect is better when T wave detection is made in the ECG signal without QRS complex.

4.2.2 Wavelet transform for the T wave detection

As is analyzed at the beginning of this section, the T wave is not as obvious as the QRS complex, so the study of the T wave is far less mature than that of the QRS complex. Additionally, because the boundary of the T wave is often blurred, it is difficult to check the result of recognition in a wide range, only a rough estimate can only be done in a small range by visual inspection.

In the light of the previous work, the QRS onset and offset have been determined. With regard to the correctness of results, it is inevitable to remove the interference from ECG signals, that is, in the first place, the ECG signal needs to be processed so that some essential parameters are extracted.

By linear fitting of the segment of the QRS complex in the ECG signal, the QRS complex can be removed and the signal including the P wave and the T wave is obtained. Then, due to further work, the baseline is in demand by using the algorithm for removing baseline drift.

P and T wave characteristics are both not obvious, and the circumstance like the flattened T wave and the P wave exists in some ECG signals, so it is impossible to use uniform

threshold to include all cases. However, the alternating appearance of the P wave, the QRS complex and the T wave. This feature allows them to be detected by determining the two most visible waves between two QRS complexes. Manifestly, the front one is the T wave, the latter one is the P wave. But it is a vague statement that must be clarified in the algorithm. In this tesina, the most obvious wave is defined as the maximum difference between the peak and the Q peak / S peak.

The specific steps for T wave detection: firstly, the local extremum is detected in each S-Q interval. In the region near the S peak, the local extremum with the maximum difference between the point and the S peak is determined as the T peak. Similarly, in the region near the Q peak, the local extremum with the maximum difference between the point and the Q peak is determined as the P peak. Taking into account the T wave inversion, the value of the S peak, the Q peak and the extremum are recorded as the distance to the baseline which is the new one calculated in the ECG signal without the QRS complex. Because the starting and the endpoint of the T wave are points with the absolute slope value close to zero, so the T peak is in the core, through forward and backward looking for the point satisfied the condition, the point is determined as the starting or ending point. The process is shown in Figure 24.

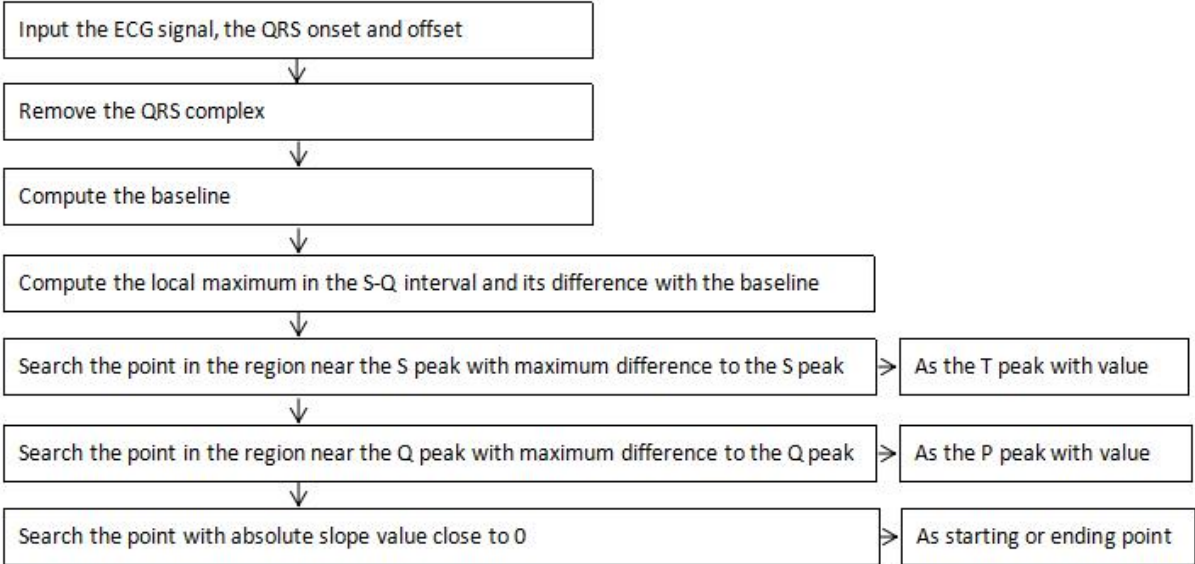


Figure 24. Specific flow chart for T wave detection by wavelet transform

T wave morphology is to set a peak threshold in the range of the T wave, from the starting point to the endpoint, thus determining whether there is one or two peaks. If there are two peaks, the T wave is determined as a biphasic or bimodal one that depends on the positive or negative T peak. If there is one peak, T wave morphology depends on the amplitude of the T peak and medical theory.

The example result is shown in Figure 25.

