UNIVERSITY OF TURKU

The Design and Implementation of Intelligent Labor Contraction Monitoring System based on Wearable Internet of Things

Smart Systems

Master's Degree Programme in Information and Communication Technology

Department of Computing, Faculty of Technology

Master of Science in Technology Thesis

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In current clinical practice, pregnant women who have entered 37 weeks cannot correctly judge whether they are in labor based on their subjective feelings. Wrong judgment of labor contraction can lead to adverse pregnancy outcomes and endanger the safety of mothers and babies. It will also increase the healthcare pressure in the hospital and the healthcare efficiency is reduced. Therefore, it is very meaningful to be able to design a system for monitoring labor contraction based on objective data to assist pregnant women who have entered 37 weeks in deciding the suitable time to go to hospital. For the above requirements, this thesis designs and implements an intelligent labor contraction monitoring system based on wearable Internet of Things. The system combines the Internet of Things technology, wearable technology and machine learning technology to collect contraction data through wearable sensing device. It uses the Long Short-Term Memory (LSTM) neural network to classify and identify the collected contraction data and realize real-time processing. It improves the accuracy of model recognition to 93.75%. And the recognition results are fed back to the WeChat applet so that pregnant women can view them in real time. The prototype of the wearable sensing device has been integrated by 3D printing and the proof-of-concept system has been demonstrated. Pregnant women can use this system to detect the contraction status and view the contractions in real time through the WeChat applet results. They can judge whether it is suitable for labor, and this system assists in making decisions about the best time to go to hospital.

Keywords: Internet of Things, Wearable, Machine Learning, Contraction Detection, Intelligent Electronic System

CONTENT

Chapter 1 Introduction

In recent years, people have paid more and more attention to the health of pregnant women and fetuses. Prenatal and postnatal care has become a concern of people. The labor period is an important stage before and after delivery of a pregnant woman. It generally refers to the period from the 37th week of pregnancy to the delivery stage. Pregnant women in the labor period will have more obvious and frequent contractions, so effective monitoring and measurement of contractions are very important for pregnant women in labor.

In China, with the implementation of the “full two-child” policy [1], China has ushered in a new round of birth peaks. Families are more willing to invest more in maternal and infant smart devices nowadays. The society is paying more and more attention to the development of maternal and infant smart healthcare [2]. The scale and growth rate of the maternal and child consumption market has been increasing year by year. Figure 1-1 reveals the scale and growth rate of China’s maternal and child consumption market from 2012 to 2020 [3]. The realization of "prenatal and postnatal care" is particularly important for modern families.

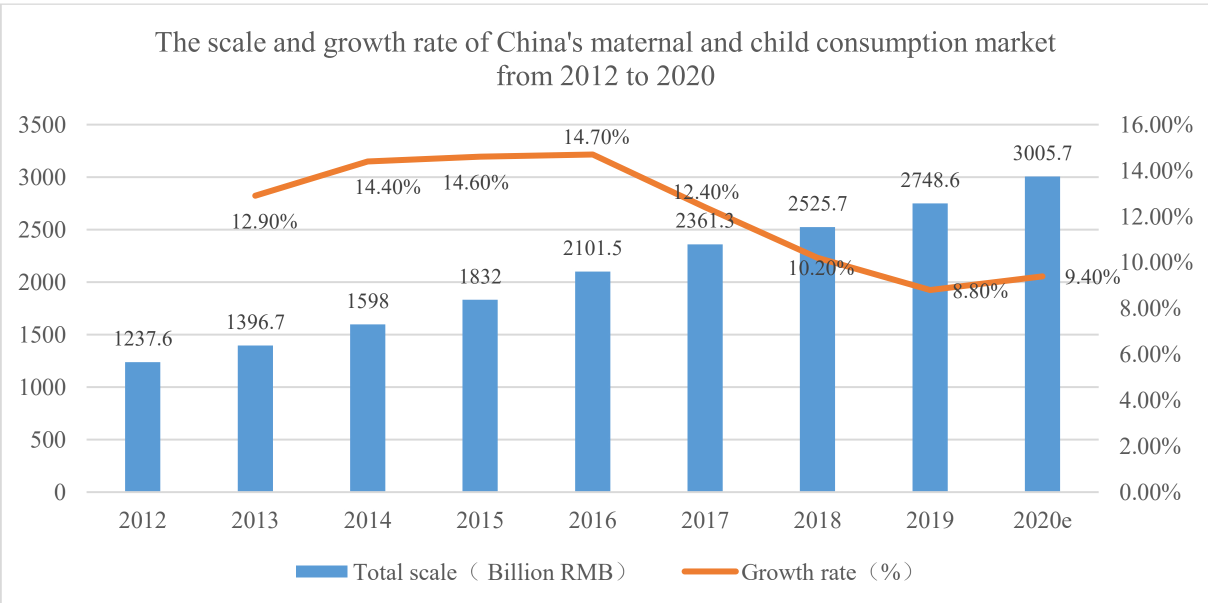


Figure 1-1 The scale and growth rate of China’s maternal and child consumption market [3]

Contraction is an important physiological characteristic of pregnant women, and it is also a very important clinical parameter [4]. When a pregnant woman enters full term (37 weeks of pregnancy), regular contractions may occur at any time at this stage. Before the labor, the contractions of the pregnant woman become regular, and the contractions will first from weak become strong, and after a certain period of time, it gradually weakens until it disappears, and it is directly manifested as the skin from soft to hard [5]. However, pregnant women cannot judge the correct labor conditions based on their own subjective feelings. It is easy to worry about frequent healthcare treatments when they have contractions, and they are most likely to be found that at this time they were not suitable for labor after examinations in the hospital, so the doctor asked them to go home for awaiting delivery. Limited by current healthcare resources, pregnant women can only go to the hospital regularly for antenatal check-ups, and doctors only know the health of the pregnant women and the development of the fetus during the check-ups. Due to the cost of time to go to the hospital, the interval time is relatively long, pregnant women cannot be timely informed of the health changes of the fetus. Meanwhile, hospitals, doctors, beds, equipment and other high-quality resources are always limited, and the inability of pregnant women to get good healthcare services is likely to cause conflicts. At the same time, the fragmented frequent consultations of pregnant women also occupy unnecessary hospital high-quality resources. The majority of women who are pregnant for the first time have no pregnancy experience and are less able to judge contractions. Therefore, the difficulty of judging contractions, the cost of unnecessary transportation and time may lead to the generation of pregnant women's bad mood, which in turn will affect the final pregnancy outcome, and also lead to the rise of healthcare pressure. However, during this period, if effective monitoring is not carried out, the uterine contraction pressure [6] may be very large to affect the blood circulation and flow in the uterus, leading to hypoxia of the fetus, and high morbidity and mortality of the fetus and the mothers. Most of them only realize the danger when they feel strong abdominal pain accompanied by vaginal bleeding and breaking water [7]. At this time, the fetus' fetal heart rate usually has changed, resulting in premature delivery or abortion [8].

In order to protect the health of pregnant women and the healthy development of the fetus, monitoring and reminding through healthcare device during this period is particularly important. At present, the fetal heart rate monitor application products on the healthcare device market are mainly fetal heart rate monitors used in hospitals. The representative products are shown in Figure 1-2 [9]. This type of product is currently the main clinical application, which can effectively monitor the health of the fetus in the perinatal period, and evaluate the health of the fetus in the uterus through the fetal heart rate, contraction pressure and fetal movement. It can accurately and quickly display the fetal heart rate and contraction pressure curve. Clinicians can combine the fetal heart rate curve, contraction pressure curve and fetal movement and follow the clinical fetal heart rate monitoring non-stress test (NST) [10] and other scoring standards to make a score. These traditional clinical healthcare fetal monitoring products are expensive and require a clinician to make a diagnosis. They can only be used in hospitals, and it is difficult to meet the needs of the majority of pregnant women. On the one hand, this method of obstetric examination is limited by time, so that pregnant women can only be tested at the specified time. Pregnant women usually have to wait for several hours, and the monitoring time is short. On the other hand, the monitoring device is too expensive and bulky. It is unrealistic for pregnant to use at home.

Figure 1-2 Common clinical fetal monitors (a) Sanrui (b) Philips (c) Oxford (d) Siemens [9]

With the rapid development of artificial intelligence, technologies such as machine learning and deep learning have begun to be researched and implemented in the healthcare field [11]. Machine learning technology is a powerful computing tool that can automatically learn features from data to perform specific tasks. Faced with massive amounts of data, machine learning algorithms can do things that traditional algorithms cannot achieve, and the output results will be more accurate as the amount of processing data increases. From the perspective of healthcare data, many patients have large differences in data due to their height and body shape. Machine learning builds a fitted model through training on massive healthcare data to improve the accuracy of recognition and generalization ability [12]. Making judgments and predictions are of far-reaching significance in the healthcare field.

The concept of Internet of Things (IoT) refers to the fact that we can connect all things that can perform independent functions to the Internet through information carriers such as the Internet and traditional telecommunications networks, and intelligently identify and manage them [13]. As the highly integrated and comprehensive application of a new information technology, the IoT has been integrated into the healthcare field, and has comprehensively promoted the informatization of the healthcare industry. The current development of IoT in healthcare is still facing problems such as information islands, data security and lack of talents. With the advancement of new infrastructure, the new infrastructure will promote the deep integration of IoT technology and smart healthcare, help smart healthcare go offline, and give birth to new directions in the healthcare industry. It is predicted that the growth rate of Chinese healthcare IoT market will exceed 25%, which will surely enhance the supply capacity of healthcare industry and promote the transformation and innovation of smart healthcare. Related research hotspots in the IoT healthcare field include "health management" and "telemedicine", "Smart Pension", "Smart Hospital", etc. [14]. It mainly includes the collection, sorting, analysis and storage of healthcare information and data, providing information and data online, and providing professional healthcare services offline, making the testing, diagnosis, and treatment processes and intelligent in the treatment process. While reducing the workload of healthcare staff and improving work efficiency, certain conditions of patients can be detected in time or even in advance, and the cure rate can be improved. For example, some diseases related to obstetrics and gynecology are common among pregnant women. Remote healthcare monitoring at home can be realized. Effective and data-sufficient vital signs information can be monitored at the pregnant women's home [15-16], so that healthcare staff can get timely, effective and adequate analysis offline. The data provides an important reference for healthcare staff in their next diagnosis, and then provides professional healthcare services to pregnant women.

Wearable device in healthcare is developing rapidly and has broad prospects. It can realize real-time monitoring, allowing users to understand personal health in real time [17], And it saves the user the cost of going to the hospital for inspection and measurement. It also reduces the user's use cost and time cost. The instant information collected by wearable wireless devices has proven to be beneficial in a wide range of healthcare applications. It is likely to be a new technology that fundamentally changes human healthcare [18-19]. Although most wearable devices in healthcare currently only provide data monitoring functions, in the future, the treatment functions of wearable devices will be more commonly used. It will be able to provide users with integrated services of diagnosis, monitoring and intervention in healthcare, and provide users with the most convenient and practical mobile healthcare benefits [20].

Based on the above background, this thesis designs an intelligent labor contraction monitoring system, which involves IoT technology, machine learning and wearable technology. The function realized by the system is to use the WeChat applet at home assists in judging whether it is suitable for labor according to the contraction. At the same time, a wearable device for intelligent labor contraction detection is designed. It is placed at the bottom of the pregnant woman's uterus and it is very portable. This reduces the pregnant woman's time and risk costs. At the same time, the hospital can also realize remote monitoring, and doctors can perform remote diagnosis. It alleviates healthcare pressure and improves healthcare efficiency.

1.1 Thesis work and contributions

As introduced in the previous section, IoT technologies, wearable devices, and machine learning technologies have far-reaching significance in the healthcare field. They are booming nowadays. However, these technologies are rarely used in the field of labor contraction monitoring, and there is no research to combine deep learning with labor contraction monitoring. And the hospital's contraction monitoring device is too large, expensive, and too professional with many technical specifications. It is unrealistic for pregnant women to use it at home. However, the monitoring of contractions during labor is very necessary. It can ensure the safety and save the time cost of pregnant women. It can also save the labor cost of the hospital. There are also some monitoring products on the market. As described in 2.4, some of these products are early products, which are very inconvenient to implement, some are not easy for pregnant women to use quickly, and some are technically implemented well like Belli, but the price is too expensive and cannot be purchased in China.

Based on the above analysis, this project cooperates with the Obstetrics and Gynecology Hospital of Fudan University to customize requirements. It realizes a safe, accurate, portable, low-cost, and easy-to-use labor contraction monitoring wearable system, combined with IoT technology, wearable technology, and machine learning technology. As shown in Figure 1-3, this system consists of three parts: wearable sensing device, cloud service platform and WeChat applet. Wearable sensing device is used to collect contraction data of pregnant women during labor. Its specific introduction is in chapter 4. Cloud service platform uses Long and short term memory (LSTM) algorithm to classify and identify the collected contraction data and realize real-time processing. Its specific introduction is in chapter 5. WeChat applet receives recognition results for pregnant women to view them in real time and assist in making decisions about the best time to be admitted to hospital. Its specific introduction is in chapter 6.

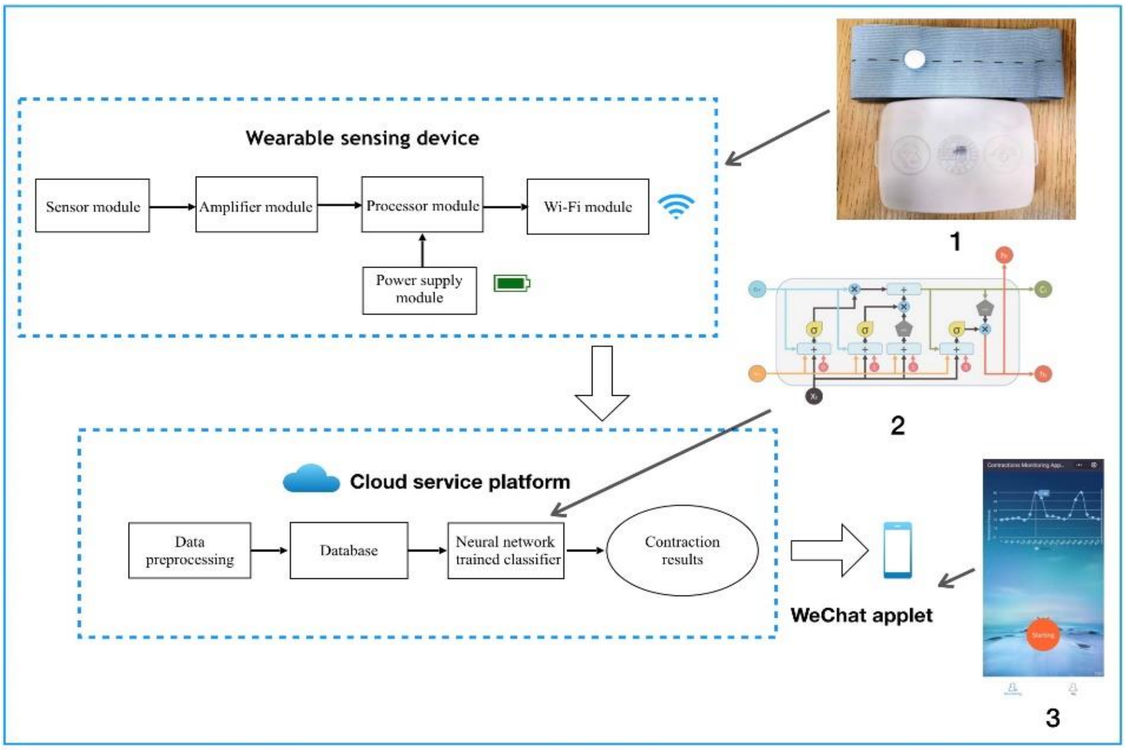


Figure 1-3 Illustration of wearable IoT system for monitoring labor contraction

The main work and contributions of this thesis include:

(1) Hardware design of the wearable sensing device: The contraction data acquisition circuit mainly includes five modules: the pressure sensor module, the amplifier circuit module, the processor module, the Wi-Fi module and the power module. Firstly, the pressure sensor module realizes the acquisition of the contraction pressure data. Secondly, the amplifying circuit module filters and amplifies the millivolt voltage. Thirdly the processor module performs A/D sampling through the data. Fourthly Wi-Fi module realizes the function of transmitting contraction data to the server through ESP8266. Finally, the Li-ion battery module matches the charging and discharging modules, and realizes the function of outputting a 5V regulated power to supply power to all modules.

(2) Design of the algorithm for monitoring labor contraction: The module preprocesses and extracts features of the collected contraction data. It uses LSTM neural network to identify and classify the processed contraction data. This algorithm divides them into three categories: regular contractions, pseudo contractions and non-contractions. Through adjusting the hyperparameters and the network model, it improves the accuracy of model recognition to 93.75%. Also, this part compares it with support vector machine, random forest and other algorithms.

(3) Design of the server and WeChat applet: The server completes the basic environment configuration and realizes the deployment of the network model. It also realizes the storage of the contraction database, and the transmission of the contraction monitoring results to the WeChat applet. Besides, the WeChat applet realizes the login function of the applet user and the function of personal information recording. It also realizes the display of the contraction result and the drawing function of the contraction curve.

Finally, a safe, accurate, portable, low-cost, and easy-to-use labor contraction monitoring wearable system is designed to solve the actual labor contraction problem. This system relieves the anxiety of pregnant women and allows safer monitoring of pregnant women during the period of labor.

Chapter 2 Literature Review

2.1 IoT in healthcare

With the rise of the Internet and the public's attention to healthcare, IoT technology has developed rapidly in the healthcare field in the past 10 years, gradually evolving from early monitoring functions to various functions. Many scholars at home and abroad have applied the IoT technology to healthcare. There are some research achievements in rural health monitoring, lower limb activity evaluation and rehabilitation, environmental and physiological parameter monitoring, and neonatal monitoring.

In 2017, C.Raj *et al.* [21] presented a low-cost health sensor platform for rural health monitoring with a well-structured and secure interface between healthcare experts and remote centers for sharing of important healthcare parameters. As shown in Figure 2-1, the system serves for rural areas. Doctors diagnose patient under treatment remotely, and the results of diagnosis and analysis are stored in the cloud.

