工学硕士学位论文

脉象特征提取方法研究

A STUDY OF FEATURE EXTRACTION METHOD FOR PULSE DIAGNOSIS

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哈尔滨工业大学

2011 年 12 月

国内图书分类号:TP391.41
国际图书分类号:681.39

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答辩日期: 2011 年 12 月

授予学位单位: 哈尔滨工业大学

Classified Index: TP391.41
U.D.C: 681.39

Dissertation for the Master Degree of Engineering

A STUDY OF FEATURE EXTRACTION METHOD FOR PULSE DIAGNOSIS

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Date of Defence: December, 2011

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摘　要

摘要是论文内容的高度概括,应具有独立性和自含性,即不阅读论文的全文,就能获得必要的信息。摘要应包括本论文的目的、主要研究内容、研究方法、创造性成果及其理论与实际意义。摘要中不宜使用公式、化学结构式、图表和非公知公用的符号和术语,不标注引用文献编号。避免将摘要写成目录式的内容介绍。

关键词: 关键词 1;关键词 2;关键词 3;……;关键词 6(关键词总共 3 — 6 个,最后一个关键词后面没有标点符号)

ABSTRACT

Externally pressurized gas bearing has been widely used in the field of aviation, semi-conductor, weave, and measurement apparatus because of its advantage of high accuracy, little friction, low heat distortion, long life-span, and no pollution. In this thesis, based on the domestic and overseas researching……

Keywords: keyword 1, keyword 2, keyword 3, ……, keyword 6 (no punctuation at the end)

DEDICATION

To ZHANGJING

ACKNOWLEDGEMENT

I would like my girlfriend. She appears everytime I was dispointed. Then I want to thank the conduction of my boss Mr. Lu. He is a nice teacher.

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CHAPTER 1

INTRODUCTION

The Chapter gets started with the history of Traditional Chinese Medicine, and the modern digitization of wrist pulse diagnosis. Due to the importance of wrist pulse features for analysis of illness, there is a necessity to delve into the background and significance of its case.

1.1 Background

Chinese pulse diagnosis, one of the four diagnosis methods of Traditional Chinese Medicine (TCM), namely inspection, 'auscultation and olfaction', inquiry and palpation, has been practiced for health detection for more than 2000 years in China.[1, 2] In the inspection approach, TCM practitioners observe abnormal changes in the patient's vitality, color, appearance, secretions and excretions. The vital signs encompass eyes, tongue, facial expressions, general and body surface appearance. The inter-relationship between the external part of the body such as face and tongue is used to assist TCM practitioners to predict the pathological changes of internal organs. Auscultation refers to listening of the patient's voice, breathing, and coughing and is used to judge the pathological changes in the interior of the patient's body, whereas olfaction refers to smelling of secretion or excretion products. Inquiring or interrogating is to query patient's family history, feelings in various aspects, e.g. chills and fever, perspiration, appetite and thirst, as well as pain in term of its nature and locality. Palpation approach involves pulse diagnosis. It contains profuse information of the health condition of human body.

From a hydrodynamics perspective, wrist pulse origins from the disciplinary beats of heart. In the view point of TCM, the heart is the main organ to perform pulse, and the blood and breath air constitute the substantial foundation of pulse. When the heart beats periodically between systole and diastole, the blood ejected from left ventricle pounds the aorta valve and wall, generating a sort of vibration in a form of waveform transmitting from the root of the aorta to any other arteries, which is called *Forward Wave*. If the forward wave is affected by surrounding arterial branches, it reforms to the waveform in the inverse direction, that is, *Reflection Wave*. The combination of both forms so-called pulse waveform.[3] During the transmitting process, much body mechanism information has been merged into the waveform. Thus They reflect the entire body function involved with the breath activity of lung, the biochemistry of spleen, evacuation of liver, and the warmth promotion of kidney. Besides, the wrist pulse is influenced by the cardiac status, characteristics of the artery (including geometrical feature and physical feature), vascular arguments, and other factors. Therefore, the pulse diagnosis can provide important evidences for the feature and trends of kinds of diseases. That is the reason why pulse diagnosis is payed much attention to.

Compared with Western Medicine (WM), traditional pulse diagnosis also predominates on the cost of armarium. Western approaches regularly requires sophisticated equipment or extensive chemical processing, while in pulse diagnosis merely needs experience of doctors. Table 1.1 shows a detailed comparison of them. TCM diagnosis and treatments are popular in East Asia due to its low cost.

	Traditional Chinese Medicine	Western Medicine
Cost	Low	High
Device	Simple	Sophisticated
Foundation	Experience based	Evidence based
Process	A summary of clinical observation	The result of laboratory experimentations
Treatment	Herbs and nature agents	Chemical compounds
Aims	Maintain health	Manage diseases
Methodology	Inductive and synthetic	Reductive and analytical

Table 1.1: Philosophical difference between Chinese and Western Medicine

However, fuzziness and uncertainty always are the two main problems impeding the wide spread of TCM application. In thousand years of TCM application, pulse practitioners relied on the imprecise information from the fingertip feeling by touching the wrist of patient. Different practitioners may not give identical results to the same patient. Moreover, the attribution of pulse waveform expressed was usually obscure. No standard was established to describe all types of pulses. It eventually caused bifurcations in the traditional medicine. Pulse diagnosis always requires a long experience, a comprehensive knowledge base and a high level of skill of a doctor, and is subjective and deficient in qualitative criteria of diagnosis. The instability and fuzziness to some extent decrease the reliability and repeatability of pulse diagnose. It is necessary to do researches concerning TCM modernization by computerized techniques which allow researchers to organize and analyze information more efficiently, more preciously than the people-based fingertip feeling method.

1.2 Research objectives

The objectification of human skin layer information has experienced a long period. Such representative information as continuous electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), respiratory wave and so on reflect complementarily and directly the vital information of health activities. Pulse research has been a long history and has firmer theory support, so it makes sense to further research.

By the modernization of pulse diagnosis we can eliminate the uncertainty and subjectivity from practitioners. Wrist pulse assessment is a matter of technical skill and subjective experience, [4] so the computerized analysis of digitalized pulse signal tends to be more objective and persuasive. The pulse image from data collection by devices shows a more precise and objective information. New features that may not be perceived in fingertips feeling method can be discovered to indicate diseases. Doctors could lightly distinguish the notch or abnormality in pulse waveform from the computer screen rather than to conceptually describe the wrist pulse in a form of metaphor.

Although pulse diagnosis was gradually less used in the clinical diagnosis in Western Medicine after the development of bacteriology and anatomy, it is still widely applied in Chinese and India as an auxiliary method. TCM now confronts a huge challenge in the modern information era that prompts us do move forward objectification of TCM. Moreover, pulse image gives a boost on physiology and psychology as well as clinical pathology.

So far, pulse objectification has scored a certain amount of achievement. As a branch of biological recognition architecture, computerized pulse diagnosis has effectively binded traditional pulse diagnosis with modern information technology, fulfilling a goal to automatically collection, processing, recognition over pulse signals and final diagnosis of diseases. Pulse devices with high resolution transducers are invented to collect pulse waveforms, and save them into a database in favor of administration and review. Consequently, digitalized pulse diagnosis plays an important ancillary role in modern medicine due to its characteristics of painlessness, harmlessness and real-time.[5]

With development of science and technology, such fields bio-information, genetic engineering and nanotechnology and so forth have derived profit from advanced equipments and approaches. The combination of TCM and modern technology is an inevitable trend as well. Hence, it is still a mission to utilize fruits of current techniques to carry forward and further develop the legacy the ancestors left.

1.3 Research status

Pulse image represents the synthetic form of changes on frequency, rhythm, sink-float, strength from the touch and pressure sense when the doctor put his fingertips on patient's wrist. But the interpretation of Western Medicine on pulse image merely rests on the analysis of features such as frequency, rhythm, amplitude. Based on physiology, pathology and local anatomy etc., WM deduces the position and reason of pathology changes, rather than relating pulse image to the whole organism. In this case, western local anatomy method is not suitable for TCM objectification. In other words, the current study in the western world betrayed the original goals of pulse image. There remain India and Chinese employing the traditional pulse diagnosis method yet.

For the past many years, massive work on objectification of pulse diagnosis has been done. Scholars in all parts of China has made contribution to the objectification of pulse since 1950s. [6–12] Besides, scholars in other countries also has reached satisfactory scores.[13–17]

The objectification research of pulse diagnosis can be bifurcated into two main aspects, the digitalized features analysis of pulse signals and the designing of pulse collecting system. The digitalized features analysis is the core of objectification process of pulse diagnosis, and also the focal point of this paper. The designing of pulse collecting system paves the foundation of the entire research. An excellent result and discovery could not come out without a qualified pulse collecting system.

1.3.1 The designing of pulse collecting system

Some investigators upgraded merely a pulse transducer while some others designed an integrated pulse analytical instrument. Both of them are aspects of the pulse collecting system. Transducer plays a crucial role on the result of final analysis, and eventually involves the performance of whole system. In 1886, Vierordt first recorded pulse image using sphygmograph based on lever and pressure. The sphygmograph was not introduced into China until 1970s. After decades of research, pulse sensors has significantly improved in precision, sensitivity and repeatability. There are mainly three types sensors in common use at the present stage.

1. Piezoresistance transducer. It is constructed on the property that resistivity is subject to variation of stresses.

2. Piezoelectric transducer. It transforms the pressure signal of pulse to electrical signal.

3. Piezomagnetic transducer. It is also called magnetoelastic transducer, which appeared in recent years. The operating principle is built on the basis of magnetoelastic effect, i.e. variation of pressure changes the magnetoconductivity of transducer, and then causes the change of electrical signal. However, limited to premature of related theory and technology, the piezomagnetic transducer failed to prevail.

