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ORIGINAL

Monitoring and Optimizing Athlete Training Loads in Real Time with Wearable Sensor Data

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ABSTRACT

For competitive sports, the key to achieving excellent athletic performance lies in how to train scientifically and arrange the training load, as well as how to use scientific means to monitor the training load in a comprehensive manner, and the booming development of wearable sensors is expected to promote the development of this field. Therefore, this paper proposes a multi-sensor-based training load monitoring system for athletes, and develops a flexible wearable intelligent non-invasive device with high safety, flexibility and portability for monitoring the movement and changes in corresponding physiological parameters of the human body. The device is based on a Bluetooth 5.0-enabled processing chip manufactured by a company, as well as temperature and humidity sensors, heart rate and blood oxygen sensors, and all components are integrated on a flexible substrate. The device can effectively measure the subject's heart rate, blood oxygen data and current respiratory status by simply sticking it on the skin area under the nose, which is harmless to the human body and greatly improves the comfort of the athletes. At the same time, this paper compares the test results with the commercially available finger-clip heart rate and blood oxygenation devices, and verifies the stability and reliability of the whole system. This study provides a new program for monitoring the changes of physiological parameters caused by cerebral infarction and cardiac infarction in the course of athletes' training as more portable as possible, which is of positive significance for the development of flexible athletes' training load monitoring.

KEYWORDS: Monitoring Athlete Training Loads, Optimizing Athlete Training Loads, Wearable Sensor Data, Real Time Monitoring

1. INTRODUCTION

With the development of high-level competitive sports, in order to allow athletes to serve for a long time for competitive sports, as far as possible to prolong the athletes' sports career, each country has invested in scientific training teams for competitive sports teams (Bartlett & Drust, 2021; Fozilov, 2022; Luczak, Burch, Lewis, Chander, & Ball, 2020), through the use of different scientific means and physiological and biochemical indicators (Hackfort & Schwenkmezger, 2021) to monitor the changes in the athletes' body indexes, so that the amount of training loads (Gabbett, 2020; Kalkhoven, Watsford, Coutts, Edwards, & Impellizzeri, 2021; Oliveira et al., 2019), through the reasonable arrangement of sports training loads to minimize the damage to the athletes' bodies. The training load is quantified, and the damage to the athlete's body is minimized through reasonable arrangement of the training load. In the monitoring of sprinting training (Beato, Drust, & Iacono, 2021; Hogan, Binnie, Doyle, Lester, & Peeling, 2019; Pollock et al., 2019), the physiological and biochemical indicators generally collected for the monitoring of training load are heart rate (HR), blood lactate (CK), blood urea (BU), hemoglobin (Hb) and so on. A subjective training session load (RPE) is usually monitored ten minutes after the end of the training session. The testing of physiological and biochemical indicators can indirectly understand the stimulation of the training load on the athlete's body functions, and then assess the reasonableness of the exercise load as well as the athlete's physical recovery according to whether the data of different biochemical indicators are abnormal. At the same time, with the continuous development of science and technology, the wireless heart rate sensor and GPS wearable technology (Adesida, Papi, & McGregor, 2019; Aroganam, Manivannan, & Harrison, 2019; Benson, Räisänen, Volkova, Pasanen, & Emery, 2020; Luczak et al., 2020) used in the sprinting program is becoming more and more mature, every athlete will wear a heart rate strap and heart rate watch, equipped with GPS and the use of wireless remote sensing technology on the training ground, not only in the training time to monitor the athlete's heart rate indicators, but also the athlete's sprinting data recorded in real time. Intelligent equipment and digital technology for competitive sports, breaking through the limitations in the use of the environment, distance and speed, through the transmission of data after the integration of intuitive digital feedback (Brunauer, Kremser, & Stöggl, 2020; Willwacher, 2018) to the coaches and researchers.

In the process of quantitative monitoring of training load in competitive sports, it is not only a single indicator as the standard of load change, but also needs to be monitored from various training perspectives during the whole training process(Ghasemzadeh, Loseu, & Jafari, 2009; Patel, Shah, & Shah, 2020). The continuous progress of training load monitoring means cannot be separated from the development of science and technology, and the use of intelligent equipment can facilitate coaches and athletes to grasp the real-time training situation, provide effective feedback on training, and also play a greater role in the development of scientific and systematic training programs. The progress of science and technology to promote the development of competitive sports (Liu & Bhanu, 2019; Tuggle, 1997), making the training load monitoring more comprehensive, some of the practical application of training problems will also be solved, the future development of intelligent training load monitoring means is an inevitable trend.

In the scientific training process of competitive sports, the implementation of scientific monitoring of the training load is an important means to achieve the optimization of sprint training effect. When coaches arrange the training load, according to the training status of the athletes, it should be as scientific, detailed and dynamic as possible. Because too small or too large a load will not only lead to the loss of training effect, but also increase the chance of athletes' sports injury, so how to reasonably arrange the training load of sprinters is particularly important. Through the analysis and research of related studies, we found that there are some problems in the arrangement of training load: most of the coaches are retired athletes (Buckley, Hall, Lassemillante, Ackerman, & Belski, 2019; De Beaumont et al., 2009; McCrory, Meeuwisse, Kutcher, Jordan, & Gardner, 2013), although their own competitive level is high, but they don't have a clear enough understanding of the characteristics of the training load; the relationship between the training status of the athletes and the arrangement of the training load is not too deep; and we don't know whether the training load can reach the real intensity of the competition. The training load is not known whether the training load can reach the real race intensity or not. In training, in order to deeply understand the development law of sprint training load, through the analysis of the annual training load of a male athlete's Olympic cycle in the year of reinforcement, the training load structure, training load volume, training load intensity, and changes in physiological and biochemical indexes combined with the relevant test results to make a detailed statistical analysis, it is necessary to summarize the characteristics of the annual training load of a male sprinter's reinforcement year in the cycle of preparation for the Tokyo Olympic Games. It is necessary to summarize the annual training load characteristics of male sprinters in the big cycle of preparation for the Tokyo Olympic Games.

