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Human Motion Monitoring Based on Carbon Nanotube Flexible Strain Sensor

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Aiming at the problems of traditional methods such as hysteresis, low accuracy of monitoring results, low motion recognition rate and poor sensitivity, a human motion monitoring method based on carbon nanotube flexible strain sensors is proposed. To realize human motion monitoring, first, the carbon nanotube flexible strain sensor is configured to obtain its performance parameters; Secondly, the human body motion acceleration data is collected through the window processing method, and the preprocessing is performed to filter out the noise data; A feature extraction model of human motion posture is established based on the data preprocessing results, which is used to extract human motion posture; Finally, by establishing a position model of human body motion node based on the carbon nanotube flexible strain sensor, the monitoring of human body motion is realized. The experimental results show that the proposed method has high accuracy (up to 90%), excellent recognition rate, with the maximum sensitivity coefficient close to the optimal value of 1.0, indicating practical application value.

Keywords: carbon nanotube flexible strain sensor; motion monitoring; motion acceleration data; sensitivity

1. INTRODUCTION

In contemporary society, the pace of life is fast, people have less and less time for taking exercise, leading to worse health condition. Some medical research shows that less physical activity will threaten human health, and lack of physical activity has a high correlation with the incidence of some chronic diseases [1-3]. Overnutrition or imbalance of body energy metabolism caused by people’s unreasonable diet is an important factor leading to chronic diseases. Therefore, a reasonable diet and scientific exercise are very important. For most people, a reasonable exercise intensity can improve the body’s physical fitness and health level [4,5]. The exercise status recognition technology can monitor people's daily exercise, identify the daily exercise status of the human body, and calculate the calories consumed, allowing people to understand their exercise status well, so as to formulate a reasonable exercise plan [6].

In order to accurately monitor the body function changes during human movement, experts and scholars have conducted relevant researches on human movement monitoring. In reference [7], a real-time identification method of motion posture based on laser three-dimensional detection technology is proposed. Firstly, according to the principle of laser three-dimensional imaging technology, a dynamic model of human posture is created, and quaternion is used to transform the coordinates in the dynamic model to obtain the actual posture angle of human motion. The human body space rectangular coordinate system is constructed, the peak changes of each axis in the coordinate system are analyzed according to the attitude angle solution method, and the identification structure of human body motion posture is obtained. On this basis, a real-time monitoring platform is created to realize the remote real-time monitoring of human motion posture. The simulation results show that the method can identify the human body's motion posture accurately in a real time manner without affecting motion acceleration, indicating high practical application value. However, this method has low recognition rate and shows some hysteresis in motion monitoring, which affects the real-time performance of the monitoring results. In reference [8], a three-dimensional human posture tracking method based on dual Kinect sensors is proposed. In order to improve the stability of human posture tracking, the human motion posture is represented by the degree of freedom vector of human joint points, the human posture is tracked by the unscented Kalman filter method, and a human posture tracking system based on dual Kinect sensors is built. The simulation results show that the system can accurately and stably track the three-dimensional human posture under simple movements, reflect the special properties of the movement process under complex movements, which is suitable for the performance evaluation of sports biomechanics. However, the system has low accuracy of monitoring results and shows hysteresis in certain degree. In reference [9], based on the algorithm of motion data acquisition and calculation, and improved median average filtering algorithm and an improved EWMA algorithm are proposed. The improved median average filtering algorithm introduces adaptive filtering factor and offset pre measurement in the calculation of filter output node position, and the improved EWMA algorithm introduces adaptive weight dynamic allocation function in the calculation of angle smoothing. In the data simulation test of the algorithm, the two improved algorithms and their original algorithms are comparatively analyzed. The experimental results show that the improved algorithm exhibits high stability in filtering and smoothing when the node is basically stationary by taking into account user action changes. Time node filtering predicts the real-time performance of the position and the real-time output of the angle smoothing value. However, this method is limited in monitoring human body movement due to poor sensitivity .