Of course, There remains still other sorts of sensors, e.g. liquid sensor, photoelectric sensor, strain pressure transducer, impedance sensor, ultrasound sensor (Figure 1.1), PVDF sensor, microphone transducer[18]. . On the other hand, with the development of computer technology, all sorts of automated pulse electropulsographs were invented to simplify the pulse data collecting process, like TP-CBS pulse analyzer in Beijing, ZM-III electropulsograph by Shanghai University of TCM, electropulsograph by Paik and Yoo in German. However, There is still a long way to go for the development of pulse diagnosis device. Aside from the diversity of sensor elements, the pattern of pulse probes could be manifold, e.g. single position pattern, triple positions pattern, multiple position pattern, rigid touch pattern, soft touch pattern, in which single position pattern is the most prevalent. Nevertheless, pulse probes trend to adopt triple positions pattern. Multiple positions pattern or array pattern can eliminate the accidental error from single point measurement. But how to collect and analyze the extremely high dimentional information is

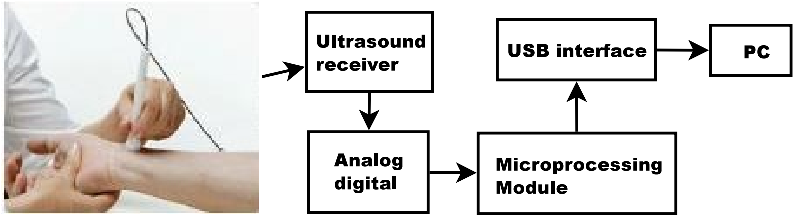


Figure 1.1: Pulse signal collection using ultrasonic blood analyzer

still a problem. The paper extends analysis upon pulse device with composite pressure and photoelectric sensors.

1.3.2 The analysis and diagnosis objectified digital features

Raw pulse data from the pulse sensors is not suitable for direct analysis. Instead, it should be preprocessed first. The analysis of pulse digital features mainly is separated into two steps, i.e. signal processing and pattern classification. The signal processing of pulse mainly solves the interference from high frequency noise, pseudo-peaks, baseline drift, and classifies and verifies the pulse signal by extracting feature argument from the waveform.

Then some diagnosis features that manage to reflect the characteristics of pulse signal are extracted, which can be time-domain, frequency-domain features and time-frequency features.[6, 19–23] For example, Leonard et al.[19] revealed that it is possible to distinguish healthy and unwell children by using wavelet power features and wavelet entropy of the pulse signal. Zhang et al.[20] proposed a wavelet transform based method to extract features from carotid blood flow signals, and used a back-propagation (BP) neural network to make the classification among 30 samples. Moreover, Zhang et al.[22] used the wavelet method to extract different pulse features, including wavelet powers, wavelet packet powers and Doppler ultrasonic diagnostic parameters. Although some of the above methods have achieved encouraging results, their effectiveness are still subject to further assessment due to the limited number of samples and types of diseases. For example, in Leonard’s research,[19] only 20 samples are used to distinguish well and unwell children, while in Zhang’s research,[22] two kinds of diseases are investigated.

In view of the pulse research centered on linear method, nonlinear dynamics as the third revolution of physics in this century is gradually applied on the pulse feature extraction. At present, nonlinear methods perform well on bio-signal to some extent for that the human body is a nonlinear system, an integral constituted by time and space. Consequently, a couple of methods based on nonlinear dynamics are used to research the law of pulse.[24–27] Wang primarily studied on the pulse mutation[24] and Rauchberger et al. studies on the quotidian variation of pulse.[25] Armando et al. devised an adapted method of plethysmography to amplify signals.[26] Moreover, Naschitz et al. used fractal and recursive graph to analyze the transmission time of pulse.[27]

When it comes to the next stage pattern classification, major methods such as multi-factor pulse image recognition, syntactic pattern recognition, adapted auto-regression modeling, fuzzy logic, clustering analysis, neural network method etc. are widely used. For example, Allen found that neural network method archived the best result comparing with linear discriminant method and K-neighbor method. Chen et al.[28] introduced Fuzzy C-Means (FCM) which aims, as a most widely used algorithm for statistical data analysis, to cluster two or more data point groups into clusters so that items in the same class are as similar as possible and items in different classes are dissimilar as possible, and found the use of membership function in FCM that means an object can belong an object several clusters at the same time but with different degrees is important for disease analysis. Some other researchers[6, 21] also proved that it is possible to identify human sub-health status based on pulse signals by using linear discriminate classifier.

In summary, the research status of computerized pulse has not yet formulated a standard to describe completely the 28 traditional pulse types by digital features. The formation of pulse is actually so complicated that solo sensor cannot represent the precise information of pulse, instead fusion of multi-sensors become more effective. Moreover, such factors as the repeatability of pulse collection, the precise position of pulse, the pressure of probe are all basic problems that we need solve. The established analysis of pulse image only relies on time domain, frequency domain and simple clustering that more incisive feature extraction method is required. Another problem is that the objectified pulse has not been well associated with concrete disease in clinical diagnosis. Combining with other diagnosis method such as ECG, tongue color, oral smell makes it more precise for prognosis as well.

1.4 Thesis organization

Fig. 1.2 shows the outline of this thesis. First, pulse data of patients with disparate health condition is gathered in Guangdong hospital of Tradition Chinese Medicine, based on an independent pulse detecting and collecting device with fusion of pressure and photoelectric transducers, and then organized as the database for later research. Second, denoising algorithms are introduced to detect and remove pseudo-peaks and singulars. Third, a new series of features proposed helps the discrimination of diseases. Finally, several classifiers are used to evaluate the representativeness of features.

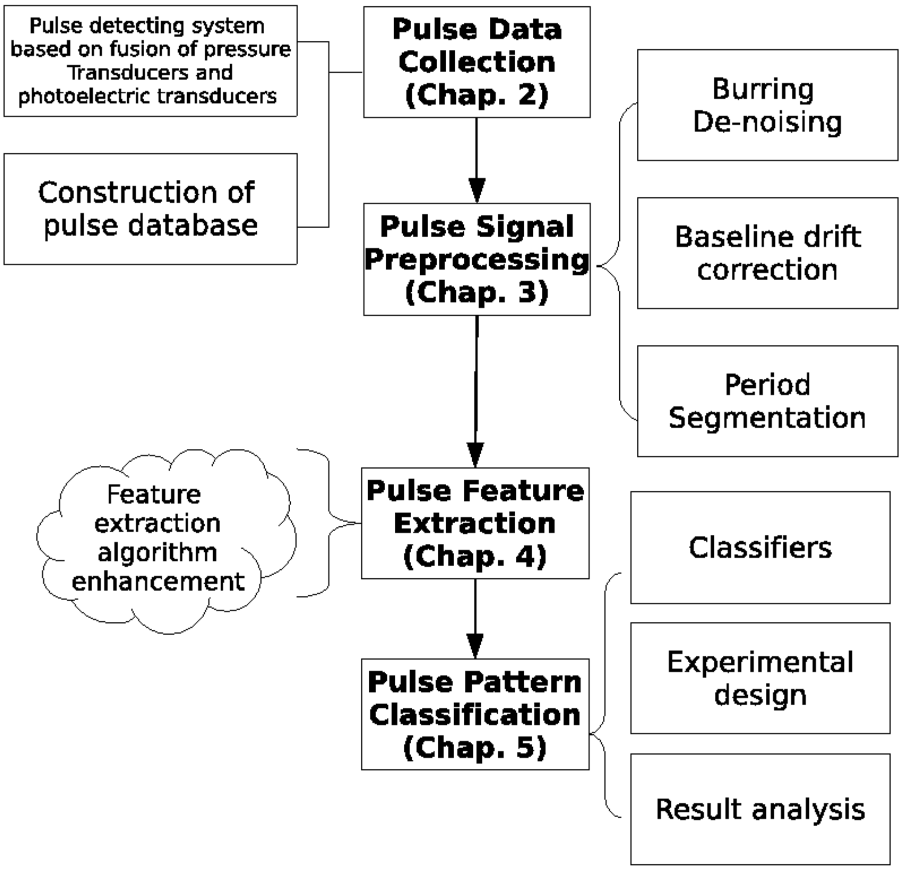


Figure 1.2: Outline of this thesis

The main content of the paper is organized as follows.

Chapter 1 introduces the background of pulse diagnosis and related research status.

Chapter 2 describes the principle and basic structure of pressure sensors and photoelectric sensors based pulse collecting system, and how to gather wrist pulse data from patients in the hospital. After that, information is well ordered and saved as an integrated database.

Chapter 3 presents a succession of algorithms to remove abnormality and smooth the pulse waveforms. First, a high-frequent burr due to the electromagnetic interference of the device power is adulterated into the pulse signal, which urges the wavelet 1-D noise filter to smooth. Second, An unknown noise is discovered and gotten rid of using low-pass linear filter. Third, a wavelet-based cascaded adaptive filter helps remove the baseline drift problem occurred during the sampling process. Finally, single periodical waveform is cut out for further analysis.

Chapter 4 illustrates improved time-domain features and other-domain features extracted. TODO

Chapter 5 compares the performance of features under three classifiers, i.e. support vector machine (SVM), Linear Discriminant analysis (LDA), K-nearest neighbor (KNN). TODO

In the end, the essay makes a conclusion to summarize and evaluate the work and addresses the prospect of pulse objectification.

CHAPTER 2

PULSE COLLECTING DEVICE AND PULSE DATABASE

The acquisition of wrist pulse plays an crucial role in the objectification, standardization and automation of pulse diagnosis. Generally speaking, the quality of pulse signals obtained in the stage has much to do with the subsequent sections, to some extent, deciding the analysis performance of overall system. In the pulse objectification history, pulse analytical instruments took on the responsibility to transform human oscillation signal to visualized images or figures easy to observe. And the designing of transducer takes up the most part of electropulsograph development. The paper uses pulse collecting apparatus based on the fusion of pressure sensors and photoelectric sensors to obtain pulse data. Then it displays the way to collect pulse information. At last, the construction of pulse database is explained in the paper.

2.1 Pulse collecting system

So far, The pulse sensor has a wide range of types, and uneven performances, which can be commonly divided into four categories by the principle of work. One is the pressure sensor, by detecting the pressure fluctuation at the position of radial artery and describe the pulse image; Second is photoelectric sensor, by perceiving the change of vascular volume to describe the pulse information; Third is the microphone, a sensor based on acoustics theories, in a way to pick up the vibration caused by the pulse, i.e. “listening” to the signal; The last one is the ultrasonic Doppler technique.

1. Pressure sensor

In the pressure sensor category, the piezoresistance pressure transducer is the most widely used, which perceives the vibration of pulse on the attribution that the resistivity changes along with the deformation degree of medium. The attribution render the limitation that the strain gauge must be attached on the test piece or the elastic element in test. In the case, the performance of adhesive will directly affect the operating feature of strain gauges (e.g. creep deformation, mechanical lag, insulation resistance, sensitivity, nonlinearity) and the extent of changes of these features over time or temperature. Consequently, it restricts the accuracy, linearity and the scope of application to the strain pressure sensor.