The main contributions are as follows:

(1) In this paper, a multi-sensor-based sprinting motion monitoring system is proposed, and a flexible wearable intelligent non-invasive motion

monitoring device with high safety, flexibility and portability is developed.

(2) This paper verifies the stability and reliability of the whole set of system monitoring, provides a new program for monitoring the changes of physiological parameters caused by cerebral infarction and cardiac infarction during athletes' training as more portable as possible, and has a positive significance for the development of the monitoring of training loads in flexible athletes.

2. Related Works

2.1. Training load

The concept of training load has not yet developed a unified understanding because the term training load has been recognized at different times with varying degrees of variability. Some scholars believe that the sports load is the training stimulus applied to the athlete's organism with physical exercises as the basic means. And proposed that "load refers to the stimulus or pressure on the carrier. Sports training activities added to the human body physiological and psychological load (Mellalieu, Jones, Wagstaff, Kemp, & Cross, 2021), collectively referred to as the training load. The understanding of the concept of training load has changed over time, initially, the sports load is the physical exercise as the basic means of training the athlete's organism to impose training training stimuli. Later, it was also called training load, and it was proposed that training load is "the training stimulus applied to the athlete's organism in the process of sports training, with physical or psychological exercises as the basic means". Some other scholars believe that the training load in sports, should be understood as the physical exercise in sports and the role of the athlete's body, so that the athlete's body function system to produce a positive response to the impact of the process, the load is understood as a "process". In sports training, if a stimulus can have an effect on the effectiveness of training, then in sports training, this stimulus can be called a training load. At the same time, there are those who consider the training load to be a functional addition, or change, caused by the exercises performed by the organism compared to the quiet state. In this paper, we consider that the amount of work endured is the stimulus to which the body is subjected, and with the addition of a time limit, it can be considered that the stimulus to which the body is subjected when exercising for a certain period of time is the training load.

2.2. Characteristics of energy supply

When the human body carries out sports, the required energy supply is mainly composed of three major energy supply systems (Ozaki, Abe, Loenneke, & Katamoto, 2020), namely, the anaerobic non-lactic acid energy supply system that does not need to utilize oxygen and does not produce lactic acid when doing short-time sports, the phosphoglycolysis system that produces lactic acid under the condition of anaerobic energy supply, and the oxidative energy system that makes full use of oxygen for energy supply. Sprinting as an endurance sport with aerobic energy supply as the main physical dominant class endurance sports, its running speed is the key to win the game, then the athlete must first experience high intensity, long endurance training, so that the body functions to obtain the maximum adaptation to the game demand, to obtain the best athletic state. Neglecting aerobic training and overemphasizing high-intensity anaerobic training with the goal of improving athletes' "lactic acid tolerance" is a common problem in the training of most endurance events. Aerobic and anaerobic energy supply is a dynamic relationship, in the whole process of different stages, the proportion of aerobic and anaerobic energy supply with the change of muscle strength changes, different sports should be combined with the actual intensity of the game to implement different training methods, sprinting as aerobic energy supply for the dominant endurance program, should be based on the different phases of the game the proportion of the different energy supply, targeted aerobic and anaerobic training, is the only way to improve the athletes' ability to improve lactic acid tolerance.

2.3. Background of the monitoring system

2.3.1. Oxygen Saturation Measurement

First of all, blood oxygen saturation is determined by oxygenated hemoglobin, first oxygen enters the lungs when the body breathes, then it enters the bloodstream, which carries oxygen to the organs of the body. The main way oxygen travels in the blood is through hemoglobin. If you compare hemoglobin molecules to a car, oxygen molecules enter the hemoglobin and travel through the body until they reach their destination. Hemoglobin without oxygen is called deoxyhemoglobin, and hemoglobin with oxygen, is called oxyhemoglobin. Oxygen saturation is the percentage of available hemoglobin that carries oxygen. If there are 16 hemoglobin units in the body and none of the 16 contain oxygen, the oxygen saturation is 0%, and so on. 8 out of 16 hemoglobin units contain oxygen, the oxygen saturation is 50%, and when all the hemoglobin units contain oxygen, the oxygen saturation is 100%. The specific measurement of the amount of oxygenated hemoglobin uses the properties of oxygenated haemoglobin, where oxyhemoglobin and deoxyhemoglobin absorb different wavelengths of light in a specific way. The wavelengths of light are very short and are measured in nanometers, with red light having a wavelength of around 650 nm and infrared light having a wavelength of around 950 nm.

Measuring oxygen saturation takes advantage of the fact that oxyhemoglobin and deoxyhemoglobin absorb different wavelengths of light in specific ways, with oxyhemoglobin absorbing more infrared light than red light and deoxyhemoglobin absorbing more red light than infrared light. Heart rate oximetry sensors analyze the proportion of arterial blood that is absorbed by oxyhemoglobin and deoxyhemoglobin at two different wavelengths and calculate the ratio of the absorption of the two wavelengths, R, which is then calculated according to the standard model formula for calculating SPO_2 to obtain the oxygen saturation, which is measured by the standard equation defined as follows:

$$SpO_2 = \frac{HbO_2}{HbO_2 + H_b} \times 100 \tag{1}$$

2.3.2. Heart Rate Detection

After obtaining the AC signal that can reflect the characteristics of arterial blood flow, that is, the PPG signal, it can be seen that the frequency of the PPG signal changes with a certain regularity, and this regularity is positively correlated with the frequency of the heart's beating, Fig. 1, that is, a standard PPG signal.