Aiming at the problems of traditional methods such as monitoring lag, low accuracy of monitoring results, low motion recognition rate and poor sensitivity, a human motion monitoring method based on carbon nanotube flexible strain sensors is proposed. Sensor is basically an instrument that transmits "feeling". The so-called "feeling" refers to all kinds of physical and chemical signals. Sensors can convert one physical signal into another observable or measurable (electrical and optical) signal, and produce electrochemical phenomena. Carbon nanotubes can be used as excellent micro-scale mechanical sensing media or sensors because of their excellent mechanical-spectral properties. Regarding its preparation, the shape memory polymer fiber is used as the substrate, the oriented carbon nanotube film is wrapped as the conductive layer, and then the conductive polymer is modified by electrochemical deposition to form the carbon nanotube/conductive polymer composite film with network structure. Strain sensor is a research hotspot in the field of medical treatment and human health, which can enable the tester to obtain human posture and physiological information in normal life, and transmit them wirelessly. Through processing and analyzing the data in background monitoring center, the tester's health level can be judged. Compared with traditional monitoring methods, strain sensor has many advantages, such as small size, low cost, low power consumption, easy to carry, etc., so it has been gradually applied in various fields in recent years [10]. In this paper, carbon nanotube flexible strain sensor is taken as the research object, and its role in human motion monitoring is analyzed, so as to improve the effect of human motion monitoring.

2. HUMAN MOTION MONITORING METHOD DESIGN

2.1 Overall scheme design of human motion monitoring

Firstly, the carbon nanotube flexible strain sensor is prepared. Secondly, the prepared carbon nanotube flexible strain sensor is used to collect the human body acceleration signal. Since the collected acceleration signal contains a lot of noise information, the it needs to be preprocessed. For noise interference, the data is separated by a windowing method, and the sample length is separated into a fixed length [11,12]. The pre-processed data needs to be extracted for feature values. The more features are not the better, and those features that are more relevant to human behavior should be selected. Due to large amount of many features, there will be redundancy between them and the amount of calculation will be increased. And the influence coefficient of the feature will also become smaller. Finally, the carbon nanotube flexible strain sensor is applied to human motion monitoring, and the sensor node position model is established to realize effective monitoring of human motion in different states. Figure 1 shows the human motion monitoring process.