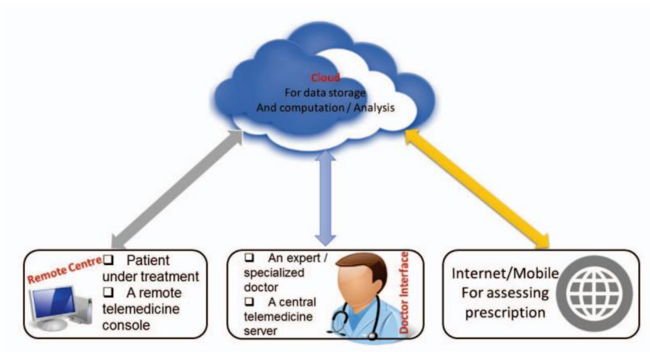


Figure 2-1 IoT system for rural health monitorin g [21]

In 2018, S.Bao *et al*. [22] proposed an IoT system for lower limb activity evaluation and rehabilitation. As shown in Figure 2-2, data collection is done through a wearable multi-modal system that allows patients to perform rehabilitation exercises according to the training plan assigned by the therapist. The training process and daily assessment data will be sent to the therapist. The updated training plan of the therapist will be sent to the patient through our recommended system. Under this system architecture, the entire process of lower limb assessment and rehabilitation will be completed in a closed loop. Therefore, the patient can achieve well rehabilitation exercises according to this IoT system.

In 2019, F.Wu *et al.* [23]presented an IoT system to connect safety and health applications. This system adopts multiple wearable sensors to monitor environmental and physiological parameters. As shown in Figure 2-3, if harmful environments are detected, the sensor node will provide an effective notification and warning mechanism for the users. And the cloud sever can realize data storage, processing and visualization.

Figure 2-2 IoT system for lower limb activity evaluation and rehabilitation [22]

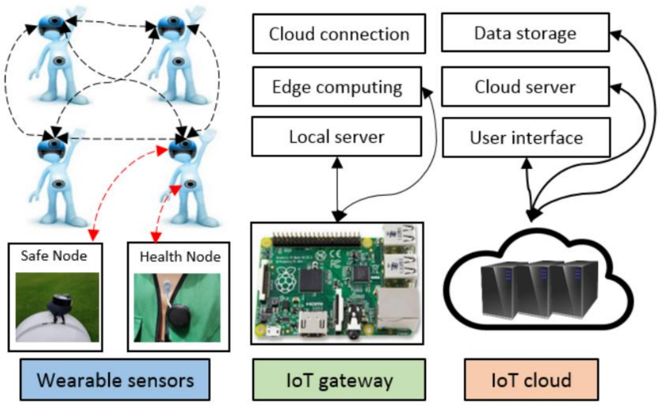


Figure 2-3 IoT system for monitoring environmental and physiological parameters[23]

In 2020, H.Chen *et al.* [24]proposed an IoT system for neonatal monitoring. As shown in Figure 2-4, a smart vest based on flexible material sensors is proposed to obtain electrocardiograph (ECG), breathing and motion signals for non-invasive monitoring of newborns. The data generated by the hardware system in the smart vest will be transmitted to the local terminal for real-time monitoring through the application. The data will also be uploaded to the cloud platform by the local terminal at the same time. Another control terminal connected to the cloud platform will help doctors analyze the health status of the newborn and provide timely treatment and assistance.

From the above research work in recent years, the IoT system has a wide range of applications and development in the healthcare field, and the whole system is gradually improving and more functional. It is becoming a mobile hardware + cloud processing and display mode.

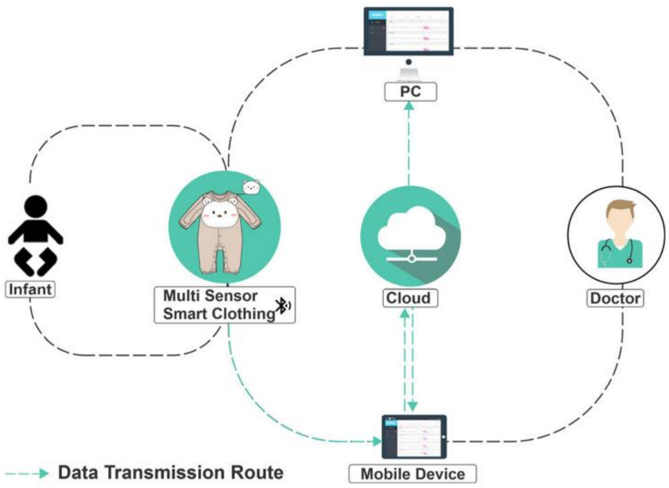


Figure 2-4 IoT system for neonatal monitoring [24]

2.2 Wearable device in healthcare

Wearable devices are developed with the development of the IoT to a certain extent. With the advancement of electronic technology and packaging technology, wearable devices have developed better and better in healthcare during recent years. They are developing in the direction of being smaller, more convenient, and more powerful.

In 2014, A.Parate *et al.* [25] proposed the wearable wristband to detect smoking gestures to reduce the number of times that people who quit smoking but smoke again. As shown in Figure 2-5, a wristband containing a 9-axis inertial measurement unit to capture changes in the orientation of a person's arm. And the mobile will display the user's smoke event state. This wearable device can detect smoking gestures with high accuracy of 95.7%. It is small in size and can be well fixed on the wrist. Therefore, it can be easily carried around.

In 2018, G.Yang *et al.* [26] designed the wearable device to monitor the condition of critically ill patients through his painful facial expressions. As shown in Figure 2-6, the entire pain assessment tool is presented. The integrated Wi-Fi sensor node is connected behind the ear, the electrode is embedded in the mask and the lead connecting the two parts. The total weight of implemented pain assessment tool is 39.08 g, which is light and has almost no burden on users during long-term use.

Figure 2-5Wearable wristband to detect smoking gestures [25]

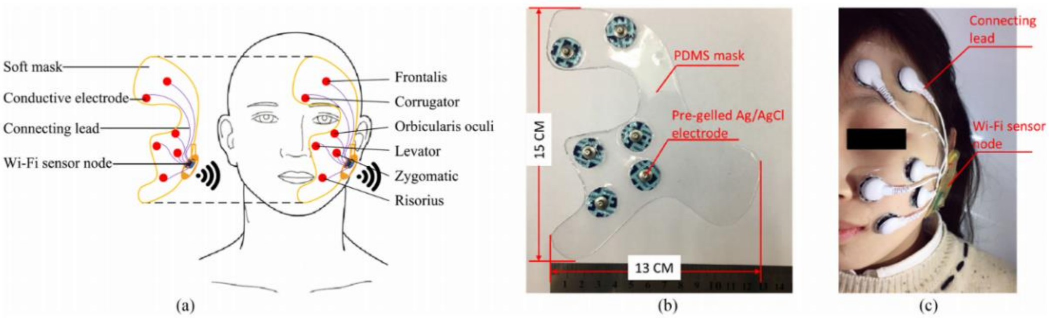


Figure 2-6 Wearable mask to detect facial pain [26]

In 2020, X.Chen *et al.* [27] designed a wearable hand rehabilitation system with soft gloves. It is used for stroke patients with hand dysfunction after surgery, and designed for postoperative hand rehabilitation training. As shown in the Figure 2-7, this wearable device is divided into two parts. One is the sensory glove, the other is the motor glove. The sensory glove is used to obtain gesture recognition signals, and the motor glove is used to drive the sick hand for rehabilitation training. This pair of gloves is valuable to stroke patients through good rehabilitation training.

Wearable devices have gradually begun to be applied in the maternal and infant field, In 2015, W.Chen *et al.*[28] proposed an intelligent pillow embedded with sensing and actuating functions to provide comfort through mediation of a parent's physiological features to the distressed neonate.

In 2020, H.Chen *et al.*[24] proposed an integrated wearable multi-sensor platform for neonatal monitoring. As shown in Figure 2-8, in the smart vest, a new stretching sensor based on Polydimethylsiloxane-Graphene (PDMS-Graphene) compound is created to detect the breathing signals of newborns; textile-based dry electrodes are developed to measure ECG signals; Inertial measurement units (IMUs) are embedded to obtain movement information, including accelerated speed and angular velocity of newborn wrists. This device can provide appropriate treatment, accurate and comfortable monitoring conditions for newborn infants.

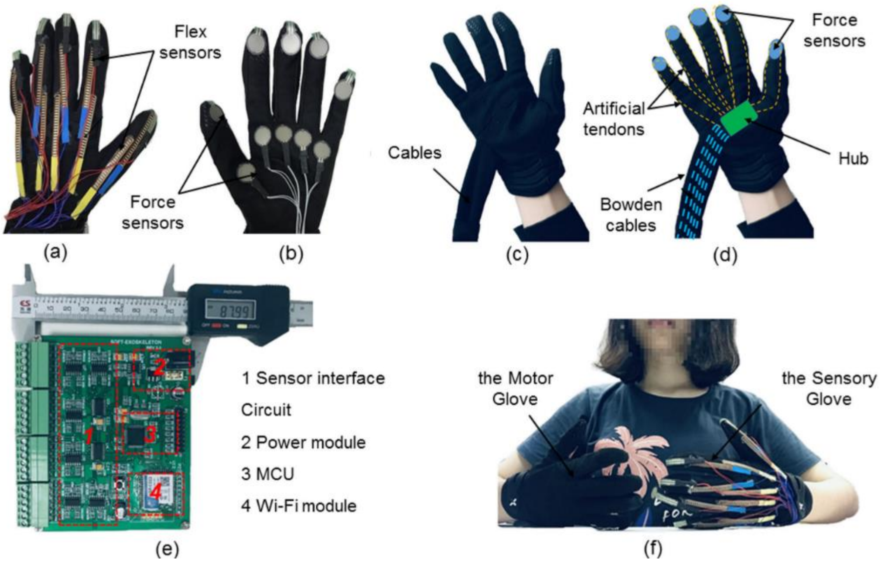


Figure 2-7 Wearable hand rehabilitation system with soft gloves [27]

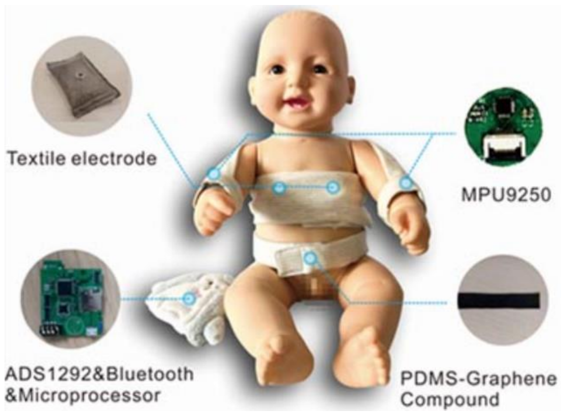


Figure 2-8 Prototype vest for neonatal monitoring [24]

From the above research work in recent years, wearable devices play an increasingly important role in healthcare. The functions of these devices are becoming more and more abundant, and the detection effect is becoming more and more perfect.

2.3 Machine learning in healthcare

With the rapid development of machine learning, it has great advantages over traditional algorithms in data prediction and classification. Therefore, it is gradually being applied in healthcare. The research work of Feifei Li's group provides strong support for time signals in the healthcare field. In 2020, X.Yu *et al.*[29] proposed two-level data compression using machine learning in time series database. Time-series data has strong time correlations. This method greatly compressed time-series data, which can be widely used in healthcare.

Machine learning is also used in disease prediction and diagnosis. In 2018, S.Ongsu *et al.* [30] proposed an adaptive cancer prognosis framework for cholangio-carcinoma based on machine learning techniques, namely “CanWiser”. CanWiser was used to automatically learn patient data sets, preprocess data, oversample data to use Synthetic Minority Over-sampling Technique (SMOTE) to solve imbalance problems, It used machine learning techniques (decision tree, random forest, naive Bayes and support vector machine) to generate prediction models, and predict the possibility of cholangiocarcinoma. At last, the proposed prediction model accuracy was 83.34%.

In 2020, F.Demrozi *et al.*[31] applied k-nearest neighbor algorithm (KNN) to recognize Freezing of Gait (FoG) in people affected by Parkinson Disease (PD). The gait was classified in three classes of events: pre-FoG, no-FoG and FoG. As shown in Figure 2-9, the data gathered by the accelerometers on the patient body were transmitted to the mobile phone. Once the data were received, they were processed by data vectorization and transformation matrix. Then they entered to the KNN classifier through training. The model finally achieved an accuracy of 94.1%.

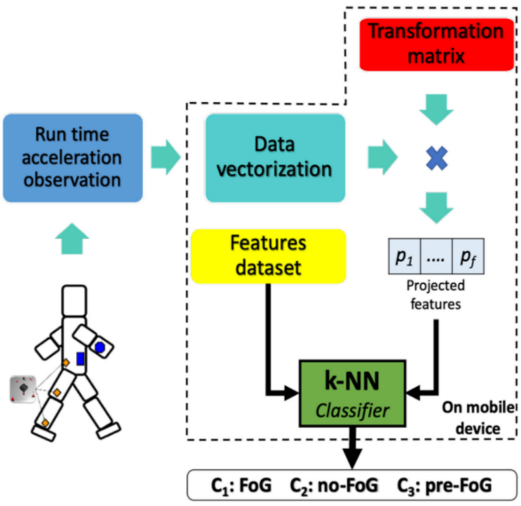


Figure 2-9 Algorithm to recognize Freezing of Gait [31]

Deep learning has in recent years set an exciting new trend in machine learning. In 2017, D. Ravì *et al.* [32] proposed a deep learning approach to on-node sensor data analytics for mobile or wearable devices. In 2019, B. Shickel *et al.*[33] researched deep learning techniques for electronic health record (EHR) analysis.

Many excellent deep learning algorithms have been proposed in healthcare. In 2018, M. H. Yap *et al.* [34] proposed convolutional neural networks (CNN) to detect breast ultrasound lesions. In 2019, L. Peng *et al.* [35] proposed a multi-scale residual network to classify and quantify of emphysema. They constructed their own emphysema database and achieved classification accuracy of 93.74%. In 2020, F. J. Martinez-Murcia et al. [36] used convolutional autoencoders to learn the manifold structure of Alzheimer's disease and achieved a classification accuracy over 80% for the diagnosis. In the same year, S. Saadatnejad *et al*. [37] proposed LSTM-based ECG classification for continuous monitoring on personal wearable devices. This method reached extremely high accuracy in different ECG data sets.

From the above research work, it can be concluded that machine learning algorithms have many applications in healthcare, showing the superiority of their algorithms.

2.4 Contraction measurements

Typically, there are two main ways to measure contractions, invasive measurement and non-invasive measurement. As early as 1976, J. D. Knote *et al.* [38] and others used an invasive measurement method to measure contractions. At that time, limited by technical level and healthcare conditions, only invasive methods could be used. This method directly puts the uterine pressure gauge through the catheter inside the pregnant woman’s uterus to detect changes in intrauterine pressure, as shown in Figure 2-10, since this method is directly placed inside the uterus, the measurement accuracy is very high, but it will cause discomfort to pregnant women. Besides, it can cause problems such as rupture of the amniotic membrane, bacterial and viral infections. Therefore, it is no longer used clinically.

In addition, B. Woodward *et al.* [39] used wireless data transmission in a monitor for the first time in 2005. The wireless method allows patients and doctors to enjoy greater freedom, and improves the comfort of wearing device for patients. More importantly, the development of wireless technology has made it possible for doctors to monitor multiple patients at the same time.

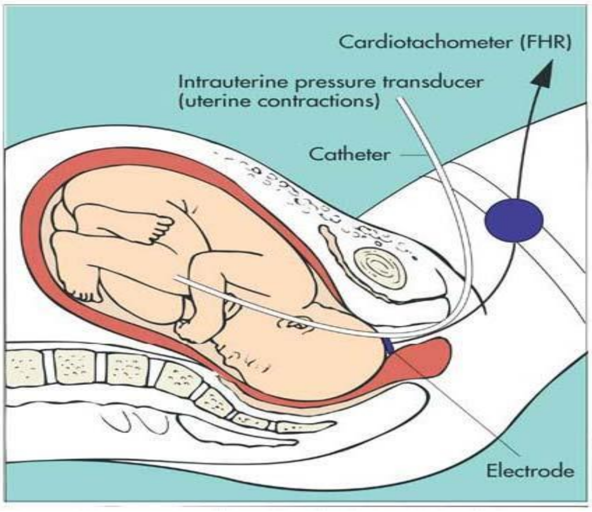


Figure 2-10 Diagram of invasive contractions detection [38]

With the rapid development and popularization of computer networks, research on contractions is not only in the detection and diagnosis equipment of hospitals, but also in combination with the Internet, cloud platforms and other tools to develop smart monitoring and remote monitoring of contractions detection New model. In 2011, M.Roham *et al.* [40] designed a wireless monitoring system based on contractions and fetal heart rate. As shown in Figure 2-11, the instrument consists of an ultrasonic Doppler fetal heart probe, a contraction pressure sensor, a cellular network gateway, and a Web server. It is a remote monitoring and diagnostic equipment. Due to the cost of research and development and the use of GPRS as wireless data transmission, the equipment is not portable and expensive and difficult to promote.

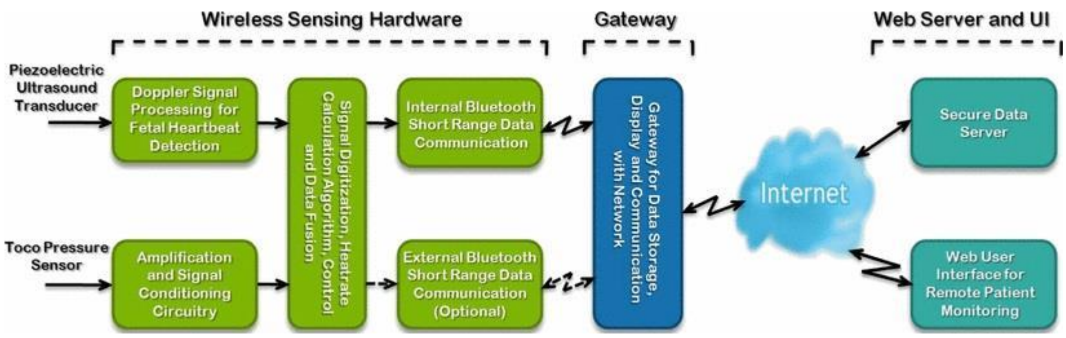


Figure 2-11 The architecture of the remote monitoring system for fetal heart and contractions [40]

In 2016, Y.Du *et al.*[41] designed a contraction monitoring system based on a positive pressure measuring contraction sensor. The system collects the pressure signals of the pregnant women's contractions through the positive pressure measuring contraction sensor. It transmits the data to the mobile phone via Bluetooth, and the mobile terminal performs display analysis. The system architecture is shown in Figure 2-12.