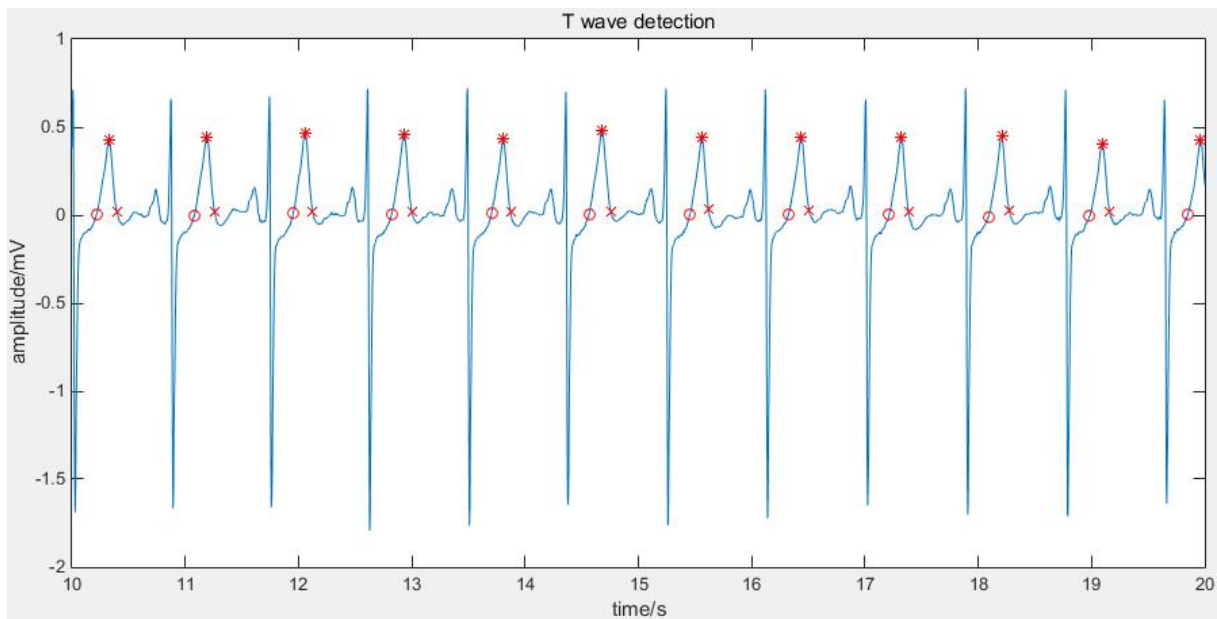


Figure 25. Sample e0106 in European ST-T Database: T wave detection by wavelet transform, where ‘*’ indicates the T peak, ‘o’, the starting point of the T wave, ‘x’, the endpoint of the T wave

4.3 ST segment detection

As described in the second chapter, many commonly used ST segment detection algorithms still have various problems, such as poor reliability or large computational capacity, difficult practical operation. In order to further improve the accuracy of ST segment recognition, reduce the computational amount, and simplify the process of ST segment morphological recognition. In this thesis, a ST segment morphological analysis method is proposed. The 4 morphological features of the ST segment, the offset level, the curve type, the slope and the camber, are used as identified criteria. At the same time, the classification of ST segment morphology are carried out gradually. The merits of this method are simple principles and convenient operation. In the end, the ST segment can be correctly identified, and the morphological classification of the ST segment is completed relative systematically.

4.3.1 ST segment morphology

The ST segment is a band from the end of the QRS complex to the T wave in the electrocardiogram. Under normal circumstances, the ST segment is parallel to, a slight upper or lower offset to the equipotential line. However, When the ventricular repolarization is affected by certain factors, the ST segment may cause abnormal elevation (ST Elevation: STE) or depression (ST Depression: STD) and corresponding changes in various forms. Besides, not all kinds of abnormal ST segments belongs to ischemia, just downsloping STD, horizontal STD and convex STE are the significant kinds in ECG manifestations of myocardial ischemia. This part will be discussed in detail in Section 5.3.