2. Photoelectric sensor

Here is its detection principle: Fluctuations in blood flow cause the change of blood volume per unit, and the amount of blood volume decides the portion of the light absorbed by blood. So when the light is cast on the tissue, the amount of light reflected varies with the fluctuation of blood flow. Finally the photoelectric transducer converts the optical signal into electrical signal to reflect the change of pulse waveform.

The photoelectric transducer implements photoelectric isolation, reducing interference to the next level of analog circuit. Hence, it has high anti-jamming capacity, high sensitivity, good linearity and frequency response characteristic. Due to insufficient acknowledgement to the internal connection between the vascular volume and pulse information, only two indicators oxygen and pulse rate can not meet the need for other blood stream arguments.

3. Microphone

The research in recent years shows wrist pulse signal is naturally a kind of infrasonic wave, a vibration transmitting over the special medium radial artery. Binghe Wang et al. adopted indirect coupling (i.e. non-contact) extraction method to acquire the spectrum characteristic of PingMai and XuanMai. An air column is set up to couple the acoustic wave produced by vibration of wrist pulse. [29]

4. Ultrasonic Doppler technique

Besides the pressure information, arterial pulse includes lumen volume, blood flow rate, three-dimensional vascular motion and other information. The solo pressure factor hardly reflects the indicator of each component in pulse. With the development of medical ultrasonic imaging technology, the application of ultrasound Doppler technique keeps its pace on the objectification of pulse image. DongYu Zhang et al. extracted pulse signal in the form of envelope line from the ultrasonic image. [22]

Although microphone and ultrasonic Doppler technique could receive more information, the principle betrays the traditional pressing type sphygmotechny. So the both hardly reflect the features of pulse correctly.

The pulse collecting apparatus adopted in the subject is jointly developed by Harbin Institution of Technology and HongKong PolyTechnic University. See Figure 2.1. In the light of a better simulation of fingertips-touch pulse diagnosis than the other sensors and its more convenient way of fixation and pressurization, the pressure sensor is preferred. For comparison purpose, photoelectric sensors are also built in the probe. Therefore, the system contains 9 photoelectric transducers and one pressure sensor in each position, totally 30 sensors. The upper screws are used to increase pressure. The probe is shown in Figure 2.2.

The pressure sensors and photoelectric transducers convert pulse signal to analog electric signal. Then the signal is optimized in the signal processing module, transformed in A/D converter and saved in computer via USB line. The biological signal of hu-

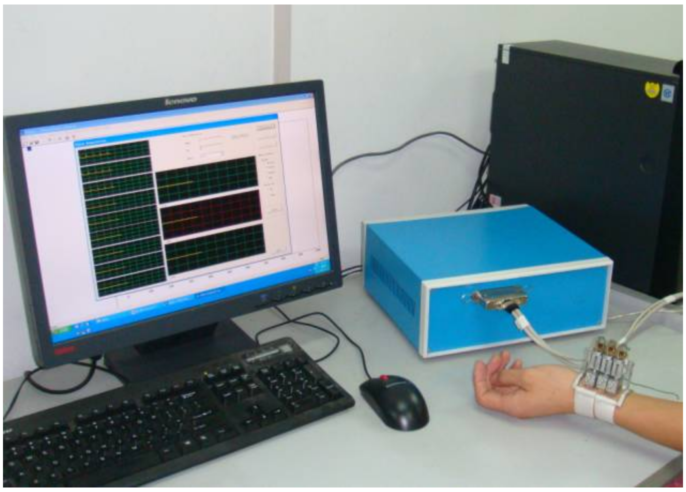


Figure 2.1: Pulse collecting system

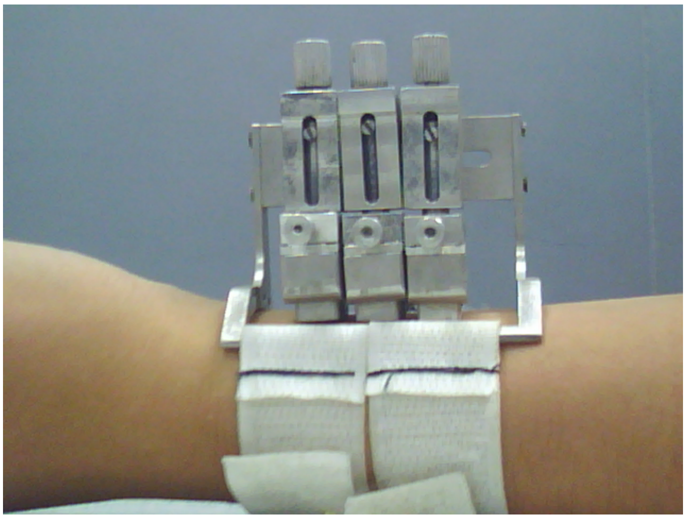


Figure 2.2: Probe head: fusion of photoelectric sensors and pressure sensors

man body is a kind of continuous time signal, which is difficult to process in computer.

Therefore, the pulse collecting apparatus fulfills this task and transmits digital signals to computer. However, the overall process may loss a certain amount of information. In other words, the digitalized signal losses part of information during conversion. That is what The theorem describes two processes in signal processing: a sampling process, in which a continuous time signal is converted to a discrete time signal, and a reconstruction process, in which the original continuous signal is recovered from the discrete time signal. According to Nyquist theorem, the sampling frequency must be at least twice the highest frequency contained in the signal, or in mathematical terms:

$$f_s \geq f_e \tag{2.1}$$

where f_s is the sampling frequency (how often samples are taken per unit of time or space), and f_e is the highest frequency contained in the signal. So our device sets default frequency as 500Hz so as to capture more details.

The system is redesigned based on the model of first generation pulse detecting system made by Harbin Institution of Technology. See Figure 2.3. Compared with the first generation system, the new system has the following advantages:

(1) Acquire more information. The pulse length and pulse width could be obtained.

(2) Plug-and-play. The system reaps the benefits of USB 2.0 which makes devices easy to use.

(3) Locate function. The photoelectric sensor array helps practitioners quickly locate the right position of radial artery.

(4) Modularized design. Six independent modules, i.e. sensors, analog circuits, digital circuits, firmware, driver and application, reduce the probability to break down and let improvement and maintenance easier.

In spite of the advantages described above, the system still exposed a few deficiencies listed as follows:

(1) Poor durability. In pulse collection period, four or five continuous working seems common. Unfortunately, some sensors malfunction as sudden with the result that signals on those channels remain null. So the incompleteness of signal information brings trouble to the further analysis.

Figure 2.3: The first generation of pulse detecting system developed by Harbin Institution of Technology

(2) Unstable. The pressure value often drifts unexpectedly during collection. Normally it wanders around 200g, but sometimes it jump to 7000g, that is impossible. Probably the bug occurs in the strain gauge. In addition, it is hard to keep the same of pressure values on three positions.

(3) Bad operability. During actual manipulation, even skilled practitioners fail to ensure all three positions detect signals. The three probe heads relates each other that adjustment on one probe head may displace others.

2.2 The collection of wrist pulse

It is worth to explain the detail of pulse collecting process for the sake of understanding the simulation of pulse diagnosis via automated apparatus.

1. Record personal information

As is known to all, lung, spleen, liver and kidney are all basic entrails as well as heart to maintain the body functions. The diversity of morphological structures and physiological characteristics to these entrails generates the corresponding the five internal organs.

Besides, in view of the tight relationship of entrails with heart, pulse, Qi in TCM, blood, the interaction and coordination among them has influence on pulse shape. Moreover, the wrist pulse may vary due to the change of mental health even though the physical organs work well. Hence, before the collection, the biological indexes (e.g. gender, age, height, weight) are also needed as a reference approach. A person information management dialog is designed in view of convenience shown as Figure 2.4.

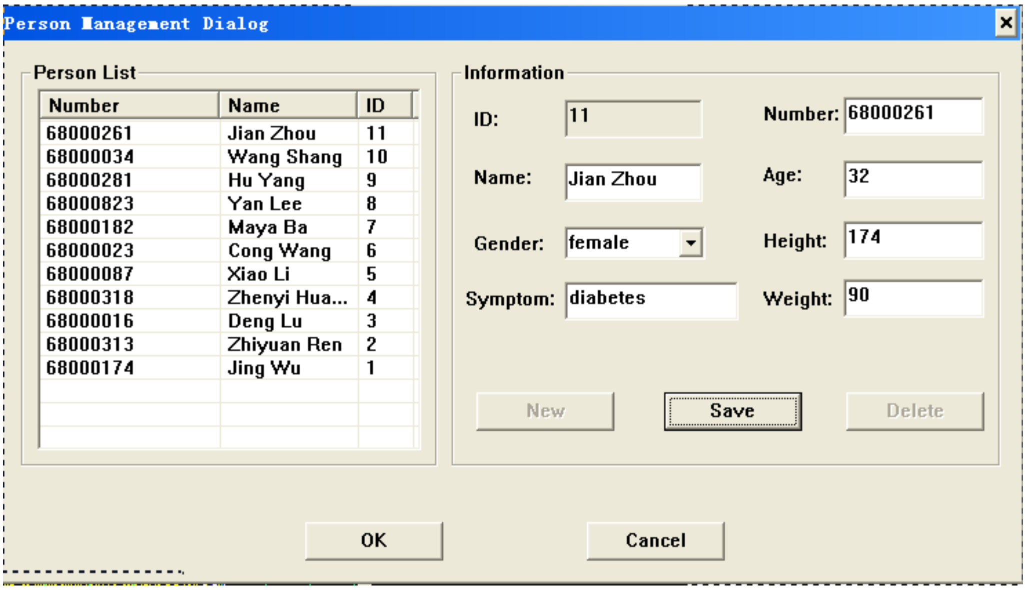


Figure 2.4: Person management interface

2. Hand selection

In TCM pulse diagnosis, the practitioners usually use three fingertips (Index, Middle and Ring fingers) to touch the left hand of patient and feel the pulse fluctuation on three positions, i.e. ‘Cun’, ‘Guan’ and ‘Chi’. Hence, in order to best simulation, the left hand is selected in this experiment.

3. Wrist pulse detecting process

The signal collection process includes usually three steps.

(1) Find a rough location in the wrist. The practitioners use the three fingertips mentioned above to feel the proper position of the wrist (the experiment adopts the left hand) to place the probe. Generally speaking, the practitioner should ensure the probe detect signals on each position.

(2) Fine tune and observation. Take the Guan part as example. There are nine photoelectric sensors in the part. If the intensity of signals detected on one side are much stronger than the other side, then it indicates that the sensor should be slightly fine-tuned towards the weak side. It also works to other two positions.

