Plastic Optical Fiber Sensor-based Smart Mattress For Sleeping Posture Remote Monitoring

Tianliang Li
School of Mechanical and Electronic Engineering
Wuhan University of Technology
Wuhan, China
tianliangli@whut.edu.cn

Qingfeng Pei
School of Mechanical and Electronic Engineering
Wuhan University of Technology
Wuhan, China
259562@whut.edu.cn

Chen Zhao
School of Mechanical and Electronic Engineering
Wuhan University of Technology
Wuhan, China
zhaochenwhut1@sina.cn

***Abstract*—This paper presents a sleep posture monitoring system for guiding the rehabilitation of patients with heart failure (HF). Eight plastic optical fiber sensors are designed and integrated into the mattress in a herringbone scheme to collect sleeping position signals. Combined with the self-made hardware module, the function of photoelectric conversion and wireless signal transmission are realized. A whale algorithm optimized support vector machine (WOA-SVM) is proposed in the system to classify data, and the accuracy of the algorithm is verified by the sleeping position recognition experiment. The monitoring results can be updated in real-time on family members' mobile phones or the monitoring center. A remote sleeping position monitoring experiment has been implemented to further prove the potential application of the system in guiding the rehabilitation of HF patients.**

Keywords—optical fiber sensor, smart mattress, support vector machine, remote sleeping posture monitoring

I. INTRODUCTION

Heart failure (HF) is a clinical syndrome caused by abnormal cardiac structure or function, which has the characteristics of high hospitalization rate and mortality. The latest European ESC-HF study [1] shows that the in-hospital mortality rate of HF patients is as high as 17%, and 44% of the patients are still unable to be discharged after 12 months. Sleeping position is critical to the recovery of HF patients, and relevant research has been conducted for more than 20 years [2]. Taking the Left log sleeping position as an example, it will compress the heart and reduce the heart rate [3]. However, medical institutions mainly rely on nurses for sleeping position monitoring, which is ineffective at night and wastes human resources [4]. The development of a hospital environment-oriented, cost-effective method for all-day sleeping posture monitoring is of great significance.

To meet the demand for sleeping posture monitoring, scholars have developed a variety of monitoring equipment, such as vision sensors [5], acceleration sensors [6], etc. Nuksawn *et al.* [7] proposed a method combining a three-axis accelerometer arranged on the chest and a camera for continuous sleep posture monitoring, and the recognition accuracy of five postures was 95.78%. However, the above monitoring equipment collects vital information at the expense of user privacy or comfort, which has become increasingly unacceptable in contemporary society.

To solve the above problems, various non-invasive sleep posture monitoring methods have been proposed, such as piezoelectric sensors [8], piezoresistive sensors [9], and optical fiber sensors [10]. Paolo Barsocchi *et al.* [11] adopted array-arranged piezoresistive sensors for sleep posture monitoring, which has the advantages of low price and short training period. However, electrical sensors suffer from circuit wear, easy corrosion, and electromagnetic interference, which limits their development in the field of medical monitoring. In contrast, optic fiber sensors have the advantages of anti-electromagnetic interference, high sensitivity, small size, etc., and are gradually showing their potential. Michiko Nishyama *et al.* [12] prepared a fiber Bragg grating pressure sensor based on fused deposition technology, which can effectively identify four sleeping positions.

Support vector machine (SVM) is favored by people because of its better classification ability, especially in nonlinear and high-dimensional pattern recognition problems [13]. Georges Matar *et al.* [14] proposed a method for body position monitoring using human pressure distribution. Then they compared the performance of various machine learning algorithms, among which the SVM has the best generalization performance. But the parameter selection of SVM has a great influence on the classification effect of sleeping position. Whale Optimization Algorithm (WOA) is a new heuristic algorithm with comparable utilization, good exploration, and high local optima avoidance ability [15]. The WOA is used to optimize the parameters of SVM and has a good application prospect in the field of sleep posture classification.