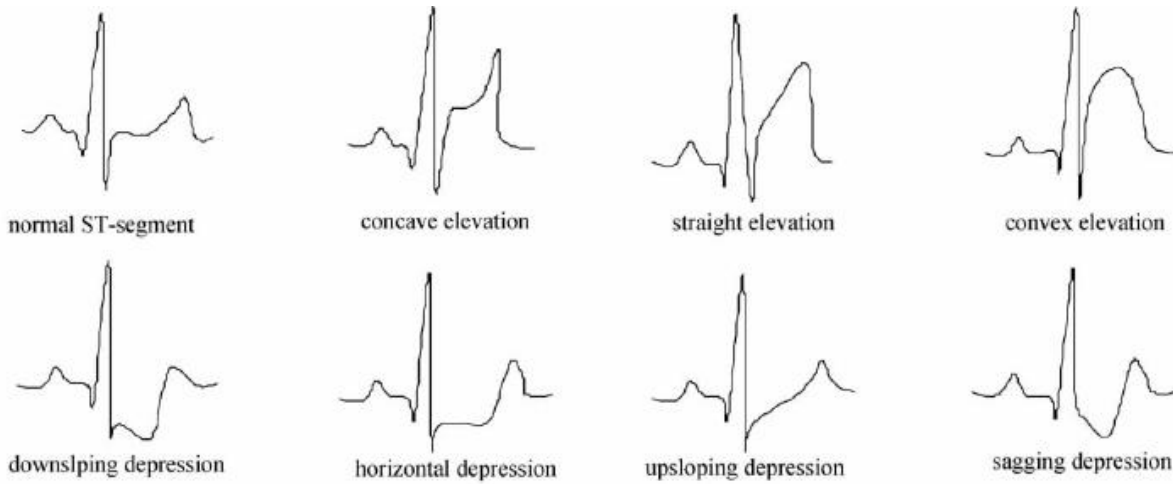


Figure 26. Some examples of typical morphologies of the ST segment: the first one is normal ST segment, the others are abnormal ST segments, but just downsloping STD, horizontal STD and convex STE are the significant kinds in ECG manifestations of myocardial ischemia.

It can be seen from Figure 26 [69], the ST segment and the T wave in many cases are difficult to distinguish completely, which makes the endpoint of the ST segment difficult to be precise located. In fact, the clinical physician just need to estimate the approximate range of the ST segment instead of precise one to analyze ST segment morphology.

By analyzing various ST segment shapes, it is found that the ST segment curve can be simply divided into linear and curvilinear type without considering the offset direction of the ST segment. Among them, straight STE, horizontal STD, downsloping STD and upsloping STD are linear type. Then, it can be divided into more concrete forms according to the slope. Furthermore, concave STE, convex STE and sagging STD are curvilinear type. Then, according to its concave-convex direction, it also can be carried on the more specific morphological distinction. So it can be concluded that four criteria should be used to recognize ST segment morphology: the offset direction, the curve type, the slope, the concave-convex direction.

4.3.2 The offset direction of the ST segment

The J point is the starting point of the ST segment, which is normally at equipotential line, while ST segment changes, tachycardia, or the rising edge of the T wave may lead to the J point shifting. The location of the J point is related to the accurate acquisition of the ST segment, especially when the traditional J + X method is used to obtain the ST segment, the J point is the key. In this tesina, using local search window to locate the J point, which is based on the basic form of the ECG signal. The J point is detected in the local search window. Through locating the deepest trough after the R wave, that is, the S wave. The J point is detected within 50 ms after the S peak.

In this tesina, the measured point of the ST segment is determined by J + X method, which is defined as follows:

$$ST_m = \begin{cases} J + 80ms & HR < 100 \\ J + 72ms & 100 \leq HR < 110 \\ J + 64ms & 110 \leq HR < 120 \\ J + 60ms & 120 \leq HR < 140 \\ J + 40ms & HR \geq 140 \end{cases}$$

(4.10)

Where ST_m indicates the time corresponding to the measured point of the ST segment, J indicates the time corresponding to the starting point of the ST segment, HR is the instantaneous heart rate (unit: bpm), $HR = 60/R-R$.

After the measured point of the ST segment is determined, the ST segment offset level is calculated with the TP segment as the equipotential line. The voltage amplitude of the ECG signal located at the sampling point n can be expressed as $x(n)$, then the ST segment offset level is

$$ST_D = x(n_{ST}) - x(n_{TP}) \quad (4.11)$$

Where n_{st} indicates the time corresponding to the measured point of the ST segment, n_{TP} indicates time corresponding to the TP segment..

According to the ST segment offset level, the ST segment offset direction can be judged:

- 1) If $ST_D \leq d$, the ST segment is judged to be STD;
- 2) If $ST_D \geq d$, the ST segment is judged to be STE;
- 3) If $d_1 < ST_D \leq d_2$, the ST segment is judged to be normal one, where d_1 and d_2 indicate predefined level thresholds that can be determined by the knowledge of clinical medicine.

4.3.3 The curve type of the ST segment

Before analyzing the curve type of the ST segment. Firstly, to determine the approximate range of the ST segment is necessary. Usually, when the ST segment is elevated, the range from the J point to the T peak is used as the ST segment analysis region. In other cases, the range from the J point to the starting point of the T wave is used as the ST segment analysis region.