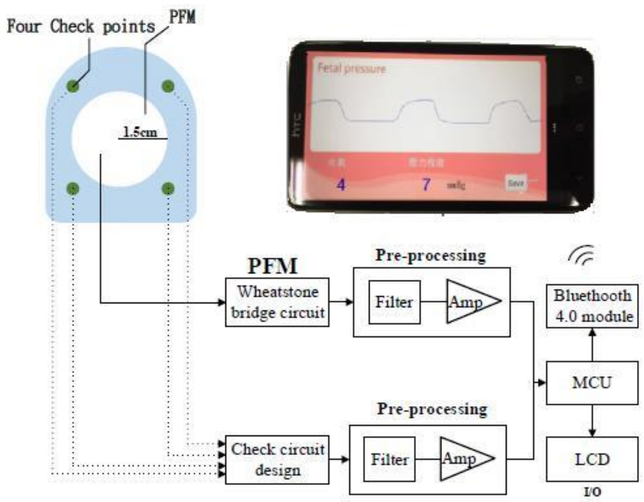


Figure 2-12 Wearable contractions monitoring system based on pressure measurement [41]

Bloomlife company is committed to researching healthcare sensors for prenatal monitoring and nursing of pregnant women [42]. The company's core product is Belli, which monitors the contraction behavior with a sensor worn on the abdomen of pregnant women through an adhesive patch, and transmits relevant data such as the duration and frequency to the app. Unlike traditional ultrasound technology, Belli uses passive non-harmful electronic monitoring technology. Clinical verification has shown that it will not cause any harm to the mother and fetus. The product is shown in Figure 2-13. This product only focuses on contraction data monitoring, records time and intensity of contraction, but does not incorporate healthcare judgment. Moreover, the price is very expensive, and it has not yet entered the market on a large scale.

At present, most pregnant women still use the contraction counter app to record contractions. As shown in the Figure 2-14, they are two contraction counter apps. Pregnant women record contractions in the app through subjective feelings of contractions. The software is completely based on the subjective feelings of pregnant women, which is very inaccurate, and some pregnant women have painless contractions. Pregnant women can't detect the status, so these apps are not suitable for recording and monitoring pregnancy contractions.

Figure 2-13 Bloomlife company's wearable contractions monitor [42]

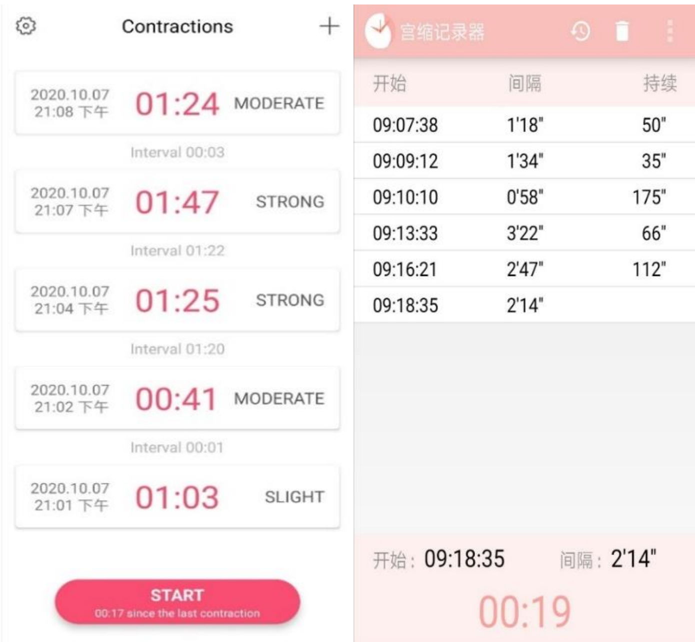


Figure 2-14 Contraction counter apps

Chapter 3 System Design

This chapter firstly introduces the theories of contraction, then introduces the design considerations, and the specific goal of the wearable intelligent system for monitoring labor contractions. Finally, it introduces system design architecture.

3.1 Theories of contraction

Contractions are the movement behaviors of the uterus, which is one of the important indexes in clinical prenatal examination. Contractions have such characteristics, generally weak to strong, and gradually weakened after reaching the peak; After reaching the baseline, there will be a period of time before the second contraction begins. Regular contractions are an important sign of labor [43]. For a single contractions signal, it can be divided into ascending phase, peak phase and descending phase. In general, contractions are described from three aspects: contraction intensity, contraction duration and contraction period. As shown in Figure 3-1, it is the pattern of contraction curve.

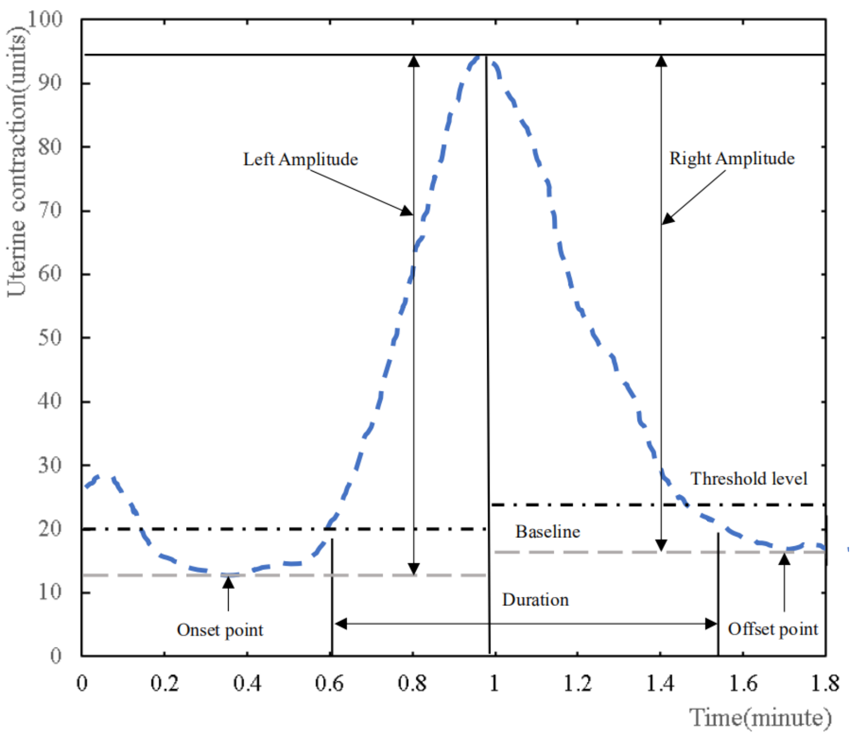


Figure 3-1 Pattern of contraction curve

Contraction intensity refers to the value of the pressure at the top of the contractions pressure curve. Since the pressure measured by the lateral method is relative, the intensity of contractions measured by the lateral method does not represent the true intensity of contractions. The peak value of the curve is also related to the position of the contraction sensor probe, the tightening procedure of the elastic band, the abdominal wall of the pregnant woman and other factors [44].

The duration of a contraction is the time from the beginning of a contraction to when intrauterine pressure returns to resting pressure. Contractions typically last between 20 and 90 seconds. In the past, pregnant women and doctors had no awareness of monitoring. Thus the duration of contractions was mainly determined by the pregnant woman's feeling or the doctor's palpation, but this kind of judgment was generally not accurate [45].

Contraction period is generally the interval between the start of two contractions. Since the lateral method obtained relative contractions pressure, the space between the two contractions peak points was taken as the contraction period.

Contractions pressure curve can be divided into three types according to the length of time required to rise and fall [46]: Type I is the type of contractions whose rise time is greater than fall time; Type II is the type of contractions where ascending time equals the descending time; Type III is the type of contractions that take less time to rise than to fall. Normally, from pregnancy to labor, the contractions stress curve transitions from type I to type III. Therefore, the intensity of type I contractions is relatively weak, while the intensity of type III contractions is relatively strong. During labor, it is mainly a type III curve, and the common contraction pressure curve is shown in Figure 3-2.

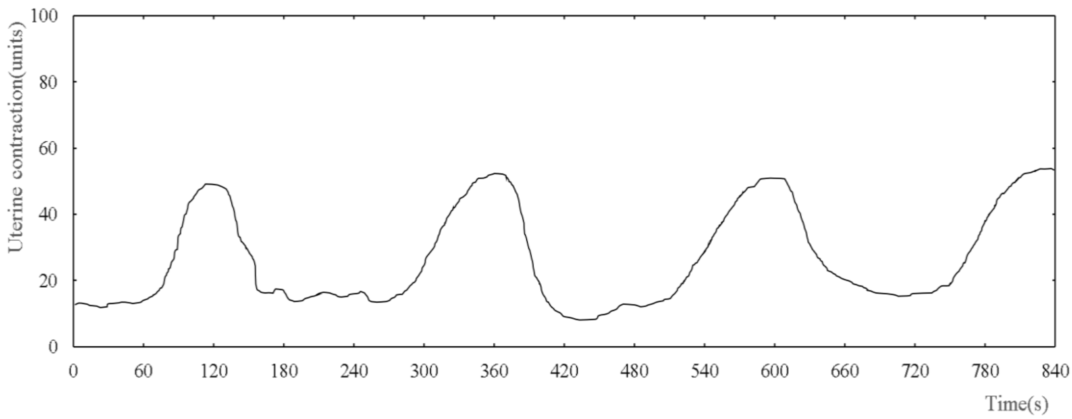


Figure 3-2 Contraction pressure curve

3.2 System design considerations

In clinical practice, pregnant women are currently unable to correctly judge whether they are in labor based on their subjective feelings, so they often go to the hospital in advance for labor when the contractions do not meet the conditions for labor. The general public generally believes that it is safer to go to the hospital early for delivery, but a large number of healthcare studies have shown that going to the hospital too early will increase the adverse emotional reactions of pregnant women. It also leads to adverse pregnancy outcomes, and endangers the safety of mothers and babies. It will also increase the healthcare pressure in the hospital and reduce healthcare efficiency.

In the context of smart healthcare, the intelligent labor contraction monitoring system based on the IoT proposed in this thesis aims to solve this problem and design a wearable sensing device that is portable, low-cost, and can be used for home use. According to the judgment result of contraction, it assists pregnant women to decide the best time to be admitted to the hospital. The intelligent system designed in this thesis has the following characteristics:

(1) This is a compact and lightweight wearable system for monitoring labor contractions. Compared with traditional contraction device, it is smaller and easier to use. Pregnant women can use it to monitor at home. It is easy to operate, and can be used to monitor anytime and anywhere without being restricted to the clinical healthcare environment.

(2) The device of this wearable system uses 3D printing, encapsulates all hardware modules in the shell, and supports bandage fixation, which can be easily fixed by pregnant women.

(3) This wearable labor contraction monitoring system is aimed at pregnant women in labor, focusing on the detection of contractions during labor. It is mainly divided into three categories of contractions, regular contractions, pseudo contractions and non-contractions. Based on objective data, it helps pregnant women decide the best time to be admitted to the hospital.

(4) This wearable labor contraction monitoring system adopts a combination of 'hardware + cloud'. It processes the data obtained by the hardware in the cloud. The cloud also realizes the storage of the data in the database, and uses suitable algorithm to detect it.

(5) This wearable labor contraction monitoring system designs the user-side WeChat applet. It is designed to realize login, information filling, contraction waiting monitoring, monitoring result display, contraction curve drawing and other functions. The interface is simple and beautiful. It is easy for pregnant women to get started quickly.

According to the theoretical knowledge and technical requirements related to labor contractions, it is required that the wearable labor contraction monitoring system based on IoT designed in this thesis can achieve the following objectives:

(1) Wearable sensing device should collect the pressure characteristic signals of pregnant women's contractions effectively and accurately.

(2) Cloud algorithms should accurately classify and recognize contractions signals.

(3) The WeChat applet can effectively and accurately display the results of cloud processing.

(4) The wearable sensing device should be as light as possible to prevent pregnant women from bearing heavy loads. At the same time, a belt should be equipped so that pregnant women can make appropriate adjustments according to their own conditions to maintain a comfortable state.

(5) All components in wearable devices should not affect the safety of pregnant women and should have low radiation. In addition, this device needs to use low-power components to improve battery life and support charging.

3.3 System design principles

3.3.1 Design principles

The intelligent contractions monitoring system proposed in this thesis should comply with some design principles, specifically as follows:

(1) Safety: Safety is the first principle that must be guaranteed and considered for intelligent uterine contractions during labor. The safety of this system is mainly divided into two aspects, one is the mechanical structure, and the other is the circuit components. The design of mechanical structure

needs to consider whether wearable device will cause accidental injury to pregnant women. Therefore, the chamfer of the device should avoid sharp, and all parts of the device except the sensor should not be in direct touch with the abdomen of the pregnant woman. About circuit components, they need to choose the modules with the minimum radiation in the circuit to avoid damage to the fetus.

(2) Comfortability: The contractions of pregnant women may be accompanied by pain, so the designed device needs to be as comfortable as possible. Also, the belt needs to be as soft as possible. The overall volume and weight of the wearable device are also factors to consider. It needs to be small and light. The wearable device is designed to ensure that pregnant women are relaxed and comfortable during monitoring.

(3) Interactivity: Interactivity is the most sensitive part of user experience. It is necessary to ensure the interaction between different interfaces of WeChat applet, and obtain the stability of interaction of contractions. It can improve the user experience.

3.3.2 Specific goals

The specific goals are shown in Table 3-1.

Table 3-1 Specific goals

Aspects	Goals
Weight	<=100g
Volume	<10cm*10cm*2cm
Detect accuracy	>=90%
Battey life	>=10h
Battey	Rechargeable
Transmission delay	<=0.5s
Mobile	WeChat applet

(1) For pregnant women's portability and wearability, the volume of the wearable device cannot exceed 10cm*10cm*2cm, and the weight cannot exceed 100g.

(2) In order to continue to supply power for the wearable device, the battery life must not be less than 10 hours. For the convenience of pregnant women and environmental protection requirements,

disposable batteries cannot be used, and the batteries must support rechargeability.

(3) In order to accurately detect the contraction signal during labor, the accuracy of the contraction classification algorithm model cannot be lower than 90%.

(4) For pregnant women's experience, the data transmission delay cannot be higher than 0.5s.

3.4 System design architecture

The design architecture of the IoT based intelligent labor contraction monitoring system proposed in this thesis is shown in Figure 3-3. This system includes three parts, wearable sensing device, the cloud service platform and the WeChat applet. The wearable sensing device includes hardware circuit design, 3D printing model design and packaging. The cloud service platform mainly deploys deep learning algorithms to identify and classify contractions data, and realize database storage of data. WeChat applet mainly realizes user interaction and contractions results display. The specific content is as follows：

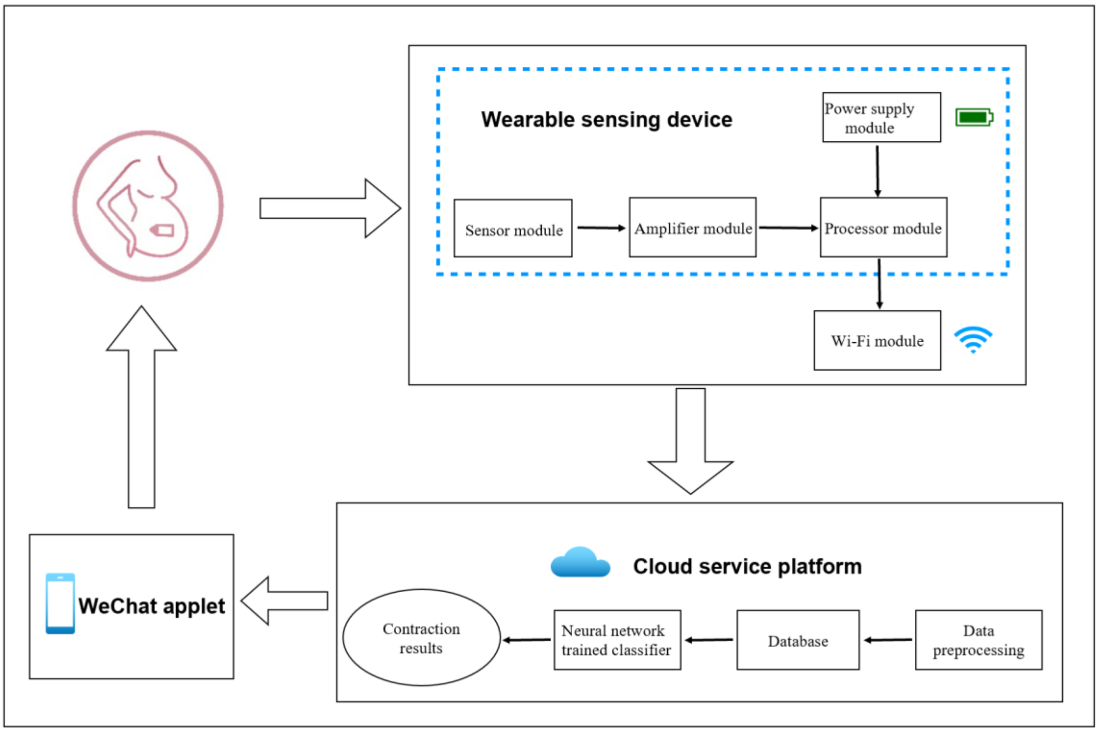


Figure 3-3 Diagram of the IoT based intelligent labor contraction monitoring system

(1) Wearable sensing device: It mainly realizes hardware circuit design. Through the pressure sensor, it obtains the signal of pregnant women's contraction pressure. After processing by the amplifier

circuit, the collected signal data is sent to the server through the processor control module using the Wi-Fi module. The server will further process the data and algorithm recognition. And the power module of the device is completed to realize power supply to all modules. Then this project completes wearable sensing device design. The wearable sensing device model is designed through 3D printing, and each module of the circuit is packaged. The 3D model leaves two handles for fixing the device with the belt.

(2) Cloud service platform: It is used for labor contraction recognition. And it mainly includes preprocessing of data, adding corresponding categories of tags under the guidance of doctors of Obstetrics and Gynecology Hospital of Fudan University, extracting features of data, selecting feature sets that can represent the characteristics of contractions, and combining all the normalized data. The processed uterine contraction signals are classified through classification algorithms. Long and short-term memory (LSTM) neural network, Support Vector Machine (SVM), Random Forest (RF) and Logistic Regression (LR) are selected for classification and recognition, and the results of these algorithms are compared. Finally, it determines that the classifier with better recognition effect is used as the final choice, and the algorithm is deployed on the Alibaba Cloud server through the python-dependent environment, so that the contraction data can be classified in the cloud, and the contraction judgment result can be obtained. In addition, the cloud service platform also provides service interface for WeChat applet side.

(3) WeChat applet: The WeChat applet uses Hypertext Transfer Protocol (HTTP) to obtain the contraction results of the server, and realizes the basic user login function. The user information filling function includes name, age, whether it is a primipara, remarks and other information. In addition, it also realizes the waiting through the middle interface animation, allowing users to wait for detection. After the monitoring time is over, the results of this monitoring will be displayed and the curve of the contraction will be drawn. Pregnant women can check the contraction results and curves in time.