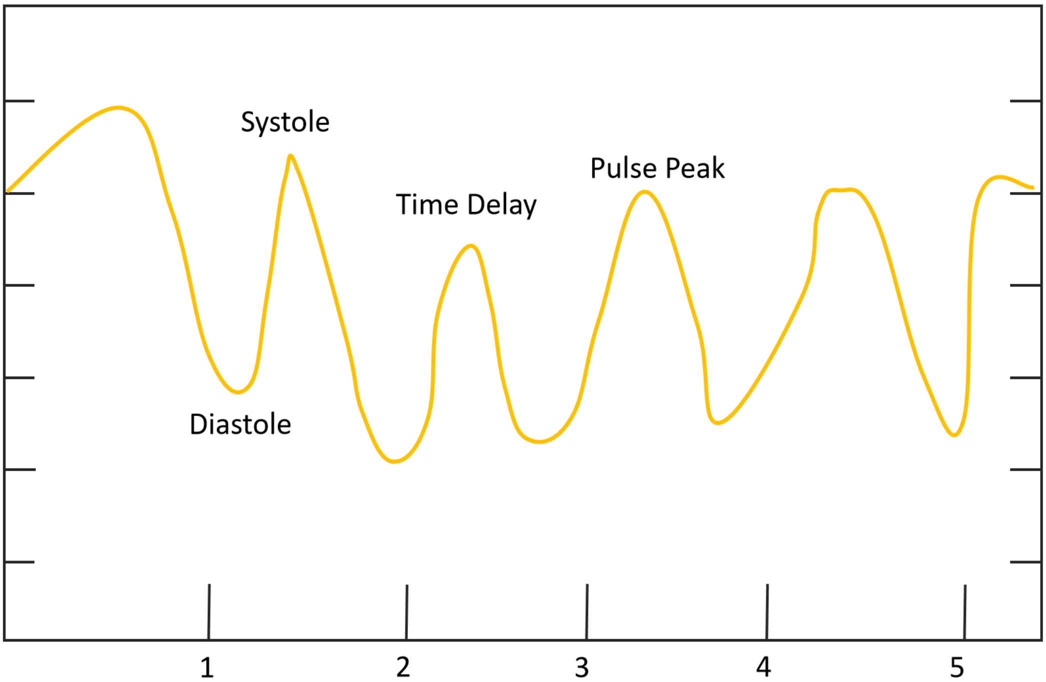

Figure 1. Schematic of a standard PPG signal

Calculating the heart rate from a standard PPG signal only requires removing the pseudo-peaks around the wave intervals and then calculating the wave intervals to obtain an approximate heart rate value.

Another way to measure the heart rate is to process it in the frequency domain. By performing an FFT transform on the resulting AC signal, the following frequency domain plot can be obtained.

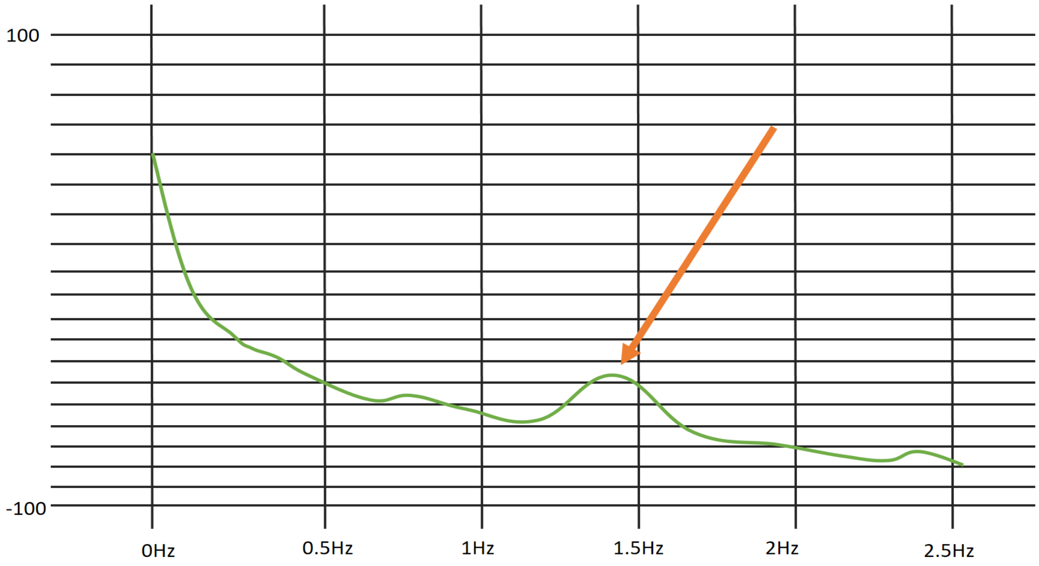

Figure 2. Schematic of a standard PPG signal

As can be seen in Figure 2, the signal at 0Hz is the strongest, and this part of the signal is the DC signal from the bones, muscles, and other tissues, and then there is a relatively prominent signal with a relatively high amplitude near the frequency of 1Hz, which is the AC signal that can reflect the blood flow. For example, in the spectrum above, the frequency peaks at f = 1.2 Hz, so the heart rate at this point is Heart Rate = f $\times$ 60 = 1.2 $\times$ 60 = 72 Hz.