(3) Repeat the foregoing steps until signals from three points are observable, including pressure sensors and photoelectric sensors. See Figure 2.5.

(4) Adjust pressure value. The paper imitates the process of pulse diagnosis to feel the intensity of radial artery signals in different pressure values. By manually twisting the screw of probe, pressure value to the radial artery could change. Figure 2.6 shows the intensity divergence of pulse signals under 130g, 200g, 250g pressures. The amplitude increases by 1.8 when the pressure increases from 130 to 200g while the amplitude yet decreases by about 0.5 when the pressure value increases from 200g to 250. Therefore, the pressure value is considered as the best value to show the pulse obtained.

(5) Record 2-3 records. Each record should last at least 10 seconds. During the sampling period, no laughing and talking is allowed.

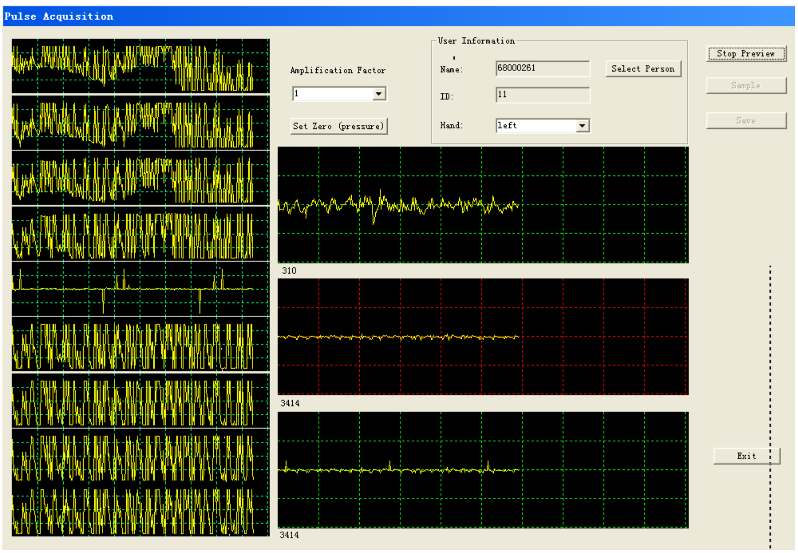
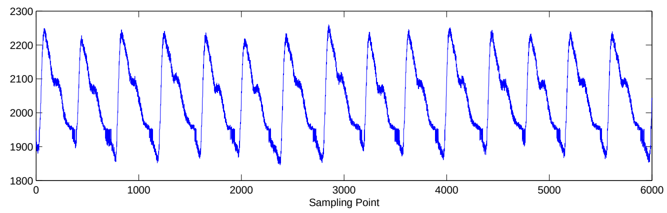
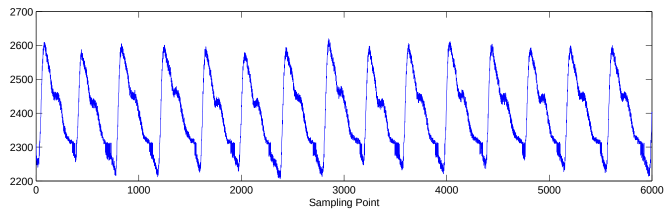


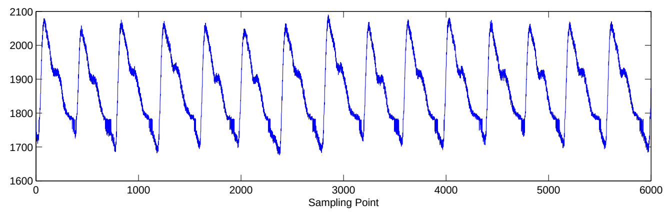
Figure 2.5: Main interface for pulse collection



(a) Pulse signal when the pressure is 130



(b) Pulse signal when the pressure is 200g



(c) Pulse signal when the pressure is 250g

Figure 2.6: Pulse signals under three different pressures

Disease	Number
healthy	150
subhealthy	879
gastrosia	28
nephrosis	54
diabetes	54
respiratory disease	33
angiocardiopathy disease	35
endocrine disease	70
cardiology	15

Table 2.1: Main part of database

2.3 Pulse database

After a month of pulse data acquisition, the team has collected in total 2247 samples, in which 1565 ones are from physical examination section and 682 ones are from wards. All the samples are from Guangdong Hospital of TCM. Table 2.1 shows the main portion of database used in the following chapters. Other sets of data are either too few in number or information insufficiency. The 1565 health examinees are mostly 30 to 40 years old while the rest 682 patients range from 16 to 70 of age. The class of samples results from western medicine diagnoses provided by the hospital. TODO再多写一点

2.4 Summary

The chapter first introduced four typical sensors: pressure sensor, photoelectric sensor, microphone, ultrasonic Doppler sensor. The pulse collecting system in the paper utilized pressure sensor and photoelectric sensor. In three positions, ‘Cun’, ‘Guan’, ‘Chi’, there is a probe head which perceives 9-channel photoelectric pulse signals and one pressure pulse signal. Second, it introduced the advantages and disadvantages of the system. Third, the paper described the entire collecting process. The quality of pulse data gathered binds the later performance of classification. Finally, a pulse database is established with the pulse information of thousands of people. In summary, the automated pulse diagnosis system, to which is widely payed attention, has important application value. Therefore, it significantly makes sense to adopt a exceptional pulse collecting system to gather accurate pulse information and establish a database of rich personal physical information.

CHAPTER 3

PULSE SIGNAL PREPROCESSING

Owing to the electromagnetic interference in surrounding environment, high frequency noise will be superimposed on the original signal amid collection, affecting the signal analysis. Meanwhile, the breathing or body movement of participant will also cause the signal baseline drift. Distortion of pulse features extracted would probably occur afterwards unless the baseline drift problem was solved. Therefore, the both problems must be properly handled towards the original pulse signal. In addition, since the subsequent pulse feature extraction is based on a single period of pulse waveform, a period segmentation algorithm fulfills the task to split signal series. The chapter employs wavelet transform to filter high-frequency noise, wavelet-based cascaded adaptive filter to remove baseline drift, and a period detection algorithm to divide periods. At last, the pulse waveform is normalized. Figure 3.1 demonstrates the outline of this chapter.

3.1 Burring

The human wrist pulse signal is a weak physiological signal that is susceptibly to high-frequency noise caused by interference of electromagnetic devices. This sort is called *burr* because the noise looks like small notches in the fringe of objects. See Figure 3.2. By careful observation, the burrs in pulse signals present a jagged form in overall, which means glitches float uniformly around the real value. In actual processing, the majority of signals may contain spikes or mutation, and the noise signal is not stable white noise yet. So does the pulse signal. Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. However, Fourier transform cannot provide any information of the spectrum changes with respect to time. Fourier transform assumes the signal is stationary, but pulse signal is always non-stationary. The traditional Fourier transform considers information merely on frequency-domain and becomes powerless to differentiate the change on a specific point. Admittedly, the traditional Fourier low pass filter could suppress the noise, it meanwhile blurs the noisy edge of one-dimension signal.

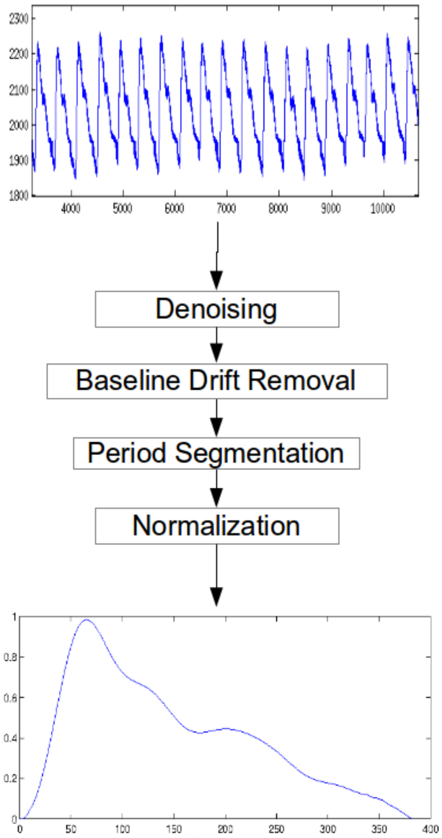


Figure 3.1: Preprocessing procedures

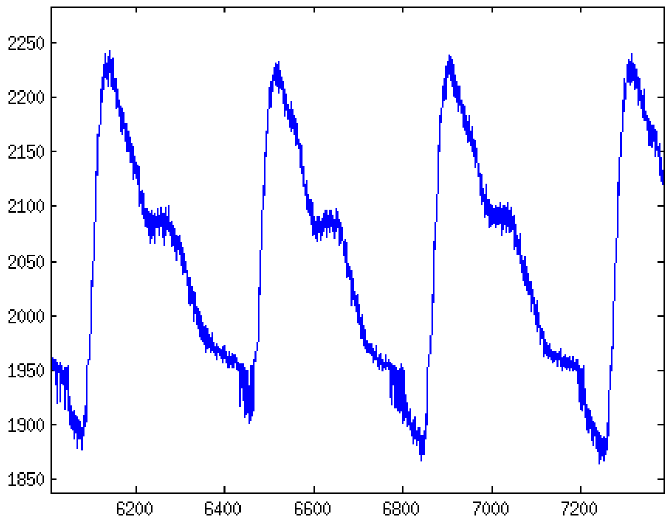


Figure 3.2: Pulse signal with burr noise

If the low-pass frequency range is narrow, high-frequency components of the mutation part will be treated as noise to be filtered, which led to a certain amount of distortion in the mutation part; If the range of low-pass frequency is set too wide, the noise may not be effectively filtered out. To overcome this deficiency, a modified method-short time Fourier transform allows to represent the signal in both time and frequency domain through time windowing function. The window length determines a constant time and frequency resolution. Thus, a shorter time windowing is used in order to capture the transient behavior of a signal; we sacrifice the frequency resolution. So, an alternative mathematical tool-wavelet transform must be selected to extract the relevant time-amplitude information from a signal. In the meantime, we can improve the signal to noise ratio based on prior knowledge of the signal characteristics.