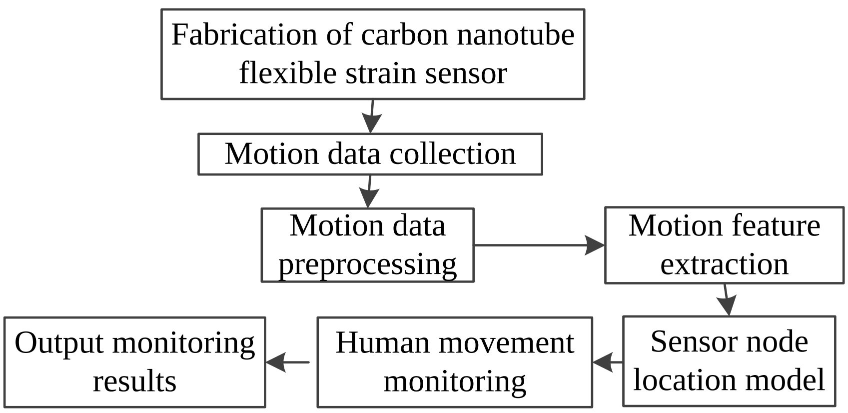

Figure 1. Flow chart of human motion monitoring

2.2 Preparation of carbon nanotube flexible strain sensor

Flexible strain sensors can be attached to the surface of human skin to measure and quantify human biological information and physiological activities. It has a broad application prospect in the fields of human-computer interaction, intelligent robots, and biomedical monitoring. Flexible strain sensors are mainly divided into piezoresistive, piezoelectric and capacitive sensors according to the difference of working mechanism. Among them, piezoresistive sensor is the most commonly used due to simple manufacturing process and low cost [13]. In order to prepare a flexible piezoresistive sensor with high tension and high sensitivity, the sensitive material can be placed on the sensor substrate through a certain preparation method. Among many sensitive materials, carbon nanotubes have excellent electrical conductivity, mechanical properties and chemical inertness. In this paper, a kind of micro convex structure on the surface is proposed by mixing MCNTs and semi cured epoxy resin substrate on the surface and brushing them on the surface sequentially with a brush. The microstructure can significantly improve the performance of the sensor. The carbon nanotube flexible strain sensor prepared by this method can meet the needs of monitoring large deformation movements such as fingers and wrists, and can be used to monitor small deformation movements such as human muscles [14].

The procedure of sensor preparation is as follow:

(1) The polyvinyl chloride mold was attached to the polyethylene terephthalate (PET) film;

(2)The epoxy resin was put into the vacuum drying oven for vacuumizing, and then poured into the mold on the PET film before standing still for 30min. Then, the multi walled carbon nanotubes were dipped in the brush and coated on the epoxy resin surface in sequence. The epoxy resin was stored at room temperature for 4h for complete curing;

(3) Finally, the epoxy tape coated with MWNTs was peeled off from the mold, the silver glue was coated on both ends of the epoxy tape with copper wire drawn out, and silver glue was cured at room temperature for 4 h.

The circuit diagram of the carbon nanotube flexible strain sensor is shown in Figure 2:

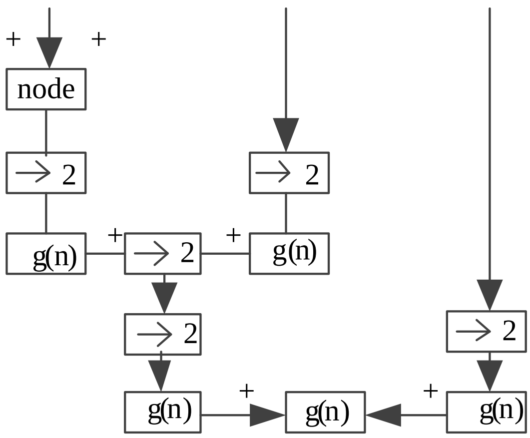

Figure 2. Sensor circuit diagram of carbon nanotube flexible strain sensor

The performance parameters of the carbon nanotube flexible strain sensor are shown in Table 1.

Table 1. Sensor performance parameters of carbon nanotube flexible strain sensor

Parameter	Specification
Voltage	3.5V~5V
Current	<30mA
Measurement dimension	Acceleration 3 dimensions, angular velocity 3 dimensions
Attitude measurement stability	0.01°
Data output frequency	0.1Hz-200Hz
Data interface	Serial TTL level
Stability	Acceleration 0.01g

2.3 Collection and preprocessing of human body motion acceleration data

The human body motion signal collected by the carbon nanotube flexible strain sensor includes the acceleration signal generated by the human body motion and the gravitational acceleration signal of the human body. Due to body shaking during exercise, the measurement noise of the system, and the interference signal in the fixed and unstable state of the equipment, the accuracy of the measurement will be affected[15]. Therefore, it is necessary to preprocess the collected original acceleration before monitoring the motion state. Common preprocessing operations include windowing, smoothing, denoising, resampling, normalization, and tilt correction. The collected raw acceleration data is the acceleration signal collected continuously for a period of time. These data contain many complete action cycles. However, such a large sample is not required for feature extraction. For example, the acceleration data during walking is collected. These data contain a lot of steps, but in fact only a complete step is needed [16]. Therefore, the first step is to window the data, that is, the longer acceleration signal is divided into many segments with the same length. Each segment is a window, and the overlapping length of adjacent windows is set to half of the window length. The schematic diagram of windowing is shown in Figure 3.