3. Proposed framework

In order to miniaturize, integrate, and expand the overall framework, we prioritize the detection position of heart rate, blood oxygen, and respiratory condition measurement on the basis of photoelectric volumetric pulse wave measurement by focusing the detection position under the nose, because for the measurement of oxygen saturation, most of the existing measurement instruments are in the fingertip position, which makes wearing a little bit uncomfortable and greatly affects the user experience. Therefore, in this paper, we select the sub nasal position that can measure the nasal airflow as the oxygen detection position, so that we can complete the detection of the respiratory state of the subject through the temperature and humidity sensor, and also through the photoelectric pulse wave integrated sensor, using red light and infrared light source, respectively, to obtain the time-domain waveforms of the intensity of the reflected light after irradiation of red light and infrared light on the skin tissues, and to extract the corresponding eigenvalues to accomplish the heart rate, blood oxygenation and oxygenation measurement through the IR waveforms and the waveforms of the red light. From the waveforms of infrared light and red light, the corresponding eigenvalues are extracted to complete the monitoring of heart rate and blood oxygen. At the same time, this framework also supports further expansion, under the premise of keeping the central Bluetooth chip MCU unchanged, new sensors can be added to form a new detection device, the new device can measure other physiological parameters in other locations of the human body, and then multiple devices can be measured in various locations of the human body's physiological parameters at the same time transmitted to the cell phone client. Currently, the overall framework solution is to measure respiratory status and heart rate and blood oxygen values by placing a single device under the nose. Or use two devices, one device placed under the nose to measure the respiratory state, a device placed in the flexor artery to measure the heart rate, blood oxygen value, this way of measuring the heart rate, blood oxygen value is more accurate and stable, but not conducive to the miniaturization of the overall framework. The overall monitoring process starts with the Bluetooth chip acquiring the raw data of all sensors, the temperature and humidity sensor that detects the nasal airflow transmits the waveform data of temperature and humidity changes during the breathing process to the Bluetooth chip through the I2C bus, and at the same time the Bluetooth chip also acts as a microprocessor, processing and calculating the current respiratory status and frequency of the subject, and at the same time transmitting the raw waveform measured by the photoelectric pulse wave sensor to the receiving app side. Database. The database is classified and counted according to the time of the user's measurements, and it supports exporting the historical data saved in the database. At the same time, Python is used to develop a visualization framework to analyze the pulse wave according to the historical data, which enables the tester to have a more comprehensive analysis and understanding of the subject's physical condition during sleep.

3.1. Hardware Design

The hardware circuit of the training monitoring system for sprinters designed in this system can be divided into the following modules, first of all all the modules are integrated on a flexible substrate, and all the functional modules include the photoelectric pulse wave sensor module, the CC2640R2F Bluetooth control module, the temperature and humidity integrated sensor SHT21 module and the power supply module. The temperature and humidity sensor collects the airflow from the nostrils of the athletes in training, and collects the temperature and humidity changes caused by the nostrils' airflow, and carries out internal A/D conversion, digital filtering, and filtering of ambient light. The microprocessor and Bluetooth chip CC2640R2F configures the photoelectric pulsed wave sensor module through the I2C interface, which mainly configures the collection parameters and operation status of the photoelectric pulsed wave sensor, and then the photoelectric pulsed wave sensor module drives the LEDs to illuminate the skin under the nose, and the microprocessor CC2640R2F reads the photoelectric converted value of the reflected light from the skin through the access of the internal FIFO of the photoelectric pulsed wave. photoelectric conversion value. The microprocessor then configures the temperature and humidity integrated sensor through the same I2C interface, configures the accuracy of the acquisition, the format of the data, gets the temperature and humidity values through the internal conversion, and then gets the respiratory status of the athlete through the algorithmic processing, and packages the measured data according to the Bluetooth 5.0 protocol.

3.1.1. SHT21 Temperature and Humidity Integrated Sensor

The SHT21 has a built-in capacitive humidity sensor and a standard temperature sensor that have been continuously improved. Its performance has been highly improved, and in terms of reliability level, it has already exceeded the previous generation of digital sensors, and it is able to maintain a stable performance in high humidity conditions, and it is packaged in the device as shown in Figure 3.

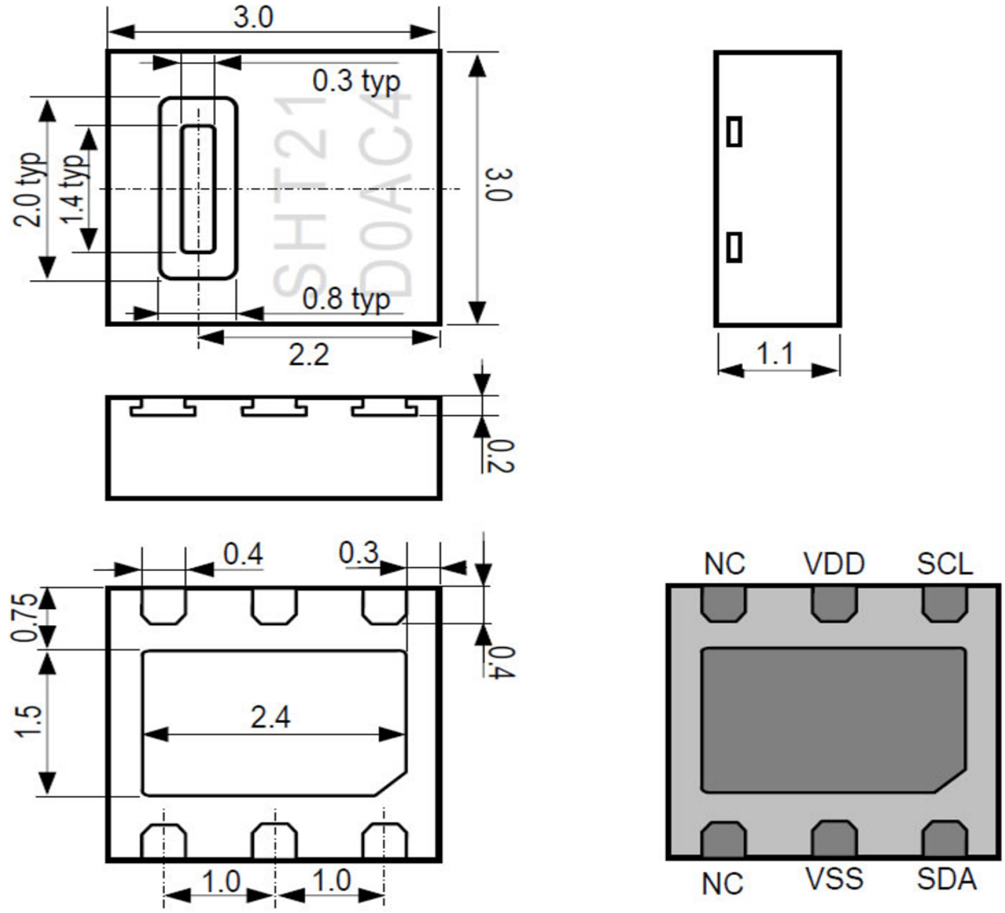

Figure 3. Schematic diagram of the SHT21 temperature and humidity integrated sensor package