Herein, a sleep posture monitoring system is proposed to guide the rehabilitation of HF patients. The sensor is designed based on plastic optical fiber and Lamina Emergent Mechanism Spring (LEMS). The thickness is only 6.9 mm, which can be integrated into the mattress without affecting the user's comfort. The theoretical model of the LEMS is derived based on the

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energy method, which can be used to guide the adjustment of the sensor sensitivity. To improve the accuracy of sleeping posture recognition, a whale algorithm optimized support vector machine (WOA-SVM) is proposed to classify sleeping posture data. The recognition results can be sent to the monitoring center and users' mobile phones through the wireless transmission module to realize remote sleeping posture monitoring.

II. SLEEPING MONITORING SYSTEM

A. *Sensor Design and Theoretical Derivation*

The designed sensor is composed of a base, a prismatic-tip optical fiber, a shrink-fit hose, two mirrors, and a LEMS, as illustrated in Fig. 1. The plastic optical fiber utilized has a diameter of 2.2 mm and a core diameter of 2 mm, which has the advantages of large light transmission capacity and low price. There is a 45 ° polished face at the end of the fiber, combined with mirror 1, the direction of the incident light can be changed by 90 ° and sent to mirror 2. The LEMS consists of four flexure hinges and a motivation platform. Mirror 2 is pasted on the lower surface of the platform. A cylindrical through hole is opened inside the base to fix the optical fiber, and the upper-end face is provided with a groove to fix the spring. When the spring is under pressure, mirror 2 can move up and down with the platform, thereby achieving the purpose of light intensity modulation.

As a force sensing element, the stiffness of LEMS is mainly affected by four dimensions: rod length l, rod width b, rod spacing c, and thickness d. since the four hinges are evenly distributed, any hinge can be selected for calculation. The force analysis is shown in the upper right corner of Fig. 1. The initial state of the hinge is horizontal, and the endpoint H is connected with the moving platform. When a force F is applied perpendicular to the endpoint H, the displacement of the platform Δ can be calculated as follows:

$$\Delta=\Delta_1+\Delta_2 \tag{1}$$

where Δ_1 and Δ_2 are the displacements caused by hinge bending and torsion, respectively.

Based on the force translation theorem, the force F can be transferred from point H to G. At this time, the force F and the bending moment M act on the rods AB, CD, and EG, and the hinge produces a Z-shaped deformation. Combined with the unit load method in the mechanics of materials, the displacement Δ_1 caused by hinge bending is expressed as follows:

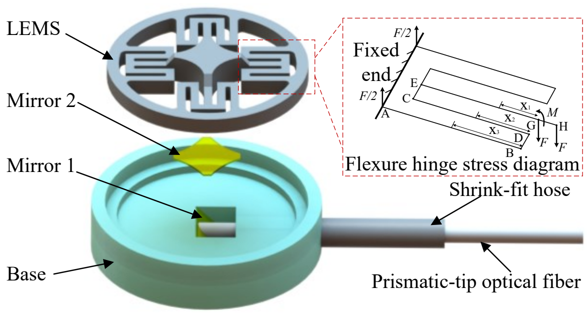

Fig. 1. Schematic diagram of sensor structure .

$$\Delta_1=\int_0^{l_1}\frac{M(x_1)\overline{M}(x_1)}{EI}dx_1+\int_0^{l_2}\frac{M(x_2)\overline{M}(x_2)}{EI}dx_2+\int_0^{l_3}\frac{M(x_3)\overline{M}(x_3)}{EI}dx_3 \tag{2}$$

Where $M(x_1)$, $M(x_2)$, $M(x_3)$ are the bending moments of any section of rods EG, CD, and AB under load F. $\overline{M}(x_1)$, $\overline{M}(x_2)$, $\overline{M}(x_3)$ are the bending moments under unit load. l_1, l_1 and l_3 are the rod length of EG, CD and AB, $l_2=l_3=l_1-b-0.3$. $I=bd^3/12$ is the moment of inertia of the rod. E is the modulus of elasticity.