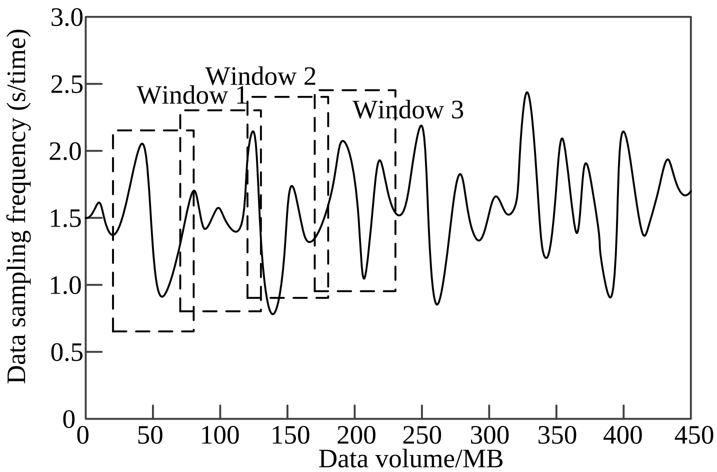

Figure 3. Schematic diagram for windowing the acceleration signal of human motion

The data will be shorter and the data length will remain unchanged through windowing, which is conducive to the subsequent feature extraction and selection. Since the collected acceleration signal contains a lot of noise, it is necessary to perform denoising processing to filter out the noise after windowing the original acceleration signal. The noise signal of the original accelerometer generally has high frequency, and the bandwidth of human motion is far less than that of the accelerometer, so it is necessary to filter out the high frequency information and retain the low frequency information. Therefore, Butterworth low-pass filter is adopted to process the original acceleration data [17]. The human motion signal before and after filtering is shown in Figure 4.

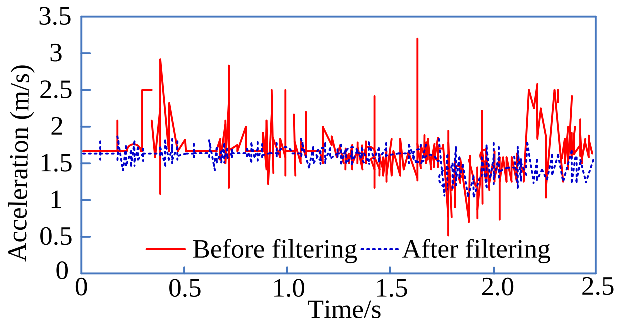

Figure 4. Human motion signal before and after filtering

According to Figure 4, it can be seen that the high-frequency signal is filtered, and the signal is in a relatively stable area, which can be well used for the subsequent extraction of human motion features.

2.4 Extraction model of human body motion posture feature

An extraction model of human body motion posture feature is established to extract postures such as support, rotation, running, and walking in the human body motion state. The model considers the calculation principle of the complementary analysis algorithm, introduces the human dynamic characteristic parameters, which meets the characteristics of the human body motion texture change:

$$r_{ij}=\sum_{k=1}^{n}\left(x_{ki}-\bar{x}_i\right)\left(x_m-\bar{x}_j\right)/\sqrt{\sum_{j=1}^{n}\left(x_n-\bar{x}_i\bar{x}_j\right)^T} \quad (1)$$

Where, n represents the body part; x_{ki} represents the rate of change of human body motion posture; $\bar{x}_i$ represents the limit value of human muscle activity; T represents the weight coefficient; $\bar{x}_j$ represents the posture correction coefficient; x_n represents the cross product of human body motion acceleration and actual acceleration; x_m represents the static state characteristic parameters of human motion.