3.1.1 Wavelet-based denoising

Wavelet transform is a inheritance and development of Fourier transform, that not only has a profound and comprehensive theory, but also emerges its wider application prospect. As is known to everyone, a $\Psi(t)$ is called a *Mother Wavelet* if it meets the following condition:

$$C_\Psi = \int_R \frac{|\Psi(\omega)|^2}{|\omega|} \mathrm{d}\omega < \infty, \quad \text{for } \Psi \in L^2(R) \tag{3.1}$$

Do a scaling and shifting operation to the mother function as

$$\Psi_{a,b}(t) = |a|^{-\frac{1}{2}} \Psi(\frac{t-b}{a}), \quad b \in R,\ a \in R - \{0\}. \tag{3.2}$$

Then The function family $\Psi_{a,b}(t)$ is called *wavelet base*, where a is the scale parameter and b is the shift parameter. If $a = 2^j, b = k \cdot 2^j,\ j,k \in Z$, then

$$\Psi_{j,k}(t) = 2^{-\frac{j}{2}} \Psi(2^{-j}t - k). \tag{3.3}$$

If $\Psi(t)$ is properly chosen, $\Psi_{j,k}(t)$ could consist of a family of orthonormal wavelet bases. So any function $f(t) \in L^2(R)$ can be expanded in the form of orthonormal wavelet series:

$$f(t) = \sum_{j,k=-\infty}^{+\infty} c_{j,k} \Psi_{j,k}(t) \tag{3.4}$$

where $c_{j,k} =< f, \Psi_{j,k} >$. The important information of signal $f(t)$ disperses into each layer. It helps people handle specifics of signals more conveniently from both time and space.

One important application of wavelet transform is signal denoising. The wavelet can efficiently remove noise on account of its good locality in both time-domain and frequency-domain. It could distinguish the mutation part and noise of signals and successfully achieve the elimination of noise for non-stationary signals. In essence, the wavelet transform carries out the function to depress the useless part of the signal and intensify the useful part at the same time. [30–32].

Therefore, the paper will give priority to employ the one-dimension wavelet transform to smooth the pulse signal. The wavelet transform denoising process usually is divided into 3 steps [33]:

(1) Apply wavelet transform to the noisy signal to produce the noisy wavelet coefficients to the level which we can properly distinguish the PD occurrence.

(2) Select appropriate threshold limit at each level and threshold method (hard or soft thresholding) to best remove the noises.

(3) Inverse wavelet transform of the thresholded wavelet coefficients to obtain a denoised signal.

Of the three steps, the most critical point is how to choose the threshold and the corresponding quantification. To some extent, it has a bearing on the effect of signal denoising. The detailed denosing process based on wavelet transform aiming at pulse signal is shown as below:

3.1.1.1 Wavelet selection

Wavelet transform is essentially a description of signal features within the space composed of a group of wavelet mother functions. The mother function plays a critical role in wavelet transform. To best characterize the spikes in a noisy signal, we should select our "mother wavelet" carefully to better approximate and capture the transient spikes of the original signal. "Mother wavelet" will not only determine how well we estimate the original signal in terms of the shape of the PD spikes, but also, it will affect the frequency spectrum of the denoised signal. There are seven factors needed to consider for better choice[34].

(1) Regularity. It is very important to obtain a smoother effect for reconstruction of the signal. Generally speaking, the more orthogonal, the better denoising effect it will reach.

(2) Compact support and attenuation. These are two important attributes of wavelet. In general, a wavelet will have a better localization capacity if it attenuates quicker. And the compact support of wavelet base is expected in time-domain.

(3) Symmetry. Symmetric or antisymmetric scaling function and wavelet function could construct compactly supported orthogonal wavelet base with linear phase characteristic.

(4) Vanishing moment property. In most situations it is useful to restrict Ψ to be a continuous function with a higher number M of vanishing moments, i.e. for all integer $m < M$

$$\int_R t^m \Psi(t) \mathrm{d}t = 0 \tag{3.5}$$

It has been proved that a wavelet with high enough vanishing moment could effectively detect the singular point.

(5) The time-frequency window and its area. The smaller the window size is, the stronger the localization capacity is achieved. Since the time-domain window and frequency-domain window is resizable, the wavelet could analyze signals adaptively.

(6) Linear phase property. Linear phase is a property of a filter, where the phase response of the filter is a linear function of frequency, excluding the possibility of wraps at $\pm\pi$. In signal processing, the scaling function and wavelet can be thought of as filter function since a filter with linear phase property or generalized linear phase at least is able to avoid the distortion during decomposition and reconstruction.

On consideration of the wavelet features above and the periodicity, the paper chooses wavelet base $sym8$ as the filter.

3.1.1.2 Level of decomposition

From the previous section, we have known the wavelet transform is constituted by different levels. The maximum level to apply the wavelet transform depends on how many data points contain in a data set, since there is a down-sampling by 2 operation from one level to the next one. In general, there is no solid criteria. However, the following formula helps quickly decide the number of decomposition level [35]:

$$J = int[log_2(f_s/f_f) - 1] \tag{3.6}$$

where f_s denotes the sampling frequency (500Hz in this paper), f_f denotes the fundamental frequency (within 10Hz in this paper), and *int* indicates to choose round number. Consequently, 5 levels would be proper.

3.1.1.3 Threshold limits and denoised result

The choice of the threshold is a very delicate and important statistical problem. On the one hand, a big threshold leads to a large bias of the estimator. But on the other hand, a small threshold increases the variance of the smoother. Many methods for setting the threshold have been proposed. The most time-consuming way is to set the threshold limit on a case-by-case basis. The limit is selected such that satisfactory noise removal is achieved. But in order to achieve a better denosing effect, it had better try different cases of thresholds. There are usually three types of threshold.

(1) Hard thresholding. For one-dimension signal, the empirical threshold is calculated as

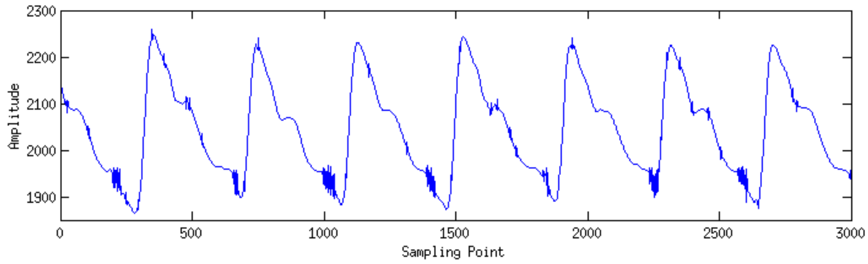
$$t = sqrt2\sigma^2 log(n)/n \tag{3.7}$$

where n is the length of the input signal and σ^2 is the variance of the noise. The variance of the noise is estimated based on the data. It is done by averaging the squares of the empirical wavelet coefficients at the highest resolution scale. Hard thresholding sets any coefficient less than or equal to the threshold to zero.

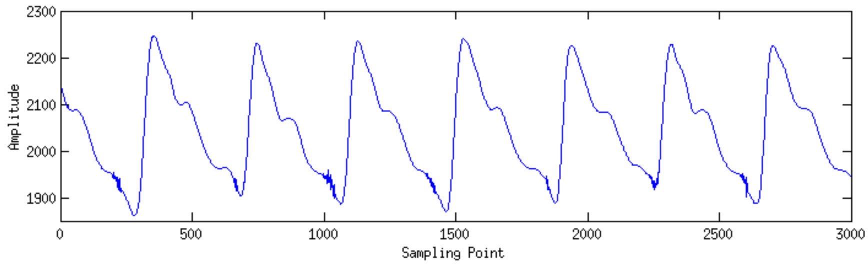
(2) Soft thresholding. The only difference between the hard and the soft thresholding procedures is in the choice of the nonlinear transform on the empirical wavelet coefficients. For soft thresholding the following nonlinear transform is used:

$$S(x) = \text{sign}(x)(|x| - t)I(|x| - t), \tag{3.8}$$

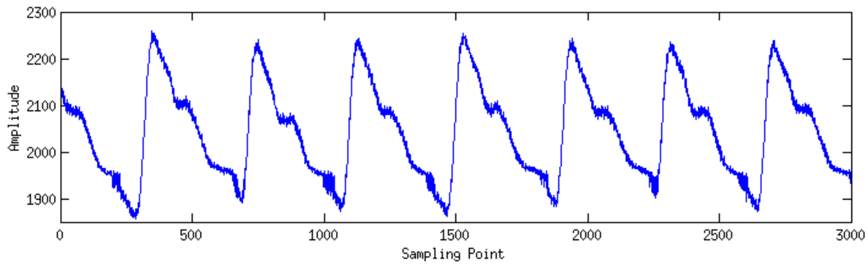
where t is a threshold. Adaptive thresholding.The threshold is subtracted from any coefficient that is greater than the threshold. This moves the time series toward zero.



(a) The denoised signal using hard threshold



(b) The denoised signal using soft threshold



(c) The denoised signal using adaptive threshold

Figure 3.3: The comparison of denoising effect with different thresholds

(3) Adaptive thresholding. The threshold selection rule is based on Stein's unbiased estimate of risk(quadratic loss function). One gets an estimate of the risk for a particular threshold value (t). Minimizing the risks in (t) gives a selection for the threshold value.

The Figure 3.3 shows the comparison of denoised signals using the three thresholds described above. From the figures, the soft thresholding method efficiently removes the high frequency noise and preserves the original useful information; The hard thresholding method still leaves out much noise not filtered; The Adaptive thresholding method fails to work properly, probably in account for its unsuitable application for this kind of noise.

Response type	Lowpass
Design method	Kaiser Window
Filter order	Minimum
Frequency Specifications	$F_pass = 48Hz, F_stop = 50Hz$
Magnitude Specifications	$A_pass = 1db, A_stop = 80db$

Table 3.1: The filter specifications

3.1.2 Removal of electric power noise

In carefully inspection to Figure 3.3b, it is found noise remaining in the tail of a period. So the frequency spectrum shown in Figure 3.5b shows the frequency distribution of noise. The signal not only contains the electric power 50Hz noise, but also noises higher than 50Hz from the internal system. The spike with frequency greater than 50Hz must be a burr noise since the human pulse signal distributes below 15Hz. [36] Hence, it is justified to remove all the noises upper than 50Hz. So a low-pass linear filter is designed to filter them.

Digital filters are typically considered in two categories: infinite impulse response (IIR) and finite impulse response (FIR). FIR has two useful properties which make it preferable to an IIR filter in this experiment: inherent stability and linear phase. Linear phase implies an important attribute because the pulse signal is a phase-sensitive application. Although the disadvantage of FIR filters is that considerably more computation power in a general purpose processor is required compared to an IIR filter with similar sharpness or selectivity, properly designed coefficients make FIR filters approximately as efficient as IIR for many applications.