The SHT21 operates between 2.1V and 3.6V, with a recommended operating voltage of 3.0V. A decoupling capacitor needs to be added between the power supply connector and the sensor's ground port, and the decoupling capacitor needs to be located near the sensor. Also, since the microprocessor can only drive the SDA and SCL pins at low levels, it is necessary to add pull-up resistors to the serial clock line (SCL) and serial data line (SDA) to bring the signals up to a high level.

3.1.2. SHT21 Temperature and Humidity Integrated Sensor

The MAX30102 is an optically integrated sensor chip from MaxicoM. It contains two internal LEDs, a red LED and an infrared LED, a photodetector, and an optimized low-noise AFE, as shown in Figure 4.

Figure 4. Schematic diagram of the PPG integrated sensor

The MAX30102 uses a 1.8V supply and a 5.0V supply voltage for the internal LEDs and is widely used in wearable applications that include heart rate and blood oxygen detection solutions that can be measured against the skin of the finger, wrist, and earlobe [28]. The sensor has a standard I2C communication interface to transmit the values collected by the sensor to the MCU, which is responsible for calculating the heart rate and blood oxygen.

3.2. Software system design

The software system is divided into two parts, as shown in Figure 5, one part is the embedded software development of the CC2640R2F Bluetooth chip side acquisition and sending program, and one part is the server side database to receive the acquired data. The program development platform for the Bluetooth chip side uses Code Composer Studio, which is a code debugger and compiler.

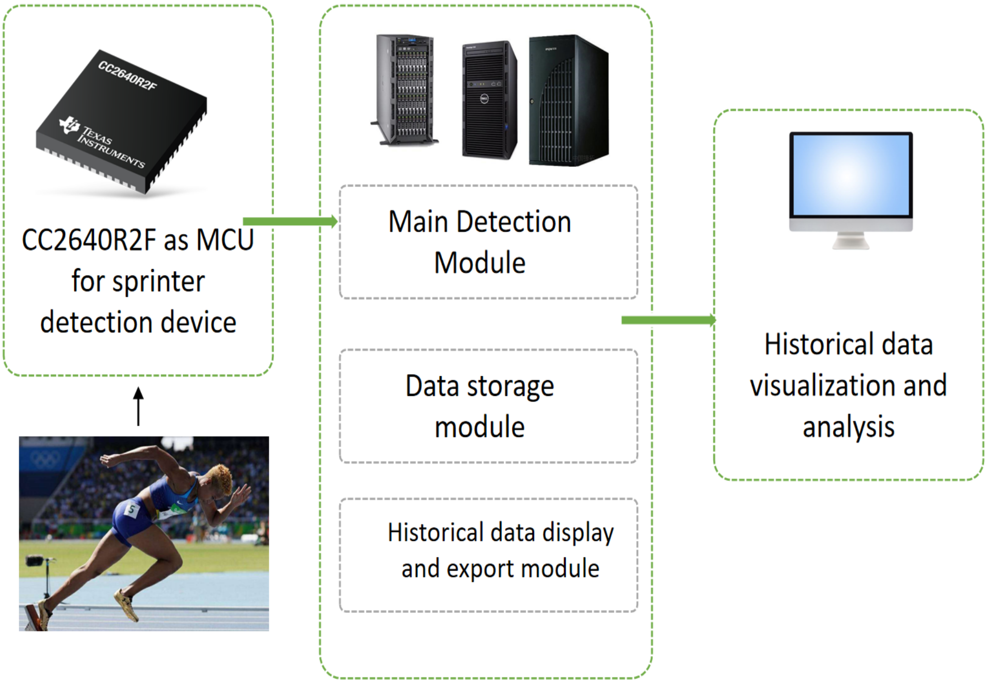

Figure 5. Schematic diagram of the overall software system architecture

3.2.1. Data transmission

The Bluetooth chip combines the temperature data from the temperature and humidity sensors, the humidity data, and the respiratory state data processed by the algorithm, and at the same time adds the raw waveform data of the optoelectronic pulse wave to the characteristics of the corresponding service and transmits them to the server-side database. Specific practice is to first determine the definition of the new service service name, service UUID, the highest number of bits of data to be transmitted, the permitted transmission attributes and permissions, the permitted transmission attributes include read (readable), write (writable), notify (notifiable), indicate, indicate and notify the difference is notifying The difference between invite and notify is that notify may lose data, while invite will definitely receive data. Through the TI official website service generator to generate the corresponding service C language code and service header files, added to the project file compiled. After importing the program file and header file of the newly created service into the project, find the initialization section of the service, and add the initialization function of the service into the initialization code block of the Bluetooth chip, then the service can be successfully added. After adding the service, you can modify the byte size that the feature value can be transmitted at one time by modifying the callback processing function. After successfully adding the corresponding service and the corresponding profile value, call the SetParameter function of the corresponding service in the timer cycle event to update the value field therein, and update the value to be transmitted in the value field in real time, and then the service side will notify and listen to the value of the corresponding profile of the corresponding service.