The specific steps are as follows:

1) Assuming n_1, n_2 are the starting point and endpoint of the ST segment analysis region separately, $x(n_1)$ and $x(n_2)$ are corresponding amplitudes of the ECG signal. The linear equation to connect the starting point and the endpoint is that:

$$y(n) = x(n_1) + (n - n_1) \frac{x(n_2) - x(n_1)}{n_2 - n_1} \quad n_1 \leq n \leq n_2 \quad (4.12)$$

2) To calculate the distance between the point from the starting point to the endpoint and the straight line is to compute the average value of the distance as the basis of determining the curve type of the ST segment.

$$d(n) = \frac{|[x(n_2) - x(n_1)] \cdot n - (n_2 - n_1) \cdot x(n) + n_2 \cdot x(n_1) - n_1 \cdot x(n_2)|}{\sqrt{[x(n_2) - x(n_1)]^2 + (n_2 - n_1)^2}} \quad (4.13)$$

3) If the maximum distance does not exceed a predetermined threshold, the ST segment is determined to be linear type, otherwise, the ST segment is determined to be curvilinear type.

$$ST_{type} = \begin{cases} 1 & \max_{n_0 \leq n \leq n_1} |d(n)| < Dis \\ 0 & \max_{n_0 \leq n \leq n_1} |d(n)| \geq Dis \end{cases}$$

(4.14)

Where ST_{type} indicates the curve type parameter of the ST segment, 1 means that the ST segment is linear type, 0 means that the ST segment is curvilinear type. Dis is a predetermined threshold of distance. The threshold is related to the sampling frequency, and the specific value can be obtained by experimental statistics.

4.3.4 The concave-convex direction of the ST segment

For the curve type of the ST segment, the concave-convex direction is necessary to be further analyzed. By the curvilinear principle, any point in the concave curve should be below the linear line between the endpoints of the curve, and any point in the convex curve should be above the linear line between the endpoints of the curve. Thus the concave-convex direction of the ST segment can be judged by analyzing the relationship between any point in the ST segment analysis area and the linear line of the region endpoints.

Assuming the set of all the ECG signal sampling points in the ST segment analysis region is represented as

$$S = \{x(n)|n \in [n_0, n_1]\}, \quad (4.15)$$

The set of all the ECG signal sampling points above the ST segment analysis region is represented as

$$S^+ = \{x(n)|n \in [n_0, n_1], x(n) - y(n) > 0\} \quad (4.16)$$

The set of all the ECG signal sampling points below the ST segment analysis region is represented as

$$S^- = \{x(n)|n \in [n_0, n_1], x(n) - y(n) < 0\} \quad (4.17)$$

The ST segment concave-convex parameter is defined as follows:

$$\begin{cases} ST_{concave} = \text{card}(S^-)/\text{card}(S) \\ ST_{convex} = \text{card}(S^+)/\text{card}(S) \end{cases} \quad (4.18)$$

Where $ST_{concave}$ indicates the concavity, the proportion of the point in the concave part for the whole ST segment; ST_{convex} indicates the convexity, the proportion of the point in the convex part for the whole ST segment. Then $\text{card}(\cdot)$ indicates the number of the elements in the set.

The procedure to judge the concave-convex direction of the ST segment is as follows:

- 1) If $ST_{concave} \geq r$, the ST segment is determined as concave one.
- 2) If $ST_{convex} \geq r$, the ST segment is determined as convex one.

Otherwise, It is considered that ST segment noise is too large to be analyzed and discarded. In this case, r is a predetermined proportional threshold, after several experiments, it is found that when r is in $0.6 \sim 0.7$, a fair discriminant effect can be obtained.

4.3.5 The slope direction of the ST segment

For the linear ST segment, the slope direction needs to be further analyzed. In existing literatures, the ST segment slope have different definitions, such as the slope defined between the J point and the measuring point, between the measuring point and the endpoint of the ST segment, and the slope of the linear regression around the measured point. Referring to clinical definition, using the starting point and the endpoint of the ST segment analysis region, that is, the slope between the J point and the starting point of the T wave, or between the J point and the T peak, which is following defined:

$$ST_s = \frac{x(n_1) - x(n_0)}{n_1 - n_0} \cdot f_s$$

(4.19)

Where ST_s indicates the slope of the ST segment (unit: mV/s), f_s indicates the frequency of the ECG signal.

According to the slope, the slope direction can be determined:

- 1) If $ST_s \geq s$, the ST segment is the upsloping one;
- 2) If $ST_s \leq -s$, the ST segment is the downsloping one;

Otherwise, the ST segment is the horizontal one. Then, s is a preset slope threshold, after several experiments, it is found that when s is in $0.1 \sim 0.2$, a fair discriminant effect can be obtained.

4.3.6 Morphological recognition of the ST segment

After the judgment of the offset direction, the curve type, the slope and the concave-convex direction for the ST segment, final ST segment morphological recognition can be obtained by combining these judgment conclusions. As mentioned before in section 4.3.2, abnormal ST segment is defined by its offset level, to check if it upwards or downwards exceeds a certain threshold. In this tesina, ST segment morphology is divided into 15 different kinds (Figure 27). Table 1 is the true table analyzed by neural network for the specific process of ST segment morphological classification. Table 2 is the summary comparison of ST segment morphology on its morphological attributes.