The FIR filter is designed as these arguments: The magnitude response of the FIR filter under these arguments is shown in Figure 3.4. By convolution filtering, the noise with frequency higher than 50Hz is highly depressed. Figure 3.6 gives the final pulse signal denoised.

3.2 Removal of pulse waveform baseline wander

Although the collecting system the paper uses is linear-bandwidth within [0.05Hz, 100Hz], the pulse waveform is yet interference by the breathing and body movement during pulse capture. Otherwise, the pulse signal of a healthy person will stay on a horizontal line, i.e. each starting point of a pulse cycle lies on this horizontal line. See Figure 3.7.

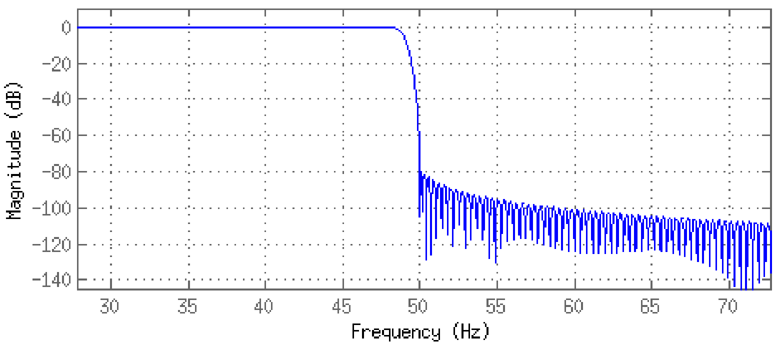
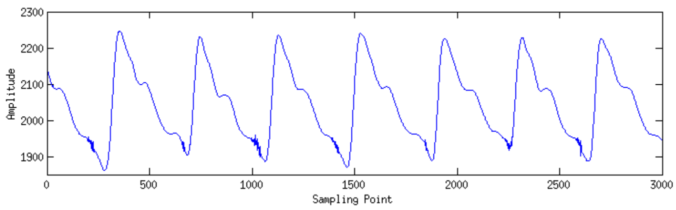
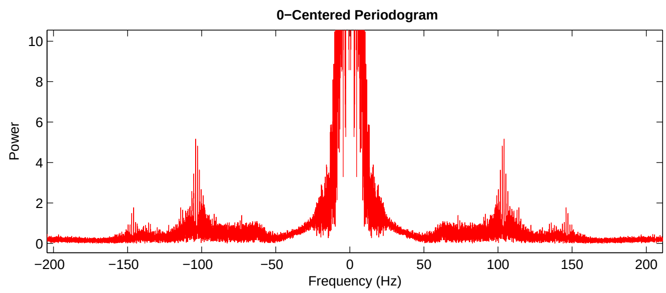


Figure 3.4: Magnitude response of FIR filter

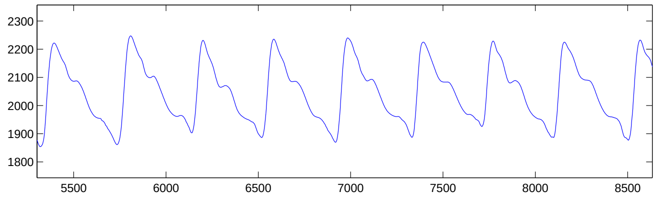


(a) Pulse wave with power electric noise

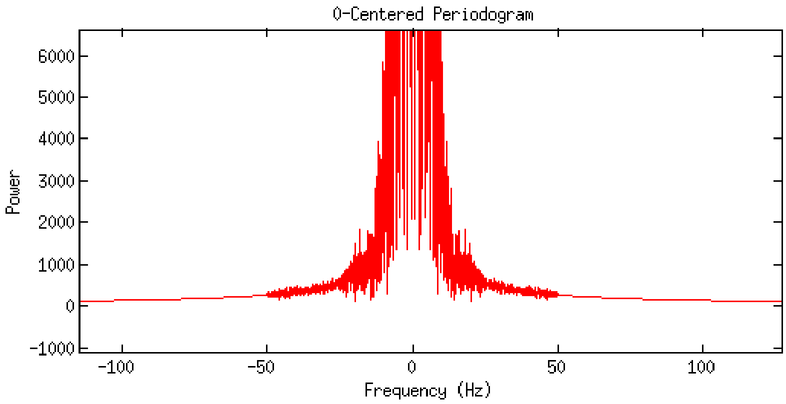


(b) The frequency spectrum

Figure 3.5: The pulse waveform before power noise removal



(a) Pulse wave after power electric noise removal



(b) The frequency spectrum

Figure 3.6: The pulse waveform after power noise removal

As similar to electrocardiogram (ECG) signal, the line is also called *baseline* in this paper. The baseline will bring waveform distortion to feature extraction so as to affect the succeeding analysis. [24, 37]

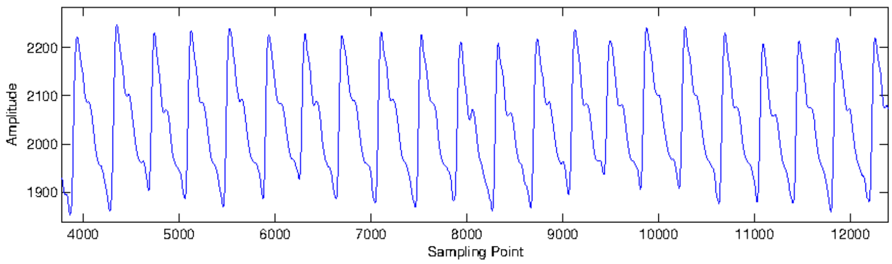


Figure 3.7: The pulse wave with baseline drift

The baseline wander issue has existed in physiological signal (e.g. ECG) in a long time and many methods have been put forward in previous work. These methods involves ensemble average, polynomial interpolation, zero-phase filtering, morphological filtering, time-varying filtering, adaptive filtering, wavelet-based filtering etc. All of them have their specific applicable conditions. With the improvement of pulse collecting system and the carefulness in actual mechanical process, the quality of most pulse waveforms are remarkable with less severity of baseline wander. Cubic spline interpolation is a simple but effective approach to estimate the hidden baseline. Therefore, the paper adopts it to remove baseline wander.

3.2.1 Starting point detecting technique

Before beginning with the cubic spline interpolation approach, we should detect where the starting point of each cycle is. To avoid controversy, the *starting point* in the paper prescribes the nadir in the ascending limb. The paper employs a concept of *sliding window*. In detail, because the sampling frequency is 500Hz while the wrist pulse frequency lies in between 48Hz and 100Hz (participants are required to calm down before collection), there must exist at least a pulse cycle in every 500 points. The paper uses a 500 points sized window to find peaks in the whole pulse waveform. A schematic diagram as Figure 3.8 can help understand.

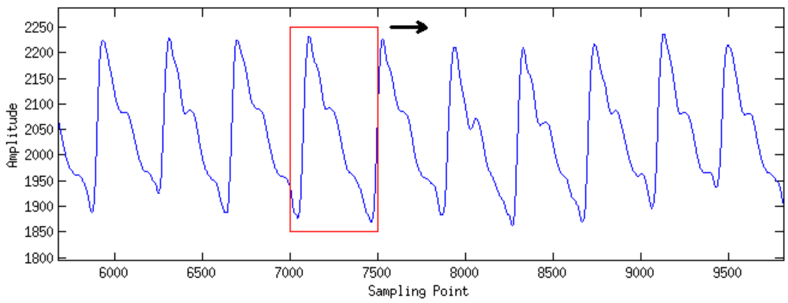


Figure 3.8: The sliding window for peak detecting

The peak detecting algorithm is described as follows:

Require: The denoised pulse waveform

Ensure: The peaks detected

set window size as 500 points

for each point *i* from left to right **do**

the window is the nearest 500 points centered on *i*

find the maximum point in the window

if the maximum point is current point *i* **then**

mark *i* as a peak

end if

end for

Then, it is easy to get the starting points just by detecting the peaks of up-down reversal pulse waveform using the algorithm above. The practice on around 500 samples shows the robustness and accuracy of this algorithm. See Figure 3.9.

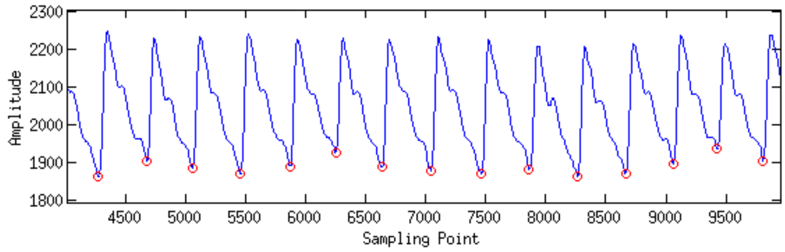


Figure 3.9: Starting points detected

3.2.2 Cubic spline interpolation

The baseline wander the breathing or body movement creates is nonlinear and smooth, so the cubic spline interpolation could predict the wandered baseline well. Estimation is actually a process of function approximation. Spline interpolation is such an approximation method to predict the major distribution from minor samples. Spline interpolation is preferred over polynomial interpolation because the interpolation error can be made small even when using low degree polynomials for the spline. Spline interpolation avoids the problem of Runge's phenomenon which occurs when interpolating between equidistant points with high degree polynomials.

Spline interpolation theory origins from the elastic ruler problem. The mathematical model is described as this: The definition domain $[a, b]$ is divided by a number of $n+1$ predefined points (the "knots") (x_i, y_i) into small intervals $[x_i, x_{i+1}$, in mathematical form of $a = x_1 <= \ldots < x_l = b$; The mission is to find a n th-order spline function $S(x)$ to piecewise estimate the objective function. A piecewise cubic spline function $S(x)$ can be denoted as:

$$S(x) = \sum_{k=0}^{3} a_k x^k + \sum_{i=1} Lb_i (x - x_i)_+^3 \quad fork = 0, 1, 2, 3; i = 1, \ldots, L \tag{3.9}$$

$$(x - x_i)_+^3 = \begin{cases} (x - x_i)^3, & (x \geq x_i) \\ 0, & (x < x_i) \end{cases} \tag{3.10}$$

where a_k and b_i denotes the polynomial coefficients and L denotes the number of knots. From Equation 3.9, the second-order differential of spline function $S(x)$ is

$$S''(x) = 2! \cdot a_2 + 3! \cdot a_3 \cdot x + 3! \cdot \sum_{i=1}^{L} \cdot (x - x_i)_+ \tag{3.11}$$

The Equation 3.11 demonstrates that the second-order differential in knot (x_i, y_i) is continuous. Since the wandered baseline is a continuously differentiable function, it implies that the second-order differential of baseline is also continuous. The cubic spline data interpolation can approach wandered baseline well. The Figure3.10 and Figure 3.11 respectively shows the wandered baseline estimated and the pulse waveform after removal of baseline wander.