3.5 Summary

This chapter mainly introduces intelligent contraction monitoring system architecture. First, it elaborates the theories related to contractions, including contraction intensity, contraction duration, contraction period and contraction curve. Then it introduces design considerations. It determines the design principles and specific goals of the system, providing a basis for the content of the following chapters. In addition, this chapter introduces the architecture of the entire system, including wearable sensing device, cloud service platform and WeChat applet. And then introduces the functions of each part.

Chapter 4 Hardware Design of the Wearable Sensing Device

This chapter introduces the hardware design of the wearable sensing device for labor contractions. The wearable sensing device is mainly fixed by a strap and placed at the bottom of the uterus of pregnant women. In order to increase the stability of the terminal, a band is configured. The hardware acquisition terminal mainly includes six modules. The selection of related modules and their advantages are introduced, and the implementation process of each module is introduced, including (1) The sensor module uses FSS series pressure sensors to obtain the contraction pressure of pregnant women and output it at millivolt level; (2) Amplifier circuit module, which amplifies and filters the millivolt level output and then inputs it to next circuit; (3) The processor module adopts the smallest STM32 development board, STM32F103C8T6. It performs A/D sampling through the output of amplifier circuit; (4) For the Wi-Fi module, ESP8266 is used to complete the network configuration and transfer the data to the server; (5) Power module: Charging and discharging module ensures the power supply of the device, so that we can work away from the power cord and take it with us. At last, this chapter introduces integration of the wearable sensing device. It consists of 3D model design, internal structure, fixing method and measuring position.

4.1 System-level design of the hardware

The system-level design of the hardware is shown in Figure 4-1. It includes sensor module, amplifier module, processor module, Wi-Fi module and power module. The sensor module is the contraction pressure acquisition module. After the signal is acquired, it is processed by the amplifier circuit module, including filtering, amplification and so on. Then, the processor module performs analog-digital sampling of the data from amplifier circuit module, and the Analog-to-Digital Converter (ADC) is 12 bits. Through IP address and port number, Wi-Fi module can transmit the contractions data to the server. In addition, the charge and discharge module is designed to control the charge and discharge of the battery and realize the stable power supply of the hardware. The technical specifications of each module in this hardware are shown in the following Table 4-1. The diagram of hardware circuit of contraction monitoring system is shown in Figure 4-2.

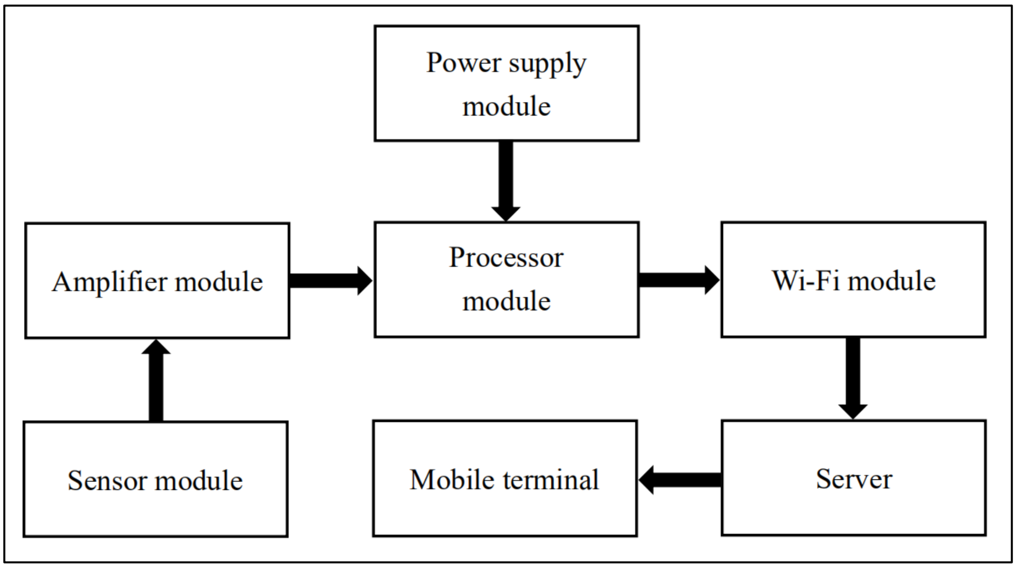


Figure 4-1 System-level design of the hardware

Table 4-1 Technical specifications of each module in the hardware

Sensor module	Type	Size	Operating temperature	Measurement range	Measurement error
	FSS1500NST	1cm*1.5cm	-40°C~80°C	0g~1500g	< ±8%
Amplifier module	Type	Size	Operating temperature	Load capacity	Output resistance
	OPA2350	2cm*1.5cm	-40°C~85°C	strong	low
Processor module	Type	Size	Operating temperature	ADC	Conversion speed
	STM32F103C8T6	5.3cm*2.25 cm	-40°C~85°C	12 bit	1μs
Wi-Fi module	Type	Size	Operating temperature	Supported protocols	Frequency range
	ESP-01s	2.5cm*1.4 cm	-40°C~125°C	IEEE 802.11b /g/ N	2.412Ghz-2.484Ghz
Power module	Type	Size	Battery	Operating Voltage	Discharge temperature
	404562	6.2m*4.5 cm	Rechargeable Li-ion battery	3.7V	-20°C~60°C

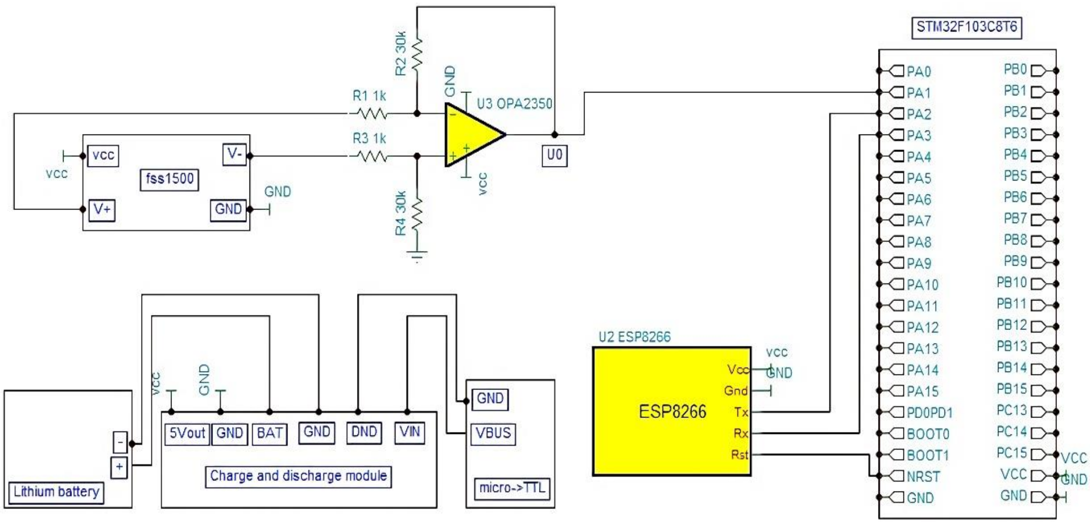


Figure 4-2 Diagram of hardware circuit of contraction monitoring system

The photo of hardware circuit of contraction monitoring system is shown in Figure4-3. It shows the composition of each module, including sensor module, amplifier module, processor module, Wi-Fi module and power module. The sensor module is fixed at the bottom to better capture pregnant women's contractions pressure signals.

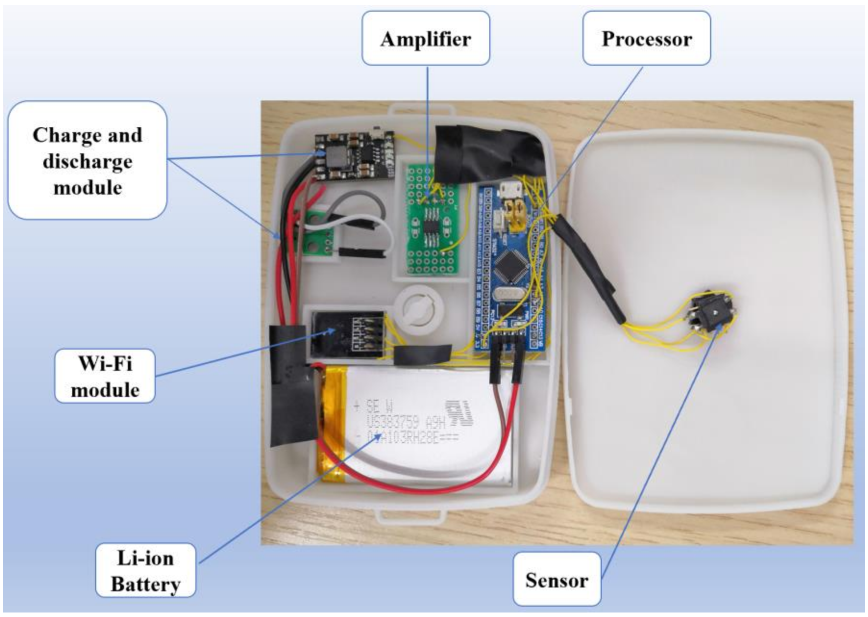


Figure 4-3 Photo of hardware circuit of contraction monitoring system

4.2 Sensor module selection and design

4.2.1 Module selection

Sensor selection is the most important step in hardware design, which is related to the accuracy of contraction data measurement. The experiment is to obtain the contractions pressure signal outside the mother body. Therefore, it puts forward a relatively high request to the sensor. The pressure range of uterine contraction is 0~200gf, and the linearity of the measurement is relatively high. Therefore, based on the accuracy and linearity requirements, the FSS1500NST sensor is selected for this device. This sensor specifically for clinical contraction measurement has a small volume and a size of 1cm *1.5cm. Compared with the uterine contraction pressure sensor with a shell, this model is small in size and more suitable as a sensor module of a wearable device for detecting labor contractions, The normal operating temperature of this sensor is -40°C~80°C.And the stability is very high, it can perform 20 million operations. The pressure measurement range 0g~1500g, its nonlinearity error of the sensor is $< \pm 8\%$, in line with national standards for contraction pressure sensors. What is more, this sensor has very low power consumption, the output is a millivolt voltage range 0.1~14mv/g, the average output voltage is 0.12mv/g, it can support long battery life. Besides, it has almost no radiation, so it will not affect the health of pregnant women, Therefore, based on the above characteristics, it meets the requirements of system design.

4.2.2 Measurement principle of the pressure sensor

The principle of the pressure sensor is that the silicon sensitive chip inside the sensor is directly acted on by the stainless steel insert rod, which causes the compression bending of the varistor and then changes the resistance value by causing ion implantation [47]. The change in resistance is proportional to the contact pressure applied. It creates a corresponding mV signal through an internal Whiston bridge circuit. As shown in the Figure 4-4, the FSS1500NST pressure sensor [48] manufactured by Honeywell is used as the pressure acquisition sensor.

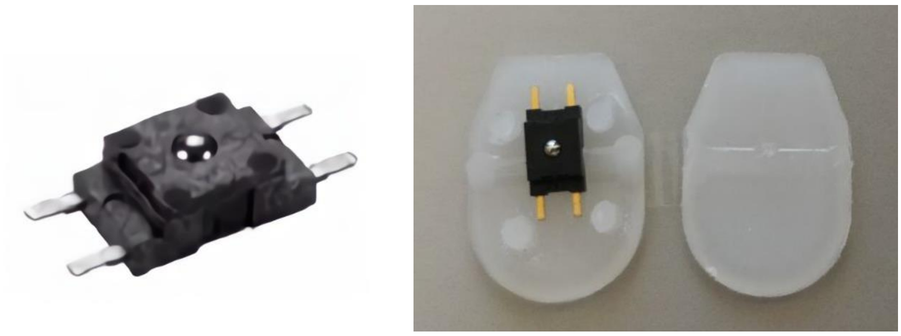


Figure 4-4 FSS1500NST pressure sensor

The FSS1500NST touch pressure sensor contains a Wheatstone bridge circuit [49], which can convert pressure signals into electrical signals. The bridge circuit is shown in Figure 4-5:

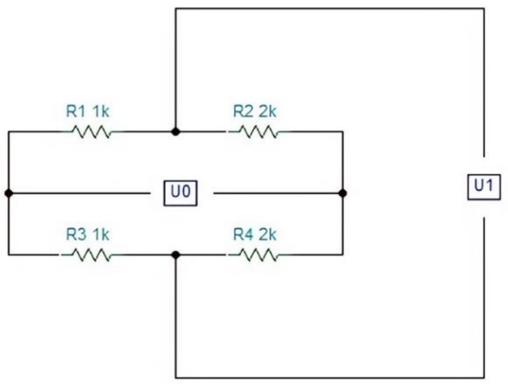


Figure 4-5 Wheatstone bridge circuit

When the pressure sensor FSS1500NST in the circuit is not under pressure, there is $R_1 * R_3 = R_2 * R_4$, the circuit is in equilibrium, and the output voltage of the circuit is $V_o = 0$. The output voltage formula can be deduced from the circuit as follows:

$$V_o = V_i * \left[\frac{R_3}{R_3 + R_4} - \frac{R_2}{R_1 + R_2}\right] = V_i * \frac{R_1 * R_3 - R_2 * R_4}{(R_1 + R_2)(R_3 + R_4)} \tag{4-1}$$

When the pressure sensor FSL1500NST is under pressure, the resistance R_1 value will change, and then the output voltage of the circuit will occur accordingly. Due to the proportional relationship, the greater the pressure, the greater the change in resistance value, the greater the output pressure value will be. The circuit converts the pressure of contractions into millivolt level voltage and outputs it to the next level circuit by touch pressure sensor. The average output voltage range is 0mv~180mv.

4.2.3 Sensor module test and placement

Based on the above characteristics, this section has carried out 5 sets of tests on the FSS1500NST sensor, respectively using the corresponding pressure to test the FSS1500NST sensor, and record the output millivolt voltage value, as shown in Table 4-2, the difference error of each test is very small.

The external pressure and voltage relationship curve is shown in Figure 4-6, the average output voltage range is 0mv~180mv. Ideally, the output voltage value is an approximate linear relationship with external pressure value, approximately equal to 0.12 times.

Table 4-2 FSS1500NST test data

External pressure /g	Group 1 /mv	Group 2 /mv	Group 3 /mv	Group 4 /mv	Group 5 /mv
150	16.9	18.3	17.8	18.3	19.0
350	41.8	42.8	40.0	43.1	41.3
550	68.1	64.1	66.7	65.5	63.0
750	88.0	89.7	86.4	90.8	91.2
950	108.2	114.8	113.1	115.3	115.7
1150	139.1	136.0	138.0	137.3	139.4
1350	163.0	165.7	162.2	156.1	163.9

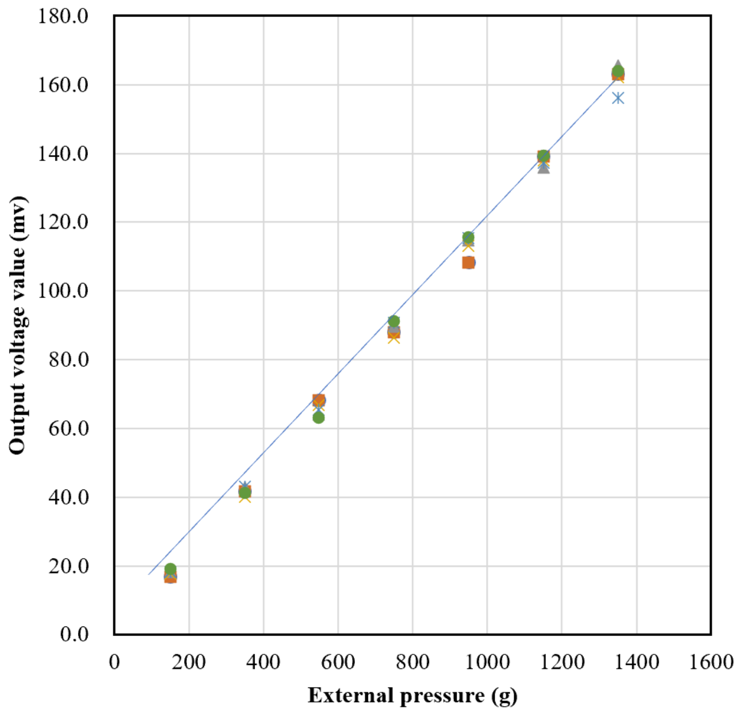


Figure 4-6 Relationship between external pressure and output voltage

From Figure 4-6, we can see that the voltage value of each test data fluctuates around the ideal value. Therefore, in this hardware circuit, the use of FSS1500NST sensor is effective. Besides, the placement of the sensor has a great influence on the measurement results. During pregnancy, the pressure at the bottom of the uterus changes most obviously. Therefore, the FSS1500NST is packaged at the bottom of the wearable device. When measuring, the device is placed on the bottom of the pregnant woman's uterus with a band fixed. Therefore, accurate measurement can be achieved by fixing the accurate position.

4.3 Amplifier circuit module selection and design

Since the output of the previous circuit is a millivolt voltage, the hardware circuit needs an amplifier circuit for further amplification, which is convenient for subsequent circuits to process. The amplifying circuit module uses operational amplifiers (OP) because operational amplifier is an electronic integrated circuit with multistage amplifier circuit [50]. Its input stage is differential amplifier circuit with high input resistance and zero drift suppression. The intermediate stage is mainly used for voltage amplification and has a high voltage amplification multiple. It is generally composed of a common emitter amplifier circuit. The output pole is connected with the load, which has the characteristics of strong carrying capacity and low output resistance. It is widely used in industrial manufacturing. Figure 4-7 is diagram of operational amplifiers.

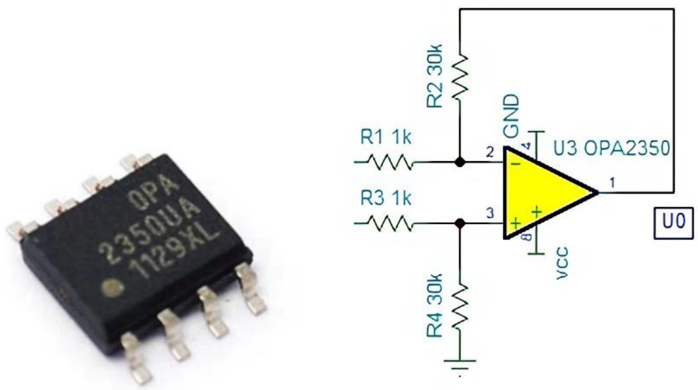


Figure 4-7 Diagram of operational amplifiers

Based on circuit principles such as virtual short and virtual broken, the following calculation formula can be obtained:

$$I_{R_1} = I_{R_2} \tag{4-2}$$

$$V^- = V^+ = 0 \tag{4-3}$$

$$V_0 = -\frac{R_1}{R_2} V_i \tag{4-4}$$

Since R_1 is set at 1K ohms and R_2 is set at 30K ohms, the actual amplification factor of this amplifier circuit is 30. This circuit has distinctive characteristics. Its reverse phase end of the circuit is low and the common mode rejection ratio of OP amp is low. Besides, the output resistance is small, and the load capacity is strong. The size of OP is very small, just 2cm*1.5cm. It has low power consumption and radiation. Therefore, based on above characteristics, it is suitable for this wearable device and meets the requirements of system design.