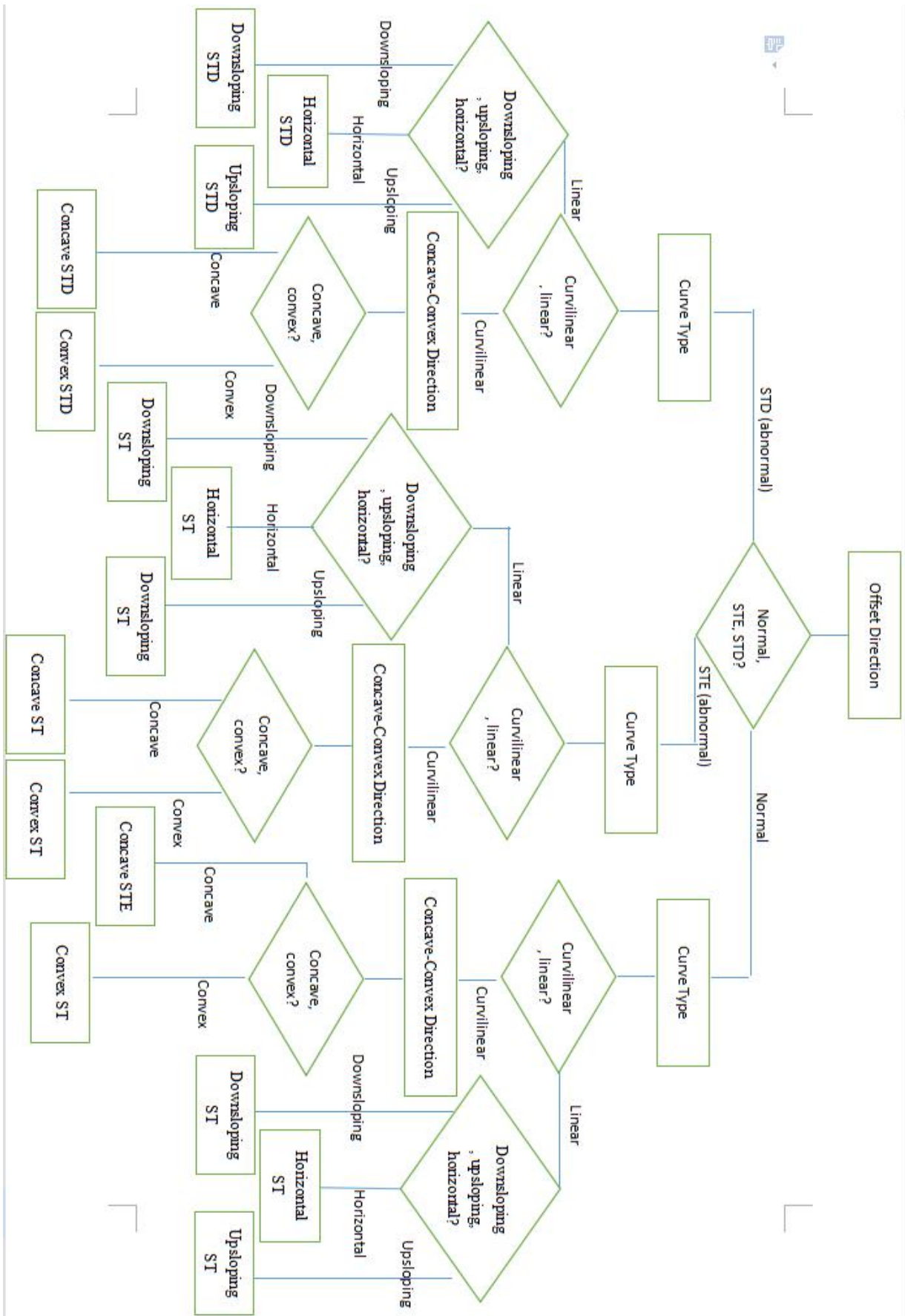


Figure 27. Specific flow chart for ST segment classification by the offset level, the curve type, the slope and the camber as identified criteria

Input				Output
Offset Direction	Curve Type	Concave-Convex Direction	Slope Direction	ST Segment morphology
Normal	Curvilinear	Convex	Don't care	Convex ST
Normal	Curvilinear	Concave	Don't care	Concave ST
Normal	Linear	Don't care	Downsloping	Downsloping ST
Normal	Linear	Don't care	Horizontal	Horizontal ST
Normal	Linear	Don't care	Upsloping	Upsloping ST
Abnormal Elevation	Curvilinear	Convex	Don't care	Convex STE
Abnormal Elevation	Curvilinear	Concave	Don't care	Concave STE
Abnormal Elevation	Linear	Don't care	Downsloping	Downsloping STE
Abnormal Elevation	Linear	Don't care	Horizontal	Horizontal STE
Abnormal Elevation	Linear	Don't care	Upsloping	Upsloping STE
Abnormal Depression	Curvilinear	Convex	Don't care	Convex STD
Abnormal Depression	Curvilinear	Concave	Don't care	Concave STD
Abnormal Depression	Linear	Don't care	Downsloping	Downsloping STD
Abnormal Depression	Linear	Don't care	Horizontal	Horizontal STD
Abnormal Depression	Linear	Don't care	Upsloping	Upsloping STD