Due to the symmetry of the hinge, only the torsional deformation of a single-sided rod needs to be considered. Δ_2 is mainly caused by the torsion of the external rod AB. The torsional deformation displacement Δ_2 is mainly caused by the rod AB, and the inclination caused by the torsion mainly occurs in the BC segment, which can be calculated as follows:

$$\Delta_2=\sigma I_{BD}=\frac{2F(b+c)^2 l_3}{GI_P} \tag{3}$$

where $G=E/(2+2v)$ is the shear modulus, $I_P=(bd^3+b^3d)/12$ is the polar moment of inertia of the rod.

The motion platform is connected to the fixed end by four hinges. When load P acts vertically on the motion platform, the force on a single flexible hinge is F=0.25P. On this basis, the stiffness k of the LEMS can be obtained as follows:

$$k=\left(\frac{l_1^3-3al_1^2+3a^2l_1}{4Ebd^3}+\frac{5(l^3-3al^2+3a^2l)}{4Ebd^3}+\frac{6(b+c)^2(l+0.9)}{G(bd^3+b^3d)}\right)^{-1} \tag{4}$$

B. *Signal Processing and Wireless Transmission*

In order to realize real-time processing and wireless transmission of sleeping posture signals., hardware design and software development have been carried out, as shown in Fig. 2. An 24-bit A/D converter (ADS1256) is chosen to convert the eight-channel sensor signal into the electrical signal, while filtering and amplifying the data. STM32F103C8T6 (F103) is the control unit of the system, which not only supports multiple interfaces, including SPI, IIC, and UART serial connections, but also has a lower price. The WiFi module is ESP8266, which communicates with the cloud platform under the control of F103. The Bluetooth module is HC-06 and it adds another way to transfer data to a computer without the internet.

The monitoring center software is developed based on the QT architecture, and its display interface is shown on the right side of Fig. 2. The eight-channel sensor signal is processed and

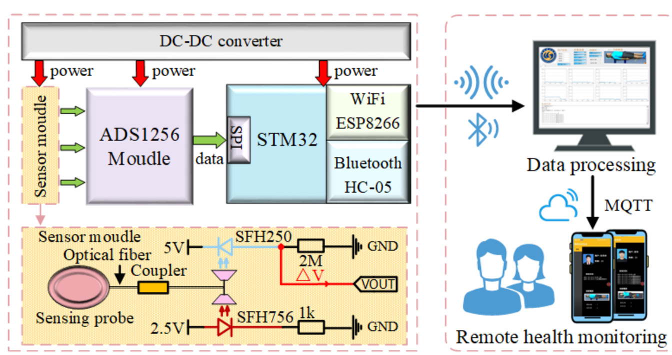

Fig. 2. Schematic diagram of mattress hardware design and signal transmission

displayed here in real-time, which is convenient for medical staff to prevent dangerous sleeping positions. The results of sleeping position recognition will be presented in the form of pictures and recorded in a log, which can play a guiding role in the rehabilitation treatment of patients. The mobile APP is developed based on the Android architecture, and can receive data from the monitoring center through the OneNET cloud platform to realize remote sleeping posture monitoring.

C. Mattress Integration

To collect patients' sleeping posture characteristics, the process of mattress integration has been studied, as shown in Fig. 3. The fabrication process of the sensor is shown in Fig. 3(a). To begin, a 2 × 10 mm mirror 1 was fixed on the 45° slope of the base. The prismatic-tip fiber is protected with a shrink-fit hose, inserted into the base along the groove and fixed with glue. Subsequently, a 5 × 5 mm mirror 2 was glued to the spring underside. Finally, the spring was inserted into the base and fixed with glue. Fig. 3(b) introduced the integration steps of the mattress. First, the base was evenly glued and connected to the mattress through holes, and then the sensor was glued to the base. Finally, an artificial leather was sewn over the sensor to block light and increase the force sensing range.