4.4 Processor module selection and design

In the design of the hardware circuit, the processor control module adopts the STM32F103C8T6 of the STM32F103 series. Compared with 51 single-chip microcomputers, it has many advantages, such as kernel, address space, on-chip memory, peripherals, development tools, operating system, etc. See the Table 4-3 below for details.

Besides, STM32F103C8T6 is the smallest development board in STM32 series. Its size is 5.3cm*2.25cm. Because of cortex-M3 architecture enhancements, it has better coding density, faster response to interrupts and lower power consumption. Therefore, it is suitable for making wearable devices. What is more, it has many excellent features and rich internal and external resources [51]. Taking into account the above advantages, this wearable device finally adopted STM32f103C86 as the processor control module.

Table 4-3 Comparison of STM32F103C8T6 and 8051MCU

Categories	STM32F103C8T6	8051MCU
Core	ARM Cortex-M3,32Bit@72Mhz	51Core,8Bit@2Mhz Max
Address space	4GB	64KB
ROM	20K-1MB	2K-64K
RAM	8K-256K	128B-1K
External device	AD, DA, Timer, DMA, USART, CRC, SPI, IWDG, etc.	Only 3 Timers and one Serial port
Development tools	UV4 and later versions	UV2 old version
Operation system	uClinux, uC/OS	RTOS

(1) Operating voltage range: 2V to 3.6V.

(2) It has 64K byte flash memory and 20K byte SRAM.

(3) It has a CRC cell, 96-bit unique ID, two 12-bit, Analog-digital converter (up to 10 channels), 7-channel DMA controller, 3 universal timers and 1 advanced control timer.

(4) It has 37 fast input and output ports, serial line debugger and JTAG interfaces, two SPI, two I2C, three USART, one USB and one CAN interfaces.

(5) Ambient operating temperature range: -40°C to 85°C.

The photo and pin diagram of STM32F103c8t6 are shown as Figure 4-8:

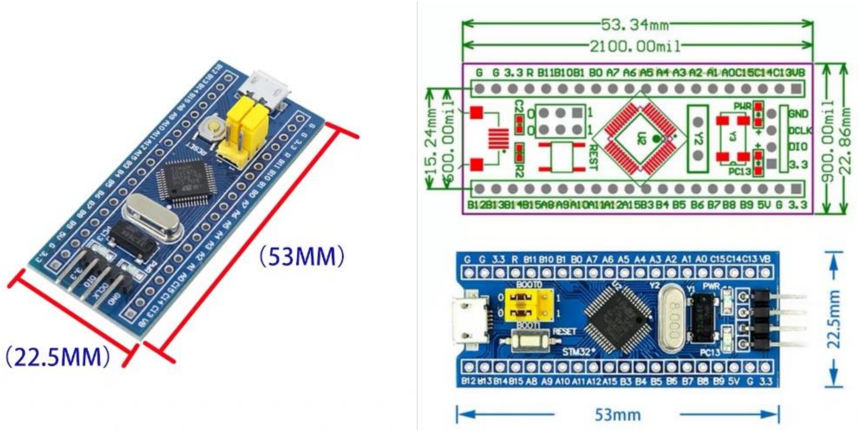


Figure 4-8 Photo and pin diagram of STM32F103C8T6 [52]

The processor control module in this circuit mainly realizes two functions. One is to take AD samples of the voltage values captured by the amplifier circuit, and the other is for the universal synchronous/asynchronous transceiver (USART) to communicate with ESP8266 to complete the next circuit function. The reference voltage of the ADC module part of STM32 F103C8T6 is 3.3v, and the conversion result of the ADC module is 12 bit. At this time, the minimum resolution of the signal will reach 3.3v/4096=1mv, so the amplifying module can detect the minimum signal as 1mv/30=0.033mv. With such a resolution, it is possible to monitor the relatively weak pressure changes of the uterine contraction, and it can also ensure that the amplified signal will not overflow. Therefore, it meets the requirements of system design.

4.5 Wi-Fi module selection and design

In this system, the contraction data needs to be stored on the server, and the neural network model needs to be deployed on the server to process and classify the data. At the same time, the WeChat applet needs to access the database and data results. Therefore, in the design of this wearable device, it is necessary to use the Wi-Fi module to send the contraction data to the server. And this system need a low-cost, low-volume and low-delay Wi-Fi module.

ESP8266 is a low-priced, stable Internet of Things chip from Le Xin. It costs only 16 RMB. Its volume is very small, only 1.1cm*1cm. Its volume is very small, only 2.5cm*1.4cm, which is not much different from a fingernail. The module supports the standard IEEE 802.11b /g/ N protocol [53,54]. It has a built-in TCP/IP protocol stack, supports multiple TCP Client connections. It also supports rich Socket AT commands. The operating voltage range is 3.0v-3.6v, and the operating temperature range is -40°C to 125°C. It has ultra-low energy consumption. Therefore, it is suitable for battery-powered applications. At the same time, its communication transmission delay is less than 10ms. Based on the various characteristics and advantages of ESP8266, it fully meets the needs of this subject. Therefore, the wearable device finally uses it as the hardware Wi-Fi module between device and server.

This circuit chooses ESP-01s of ESP8266, it works in three modes: AP mode, Station mode and Hybrid mode. The diagram of ESP-01s is shown in Figure 4-9:

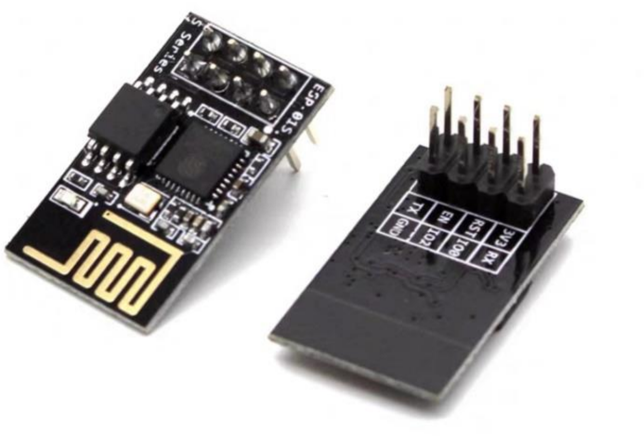


Figure 4-9 Wi-Fi module: ESP-01s

When the model of the Wi-Fi module is determined, we need to use it to transmit the contraction data. The flowchart of contraction data upload is shown in Figure 4-10.

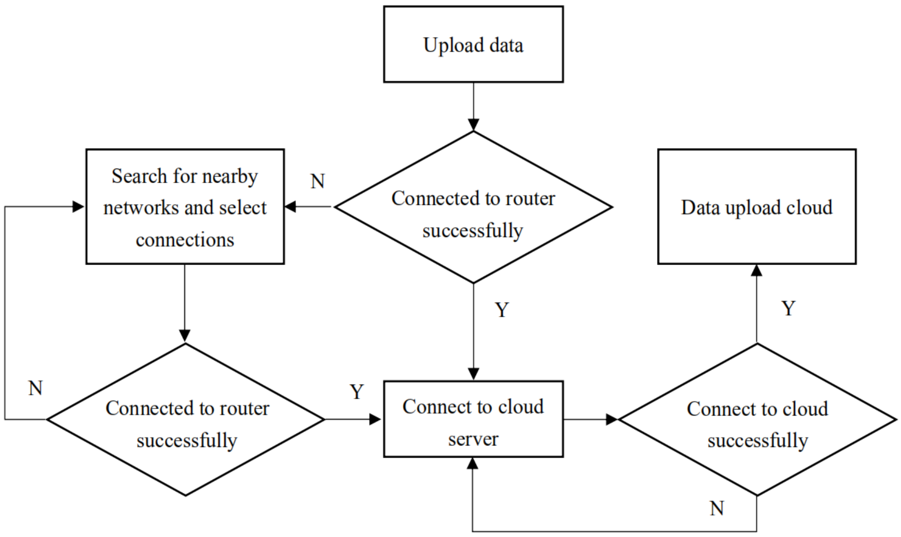


Figure 4-10 Flowchart of contraction data upload

The AT commands [55] of ESP8266 Wi-Fi module used in this thesis are shown in Table 4-4.

Table 4-4 AT commands of ESP8266

Mode setting	AT+CWMODE=<mode>	<mode> 1 STA model 2 AP model 3 AP+STA model
Query whether to connect to AP	AT+CWJAP?	1 Link successful, return AP name 2 Link failed, return ERR
Connect AP	AT+CWJAP=<ssid>, <pswd>	<ssid> AP name <pswd> AP password
Query currently available AP	AT+CWLAP	Returns the names of all nearby available hot spots
Connect to TCP server	AT+CIPSTART=<type>, <id>, <port>	<type> Server type TCP, UDP <id> Server address <port> Server port number
Transfer mode	AT+CIPMODE=<mode>	<mode> 0 Non-passthrough mode 1 Passthrough mode
Send data	AT+CIPSEND	Execute this command before sending data

The whole work flow has the following steps: First, set the Wi-Fi module to STA terminal mode through AT command "AT+CWMODE=1". Second, query whether the WI-FI module is successfully connected to the router through the "AT+CWJAP?" command. If it is connected to the router, then through the command "AT+CIPSTART=<type>, <id>, <port>" connect to the server. If it is not connected to the router, use "AT+CWLAP" command to query and list nearby networks, manually select the network and enter the password, then connect the router. After successful connection, continue to connect to the cloud.

After successfully connecting to the cloud, send "AT+CIPMODE=1" command to set the transmission mode to transparent transmission mode, and then send the AT command "AT+CIPSEND" to issue the number of transmissions. According to the instruction, the contraction data can be transparently uploaded to the cloud server for storage. This module transmits data every 200ms. As shown in Figure 4-11, the data transmits successfully.

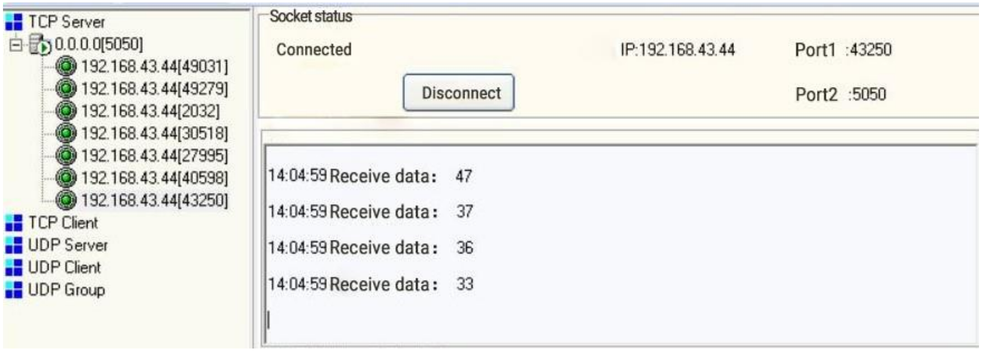
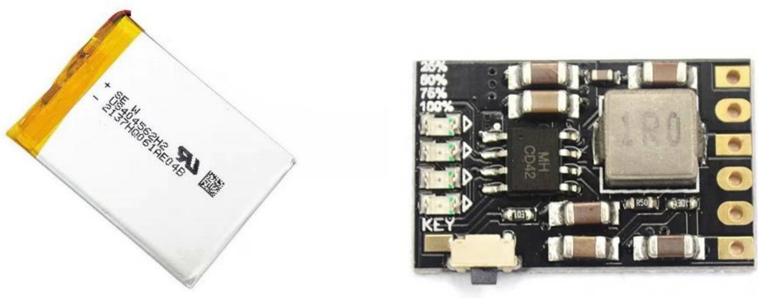


Figure 4-11 Data transmission diagram

4.6 Power supply module selection and design

Based on various functional modules described above, this system also requires a stable power supply module. It needs to lightweight and small size. Also, it can charge and discharge to ensure a better life time.

The hardware circuit adopts Li-ion battery as the power supply. This Li-ion battery is corrosion-resistant and high-temperature resistant. It can withstand temperatures of 80°C. Its size is also small, with a size of 6.2cm*4.5cm. So it is easy to carry. It has a battery capacity of 1500 mah, so that it can support 10 hours of working life. It has a voltage of 3.7V. And it can be recycled charge and discharge. These indicators fully meet the requirements of the system, so this Li-ion battery of model 404562 is used as the power supply in this hardware circuit. The Li-ion battery of model 404562 is shown in the Figure 4-12(a).



(a) (b)

Figure 4-12 (a) Li-ion battery (b)The charging and discharging module

The power module also needs a charging and discharging module to control the Li-ion battery. This hardware circuit adopts MH-CD42 as the charging and discharging module because it has the micro-USB interface. It is convenient for users to charge. When charging is connected, the output will switch to external power supply. The power is off for 0.3s, and the output voltage will be between 4.7V and 5.0V. In the discharge mode, trigger the KEY port once to open the output and trigger the KEY port twice continuously to close the output [56]. And the module allows charging and discharging at the same time. The charging and discharging module is shown in the Figure 4-12(b).

The diagram of the power module is shown in the Figure 4-13. The charging and discharging functions of the Li-ion battery are realized through the charging and discharging module. It can provide output 5V regulated power supply to supply power to all modules of the entire contraction hardware circuit.

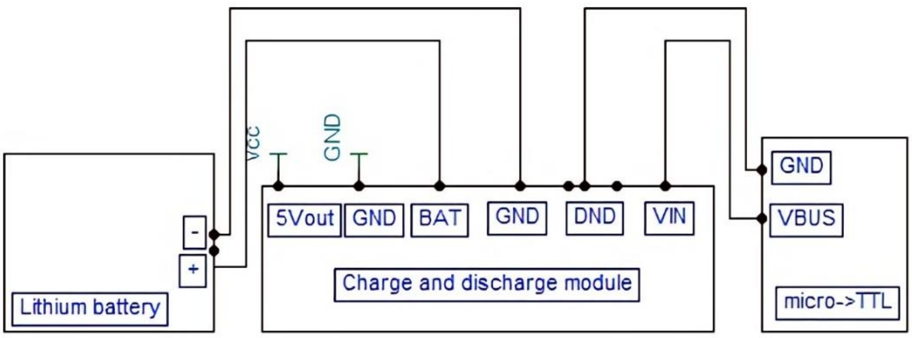


Figure 4-13 Diagram of power module

Through the actual test of the Li-ion battery, the actual standby time exceeds 10 hours, and the charging time can be fully charged in one hour, which meets the system design requirements.

4.7 Integration of the wearable sensing device

This project uses Tinker CAD software to model the wearable device, and the prototype of wearable sensing device is shown in Figure 4-14. This project is in cooperation with the Obstetrics and Gynecology Hospital of Fudan University, so three logos are designed on the front of the model. The first logo represents the device's contractions and its ease of use. The latter two logos represent the results of cooperation between Fudan University and the Obstetrics and Gynecology Hospital of Fudan University. The prototype is very simple and beautiful.

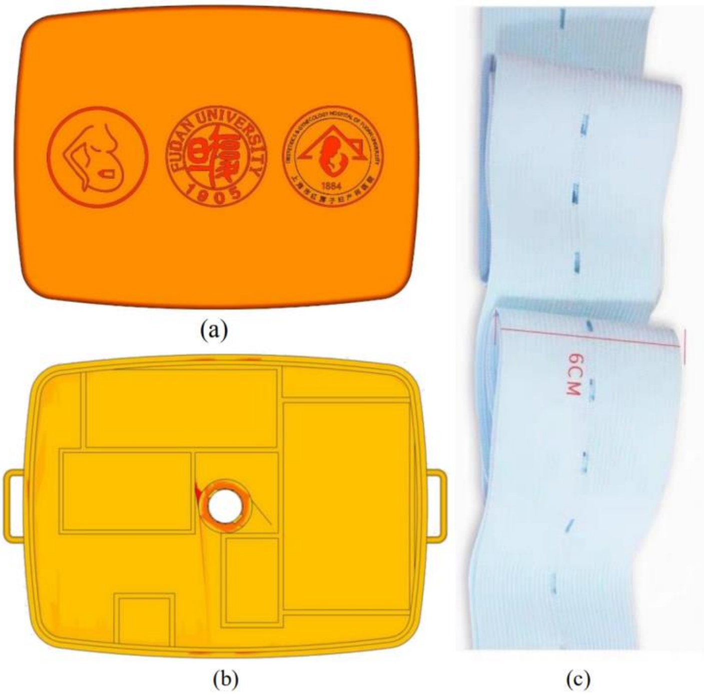


Figure 4-14 Prototype wearable sensing device of (a) Front diagram (b) Internal structure diagram (c) Fixed band

The internal structure diagram of this device is shown in the Figure 4-14. The 2cm*0.5cm mouth is left on both sides of the handle of the device, which is easy to be fixed at the bottom of the uterus with a band. The internal grooves are used to fix each module of the hardware circuit, such as sensor module, power module, processor module and so on. The circular mouth in the middle is used to place the pressure sensor, which is convenient for indirect contact with pregnant women. In addition, an open port is set aside on the side and a micro-USB charging port to facilitate users to charge the device.

After the 3D model is established, we use the 3D printer to print it. Pack each module into the groove inside the 3D model to fix it, and the power charging port and switch are exposed at the side opening. After the packaging is completed, the entire wearable sensing device is completed. Its size is 10cm*6cm*1.5cm, and the weight of the whole device is about 50g. Therefore, it is easy to carry. It is convenient to charge and can support 10 hours of battery life.