Table 1. True table for ST segment morphological classification analyzed by neural network, four inputs and one output

Input				Output
Offset Direction	Curve Type	Concave-Convex Direction	Slope Direction	ST Segment morphology
Normal ($d_1 < ST \leq d_2$)	Curvilinear	Convex	Don't care	Convex ST
		Concave		Concave ST
	Linear	Don't care	Downsloping	Downsloping ST
			Horizontal	Horizontal ST
			Upsloping	Upsloping ST
	Abnormal Elevation ($ST \geq d_2$)	Curvilinear	Convex	Don't care
Concave			Concave STE	
Linear		Don't care	Downsloping	Downsloping STE
			Horizontal	Horizontal STE
			Upsloping	Upsloping STE
Abnormal Depression ($ST \leq d_1$)		Curvilinear	Convex	Don't care
	Concave		Concave STD	
	Linear	Don't care	Downsloping	Downsloping STD
			Horizontal	Horizontal STD
			Upsloping	Upsloping STD

Table 2. Summary table for morphological classification of the ST segment by the offset level, the curve type, the slope and the camber as identified criteria: abnormal elevation means that its offset level is more than a threshold d_2 , abnormal depression means that its offset level is less than a threshold d_1 , otherwise, normal one is between them

5. Performances and Diagnoses

This Section describes the experiments performed by running the algorithm over an annotated ST-T database (Section 5.1) and evaluates the performances of the proposed algorithm (Sections 5.2 and 5.3).

5.1 European ST-T Database

European ST-T database [68] was funded in 1985 by the European Community, its data are provided by 13 research groups from 8 countries. It consists of 90 double-channel 2-hour ECG from recordings, extracted from Holter tapes (two-lead ECG's) that contain ST segments and T wave annotated on an individual lead basis by cardiologists.

The ST-T Database consists of the following three files:

1. Header file has the patient's information, lead, medication, clinical findings and recording equipment information.
2. Data file has an ECG data recording format that is of double-channel 2-hour length, resolution of 12bits and 250Hz sampling frequency, and data format of MIT-212 format.
3. Annotation file contains data information (data beat, ST and T change start-peak-end etc.).

ST and T change annotation are attached importance to this tesina, because in the following section, they help to compare the “TRUE” label with the label assigned by this algorithm to evaluate the performances of the proposed algorithm.

This database was chosen for two reasons: firstly, European ST-T database is intended to be used for evaluation of algorithm for analysis of ST and T wave changes and it includes numerous ischemic episodes of all types and thus it is very useful in evaluating ischemic detection algorithms. Secondly, this database is well-known and available by many research groups. The aim of the study is to detect ischemia in the ECG signal.

5.2 Confusion matrix

In the field of artificial intelligence, the confusion matrix comes from the fact that it can easily indicate whether multiple categories are confused (that is, a class is predicted to be another class). It is a specific and distinct matrix used to render the performance of the algorithm in a visual way, and usually used for supervised learning (unsupervised learning often with matching matrix). Its column represents an instance of the prediction class, and its row represents an instance of the actual class. In this way, the precision of the algorithm can be evaluated by some indexes of the confusion matrix.

In the predictive analysis, table of confusion (sometimes referred to as confusion matrix) with two rows and two columns is shown in Table 3, which is composed of false positive, false negative, true positive and true negative. It allows us to make further analysis, not just the accuracy. The accuracy is not a sufficient index for the performance analysis of classifiers, since if the data set is unbalanced (the number of data samples in each category is too large), it is likely that the result will be misleading.

	Total population	Predicted	
		Negative	Positive
Test outcome (Actual)	Negative	True negative (TN)	False negative (FN)
	Positive	False positive (FP)	True positive (TP)

Table 3. Table of confusion (confusion matrix)

Then, there are some useful definitions that can be used through the confusion matrix (Table 4).

Sensitivity or true positive rate (TPR)	$TPR = TP / (TP + FN)$
Specificity (SPC) or true negative rate (TNR)	$SPC (TNR) = TN / (FP + TN)$
Precision or positive prediction value (PPV)	$PPV = TP / (TP + FP)$
Negative predictive value (NPV)	$NPV = TN / (TN + FN)$
Fall-out or false positive rate (FPR)	$FPR = FP / (FP + TN)$
False discovery rate (FDR)	$FDR = FP / (FP + TP) = 1 - PPV$
Miss Rate or False Negative Rate (FNR)	$FNR = FN / (FN + TP)$
Accuracy (ACC)	$ACC = (TP + TN) / (TP + FN + FP + TN)$

Table 4. Table of some useful equations by confusion matrix

The confusion matrix is used here to evaluate the precision of the algorithm in detecting ischemia in the ECG signal. In this database, the useful annotations for this study are ST and T change annotation. Each ST and T change annotation contains a text field which describes its significance. The text field contains characters which identify the episode type ('ST' or 'T'), the signal number ('0' or '1'), The text field of an annotation which marks the beginning of an episode contains a '(' prefix, like '(ST0-'. An annotation which marks the end of an episode has a ')' appended to the end of its text field, like 'ST0-'. So the confusion matrix helps to compare beat by beat the result from the algorithm with the “true” annotation.