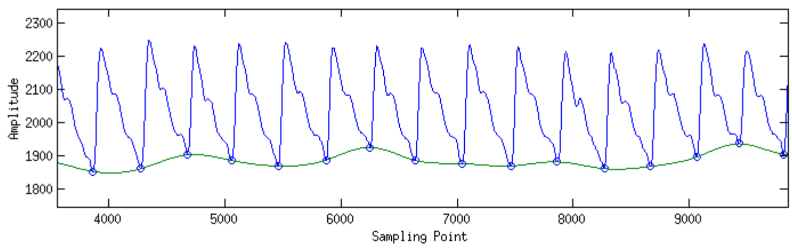


Figure 3.10: The estimated baseline wander using cubic spline interpolation

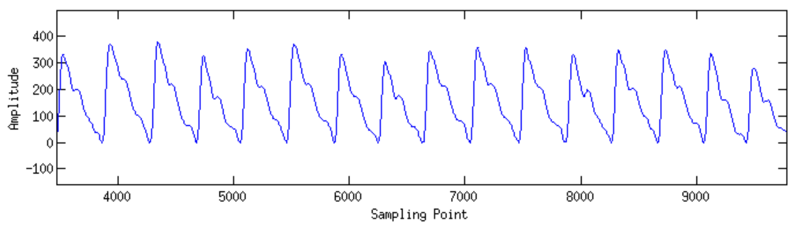


Figure 3.11: The pulse waveform after removal of baseline wander

3.3 Period segmentation of pulse waveform

The pulse image is a quasi-periodic waveforms, in which a period of waveform records most information about wrist pulse. Beginning with a single period pulse analysis is an effective way to understand in-depth meaning of pulse. The data processing in succeeding chapters of the paper is built on a single period pulse waveform. So the foregoing preprocessed pulse must split into single periods.

The period segmentation, as implied by the name, is to find the starting point and the end point. The end point is also the starting point of next period. So only starting points are necessary to find out. Remember the Section 3.2.1 introduced an algorithm detecting the starting points. The task of period segmentation comes much easier with the algorithm. Find two adjacent starting points randomly and extract the period between these two points.

3.4 Normalization of pulse waveform

Because of the diversity of collecting environment and the individual differences, the pulse may differ remarkably in amplitude. To treat them as equal, the paper will take measures to normalize the preprocessed single period pulse wave. Let x denote a small segment signal and y denote the normalized signal, the linear normalization formula is given as:

$$y = \frac{x - max(x)}{max(x) - min(x)} \tag{3.12}$$

where max, min are operations to extract the maximum and the minimum, respectively. A typical single period signal after denoising , baseline removal and normalization preprocessing is displayed as Figure 3.12.

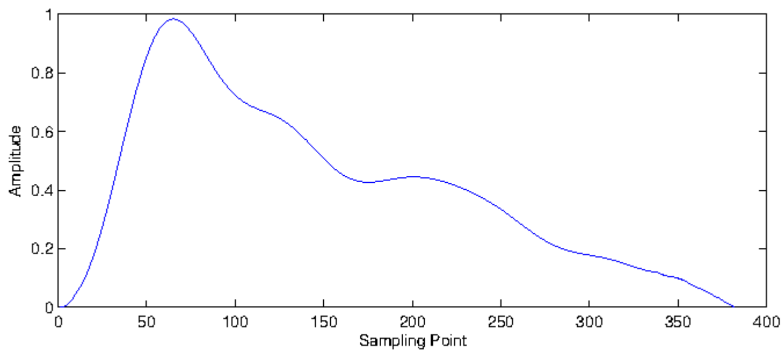


Figure 3.12: The normalized pulse signal

3.5 Summary

The chapter pre-processes the original pulse signal as needed, including burring, baseline wander removal, segmentation and normalization. First, the paper adopts *sym8* wavelet tool and digital linear filter to remove the high frequency noise. Second, the simple but effective cubic spline interpolation method is applied to solve the baseline drift issue. Finally, the optimized pulse waveform is separated into independent periods and normalized. The single period pulse waveform is the real input for the following chapters.

CHAPTER 4

PULSE FEATURE EXTRACTION

Different from the traditional pulse diagnosis, the digitized wrist pulse in the paper is an objectified, precisely quantified, standardized and automated pulse signal. As an important issue in pattern classification field, feature extraction directly affects the design and performance of classifier. If the features extracted from distinct classes sharply differ from one another, it is easy to design a high discrimination classifier. Thus, Thus, how to extract features from the sample effectively is a tremendous step in pulse patter classification process. TODO时域频域

4.1 Time-domain features

4.1.1 Time-domain features and its physiological significance

A complete cycle of pulse waveform consists of an ascending limb and a descending limb, shown as Figure 4.1. The ascending limb results from the systole activity: When systole occurs, the left ventricle ejects blood to the aorta in the sphygmic period; The increase of blood pressure causes the elastic expansion of aorta, that leads to the displacement of vascular wall. Likewise, the descending limb occurs in the late systole period when the blood ejection rate slows down; The pressure in the aorta decreases and then the vascular wall shrinks. The minimum point as point 3 in the figure is called dicrotic notch. In physiological view, it denotes a small downward deflection in the arterial pulse or pressure contour immediately following the closure of the semilunar valves and preceding the dicrotic wave, sometimes used as a marker for the end of systole or the ejection period. The secondary peak in the figure is called tidal wave while the third peak is called dicrotic wave. These peaks and troughs construct an entire pulse cycle.

The pulse image is the locus of vascular pulsation, so it has a certain amount of significance. It integrates the information of vibration in cardiac ejection period and the pulse propagation along vessels, which is reflected as the curve and inflection point in

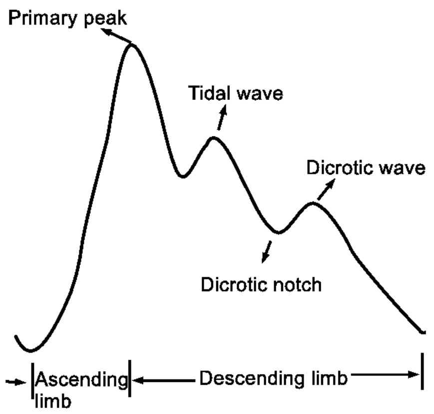
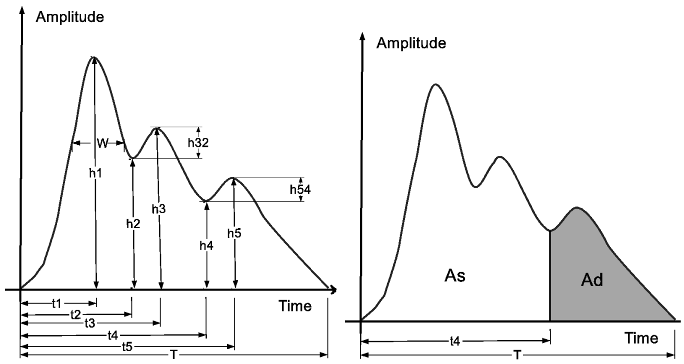


Figure 4.1: The basic structure of pulse waveform



(a) shape features (b) area features

Figure 4.2: Time-domain features

pulse image. Some critical parameter illustrated in Figure 4.2 and its explanation could reveal the physiological meaning of pulse image.

These time-domain features represent special meanings as follows:

h1: The amplitude of primary wave. It is the height from the primary peak to x-axis (time base). The height reflects the sphygmic capacity of left ventricle and the arterial adaptability. Generally speaking, the stronger of the two capacity, the higher h1 is. Otherwise, the smaller h1 is.

h2: The amplitude of primary notch. It is the trough height between the primary wave and tidal wave.

h3: The amplitude of tidal wave, i.e. the distance from the peak of tidal wave to x-axis. It reflects the arterial elasticity and peripheral resistance state. The amplitude h3 would increase either if the arterial wall tension arises or if vascular sclerosis occurs or if the surrounding resistance arises. The elevation of tidal wave is often accompanied with the advance of time phase, which demonstrates a faster propagation rate of reflected wave in a state of high arterial tension and high resistance.

h32: The peak height of tidal wave.

h4: The amplitude of dicrotic notch, i.e. the distance between the trough of dicrotic notch to the x-axis, corresponding to the diastolic pressure. It relates with arterial peripheral resistance and the aorta valve function. In general, h4 increases along with the rise of peripheral resistance. Otherwise, h4 decreases.

h5: The amplitude of dicrotic wave, i.e. the distance from the peak of dicrotic wave to the line across the trough of dicrotic notch, parallel to x-axis. The amplitude mainly reflects the aortic elasticity and aortic valve function. When the aortic adaptability diminishes or the aortic valve scleroses, h5 will eliminate correspondingly.

h54 The peak height of dicrotic wave.

T The time of a cycle, a.k.a. pulsation period, corresponding to a cardiac cycle of left ventricle. However, the pulse and ECG cardiac cycle will not be the same at the time of auricular fibrillation or extrasystole.

t1 The time from start point of a cycle to the peak point, corresponding to rapid left ventricle ejection period.

t2 The time from start point to the primary notch.

t3 The time from start point to the tidal wave peak point

t4 The time from start point of a cycle to dicrotic notch point, corresponding to the systole period of left ventricle.

t5 The time from start point to the dicrotic wave peak point.

W The dominant peak width, where the junction height is defined as 2/3 of h1.

As Area in systole period, related to the ejected blood volume.

Ad Area in diastole period.

PeakNum the number of peaks.