The final prepared mattress consists of a pillow, eight sensors, optical fibers, eight couplers, and a circuit box, as shown in Fig. 3(c). The eight sensors are arranged according to the herringbone scheme, which can effectively distinguish six basic sleeping positions. The hardware is integrated into a circuit box in the corner of the mattress for easy plugging and avoiding stepping. The optical fiber is arranged according to the position of the circuit box and the sensor, and the bending radius is more than 20 cm, which can effectively reduce the light intensity loss caused by the optical fiber bending. The sensor prepared in Fig. 3(a) is only 25 mm in diameter and 6.9 mm in thickness, which can be embedded in the mattress without compromising comfort. The overall mattress thickness shown in Fig. 3(c) is only 7 mm, which is easy to carry and has the advantage of anti-sweat.

D. Sleeping Posture Recognition Algorithm

A whale-optimized support vector machine (WOA-SVM) has been introduced to classify sensor data for high-precision sleeping position recognition. The principle and applications of WOA and SVM are introduced in the following.

Support vector machine (SVM) is a kind of generalized linear classifier that performs binary classification of data according to the supervised learning method. It has the advantages of high dimensionality and memory saving, and can effectively classify various data through the decision hyperplane. Therefore, a total of $n(n-1)/2$ decision hyperplanes are constructed for *N* class sleeping positions. The training set is denoted as $(x_i, y_n), i = 1,2,\cdots N$, where *y* is the type of sleeping position. In the solution process of introducing the Lagrange multiplier α, the classification of class *r* and class *s* sleeping positions can be expressed as the following problem solution:

$$\begin{cases} maxL(\alpha^{rs}) = \sum_{i=1}^{N} \alpha_i^{rs} - \frac{1}{2}\sum_{i,j=1}^{N} \alpha_i^{rs}\alpha_j^{rs} y_i^{rs} y_j^{rs} K\left(x_i^{rs}, x_j^{rs}\right) \\ s.t. \sum_{i=1}^{N} y_i^{rs}\alpha_i^{rs} = 0, \quad 0 \le \alpha_i \le C, \quad i = 1,2,\cdots N \end{cases} \tag{5}$$

Where $C > 0$ is the penalty factor, *K* is the kernel function, and the radial basis kernel function is adopted in this paper.

The decision function between kernel function and class *r* sleeping position and class *s* sleeping position can be expressed as follows:

$$K\left(x_i^{rs}, x_j^{rs}\right) = exp\left(\frac{-\left\|x_i^{rs} - x_j^{rs}\right\|^2}{2\cdot\sigma^2}\right) \tag{6}$$

$$F(x) = sign\left(\sum_{i-1}^{N} \alpha_i^{rs} y_i^{rs} K\left(x_i^{rs}, x_j^{rs}\right) + b^{rs}\right) \tag{7}$$

Where *b* is the decision hyperplane bias value between class *r* sleeping position and class *s* sleeping position

The voting method is used in the classification. If x_i belongs to the *r*-th sleeping position, the number of votes for the *r*-th sleeping position is increased by 1. After all the decision functions are judged, the category with the most votes is the sleeping position category of the sample point x_i. The division effect of the SVM decision hyperplane is greatly affected by the penalty factor *C* and the kernel function parameter $g = 1/(2\sigma^2)$. Therefore, the adaptive optimization of the SVM solution parameters needs to be selected in the solution process.

In order to solve the above problem, the WOA randomly generates *N* whale individuals in the search space to form the initial population. In the process of evolution, the population updates its position according to the current optimal whale individual or randomly selects a whale individual. Then, according to the randomly generated number *P* (usually 0.5), the individual whale is determined to carry out the spiral or encircling motion. Finally, the loop is iterated until the WOA algorithm meets the termination condition and the optimization parameters are obtained. The mathematical model of helical position update can be expressed as follows:

$$X(t+1) = \begin{cases} X^*(t) + (2ar - a)D & p < 0.5 \\ D' e^{bl} cos(2\pi l) + X^*(t) & p \ge 0.5 \end{cases} \tag{8}$$