For ST segment change detection and T wave change detection, here is an example confusion matrix result respectively as shown in Figure 28 and Figure 29.

Considered results refer to running the algorithm over the recording of patient e106, only.

```
confusematrix =
  102    3
   23   281
```

Figure 28. Sample e0106 in European ST-T Database: ACC of a ST segment change is 93.6% ($ACC = (TP + TN) / (TP + FN + FP + TN) = (102 + 281) / (102 + 3 + 23 + 281)$), $TPR = TP / (TP + FN) = 281 / (281 + 3) = 98.9\%$, $SPC = TN / (FP + TN) = 102 / (102 + 23) = 81.6\%$,

$$PPV = TP / (TP + FP) = 281 / (281 + 23) = 92.4\%$$

```
confusematrix =
    153    2
    33   227
```

Figure 29. Sample e0106 in European ST-T Database: ACC of a T wave change is 91.6% ($ACC = (TP + TN) / (TP + FN + FP + TN) = (153 + 227) / (153 + 33 + 2 + 227)$), $TPR = TP / (TP + FN) = 227 / (227 + 2) = 99.1\%$, $SPC = TN / (FP + TN) = 153 / (153 + 33) = 82.3\%$, $PPV = TP / (TP + FP) = 227 / (227 + 33) = 87.3\%$

5.3 Diagnostic results

According to the medical theory, in this tesina, the logical method is adopted to diagnose myocardial ischemia, automatically classify ST segment morphology and T wave morphology of each heartbeat in the ECG signal, then judge whether there are manifestations which is of myocardial ischemia according to morphological analysis, then finally diagnostic results are divided into three types.

- 1) ECG manifestations of myocardial ischemia are detected on the recording: there are three main ECG manifestations of myocardial ischemia [73 - 76], and any of them can infer that myocardial ischemia is detected on the recording:
 - a) For STDs: downsloping STD or horizontal STD;
 - b) For STEs: convex STE;
 - c) For abnormal T waves: the T peak is more than 2/3 the R peak, and the T wave almost symmetrical with the R wave, either it is upright or inverted, that is, the hyperacute T wave and the deep inverted T wave.

So in this tesina, any of them reaches a certain number of heartbeats, the diagnosis is made as “ECG manifestations of myocardial ischemia are detected on the recording”.

- 2) ECG manifestations of suspected myocardial ischemia are detected on the recording: in addition to the hyperacute T wave and the deep inverted T wave, other abnormal forms of the T wave are suspected manifestations, so if a few the above three ECG manifestations exist or other abnormal T wave occurs in the ECG signal, the diagnosis is made as “ECG manifestations of suspected myocardial ischemia are detected on the recording”.

- 3) Otherwise, the diagnosis is made as “No ECG manifestations of myocardial ischemia and suspected myocardial ischemia are detected on the recording”.

The instance of a diagnostic result is shown in Figure 30. The reasons to choose sample e0106 are that this ECG signal is not only clearer, more reliable, less interference than others, easier to be detected, but also it has certain ECG manifestations of myocardial ischemia.

```
Sample e0106 in European ST-T Database
The number of normal ST segments: 295
The number of convex STEs: 0
The number of concave STEs: 0
The number of downsloping STEs: 0
The number of horizontal STEs: 0
The number of upsloping STEs: 0
The number of convex STDs: 0
The number of concave STDs: 0
The number of downsloping STDs: 0
The number of horizontal STDs: 0
The number of upsloping STDs: 119
The number of hyperacute T waves: 67
The number of normal T waves: 347
The number of flattend T waves: 0
The number of shallow inverted T waves: 0
The number of deep inverted T waves: 0
The number of biphasic T waves: 0
The number of bimodal T waves: 0
ECG manifestations of myocardial ischemia are detected on the recording
fx >> |
```

Figure 30. The instance of a diagnostic result belongs to sample e0106 in European ST-T Database

6. Conclusions

The aim of this tesina is to detect ischemia automatically on the basis of the ECG signal analysis. In the aspect of feature detection in ECG signals, wavelet transform is the main method used in this tesina. Logical method with medical theory is used for the automatic ischemia analysis.

The primary consideration in the ECG signal analysis is signal preprocessing, namely signal denoising. The purpose of the ECG signal denoising is to reduce the effect of noise on feature detection, and it is required to ensure that the noise is eliminated as far as possible and ECG signal characteristics are kept in relative completeness. Because of the complexity of the frequency characteristic of the noise signal, ordinary low-pass, high-pass or bandpass filter is difficult to take into account in both two aspects, and generally cannot deal with a variety of the noise signal simultaneously. The multi-resolution analysis based on wavelet transform can be used to deal with the signal in different frequency bands to achieve the goal of removing the noise, thus solving the problem of signal denoising better. However, since the ECG signal during the acquisition process is inevitably affected by various kinds of interference factors, there is impossible that completely filtering out these disturbances in the ECG signal with any filtering method, so it is difficult to define a denoising method applicable to all ECG signals, resulting in the individual differences in signal preprocessing.