As can be seen from Figure 4.3, the detection of key points A, B, C, D, E, F is the critical step in time-domain features. Only if these points are detected, can the calculation of the time-domain relative features be launched. In fact, it can be seen that the feature

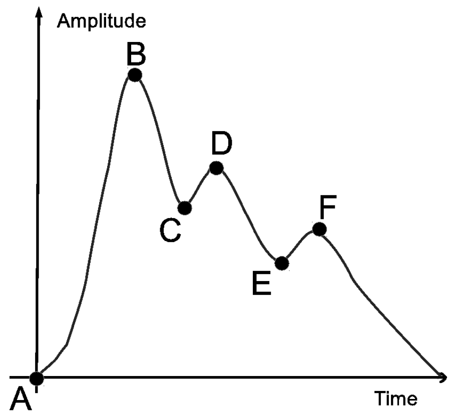


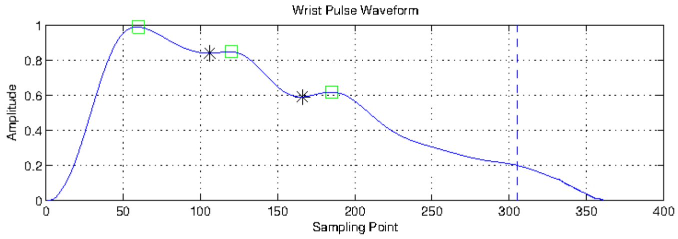
Figure 4.3: The key points in a pulse cycle

extraction is equivalent to the search of peak/trough points, where the first derivative is zero. A derivative-based zero-cross analysis is utilized for this purpose, and the peak search method are as follows:

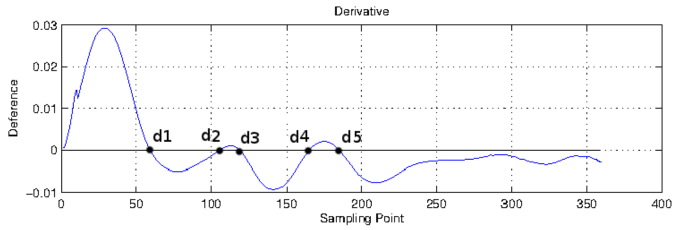
(1) Let the peak search range to be $0.85T$, which saves computing time. It is mainly because all peaks are located within the first 85% of the waveform range after careful inspection. It is illustrated as the blue dotted line in Figure 4.4a.

(2) Calculate the derivative of the signal, $d(t)$, as displayed in Figure 4.4b. Since the pulse waveform is actually a sampled discrete signal, difference operation is applied in this case. There are many finite difference methods, e.g. forward difference $\Delta f(x) = f(x+1) - f(x)$, backward difference $\nabla f(x) = f(x) - f(x+1)$, central difference $\delta[f](x) = f(x + \frac{1}{2}h) - f(x - \frac{1}{2})$. The paper choose a eclectic approach between backward difference and forward difference. The form is given as:

$$x'_i = \begin{cases} \frac{(x_i - x_{i-1}) + (x_{i+1} - x_{i-1})/2}{2}, & i = 2, \ldots, N-1 \\ x'_2, & i = 1 \\ x'_N, & i = N-1 \end{cases} \tag{4.1}$$



(a) The detected key points



(b) The first derivative of pulse waveform

Figure 4.4: The key points detected by the algorithm

$$x_i'' = \begin{cases} \frac{(x_i'-x_{i-1}')+(x_{i+1}'-x_{i-1}')/2}{2}, & i = 2,\ldots,N-1 \\ x_2'', & i = 1 \\ x_N'', & i = N-1 \end{cases} \tag{4.2}$$

This eclectic derivative estimation method has advantages over the traditional method, which considers only two points, in robustness and generality. The method considers three points at meantime and is more accurate. Because this difference method makes no sense on the first point and the last point, let the derivative of second point and the one of penultimate point approximate to them, respectively.

(3) Search the zero-cross points d_i $(i = 1\ to\ 5)$ in the derivative figure, and determine the revelent h_i and t_i.

(4) Search the first two points P_1 and P_2 whose amplitude equals to $2/3h_i$ within $[0, t_1]$ and $[t_1, t_2]$, respectively, and calculation the width $W = t(P_1) - t(P_2)$.

Of course, these shape features may differ person by person. In practice, for some pulse waveforms, the tidal wave may "disappear", i.e. the tidal wave is so close to the primary peak that the height of primary notch is still greater than the peak tidal wave. The *Xian Mai* is a typical case, shown in Figure 4.5. For such case, the zero-crossing points for h_2 and h_3 is missed. To solve the issue, the paper introduces a *tolerance* δ to find the hidden pseudo trough and peak. An automated moving line crossing point search is performed to get pseudo h_2 and h_3, which equivalent to the search of points d_1 and d_2. The algorithm is as follows:

(1) Let the search range from d_1 to d_4;

(2) Find the maximum point within the range in the first-order deference, i.e. find all the zero-cross from positive to negative in the second-order deference (Figure 4.6c). The point $d_{2(3)}$ in the first-order difference corresponds to its derivative point dd_23 in the second-order difference.

(3) Check the validity of $d_{2(3)}$.

   a) If the maximum is upper than the dotted line $-\delta$ in the first-order difference (Figure 4.6b, i.e. $d_{2(3)} < 0$ & $d_{2(3)} > -\delta$, then the sampling point $d_{2(3)}$ is a valid hidden peak of tidal wave.

   b) If the maximum is lower than the dotted line $-\delta$ in the first-order difference, i.e. $d_{2(3)} < -delta$, then the sampling point $d_{2(3)}$ is ignored.

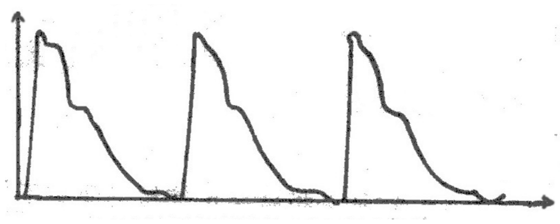
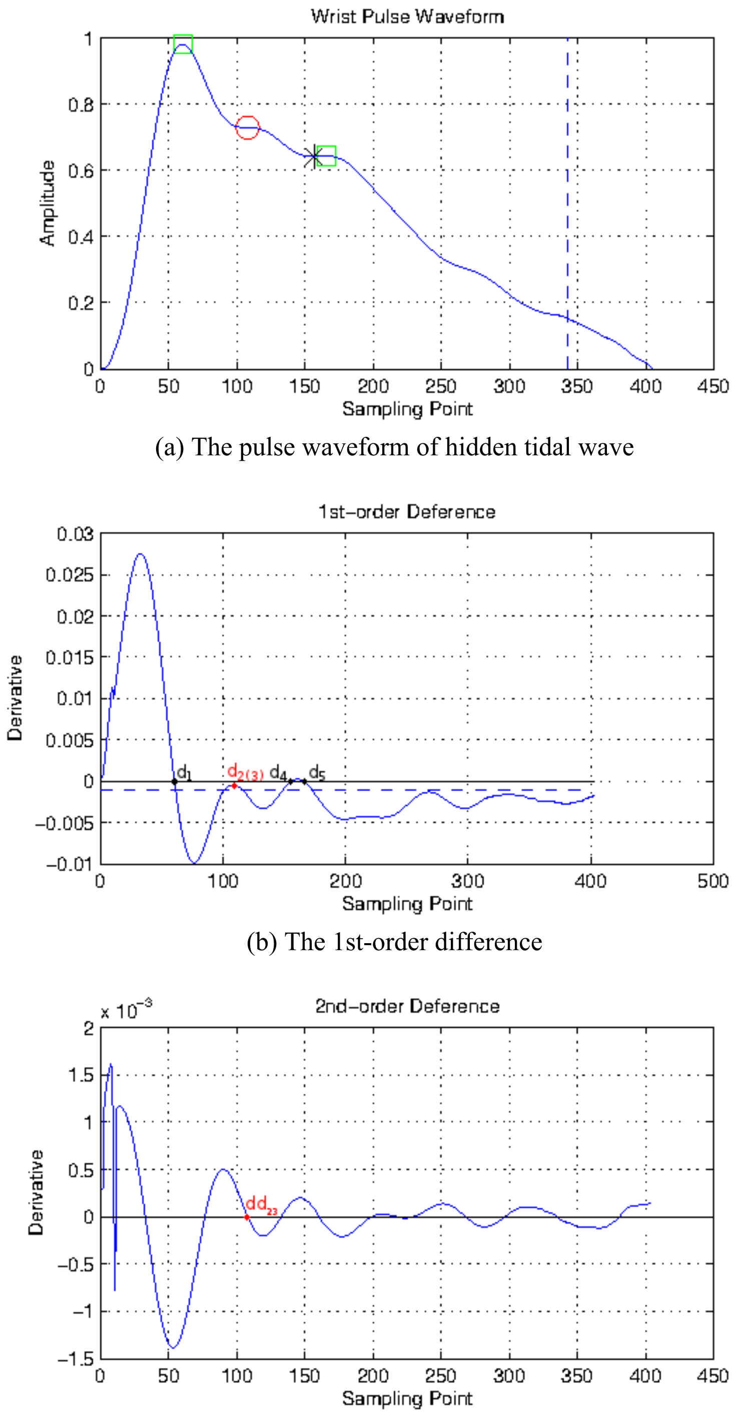


Figure 4.5: Xian Mai: hidden tidal wave

4.1.2 其他特征

TODO特征



(a) The pulse waveform of hidden tidal wave

(b) The 1st-order difference

(c) The 2nd-order difference

Figure 4.6: Illustration of the search of tidal wave

CHAPTER 5

PULSE PATTERN CLASSIFICATION

The pulse pattern classification is the key to achieving automated pulse diagnosis. The selection of classifier greatly influences the accuracy of result. Each classifier has their own applicable conditions, so the selection should depend on the characteristics of sample sets, e.g. the size of data set, the distribution of samples. Hitherto the common used classifiers includes Bayesian classifier, linear classifier, artificial neural network (ANN), k-nearest neighbor classifier (KNN), supporting vector machine (SVM) etc. TODO选分类器

5.1 Support vector machine classifier

5.1.1 Principle of SVM

Support vector machine is a supervised learning method to analyze data and classify patterns. Based on statistical theory, the standard SVM is a non-probabilistic binary linear classifier since it takes a set of input data and predicts, for each given input, which of two possible classes comprises the input. an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and decided the category based on the side they fall on.

5.1.2 Experimental design

5.1.3 SVM classification result

TODO

5.2 Linear discriminant analysis classifier

5.2.1 Principle of LDA

5.2.2 Experimental design

5.2.3 LDA classification result

TODO

5.3 K-nearest neighbor classifier

5.3.1 Principle of KNN

5.3.2 Experimental design

5.3.3 KNN classification result

TODO

5.4

<++>

5.5 Summary

TODO

CHAPTER 6

CONCLUSION

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