3.2.2. Processing of PPG signals and heart rate oximetry parameters

As mentioned above, the raw signals obtained by the photoelectric pulse wave sensor will inevitably be affected by some of the human body's own muscle movements, its own breathing, the interference of the external environment (such as fluorescent lamp light containing 50Hz high-frequency noise), and the interference of the psychological situation (such as the burr brought about by the muscle jitter), so before extracting the physiological parameters of the human body through the pulse wave, the pulse wave signal should be pre-processed before the raw signals are obtained. Therefore, before extracting human physiological parameters from pulse waves, it is necessary to pre-process the raw pulse wave signals to obtain usable pulse wave signals with waveform quality that meets the requirements, which can improve the accuracy of the subsequent physiological parameter calculations. In the actual acquisition process, there are many burrs in the original pulse waveform. Therefore, the original signal to do the median filtering process, the median filtering in this paper, the specific implementation of the method is: an analog signal approximation of the discrete digital signal sequence x (t) (t>0) filtering process, first of all, the definition of a length of 2 sampling points in the window, located in a certain moment, the window of the signal samples for the Y (t-1), Y (t), in which the Y (t-1) is to be replaced by a signal sample value. The median value of Y(t-1), Y(t) is defined as the output value of Y(i-1), which is expressed as follows:

$$Y(t-1) = \frac{(Y(t-1) + Y(t))}{2} \qquad (2)$$

The waveform after flipping the original waveform up and down and median filtering is shown in Figure 6:

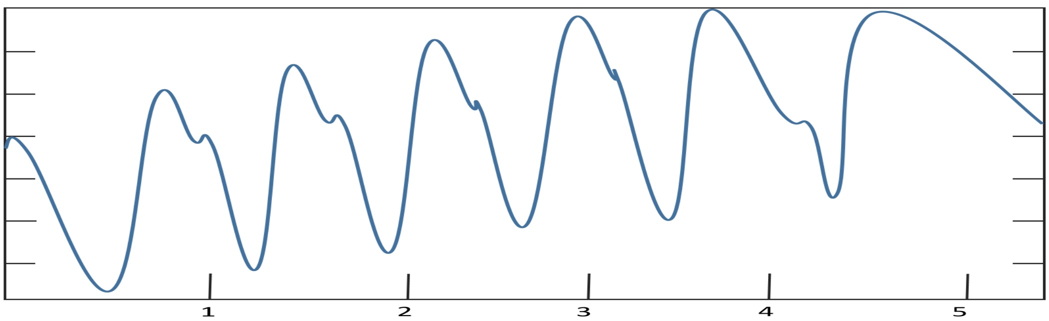

Figure 6. The effect after the first step of median filtering of the pulse waveform

4. Experiment and Results

4.1. Experimental setup

After the completion of the training monitoring system for sprinters, it is necessary to carry out systematic testing of the whole system to verify whether it can realize the functions that the system was designed to accomplish at the beginning and the corresponding reliability and accuracy. The complete monitoring device designed in this paper includes a 3.7V Li-ion battery, a reset switch, a MAX30102 device with integrated infrared and red light emitting and receiving photosensitive sensors, a SHT21 device with integrated temperature and humidity sensors, a power supply regulator chip, and a Bluetooth chip, all of which are integrated on an FPC flexible substrate, and are accompanied by a corresponding cell phone receiver software and a visualization and analysis software platform for the historical data.

The modules are all integrated on an FPC flexible substrate with corresponding mobile phone receiver software and historical data visualization and analysis software.

4.2. Evaluation indicators

In this paper, the absolute error was used to evaluate the effectiveness of training monitoring of sprinters, which was calculated by the following equation:

$$\mathrm{A}E = \left| X - L \right| \tag{3}$$

Where AE is the absolute error, X is the measured value and L is the true value.

4.3. Experimental results and analysis

This section verifies the reliability of the Bluetooth chip processing the SHT21 device containing temperature and humidity sensors inside, as shown in Figure 7, when the device is pasted under the nose to work, and the athlete is in the breathing state, the temperature and humidity stored in the database at the receiving end change curve with the respiratory airflow as follows, with the horizontal axis indicating the time, and the vertical axis indicating the temperature and humidity of the nose respiratory airflow of the sprinters during training. This study is likely conducted to verify the functionality and reliability of the sensors, the Bluetooth chip, and the data transmission system for monitoring physiological parameters during physical activities. his suggests that as the athlete breathes, the sensors detect variations in temperature and humidity that are transmitted and recorded.

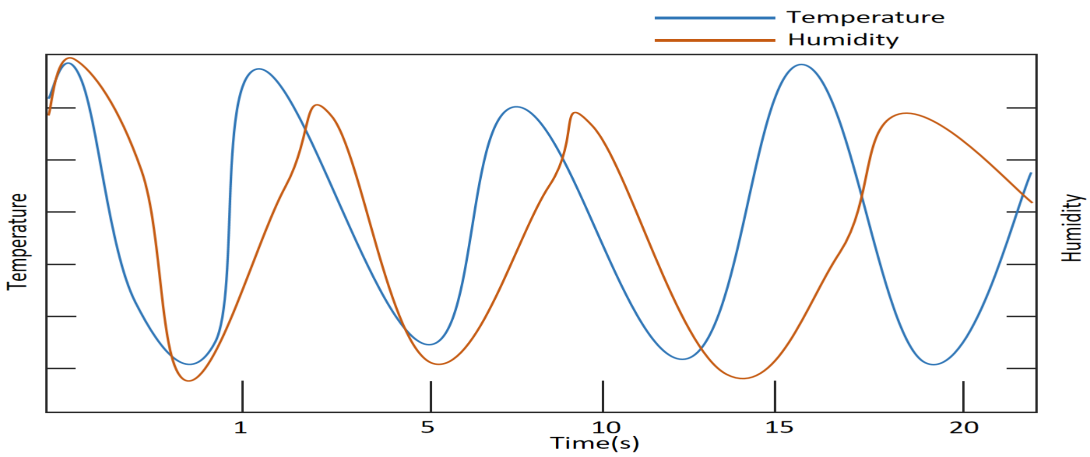

Figure 7. Waveform diagram of temperature and humidity changes when respiratory airflow is detected