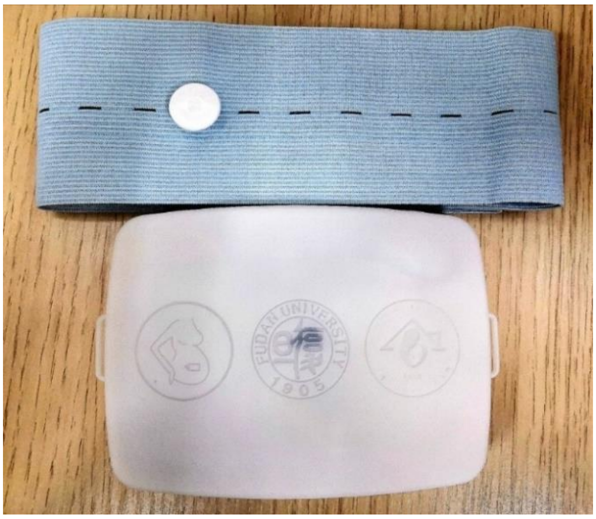


Figure 4-15 The photo of wearable sensing device

Figure 4-16 Placement of the wearable sensing device

The contraction movement at the bottom of the uterus of pregnant women is the most obvious. Therefore, this wearable device needs to be fixed at the bottom of the pregnant woman's uterus, that is, above of the abdomen. In fact, pregnant women's contractions are often accompanied by pain, this wearable device can adjust the tightness of the band by itself, so that the pregnant woman can maintain a comfortable state during use and achieve a relatively good user experience. What is more, healthcare tape is added to the position of the sensor on the back of the wearable device to better contact with pregnant women. Therefore, the device can be better applied to the abdomen of pregnant women. The photo of this wearable sensing device is shown in Figure 4-15, and placement of this wearable sensing device is shown in Figure 4-16.

4.8 Summary

This chapter mainly introduces the hardware design of wearable sensing device. The main contents include sensor module, amplification circuit module, processor module, Wi-Fi module and power module. Their principles and advantages are introduced respectively. Hardware design is one of the most important parts of intelligent contraction monitoring system. During the design, sufficient demand analysis and comparison were made for wearable devices, and finally the choice of each module was determined. At last, the chapter introduces the 3D model of the wearable device. It analyzes the size, weight, volume and placement. It considers how to consider the connection with the parturient, and how to apply it well.

Chapter 5 Algorithm Development for Contraction Detection

This chapter mainly introduces the design and evaluation of the algorithm module of the intelligent labor contraction monitoring system, which mainly includes the construction of the uterine contractions data set for pregnant women, the construction and implementation of the algorithm model and the comparison & evaluation of the algorithm. The data set of uterine contraction for pregnant women mainly introduces the distribution and types of the data set, and records the collected information of pregnant women as well as the characteristics of regular contraction, pseudo contraction and non-contraction signals. The construction of the algorithm model mainly introduces the process of the preprocessing of the contractions, including the extraction of features, the selection of appropriate hidden layer to construct the LSTM network model. It solves the problem of overfitting and improves the generalization ability of the model. Algorithm evaluation mainly introduces the effects of several common machine learning algorithms, support vector machine, logistic regression and random forest algorithm in the classification of contractions. This chapter also introduces the advantages of LSTM among them and finally determines the network model of LSTM as the algorithm module of intelligent labor contraction monitoring system.

5.1 Construction of the contraction dataset

This project is in cooperation with the Obstetrics and Gynecology Hospital affiliated to Fudan University. With the consent of the pregnant woman, we used the wearable sensing device to collect the signal of contraction of the pregnant woman. The data sampling rate was 5Hz, and the conditions of pregnant women were divided into three categories: those with regular contractions, pseudo contractions, and those with non-contractions. Contractions of pregnant women were collected for 7 minutes each time. 219 contractions were collected, with 2,100 pieces of data collected from each sample. The data set was divided into three categories: regular contractions, pseudo contractions, and non-contractions. 31 pregnant women from the Obstetrics and Gynecology Hospital of Fudan University participated in the experiment. An average of 7 sets of contractions were collected for each pregnant woman, corresponding to different contractions.

The information of pregnant women about contraction collection is shown in the following Table 5-

1. The subjects of our experiment are all primiparas, which means women who have not given birth before.

Table 5-1 The information of pregnant women about contraction collection

Pregnant women number	Age	Whether Primipara	Acquisition time (min)	Duration of the first contractions (s)	Collection numbers
1	25	Y	7	30	7
2	24	Y	7	28	7
3	23	Y	7	31	7
4	25	Y	7	27	6
5	26	Y	7	26	7
6	22	Y	7	20	7
7	31	Y	7	10	8
8	27	Y	7	28	7
9	26	Y	7	30	7
10	25	Y	7	12	7
11	27	Y	7	0	8
12	32	Y	7	28	9
13	29	Y	7	28	7
14	23	Y	7	11	6
15	26	Y	7	31	6
16	34	Y	7	27	8
17	24	Y	7	30	7
18	25	Y	7	18	6
19	23	Y	7	32	8
20	26	Y	7	21	6
21	27	Y	7	28	6
22	24	Y	7	27	6
23	26	Y	7	26	7
24	23	Y	7	24	7
25	24	Y	7	19	7
26	26	Y	7	31	7
27	25	Y	7	28	7
28	27	Y	7	27	6
29	24	Y	7	24	8
30	28	Y	7	26	7
31	29	Y	7	30	8

The contractions of pregnant women collected at hospital can be roughly classified into the following categories.

(1) Regular contractions: Regular contractions are the sign of labor. They occur every 2 to 3 minutes and last about 30 seconds, which is directly manifested by the change of the skin from soft to hard. It also accompanies with obvious aggravation of low back pain. A few people will have painless regular contractions [57]. Regular contraction waveforms based on test data are shown in Figure 5-1.

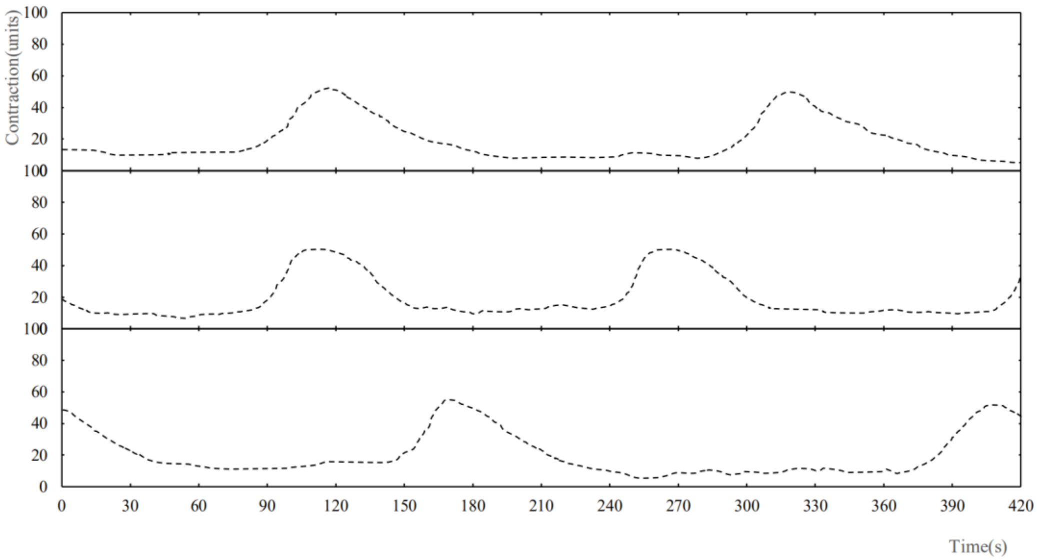


Figure 5-1 Regular contraction waveforms based on test data

(2) Pseudo contractions: Uterine muscles are more sensitive in the weeks before delivery. Pseudo contractions may occur at this moment. It may be short in duration, weak in strength, or limited to lower part of uterus. Pseudo contraction waveforms based on test data are shown in the Figure 5-2.

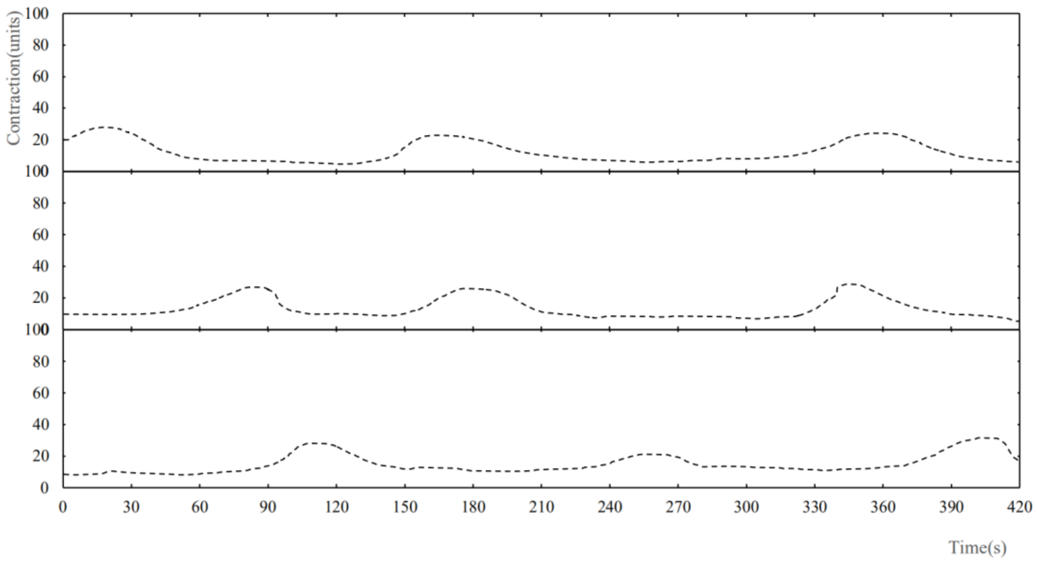


Figure 5-2 Pseudo contraction waveforms based on test data

(3) Non-contractions: There are two types of non-contractions. One is that there is pain but no contractions, and the other is that there is no pain and no contractions. It is used to distinguish between regular contractions and pseudo contractions. Non-contraction waveforms based on test data are shown in the Figure 5-3.

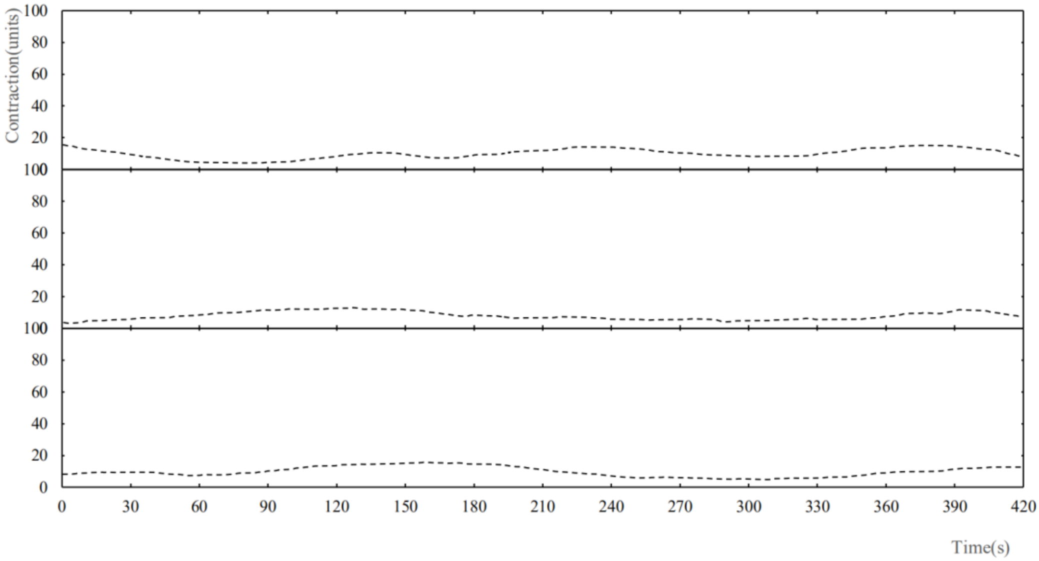


Figure 5-3 Non-contraction waveforms based on test data

5.2 LSTM algorithm

LSTM from the initial reference to now commonly used to process and predict the time series of long columns [58]. The structure of LSTM model is shown in Figure 5-4.

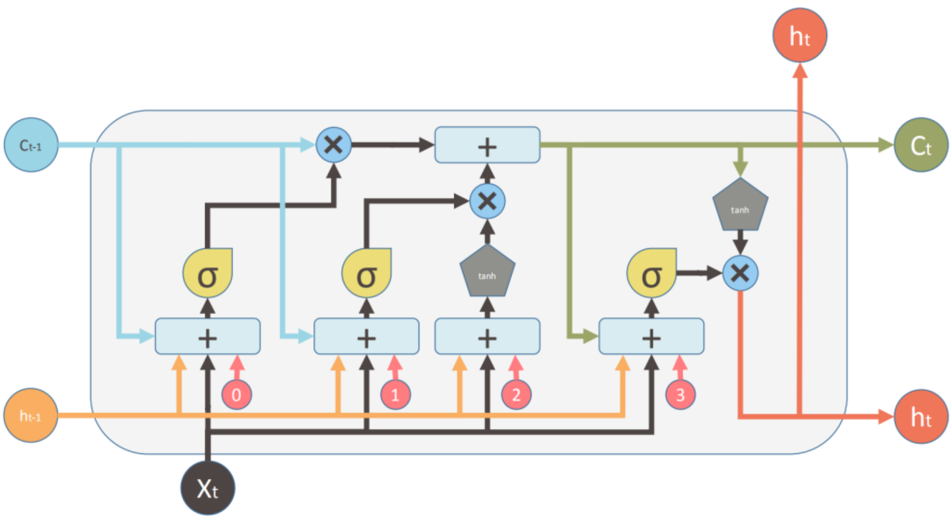


Figure 5-4 Structure of LSTM model

There are four layers of structure, including forgetting gate, input gate, output gate and memory unit. Input information is transmitted from front to back on the cell state, passing through the input gate, forgetting gate and output gate in turn [59-61]. And input information is controlled by "sigmoid". According to the output h_{t-1} at the previous time and the current input x_t, a value of f_t from 0 to 1 is generated to determine whether the information learned at the last time c_{t-1} is allowed to pass.

(1) In LSTM model, a certain probability is used to determine whether the hidden cell state of the previous layer is forgotten [62]. It indicates how much of the cell state of c_{t-1} is saved to c_t at the current moment.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5-1}$$

Where σ is a sigmoid function. There are three sigmoid functions in the LSTM, with output ranging from 0 to 1. They act as soft switches to decide which signals should go through the doors. f_t is 0 for "do not allow" and f_t is 1 for "do allow". b and W are the bias term and the weight coefficient matrix respectively.

(2) After the input information is passed, it needs to determine whether it is updated. It determines how much input x_t at the current moment is saved to the state unit c_t. The input layer first determines the update value through the sigmoid function. Secondly, the $tanh$ layer generates a new candidate value (alternative cell state to be updated) to update the value by combining the two parts. The updated cell state c_{t-1}, that is, c_{t-1} updates to c_t.

$tanh$ is the hyperbolic tangent activation function. Leave useful information behind and forget unnecessary information. The new cell state is the combination of the original cell state and updated information under the action of forgetting gate [63-65]:

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \tag{5-2}$$

$$\tilde{C}_t = tanh(W_c * [h_{t-1}, x_t] + b_c) \tag{5-3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5-4}$$

(3) It needs to determine output of model, controlling the ratio of C_t output to the LSTM output h_t of the control unit state. The initial output is obtained through the sigmoid layer. Then use the $tanh$ function to change C_t value from -1 to 1, and multiply the output from sigmoid pair by pair to get the output of the model.

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \tag{5-5}$$

$$h_t = o_t * tanh(C_t) \tag{5-6}$$

The algorithm evolution and iteration are guided by the minimum output and actual training sample differences. Through a non-scrolling structure, information about the current time step size can be stored and maintained, thereby influencing the LSTM output of future time steps.

5.3 Data preprocessing and algorithm model construction

The data read by a library of Python (pandas) will be merged and loss values will be processed. According to the distribution of data, tags 0, 1, 2 will be added respectively under the professional guidance of the doctor of the Obstetrics and Gynecology Hospital affiliated to Fudan University, corresponding to regular contractions, pseudo contractions and non-contractions. There are five time-domain eigenvalues, the maximum pressure value, the absolute value of the average pressure, the root mean square of the pressure, the standard deviation of the pressure, and the maximum value of the pressure change. These characteristics are input into the LSTM neural network, and the training model is used to judge the contractions categories. The meaning and calculation method of these five time-domain eigenvalues are as follows:

(1) Maximum pressure value: In the time dimension, the peak value of contractions signal fluctuations is recorded for the convenience of learning and recording the network model later.

$$x_{max} = \max(x_1, x_2, x_3, \dots, x_n) \tag{5-7}$$

(2) Absolute average pressure: It reflects the intensity of contractions signal. The higher the absolute average value, the greater the energy provided by contractions.

$$x_{mav} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{5-8}$$

(3) Root mean square pressure: it reflects the dispersion degree of contractions signal in the time dimension. The larger the mean square value is, the more discrete the contractions signal will be.

$$x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{5-9}$$

(4) Pressure standard deviation: it reflects the stability of the signal energy of contractions to a certain extent.

$$x_{sd} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{5-10}$$

(5) Maximum change of pressure: it reflects the maximum change of contractions signal at the adjacent time in the time domain.

$$x_{vm} = max(x_{i+1} - x_i) \quad i = 0,1,2, \ldots N \tag{5-11}$$

There are physical differences because pregnant women are different in height, fat and thin. Therefore, the experiment firstly normalized the sample data, and uniformly mapped the data to the interval from 0 to 1. The deviation standardization method, also known as the $min - max$ standardization method, is adopted in this thesis. The formula is as formula (5-12):

$$x^* = \frac{x - X_{min}}{X_{max} - X_{min}} \tag{5-12}$$

X_{max} is the maximum sample data and X_{min} is the minimum sample data. After normalization of contractions data samples, the LSTM model is established by taking 60% of the sample information as training set, 20% of the sample as verification set, and finally 20% of the sample as testing set. The adopted optimizer is RMSprop, whose principle is similar to momentum gradient descent algorithm. The RMSprop optimizer limits the oscillation in the vertical direction, so that our algorithm can take bigger steps in the horizontal direction for faster convergence [60]. The following is equation for the

RMSprop optimizer calculation (the momentum value is represented by beta and is usually set to 0.9):

$$v_{dw} = \beta \cdot v_{dw} + (1-\beta) \cdot dw^2 \tag{5-13}$$

$$v_{db} = \beta \cdot v_{dw} + (1-\beta) \cdot db^2 \tag{5-14}$$

$$W = W - \alpha \cdot \frac{dw}{\sqrt{v_{dw}} + \epsilon} \tag{5-15}$$

$$b = b - \alpha \cdot \frac{db}{\sqrt{v_{db}} + \epsilon} \tag{5-16}$$

The increase of number of hidden layers can effectively reduce the network error. However, it also increases the training time and complexity of the network, resulting in the overfitting [66]. Based on the contractions data sample, this thesis collects the status value of the contractions period in a cycle of 7 minutes. The appropriate number of hidden layers is selected by adjusting the number of hidden layers to observe the amount of loss and the accuracy.