Where $D'=X^*(t) - x(t)$ is the distance between the *i*-th whale and prey; *b* is a constant and used to define the shape of the helix. *l* is a random number of [-1,1]. *t* is the current iteration number. X^* is the currently obtained prey position vector. *X* is the whale position vector. *p* is a random number on [0,1]. *a* is the

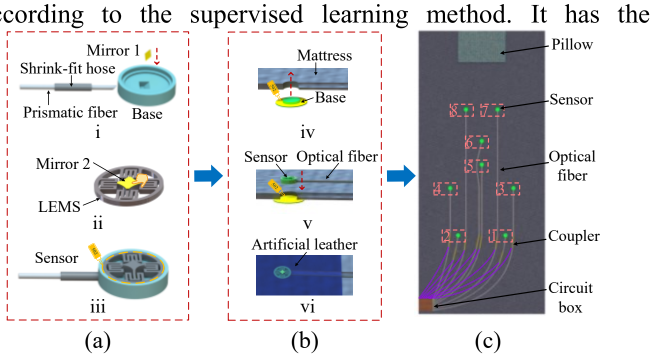

Fig. 3. Mattress packaging flow chart. (a) Sensor preparation, (b) Sensor integration into mattress, (c) Schematic diagram of mattress

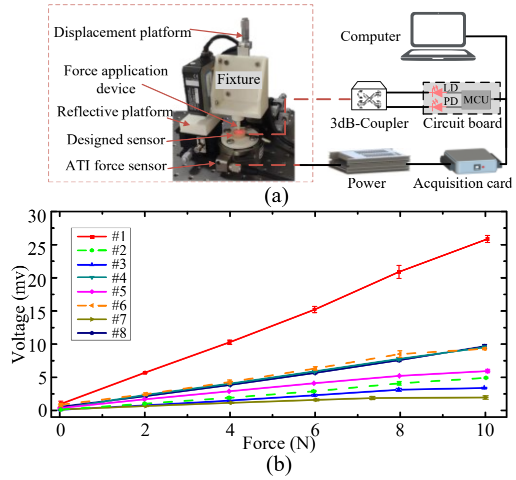

Fig. 4. (a) Experimental setup for static experiment (b) Force-voltage response curve

convergence factor, which decreases from 2 to 0 as the number of iterations increases. r is a random value between [0,1].

Using WOA to optimize the parameters of SVM can avoid the process of traditional manual trial and error. Combined with the characteristics of WOA, such as few adjustment parameters, simple structure and fast convergence speed, the penalty factor c and kernel parameter g of SVM can be quickly optimized to improve the accuracy of WOA-SVM state recognition. In this paper, WOA parameters are set as follows: the number of whale populations is 20, the dimension of variables is 2, the maximum number of iterations is 30, the upper limit of C and σ is 100, and the lower limit is 0.01.

III. Experiments And Results

A. Static Calibration Experiment of the Sensor

The experimental system for static calibration of the sensor is shown in Fig. 4(a), which consists of two parts: the optical fiber sensing system, and the ATI force sensing system. The designed optical fiber sensor was fixed above the ATI force sensor, and the load was applied to the sensor by combining the displacement platform and the force application device. The experiment was carried out under shaded conditions, and four loading-unloading cycles were performed in the range of 0-10 N with a step size of 2 N. The output voltage of the optical fiber sensor and the output force value of the ATI sensor were recorded through the acquisition equipment and computer.

The experimental results are shown in Fig. 4(b). The sensors perform well in terms of linearity, but their sensitivity consistency needs to be improved. One possible reason is that mirror 2 is not kept level, and the other reason is that the distance between mirror 2 and the fiber is different, both of which will bring about a large loss of light intensity.