As can be seen from Figure 7, the change curves of temperature and humidity obtained by the monitoring device when the sprinter is in the respiratory state and in the apnea state are very different, which is in line with the change rule of the temperature and humidity values in the two different situations, and it confirms that the Bluetooth chip acquires the data from the SHT21 integrated sensors and wirelessly transmits it to the server-side database, and that the results of the sensor data are reliable. In order to test the accuracy of this device in detecting heart rate and blood oxygen saturation, two different subjects were selected for heart rate measurement experiments, aged between 20 and 30, and the measurements were performed simultaneously in a stationary state, with three measurements for each measurer, the device was pasted under the subject's nose, and the JUMPER Oximeter was fixed to the tip of the index finger of the left hand of the human body. The changes in heart rate and oxygen saturation of subject A as measured simultaneously by the JUMPER Oximeter and the device are shown in Figures 8 and 9.

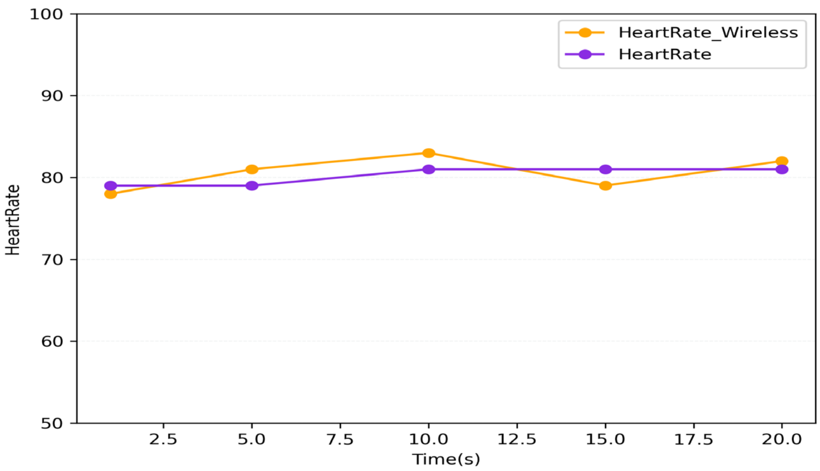

Figure 8. Comparison results of heart rate change curves

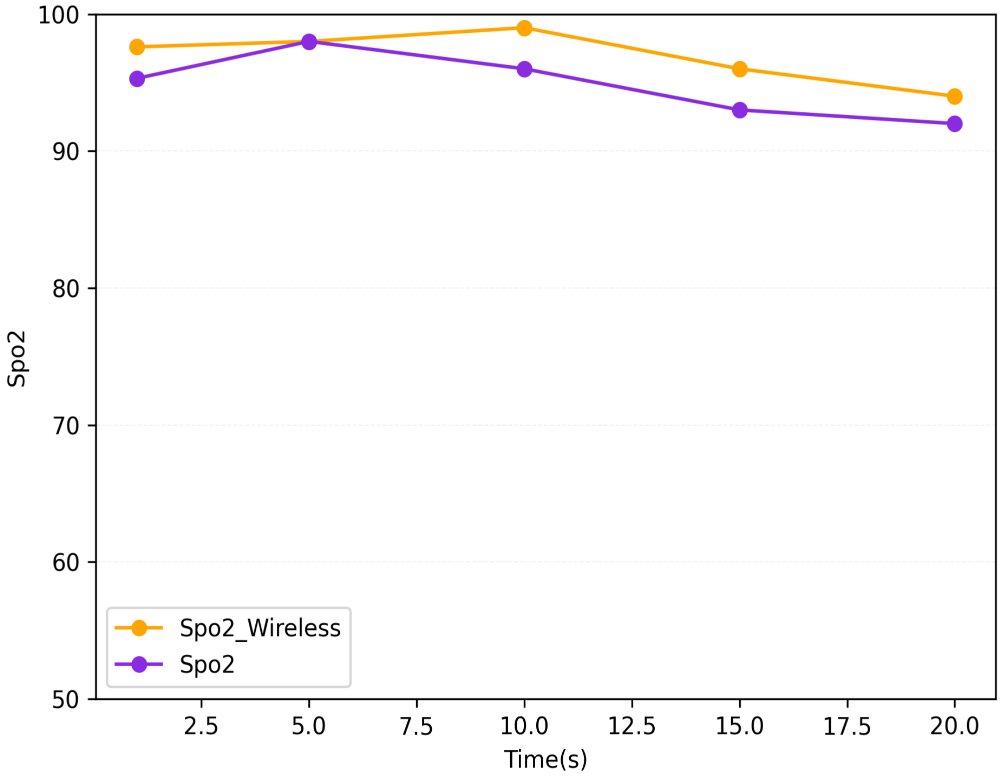

Figure 9. Comparison results of oxygen saturation curves

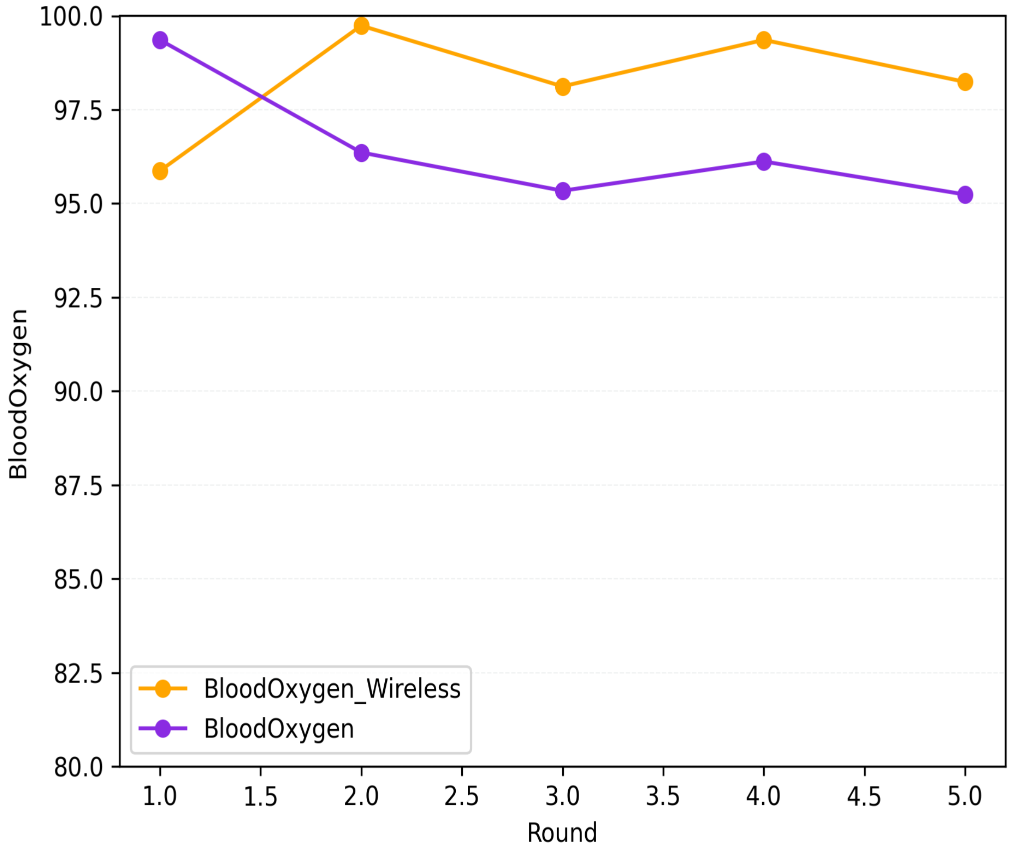

Figure 10. Comparison results of oxygen saturation curves

From Figures 8 and 9, it can be seen that for sprinter A in this measurement, the error of heart rate measurement by this monitoring system can be controlled within ± 6bpm in most cases, and the error of heart rate measurement by this monitoring system can be controlled around ±4bpm in most cases.

In most cases, the error of blood oxygen saturation measurement of this device can be controlled within ±2%. Therefore, it can effectively detect the training load of sprinters. In addition, we also give the detailed data of sprinter B as shown in Table 1 and 2.

Table 1. Experimental results of heart rate monitoring

BREATHING RATE	**SPRINTER B**		
	Heart rate measured by the device	Actual Heart Rate	Absolute error
	104.2	105.1	1.1
	102	99	3
FREQUENCY	104	102	2
	108	107	1
	109	105	4
	107	106	1
	106	108	2
	105	107	2
	101	104	3

Table 2. Experimental results of respiration monitoring

BREATHING RATE	**SPRINTER B**		
	Blood oxygen measured by this device	Actual blood oxygen	Absolute error
	96.1	97.3	1.2
	95.4	96.8	1.4
FREQUENCY	97.0	99.1	2.1
	96.7	95.3	1.4
	95.8	96.9	1.1
	97.2	98.9	1.7
	99.1	97.1	2.0
	98.2	97.1	1.1
	96.3	98.4	2.1

Table 3. Experimental results of respiration monitoring

BREATHING RATE FREQUENCY	SPRINTER B		
	Breathing rate measured by this device	Actual respiratory rate	Absolute error
	12	15	3
	10	11	1
	11	14	3
	14	15	1
	13	12	1
	15	13	2
	12	14	2
	11	14	3
	15	12	3