Use this model to extract features of human motion posture:

$$\sigma_{ki}\left(t\right)=\frac{\sigma_{ki}\left(t+1\right)+\eta\left(y'-y\right)\lambda_{ki}\left(t\right)}{(a,b,c)} \quad (2)$$

Where $\sigma_{ki}\left(t\right)$ represents the human body motion posture feature vector; y represents the human motion bone node; y' represents the adjacent node connected to the motion bone node; x_i , y_i and z_i represent the three-dimensional coordinates of the node, respectively; (a,b,c) represents the three-dimensional coordinates of the human body. According to the formula (2), the following equations of the determinative characteristic of human motion nodes are derived:

$$\begin{cases} r_{pp} = \cos\theta + R\times\sin\left(\partial_1\right)\times\cos\theta - y_0\times\sin\theta \\ r_{qq} = \cos\theta\times[R\times\cos\left(\partial_1\right)\times\sin\theta + y_0] \\ r_{pq} = \cos\theta - y_0\times\sin\theta \\ r_{qp} = \sin\theta + R\times\sin\left(\partial_1\right) \end{cases} \quad (3)$$

Where $\cos\theta$ represents the human motion angle; $\sin\theta$ represents the limit value of the human motion angle; ∂_1 represents the feature vector; R represents the correlation degree of the human motion acceleration data on different coordinate axes. Then, following calculation formula is obtained:

$$R=\sqrt{\left(\frac{l}{2}\right)^2+\left(\frac{m}{2}\right)^2} \quad (4)$$

Where l represents the geometric mean of human body motion acceleration data; m represents the output value of the sensor.

Using the human body motion texture change model, parameters such as the force characteristics of the bones, the motion angle, and the muscle activity characteristics of the human body can be obtained.

2.5 Human motion monitoring based on carbon nanotube flexible strain sensor

In general, traditional strain sensors are prepared by depositing conductive materials on the surface or inside of a flexible substrate. For example, a strain sensor with a special three-dimensional conductive network has good durability and stability, and can convert the structural deformation of the conductive material caused by an external strain stimulus into a resistance change, thereby realizing the detection of strain. However, there is a trade-off relation between high sensitivity and the excellent performance of conductive network of the sensor. Although strain sensor has a broad application prospect, it is still a huge challenge to manufacture strain sensors with high sensitivity [18].In this work, the carbon nanotube flexible strain sensor prepared in section 2.2 is used to improve the sensitivity of the traditional strain sensor.

The position model of the human body motion node based on the carbon nanotube flexible strain sensor is established, and its partial topological structure is shown in Figure 5.

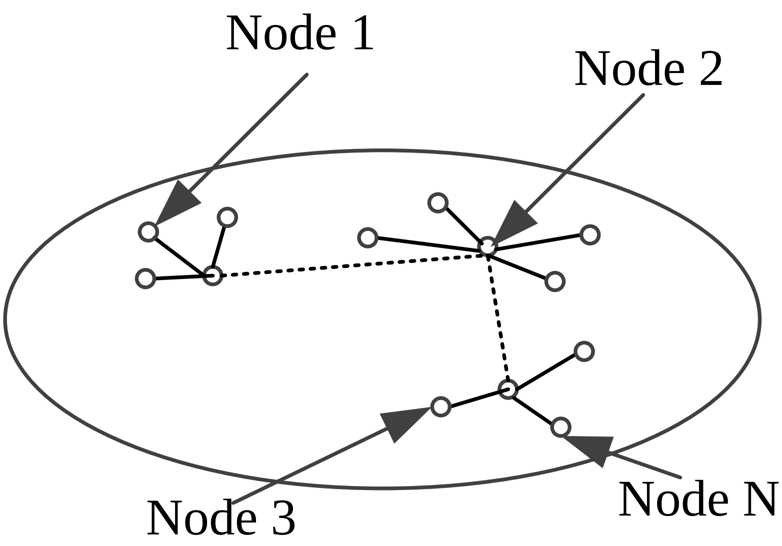

Figure 5. Position model of human body motion nodes

Set the collinearity of 3 axes included in the human motion node position model, the expression is as follows:

$$\delta_k = \arctan\left(\frac{m}{l}\right) - \left(\sigma\omega_1 + \frac{1}{\omega_2 C}\right) \quad (5)$$