B. Sleeping Posture Recognition Experiment

In this section, a sleeping posture recognition experiment has been carried out to verify the effectiveness of the proposed algorithm. Six healthy subjects (5 males, 1 female) were recruited for the experiment. Each subject laid on the bed in the order of Supine (Sp), Left log (Ll), Left fetal (Lf), Prone (P),

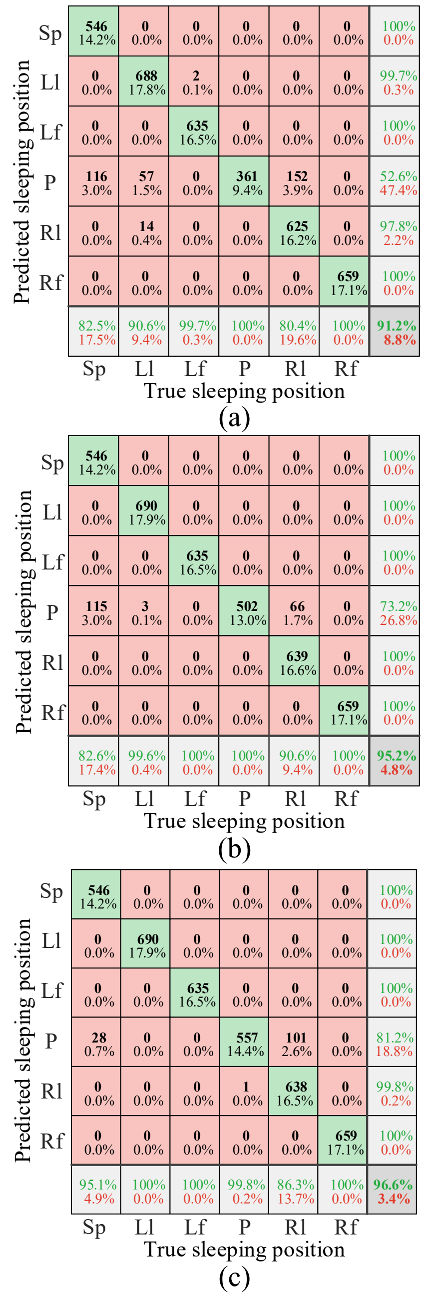

Fig. 5. Confusion matrix of sleeping position recognition experiment (a) Traditional support vector machine (b) Particle swarm optimized support vector machine (c) Whale algorithm optimized support vector machine.

Right log (Rl), and Right fetus (Rf). Held each pose for 40 seconds and recorded the force measured by the eight-channel sensor. In order to verify the performance of WOA-SVM, traditional support vector machine (SVM) and particle swarm optimized support vector machine (PSO-SVM) were used for comparison. The confusion matrices of the three are shown in Fig. 5. The recognition accuracy of P by SVM and PSO-SVM is only 52.6% and 73.2%, which cannot meet the actual needs. In contrast, when using WOA-SVM, the recognition accuracy of Sp, Ll, Lf, and Rf are all 100%, while the recognition accuracy of P is 81.2%. The average recognition accuracy reaches 96.6%, which is also a big improvement in comparison. The

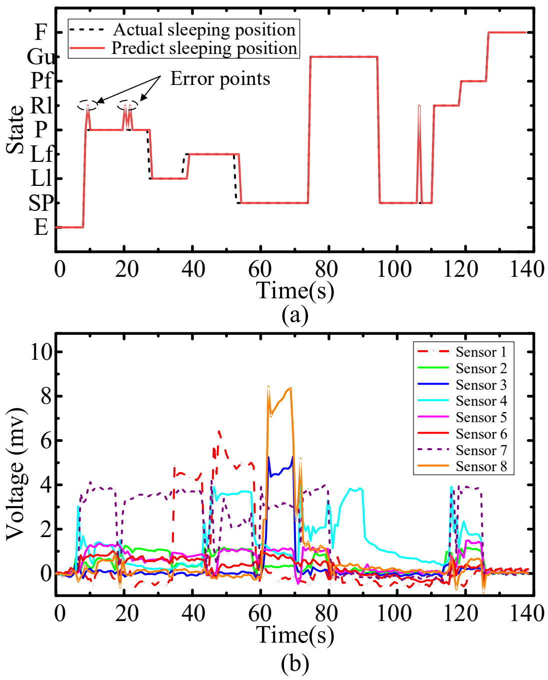

Fig. 6. Remote monitoring experiment (the words Sp, Ll, Lf, P , Rl, Rf, E, Gu and F correspond to Supine, Left log, Left fetus, Prone, Right log, Right fetus, Empty bed, Get up, Falling respectively) (a) Offline recognition result of sleeping posture in the experiment (b) Force measured by 8 sensors in the experiment.

experimental results demonstrate the effectiveness of the proposed sleep posture recognition algorithm.