Feature detection of the ECG signal includes QRS complex detection, T wave detection and ST segment detection. The QRS complex is the most prominent waveform in the ECG signal, so feature detection usually starts from the QRS complex. The method based on time domain is often difficult to take into account the various morphological features belongs to different kinds of QRS complexes, and it tends to make wrong identification in mutated ECG signals. The method based on frequency domain is too poor to resist disturbances, after all, the noise suppression cannot be done completely. The wavelet transform can take into account both time domain and frequency domain, so it is suitable to QRS complex detection.

As a result of its sensitivity to signal mutation, wavelet transform is adopted to implement QRS complex detection. Most of the methods used to determine peaks of the QRS complex over zero crossings or modulus maxima at one or more scales using wavelet coefficients, however, the time shift between the actual peak position and the zero crossing of the modulus maxima pair makes inaccurate peak detection. In this tesina, the shortcoming of the wavelet method is concerned, firstly, the interval of the peak is roughly estimated by the wavelet coefficient, then return to the ECG signal to locate the peak precisely. The QRS complex is detected through combining the information of wavelet transform coefficients and the original ECG signal, causing a significant improvement in the peak detection of the QRS complex. Then, a reformative method based on wavelet transform is proposed to locate the QRS onset and offset. However, the research on this method is not deep enough and it is need to be further optimized.

T wave detection is always a difficulty in feature detection of the ECG signal. Theoretically, the P wave and the T wave exist in the S-Q interval. Therefore, in this tesina, after the QRS complex is recognized, the T wave is detected by extracting the slope and amplitude in the S-Q interval and after that, T wave morphology is processed. This method avoids missed detection of small amplitude waveforms, which works mostly better in clear and normal ECG signals. However, due to some wrong detections on the QRS complex, plus the influence of residual noise, it is still unsatisfactory to detect some ECG signals with poor qualities and irregular waveforms, and further research is in demand.

Most of the current research focus on ST segment deviation as the analysis of ST segment change, and rarely involve the analysis and recognition of ST segment morphology.

In this tesina, a method is proposed for analyzing ST segment morphology in the ECG signal. This method refers to clinical analysis process, adopts the ST segment waveform in the approximate range as the research object, and extracts the offset level, the curve type, the slope and the camber as essential morphological characteristics of ST segments, then realizes ST segment morphology recognition by some simple judgments. The method has the advantages of simple principle, convenient realization and good effect.

In the diagnosis of myocardial ischemia, it is based on the feature threshold of myocardial ischemia and mathematical expression, then a logical method is implemented for the final diagnosis.

Due to the complexity of the ECG signal, the individual difference and the diversity of the mutated signal, it is difficult to guarantee that it can fit all electrocardiograms regardless of methods, which will also affect the subsequent analysis and diagnosis. As of now there is relatively less the overall ST-T segment morphological analysis, and whether it has higher application value to myocardial ischemia remains to be explored in the future. Therefore, how to further improve existing methods of the ECG analysis is still a prospective research topic.

It is, moreover, insufficient to diagnose myocardial ischemia relying solely on ECG signals. Many elements can cause similar characteristic changes in the ECG signal, so it is indispensable to refer to the clinical manifestation in detecting myocardial ischemia. If the changes of heart rate, pulse and blood pressure are in the absence of blood, the false rate of myocardial ischemia can be reduced, and computer automatic detection can be realized, thus assisting doctors to get accurate diagnosis results.

If combined with heart rate, pulse, blood pressure and other changes in the ischemic process, it absolutely can reduce the misdiagnosis rate of myocardial ischemia, and realize the automatic intelligent detection, so as to assist physicians to render accurate diagnoses.

From the ECG signal preprocessing to feature detection, and then to the automatic identification of myocardial ischemia, there is a long way to go. Anyway, it is necessary to further improve and go into relevant algorithms, ultimately attain the goal of becoming the diagnostic assistance.

6.1 Further research activities

Major activities for further research will cover:

- 1) Run the algorithm over all the recordings of the European ST-T Ischemia Database.
- 2) Test and rate the performances over mode data and more archives.
- 3) Make the algorithm parametric on the sampling frequency and on the quantization levels.

Since there is limited time and energy, in this tesina, the first step to automatic identification of myocardial ischemia is finished, but there are still many different ECG recordings left to be analyzed in that ischemia database. As mentioned before, due to the individual difference and the diversity of the mutated signal, this algorithm needs to be improved to fit it by running the algorithm over other ECG recordings, Anyway, the feasible research activities are worthy to be done and they can realize the better performance on ischemia detection in the future.

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