Where C represents the inner angle of the triangle formed by the 3 axes in the monitoring sensor; ω_1 represents the energy consumption of the exercise; ω_2 represents the exercise intensity; σ represents the geometric average of the acceleration of the 3 axes, of which the calculation formula is:

$$\sigma = \frac{1}{T}\int_{T_0}^{T_1} u(t)\, i(t) \quad (6)$$

Where T_0 represents the time-domain characteristics of human motion; T_1 represents the time-frequency characteristics of human motion; $u(t)$ represents the degree of dispersion of the acceleration signal; $i(t)$ represents the body mass index coefficient. When $\delta_k = 1$, the nodes on the 3 axes are completely collinear.

According to formula (5) and formula (6), when the collinearity of the nodes on the 3 axes is $\delta_k = \arctan\left(\frac{q(t)}{s(t)}\right)$, the error of human motion monitoring results is the smallest.

When the node information on different coordinate axes is received, the collinearity of the closer nodes among the unknown sensor nodes is calculated as follow:

$$\delta_a = \cos(y_a l_a) - Z_a \sin(y_a l_a) \quad (7)$$

Where $\cos(y_a l_a)$ represents the position estimation result of the anchor node group; $\sin(y_a l_a)$ represents the neighbor anchor node information; Z_a represents the topological relationship between the anchor node and the unknown node.

According to the calculated node collinearity, the position information of the unknown sensor node is further solved. When using the carbon nanotube flexible strain sensor to automatically select the anchor node closest to the center node as a candidate anchor node, the following conditions need to be met:

$$\tau_i \cdot t^p \cdot C\left(\Pr_i\right) \geq \tau_i \cdot t^b \cdot C\left(\Pr_j\right) \quad (8)$$

Where τ_i represents the distance vector; t^p represents the target area of node distribution; t^b represents the actual area of node distribution; $\Pr_i$ represents node scheduling; $\Pr_j$ represents virtual coordinate information.

Assume that the carbon nanotube flexible strain sensor node is constructed by a node with an unknown location (i.e., a known node for human motion monitoring) and a sensor layer node with a known location (i.e., the anchor node of the human motion monitoring sensor) [19,20]. N_i represents the number of monitoring nodes, and M_i represents the number of anchor nodes. Then in the three-dimensional plane, the parameters of the monitoring nodes are:

$$N_i = \frac{M_i}{(x_i, y_i, z_i)} \quad (9)$$

The node position parameter of the carbon nanotube flexible strain sensor is α, which can be expressed as follows:

$$\alpha = \left[\theta_x, \theta_y, \theta_z\right]^T \quad (10)$$

Where θ_x, θ_y and θ_z represent the position parameter of the carbon nanotube flexible strain sensor node; T represents the limiting threshold. The human body motion parameters are output through the node position of the carbon nanotube flexible strain sensor, so as to realize the real-time monitoring of the human body motion parameters.

3. SIMULATION EXPERIMENT AND DISCUSSION

In order to verify the effectiveness of the human motion monitoring method based on the carbon nanotube flexible strain sensor, a simulation experiment is designed. The comparative analysis was carried out between the proposed method and the methods in reference [7] [8] [9].

3.1 Experiment preparation

In this paper, 10 boys and 10 girls were enrolled as volunteers to collect human motion data. The carbon nanotube flexible strain sensors were worn at the waist and connected to mobile APP through Bluetooth. Each person did jogging, fast walking, fast running, basketball and football, respectively. The carbon nanotube flexible strain sensor was used to collect the signals of six kinds of sports of the 20 volunteers. The acquisition frequency was 25Hz, and 1500 data were transmitted per minute. The collected data were sent to the computer for data processing through MATLAB software.