C. Remote Monitoring Experiment

To verify the effectiveness of the system for sleeping posture monitoring, an offline remote monitoring experiment was conducted. The mattress and the monitoring center were separated in the experiment to simulate the real nursing environment. Subject randomly changed the sleeping position, which included Supine (P), left log (Ll), Left fetus (Lf), Prone (P), Right log (Rl), Right fetus (Rf), empty bed (E), getting up (Gu), and falling (F). The subject's sleeping position changes were recorded through the video. The eight-channel sensor data during the experiment was wirelessly transmitted through the hardware circuit and stored in the monitoring center. The sleeping position recognition experimental model is used in data processing to distinguish six basic sleeping positions. In addition, the posture of falling and getting up can be recognized by the decision in the monitoring center. Finally, the predicted sleeping position is compared with the actual sleeping position to evaluate the performance of the system.

The results of the offline recognition experiment are shown in Fig. 6(a). The three sets of P sleeping position data are incorrectly identified as R1, which is due to the poor recognition accuracy of the model for P sleeping position. The eight-channel sensor data during the experiment is shown in Fig. 6(b), and the subject states correspond to various force combinations. The sensors produced larger measurements when the subject switched sleep positions due to shock loading. These force values are all within the range of the sensor.

IV. Discussion

In this section, some experimental results are discussed to further analyze the performance of the system. As shown in Fig. 4, the average linearity of the sensor is only 2.74%, but the sensitivity consistency is poor. The reason is that manual packaging brings large errors to the light intensity reflective sensor, which can be reduced by improving the packaging process. The developed mattress refers to the pressure distribution map of the human body in different sleeping positions to arrange the sensors, combined with the skin to expand the sensing range, which can effectively collect the user's sleeping position characteristics. Fig. 5 shows the results of the sleeping posture recognition experiment. The recognition accuracy of WOA-SVM for six sleeping positions can reach 96.6%, which is significantly higher than that of SVM, and it is also a huge improvement over the classic PSO-SVM. However, the prediction accuracy of the three algorithms for P sleeping position is always low, which can be solved by increasing the training set data of P sleeping position or adjusting the algorithm. It is worth mentioning that in the sleeping posture recognition experiment, the subject maintained each sleeping posture for the same time, which could make the data volume of each sleeping posture in the training set roughly the same. In the remote monitoring experiment, the subject randomly changed their sleeping positions to simulate real sleeping position monitoring scenarios. As shown in Fig. 6, only four points were identified incorrectly, which further verified the performance of the system.

V. Conclusion

This paper proposed a plastic optical fiber sensor-based remote monitoring system, which can be used to identify six sleeping postures and prevent dangerous situations such as the falling bed. A novel LEMS was proposed to sense pressure signals and the stiffness model was derived to guide the adjustment of the sensor sensitivity. Combined with prismatic-tip optical fiber, the thickness of the prepared sensor was only 6.9 mm, which can be integrated into the mattress without affecting user comfort. A hardware circuit based on STM32 was designed to realize real-time processing and wireless transmission of eight-channel sensor signals. The integrated process of the mattress was studied, and the prepared mattress has the advantages of portability, waterproof and anti-electromagnetic interference. A WOA-SVM was proposed for sleeping posture recognition, and the effectiveness of the algorithm was verified through the sleeping posture recognition experiment, and the accuracy for six basic sleeping postures was up to 96.6%. In addition, only four data points were misidentified in the offline remote sleeping posture monitoring experiment, indicating the system's ability to work in a real nursing environment. Benefiting from its good reliability and practicability, the sleeping posture monitoring system shows excellent application potential in assisting the rehabilitation of HF patients.

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