It can be clearly seen from Tables 1,2 and 3 that when measuring the heart rate of sprinters during training, the mental state of different athletes at different times and the change of body position during the measurement will have an impact on the final test results and increase the error. When performing blood oxygen saturation measurements, since the sprinter population is a healthy population, the blood oxygen saturation is basically in the normal range, so the measurement error in the high blood oxygen saturation interval will be relatively small, and is closer to the measurement value of the comparison equipment. In the measurement of the number of breaths and the number of apneas, due to the use of sprinters to simulate the occurrence of apnea, it is inevitable that there will be a small respiratory airflow in the simulation of apnea occurs leading to the actual monitoring of the number of apneas is lower than the actual number of apneas. At the same time, due to the influence of the external environment, the number of respirations obtained by the algorithm may be misjudged, resulting in the actual number of respirations monitored to be slightly more than the actual number of respirations. Since the algorithm of the finger-clip oximetry device is different from the algorithm designed in this paper, it is inevitable that the measurement process will also bring some errors.

5. Conclusion

In this paper, we propose a multi-sensor-based athlete training load monitoring system and develop a flexible wearable intelligent non-invasive device with high safety, flexibility, and portability to monitor changes in sports and corresponding physiological parameters of the human body. This device is based on a processing chip that supports Bluetooth 5.0 and is produced by a certain company, as well as temperature, humidity sensors, heart rate and blood oxygen sensors. All components are integrated on a flexible substrate. The device only needs to be pasted on the skin area under the nose to effectively measure the subject's heart rate, blood oxygen data and current breathing status. It does no harm to the human body and greatly improves the athlete's comfort. At the same time, this article compares the test results with finger-clip heart rate and blood oxygen equipment on the market to verify the stability and reliability of the entire system monitoring. This study provides a new solution for monitoring changes in physiological parameters caused by cerebral infarction and myocardial infarction during athletes' training as more portable as possible, and has positive significance for the development of training load monitoring for flexible athletes.

Conflicts of Interest

The authors do not have any possible conflicts of interest.

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