3.2 Experimental hardware environment

This experiment was carried out in the experimental environment shown in Table 2.

Table 2. Experimental hardware environment

Parameter	Specification
Simulation platform and version	NS2
Letter of agreement	Zigbee
Maximum stay time of nodes in the network	0.5 s
Transmission channel Doppler frequency	0.5
Output signal strength	24dB
Testing time	60min
RAM	8G
Operating system	Windows 10

In the above-mentioned experimental environment, the monitoring performance of different methods was tested, and the specific test results were analyzed.

3.3 Analysis of experimental results

(1) Motion recognition rate

The recognition rates of 20 volunteers for slow walking, fast walking, jogging, fast running, upstairs and downstairs movements were tested, and the results are shown in Table 3.

Table 3. Motion recognition rate

Exercise type	Recognition rate/%			
	The proposed method	Reference [7] method	Reference [8] method	Reference [9] method
Walk slowly	95	74	79	75
Go fast	92	72	76	73
Jogging	91	69	73	70
Run fast	90	67	70	67
Basketball	89	65	69	63
Football	87	61	67	60

It can be seen from table 3 that the recognition rate of traditional methods for different types of sports is under 80%, while that of the proposed method is more than 90% except for basketball and football. Among them, the recognition rate of jogging is 95%, which indicates that the proposed method can well recognize different human motion states on the whole, with high recognition rate.

(2) Hysteresis analysis

Ideally, the hysteresis curve of the sensor is a repeating curve. However, due to the sensor's own response and material defects in the manufacturing process, there is a difference between the positive stroke and the reverse stroke. Figure 6 shows the hysteresis curve of the strain band of the carbon nanotube flexible strain sensor designed in this paper.

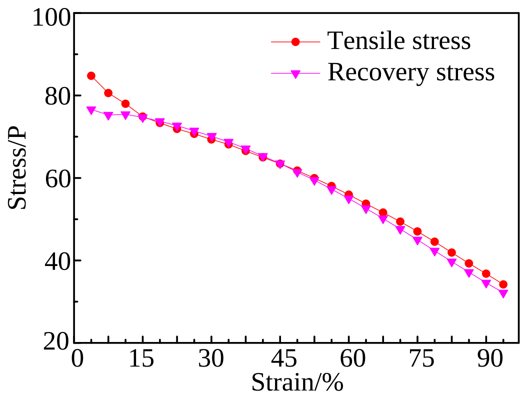

Figure 6. Hysteresis curve of strain band of carbon nanotube flexible strain sensor

It can be seen from Figure 6 that under the same strain, the stress change rate of the carbon nanotube flexible strain sensor during the recovery process is relatively close to the stress change rate during the stretching process, and the maximum change rate difference is about 2%. Only when the stress is less than 15%, the required stress during the stretching process is greater than that during the recovery. This is because during the recovery process, a creep phenomenon will occur, and it will take a certain time to recover to the original length, and the creep will make the stress smaller. The above analysis shows that the hysteresis performance of the strain band of the carbon nanotube flexible strain sensor is better.

(3) Sensitivity test

Sensitivity is one of the important indicators to evaluate the performance of the sensor. It specifically refers to the ratio of the output of the sensor to the input in the temperature state, which can be obtained from the rate of change of resistance in the dynamic test:

$S = \Delta R / R_o$ (11)

Where S represents the rate of change of resistance; ΔR represents the resistance of the sensor strain band after being stretched; R_o represents the resistance of the sensor strain band before being stretched. According to formula (11), the sensitivity of the sensor can be obtained as:

$G = S / \varpi_i$ (12)

Where S represents the sensitivity of the sensor; ϖ_i represents the gage factor.

According to the above formula, the human motion monitoring sensitivity under different methods is calculated, and the results are shown in Figure 7.