As shown in Table 5-2, this table records the relationship among the loss of LSTM model, the accuracy of training set and testing set and the number of hidden layers. It can be seen from the table that, when there are too many hidden layers, overfitting is easy to occur, and the training set accuracy is high, while the testing set accuracy is low. Therefore, when the number of hidden layers is 3, the model will have better generalization ability.

Table 5-2 The relationship with different hidden layers

Hidden layer numbers	loss	Training set accuracy	Test set accuracy
3	0.4084	0.9333	0.9223
4	0.5123	0.9117	0.8774
5	0.4021	0.9337	0.8993
6	0.3912	0.9397	0.8824
7	0.3814	0.9413	0.8803

Based on the previous analysis, this thesis adopts the following LSTM variant network structure to realize the effective recognition of contractions, as shown in Figure 5-5.

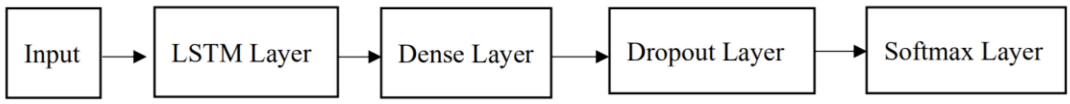


Figure 5-5 Algorithm model structure

(1) Input layer: The contractions recorded data and five time-domain features, which are processed into a one-dimensional vector of 2105*1.

(2) The principle of LSTM layer has been basically introduced in Section 4.2. This layer is mainly used to learn the correlation of time series and solve the problems of gradient disappearance brought by Recurrent neural network (RNN) and long-term dependence of long time series.

(3) The Dense layer is mainly used to connect all parameters of adjacent network nodes. Due to too many parameters of the full connection layer, it may cause overfitting problem. Usually, the Dropout layer which can prevent overfitting is connected behind the full connection layer, and finally it puts into Softmax regression layer for classification.

(4) Dropout layer: Through the Dropout process, it can be regarded as a network that only half of the hidden layer units are trained each time. Moreover, the hidden layer units of these training are not fixed and random, which is equivalent to the network structure of each training is different. But the weights are shared by all the network structures trained during iterative updates. After each training iteration update, a classification result will be obtained. With the progress of iterative updating, most networks will give correct classification results. A few mis-segmented networks will have less and less impact on the network as a whole. Therefore, the addition of Dropout layer not only speeds up the training time and prevents overfitting, but also effectively extracts more robust input features [67].

(5) Softmax layer: It is used for different object allocation probability, through $evidence_i = \sum_j W_{i,j}x_j + b_j$ weighted summation [68]. Then Softmax function is used to convert these evidences into probability y, that is, $y = softmax(evidence)$ [69], and it finally completes the classification of contractions signals.

The experiment results are shown in the Figure 4-6, Figure 4-7. Figure 4-6 indicates the relationship among training accuracy, validation accuracy and the number of epochs. Figure 5-7 indicates the relationship among training loss, validation loss and the number of epochs. It can be seen that the loss degree and training set of this model converge very well. As the number of iterations goes on, the convergence becomes more accurate. After model training, when the training batch was 22, the model was no longer overfitting. The recognition accuracy of the training set was 95.33%. The recognition accuracy was significantly improved, and the generalization ability of the model was further enhanced.

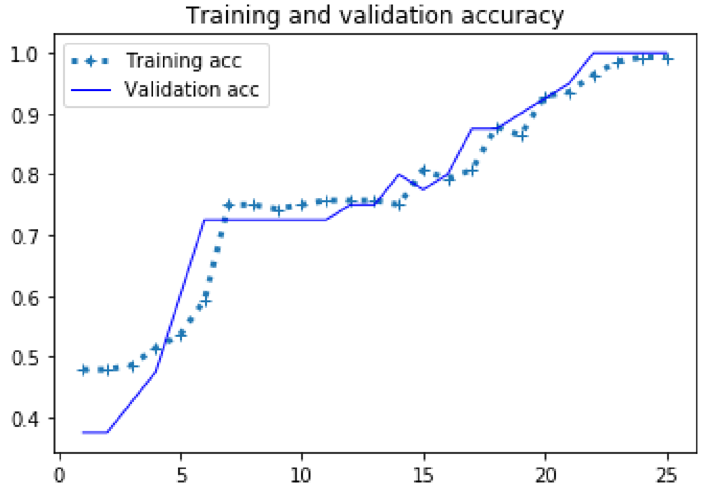


Figure 5-6 Relationship among training accuracy, validation accuracy and epochs

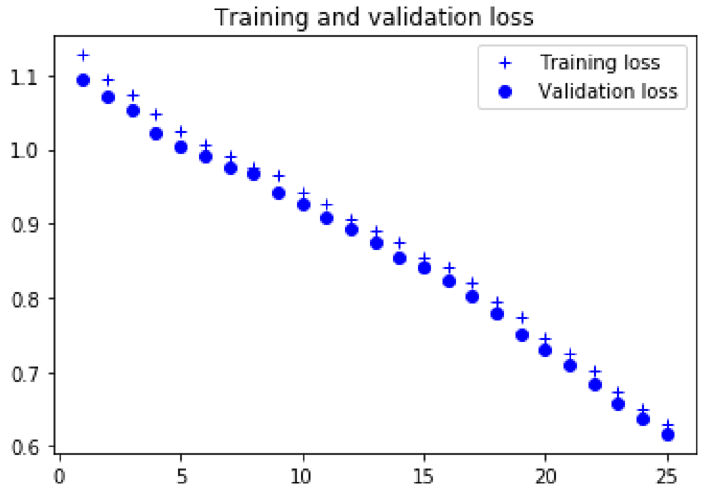


Figure 5-7 Relationship among training loss, validation loss and epochs

5.4 Algorithm model test

The accuracy of the test set is an important indicator to measure a network model. The accuracy of the test set is defined as formula (5-17):

$$test\ set\ accuracy = \frac{Number\ of\ correctly\ classified\ test\ samples}{Total\ number\ of\ test\ samples} \quad (5\text{-}17)$$

In order to evaluate the performance of different feature sets and perform better testing, this experiment uses a cross-validation method for testing. Each time 20% of the data sample is randomly used as the number of test samples, that is 44 contraction samples. The classification results are converted through the LSTM network, then the actual results are compared with them. Record each correct sample and wrong sample, and finally calculate the test set accuracy. Randomly draw the test sample set 8 times, and take the average of the accuracy of the 8 tests as the final test set accuracy. The table record of each test is reflected in Table 5-3.

Table 5-3 Test records of true and false samples

Test times	Number of True samples	Number of False samples	Test set accuracy
1	41	3	0.9318
2	42	2	0.9545
3	41	3	0.9318
4	40	4	0.9091
5	41	3	0.9318
6	42	2	0.9545
7	41	3	0.9318
8	42	2	0.9545

By calculating the average of the accuracy of the 8 test sets, the accuracy of the final test set is 93.75%. This model meets the requirements of the intelligent labor contraction monitoring system for classification accuracy.

5.5 Evaluation and comparison of the algorithm

The current mainstream machine learning classification algorithms include support vector machine (SVM), logistic regression (LR), and random forest (RF). This chapter compares the accuracy rate, recall rate and f1-score of these algorithms through experiments, and compares them with the LSTM model which finally adopted in this thesis.

(1) SVM is an algorithm based on the statistical theory that uses the optimal classification surface and kernel function to divide the limited sample space [70]. The basic idea of SVM learning is to solve the separation hyperplane that can correctly divide the training data set and has the maximum

geometric spacing, as shown in the Figure 5-8. For linearly separable data sets, there are an infinite number of such hyperplanes (that is multilayer perceptron), but the separated hyperplanes with the greatest geometric spacing are unique. SVM can get much better results than other algorithms on a small sample training set. It is one of the most commonly used and performs best classifier, lies in its good generalization ability [71]. The optimization goal is structured minimum risk, rather than the empirical risk minimum. Therefore, through the concept of margin, a structured description of data distribution is produced. It can reduce the size of the data and the requirements of data distribution.

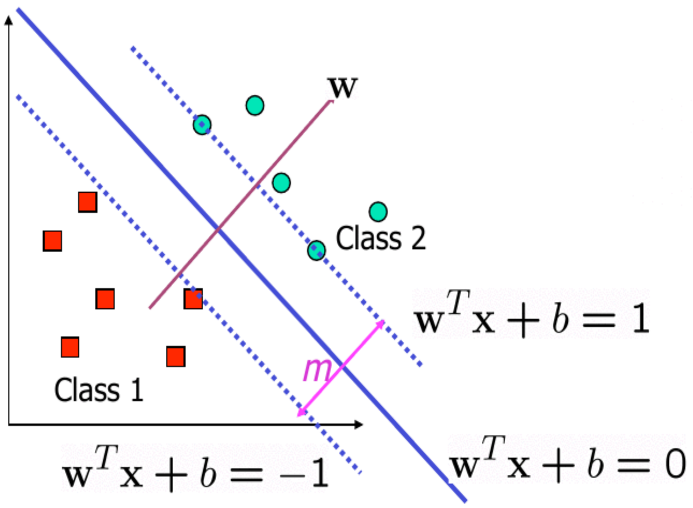


Figure 5-8 Illustration of SVM

(2) Logistic Regression is a generalized linear model. It assumes that the dependent variable y obeys Bernoulli distribution, which is theoretically supported by linear regression. It considers nonlinear factors through sigmoid function, so it can handle simple classification problems [72,73].

(3) Random forest is an algorithm that integrates multiple trees through the idea of ensemble learning. Its basic unit is decision tree, while its essence belongs to a large branch of machine learning. It is ensemble learning method. Each decision tree is a classifier and for an input sample, N trees will have N classification results. The random forest integrates all the classification voting results and assigns the category with the most votes as the final output [74]. The models are independent of each other. Using the same training data, multiple independent classification models are built at the same time, and then the final classification decision is made according to the principle of the minority obeying the majority by voting [75].

The results of three common machine learning algorithms on the contractions data set are compared as follows in Table 5-4.

Table 5-4 Comparison of machine learning algorithms

algorithm	accuracy
LSTM	0.9375
SVM	0.8864
Logistic Regression	0.7500
Random Forest	0.7727

It can be seen from the table that among the three machine learning algorithms, SVM algorithm has better classification effect. However, compared with other algorithms, LSTM network performs better in the classification of contractions data due to the time series of contractions data. LSTM can exclude irrelevant information by forgetting gate, supplement and increase information by input gate, and record states by cell state. LSTM is mainly used to learn the correlation of time series and solve the problems of gradient disappearance brought by recurrent neural network (RNN) and long-term dependence of long time series. It has a better judgment on the correlation between time series. Therefore, this system finally uses LSTM network and deploys on the server side to classify and identify the contraction data.

5.6 Summary

This chapter introduces the construction of contraction data set, including the introduction of pregnant women's collection samples, the introduction of data categories and characteristics, the construction of LSTM recurrent neural network model, the preprocessing of contractions data, feature extraction, and the evaluation of algorithm model. Because the better judgment of LSTM correlation in time series, irrelevant information can be excluded by forgetting gate, input gate, cell state and output gate, and the time correlation sequence that needs to be learned can be retained. Compared with other machine learning algorithms, LSTM has great advantages. In this thesis, LSTM network model is used as the algorithm module of this system.

Chapter 6 Mobile Application Development

The intelligent labor contraction monitoring system needs a front end to display the results of contractions, which is convenient for pregnant women to use and know their contractions more intuitively. Therefore, this chapter has designed a WeChat applet. The WeChat applet can be cross-platform and can be used on both Android and IOS platforms. Through the WeChat applet design, the contraction monitoring system becomes more complete. This chapter mainly introduces the framework of WeChat applet, and then introduces the function design and the evaluation of it.

6.1 WeChat applet introduction

WeChat applet is an application that can be used without downloading and installing [76]. It is cross-platform and can be used on both Android and IOS platforms. The intelligent labor contraction monitoring system needs a front end to display the results of contractions monitoring, allowing users to see the results of contractions more intuitively and easier to use.

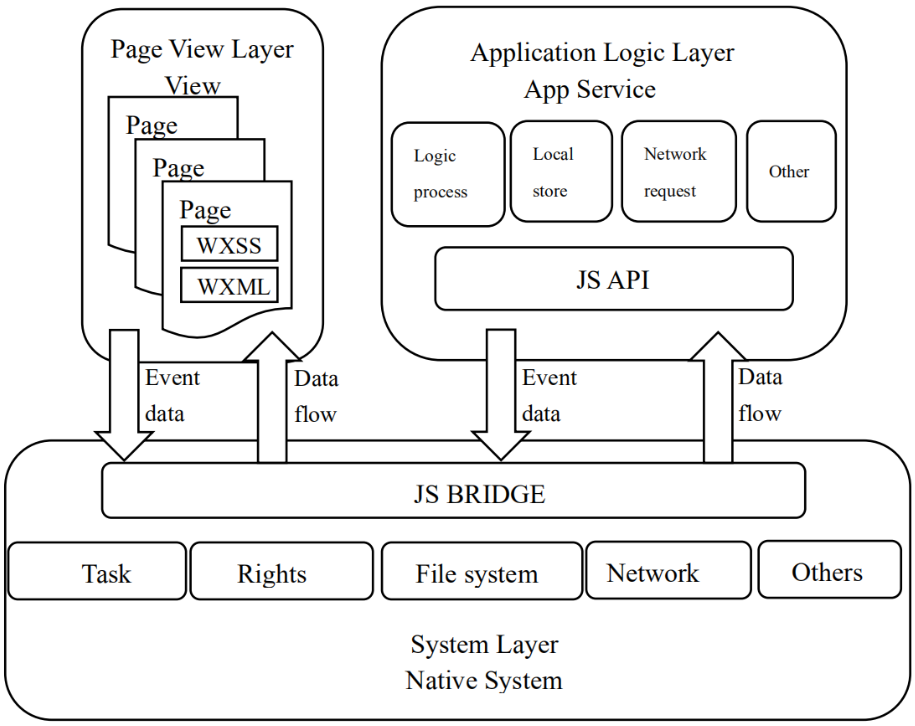


Figure 6-1 MINA framework [77]

WeChat applets mainly use MINA framework [77]. As shown in the Figure 6-1, MINA framework is a network communication application framework. At its core, it is a responsive data binding system with a running speed close to that of native APP, which fully displays the IOS and Android terminals. The framework contains four types of documents: Javascript (JS) file, WeiXin Markup Language (WXML) file, WeiXin Style Sheets (WXSS) file and JSON file. JS file belongs to the logical layer framework, which is used to handle transaction logic, data management and communication of network. WXML file is a tag language of design, which is similar to HyperText Markup Language (HTML) on the web. WXSS file belongs to the component style that describes WXML, similar to CSS in the web. JSON file belongs to a configuration file. It is used for configuration of individual pages and entire projects. It can be seen from the structure of MINA framework that data and event interactions between the page view layer and the application logic layer need to be realized through the system layer. The biggest advantage is that when developers work with data, they only need to consider about the logical layer of data processing, the view layer automatically makes corresponding updates.

6.2 Server configuration

The server implementation block diagram is shown in the Figure 6-2. The WeChat applet sends an HTTP request to the Flask to process the request, It need to pass through the web server layer, WSGI layer and web framework layer respectively.

(1) Web server is a special kind of server whose function is mainly to receive HTTP requests and return responses. Common web servers are Nginx, Apache, IIS and so on. In Figure 6-2, the web server is the first to receive WeChat applet request and return the response result to the applet.

(2) WSGI is not a server. It is also not an Application Programming Interface (API) for interacting with programs. It is a Web Server Gateway Interface. WSGI is just an interface for the Python language, and it defines the interface specification between a web server and a web application. Deployment using Nginx and WSGI can achieve load balancing and concurrent operations.

(3) The system uses a lightweight web application framework: Flask [78-79]. It is written in Python. The Flask is chosen because the machine learning algorithm model is mainly developed in Python. The whole system is in a unified development language, which is easy to develop and maintain in the later period. Flask's basic schema is to assign a view function to a URL within the application. Then, every time the user accesses the URL, the system executes the view function assigned to the URL,

gets the return value of the function, and displays it to the client [80].

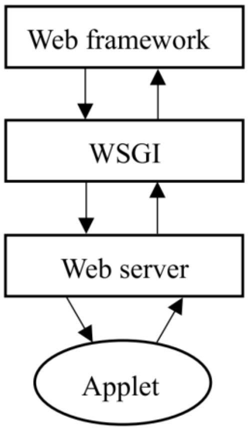


Figure 6-2 The server implementation block diagram

By the way, this system uses MySQL database to store the information of pregnant women and the data of uterine contraction. The algorithm model is deployed on the server to realize the real-time processing of intelligent labor contraction monitoring system.

6.3 WeChat applet function design

6.3.1 WeChat applet structure

This program adopts the design idea of three-layer architecture. It consists of the presentation layer (front-end interface), the business logic layer, and the data access layer (persistent layer) [81].

(1) The presentation layer is the front-end display interface. It adopts WXML and WXSS as its technical route. WXML is a tag language by design, similar to HTML in the web. WXSS is a style that describes WXML components. It is similar to CSS in the web.

(2) Logic layer is a layer whose technical path is implemented by the native interface of WeChat applets. The applet's users are mainly pregnant women. In a WeChat applet, pregnant women can fill in personal information to log in and monitor their contractions. The user can get the results of the contractions and graph, and record the contractions.

(3) Data access layer is layer that realizes data storage for each contraction and data acquisition during monitoring.

The WeChat applet mainly realizes the user's login and the contractions result display. The data of contractions are maintained and updated by the database to realize the real-time processing of contraction detection.

6.3.2 WeChat applet function implementation

(1) As shown in the Figure 6-3, this module completes the login function of pregnant women. When the user clicks the login module, he can authorize to obtain WeChat login information, and complete user login through WeChat.