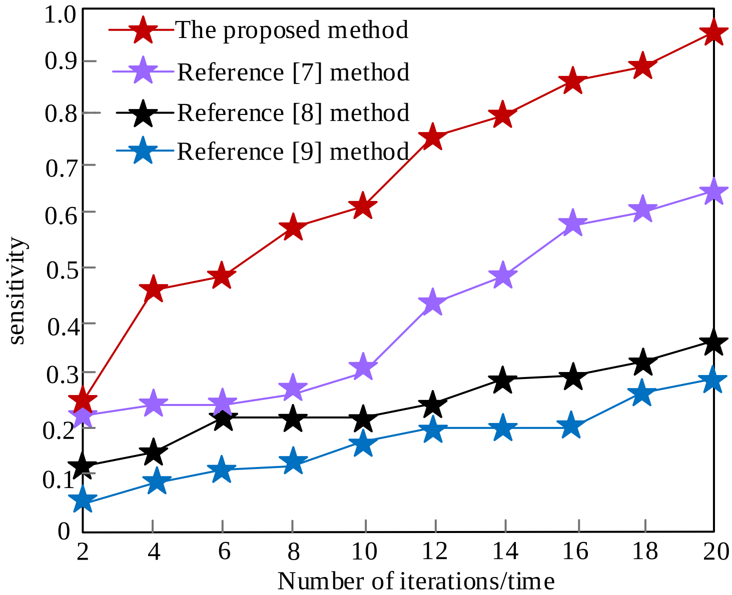

Figure 7. Comparison of the sensitivity of human motion monitoring by different methods

It can be seen from Figure 7 that the human motion monitoring sensitivity of the proposed method is significantly higher than that of the traditional method, and the highest sensitivity coefficient of the proposed method is close to 1.0, while that of the traditional method is less than 0.7. It shows that the proposed method is more sensitive and can realize flexible monitoring of human movement.

In order to further verify the applicability and effectiveness of the proposed method, it is compared with traditional methods from monitoring accuracy. The results are shown in Figure 8:

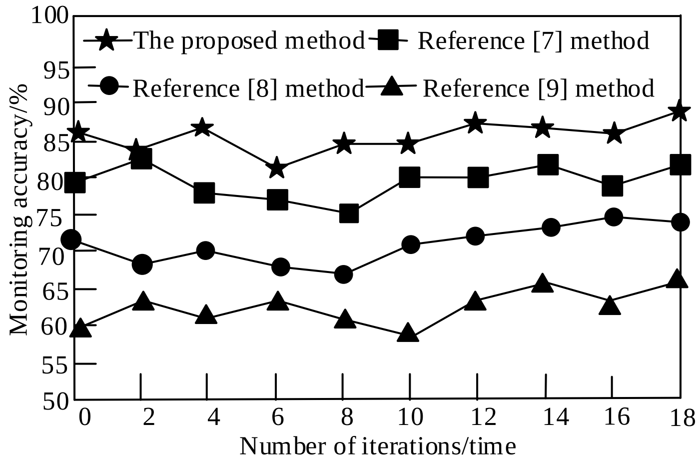

Figure 8. Comparison of recognition accuracy of different methods

It can be seen from the monitoring accuracy curve in Figure 8, the proposed method has advantages over the traditional method. According to Figure 8, the accuracy of the human motion monitoring of the proposed method can reach 90%, and that of the method in reference [7] [8] [9] is only 84%, 75% and 66%, respectively, indicating that the proposed method is more reliable than the traditional methods.

4. CONCLUSION

In order to improve the monitoring accuracy, motion recognition rate and sensitivity of human motion monitoring methods, a human motion monitoring method based on carbon nanotube flexible strain sensors is proposed. The experimental results show that the proposed method can well recognize the different motion states of the human body with a high recognition rate; the hysteresis performance of the carbon nanotube flexible strain sensor strain band is better; the highest sensitivity coefficient is close to 1.0; The accuracy of motion monitoring results can reach 90%. The above experimental results fully verify the effectiveness of the proposed method.

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