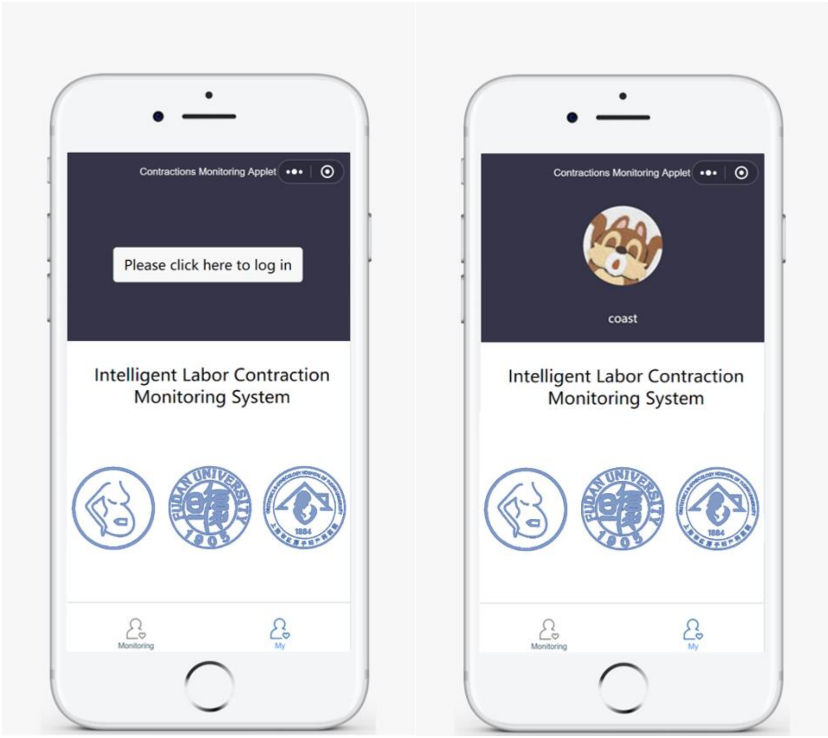
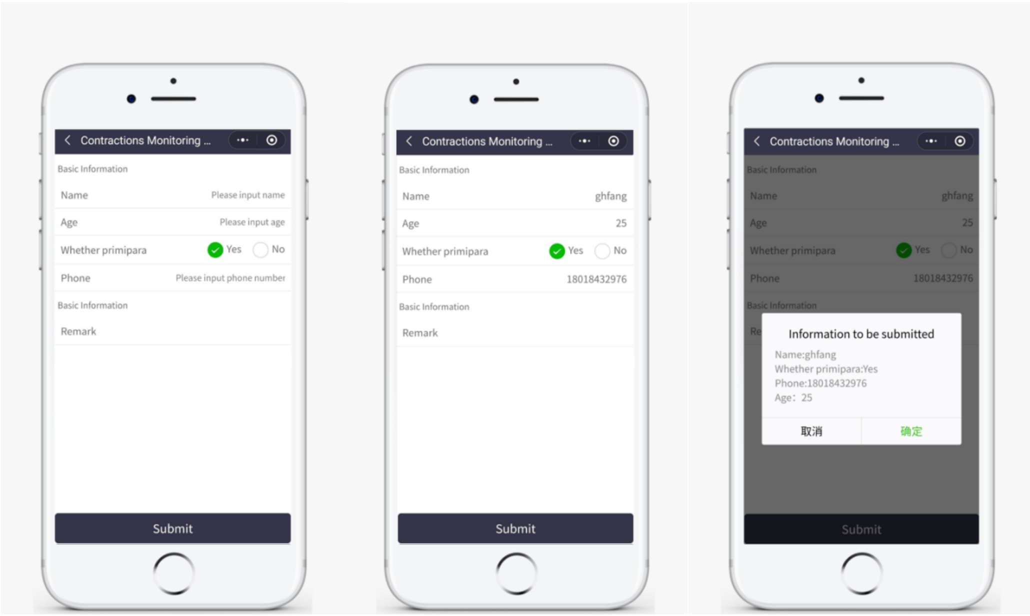


Figure 6-3 Login function of WeChat applet

(2) This module completes the function of pregnant women filling in personal information. It mainly includes the information of name, age, primipara, phone number and so on. It can also fill in the remark information. The function is realized as shown in the Figure 6-4(a). For example, personal information is shown in the Figure 6-4(b). After filling in the personal information, the information can be submitted, which can be saved as shown in the Figure 6-4(c). This functional module can record the information of pregnant women well, which is convenient for pregnant women to view and better compare the information at various moments next time.



(a) (b) (c)

Figure 6-4 Person information function of WeChat applet

(3) After the above functions are realized, contractions shall be monitored. The monitoring and waiting interface is shown in the Figure 6-5. It indicates the contractions monitoring time and supplemented by the GIF display effect, respectively corresponding to the three categories of contractions.

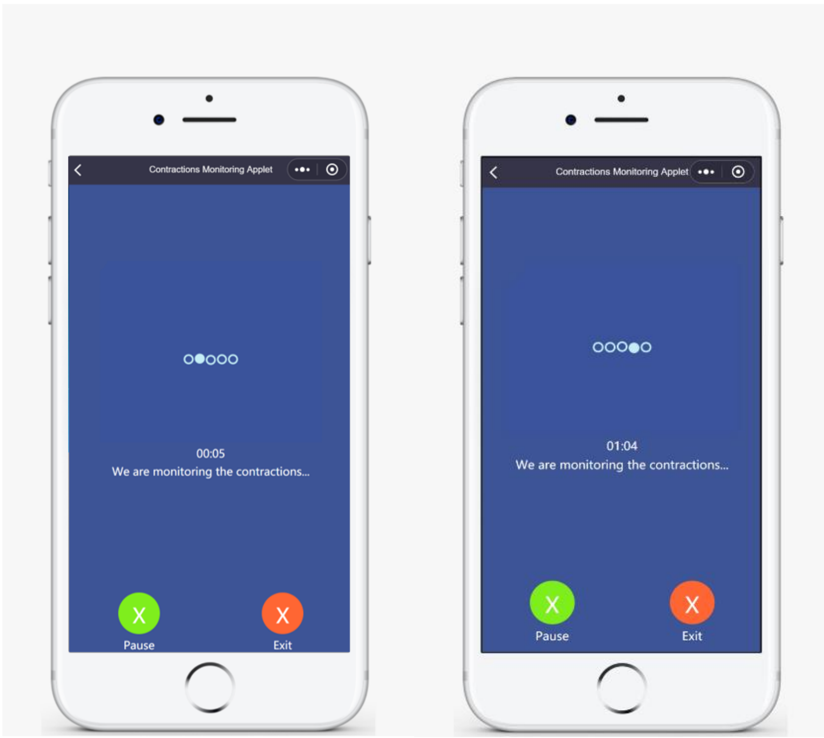
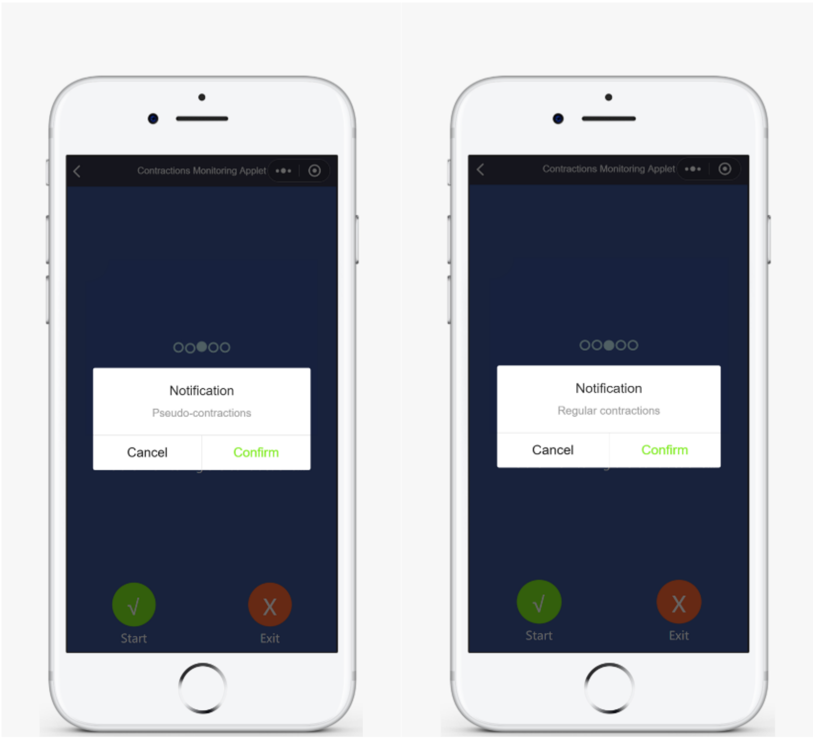


Figure 6-5 Function of waiting for detection

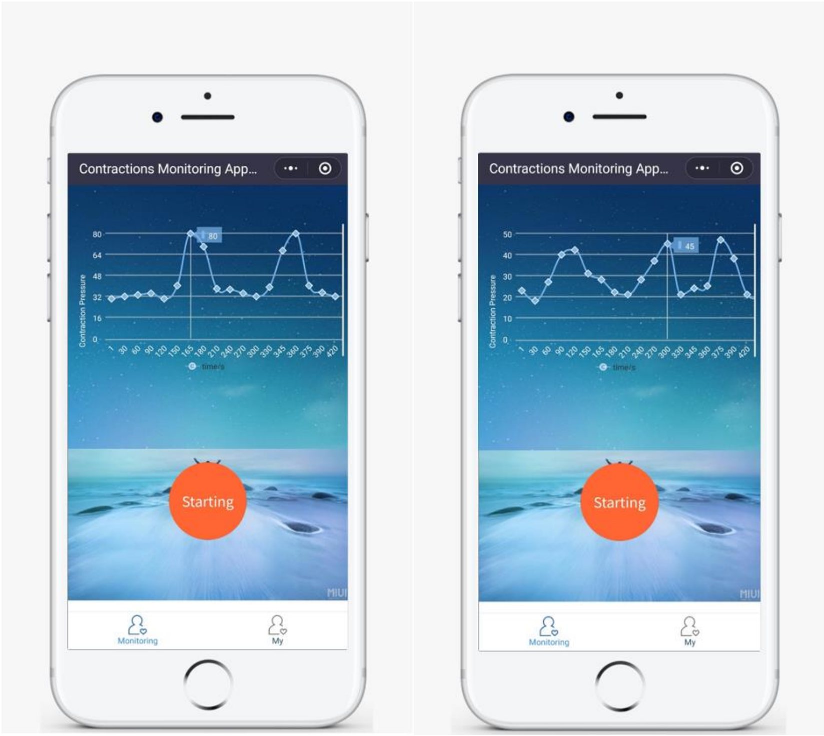
The three contractions are the regular contractions, pseudo contractions, and non-contractions mentioned above. The result of pseudo contraction is shown in the Figure 6-6(a). And the result of regular contraction is shown in the Figure 6-6(b).



(a) (b)

Figure 6-6 Function of displaying contraction result

(4) After obtaining the result of the monitored contractions, it will jump to the home page and draw the contractions curve. As shown in the Figure 6-7(a) and Figure 6-7(b), the horizontal axis of the contractions curve is the time dimension, and the vertical axis is the contractions pressure. The contractions curve can be intuitively seen, and the contractions pressure value corresponding to each point can be obtained by clicking. From the result, we can see that Figure 6-7(a) is regular contractions. Regular contractions are the sign of labor. They occur every 2 to 3 minutes and last about 30 seconds, which is directly manifested by the change of the skin from soft to hard. It also accompanies with obvious aggravation of low back pain. This contraction curve conforms to regular contractions. Figure 6-7(b) is pseudo contractions. Irregular uterine contractions may occur at this moment. It may be short in duration, weak in strength, or limited to the lower part of the uterus. This contraction curve conforms to pseudo contractions. Through the function of these operations, pregnant women can use the WeChat applet to know about the state of contractions intuitively.



(a) (b)

Figure 6-7 Function of contraction curves drawing

6.4 WeChat applet evaluation

This designed WeChat applet has a simple and beautiful interface. It realizes the basic user login function and the user information filling function, including name, age, whether it is a primipara, remarks and other information. In addition, it also fulfills the most important function of this part: detecting contractions. Through the waiting of the middle interface animation, the user is allowed to wait for the detection. After the monitoring time is over, the result of this monitoring will be displayed and the curve of the contraction state will be drawn, so that pregnant women can easily check their contractions.

Compared with the traditional contraction counting software, this WeChat applet is more efficient. Traditional contraction counting software is based on the pregnant woman's own judgment. It is too subjective and the data is easy to be inaccurate. However, this applet is based on objective data. It can understand the contractions more intuitively, and displays the results more reliable than pregnant women's own counting. Pregnant women can check their own results anytime, anywhere.

As shown in Figure 6-8, this pregnant woman used our wearable sensing device at home. She used our WeChat applet to monitor her contractions in real time. Through the contraction results, she can judge whether she is suitable for labor. Thus this device assisted in making decisions about the best time to go to hospital.

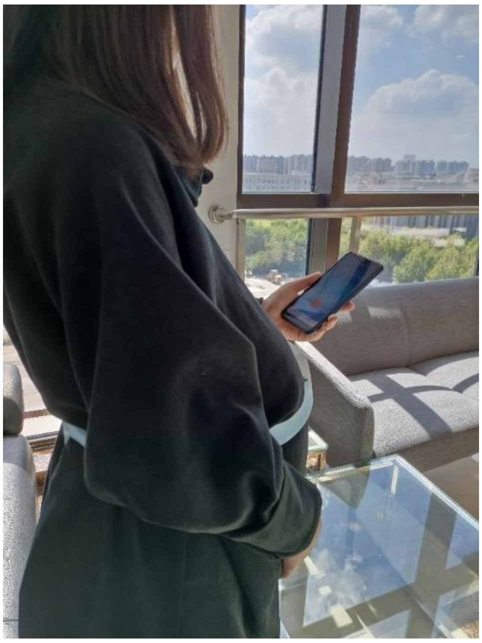


Figure 6-8 Use of this wearable sensing device

The WeChat applet is designed to meet the daily habits of pregnant women. It is easy to use, and rich in functions. The results of all functions have been shown in the previous section. Therefore, the smart contraction monitoring system finally adopted the design of this WeChat applet as mobile application development.

6.5 Summary

This chapter introduces the WeChat applet design of intelligent labor contraction monitoring system. Firstly, the MINA framework of WeChat applet is introduced. Then, the main structure of the server side is introduced, including web server, WSGI layer and web framework layer about flask. What is more, the realization of applet function is introduced, including the function of logging in pregnant woman, filling in personal information, submitting function, contractions monitoring function, detecting the state of contractions, drawing the contractions curve, reading the contractions pressure and so on. At last, this chapter evaluates the WeChat applet and compares with other traditional contraction counting software.

Chapter 7 Conclusion and Future Work

7.1 Conclusion

In this thesis, the system is designed and implemented for pregnant women who don't know when they can choose the best labor time in the absence of healthcare resources. The system collects contraction data through the wearable sensing device. And the designed hardware mainly includes five parts: pressure sensor module, amplifier circuit module, processor module, Wi-Fi module and power supply module. The collected contractions data are identified and classified by LSTM algorithm, and are divided into three categories: regular contractions, pseudo contractions and non-contractions. By adjusting parameters and network models, the algorithm has reached an accuracy of 93.75%. It is compared with algorithms such as SVM and Logistic Regression. Besides, the network is deployed to the server to realize real-time processing. And the results are fed back to the WeChat applet. The login function for applet users and the display function of the result of contractions are designed so that pregnant women can view it in real time. In the end, a 3D printing model is designed, all modules are packaged, and a home portable contraction wearable sensing device has been designed. It is made to monitor whether the contractions of pregnant women are suitable for labor, and feedback the results and contraction curve to the pregnant women in real time.

The advantage of this system is that the results of uterine contraction monitoring can be directly obtained through WeChat applet on the mobile phone. And it can be used as an auxiliary judgment tool to determine whether it is suitable for labor at this time. In the future, through large-scale data model training and clinical certification practices, it can greatly relieve the pressure of healthcare resources and reduce the time cost and risk cost of pregnant women.

7.2 Future work

Due to the limitation of time and experimental materials, there are still some shortcomings in the design of the intelligent labor contraction monitoring system in this thesis, which needs further improvement and perfection. According to the design and experience in the contraction monitoring system, the following opinions are proposed for future research:

(1) Since the contraction data was collected during the coronavirus disease period, the categories of

data sets are not rich enough. In the future, we can go to the hospital to continue collecting, and use the Generative Adversarial Networks(GAN) network to enhance the data set based on the existing data set, so that the model can get better generalization ability.

(2) The electronic system can be further integrated, and the wireless module can be implemented with a Bluetooth module instead to realize data storage on the mobile phone. And the WeChat applet we designed is currently a demo and used for experiment. It can be further optimized in the future to provide richer functions.

(3) It is possible to continue to strengthen cooperation with the Obstetrics and Gynecology Hospital of Fudan University to collect more pregnant women's early data to predict the risk of premature delivery and dystocia of pregnant women, so that the system will be more perfect and enriched.

(4) During pregnancy, there is still fetal heart rate monitoring in hospital. Therefore, in the future, a fetal heart rate monitoring module can be designed, combined with the contraction monitoring module, to achieve a more robust labor monitoring system to monitor all the conditions of the pregnant woman and realize really at-home inspection. Also, doctors can realize remote monitoring and treatment through this system.

With the rise of big data and artificial intelligence, smart healthcare becomes one of the top priority for future development. The healthcare industry can get more support and help, thereby promoting social progress. Home inspection will be realized in the future, and we can accurately predict diseases through artificial intelligence algorithms, improve living standards and enhance society's healthcare capabilities.

Acknowledgement

In a flash, the nearly two-and-a-half years of postgraduate study at University of Turku and Fudan University is coming to an end. Looking back on this learning experience, too much emotion is beyond words. Although a lot of hard work has been made, I deeply feel that the effort is worth. Through this period of study, I have gained a lot. I have learned a lot of valuable knowledge and experience from the surrounding teachers and classmates at University of Turku and Fudan University.

First of all, I would like to sincerely thank my instructors, Dr Zhuo Zou and Director Yan Ding. The two teachers have created a good learning environment and a strong learning atmosphere for me in the past one year. The knowledgeable, approachable, rigorous academic attitude and practical work style of teachers have left a deep impression on me and build a role model for my future career and life. I would like to thank the Dr. Zhuo Zou for his teaching and help, and thank Dr. Yan Ding for the support of Obstetrics & Gynaecology of Fudan University. The two teachers will continue to inspire me to continue to work hard, and be a useful person for my country in the future. I would like to thank Dr. Tomi of University of Turku for helping me while studying in Finland, and for giving sufficient guidance to the project. At the same time, I would also like to sincerely appreciate all the teachers who taught, cared about and helped me in the two and a half years of study at University of Turku and Fudan University.

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In view of my limited level, the research on the intelligent contraction monitoring system is still in the forming stage, and there are still many shortcomings. In the future, I will continue to think and summarize the theoretical knowledge in practical work.

How time flies, the two-and-a-half-year postgraduate career is almost over in a blink of an eye. The study experience in Fudan University and Turku University will always be a precious memory in my life. I wish Fudan University and University of Turku will become better and better.

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