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ORIGINAL

ATHLETE TRAINING LOAD MONITORING USING SENSOR-BASED TECHNOLOGY AND MOTION IMAGE ANALYSIS

Changdi Luo[1], Hong Yang[1]*

[1] Sports Academy, Henan Normal University, Xinxiang City, Henan, XinXiang, 453007, China.
E-mail: 18483641668@163.com

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ABSTRACT

Currently, training load monitoring is mainly divided into vision-based motion monitoring and wearable sensor-based motion monitoring. Vision-based motion monitoring tends to have a poor monitoring range and is affected by the environment, which makes it difficult to carry out long-term accurate monitoring and at the same time violates privacy. Wearable sensor-based motion monitoring is not affected by the above factors, this paper combines the advantages of the two, and proposes a training load monitoring method for athletes based on sensor technology and motion image analysis, which can be used for motion monitoring anytime and anywhere. In traditional wearable IMU-based motion monitoring algorithms, a large number of features usually need to be extracted for recognition, however, the extraction of features often requires specialized domain knowledge, and if the extracted features are not suitable it will lead to difficulties in improving the accuracy of the algorithm. Therefore, this paper proposes a two-stage neural network motion monitoring algorithm to identify periodic and non-periodic motions separately, which can effectively reduce the complexity of the network and also improve the accuracy of the recognition of each motion. In addition, this paper proposes a data enhancement algorithm based on acceleration data, which solves the problem of fewer data samples in some datasets, greatly increases the number of samples without re-collecting data, and is more suitable for end-to-end neural network training to further improve the accuracy of the algorithm recognition, and the results of the simulation experiments show that it can be applied to the actual situation.

KEYWORDS: Athlete Training Load Monitoring; Sensor-Based Technology;

Motion Image Analysis; Medical Neural Network; Deep Learning

1. INTRODUCTION

With the increasing attention to physical education, the scientific nature of physical training and education has received increasing attention, and the construction of real-time monitoring of physical training load data, combined with the quantitative analysis of physical training load data, analysis of the correlation characteristics of the constraints on the effect of physical training, the establishment of how the human body individual variability characteristics of the real-time monitoring of the physical training load data model, to improve the relevance of the physical training and real-time analysis capabilities, the relevant research on physical training methods has attracted great attention (Fox, Stanton, Sargent, Wintour, & Scanlan, 2018; Jaspers, Brink, Probst, Frencken, & Helsen, 2017; McLaren et al., 2018).

To establish a real-time monitoring model of physical training load data to improve the relevance of physical training and real-time analysis ability, the research on real-time monitoring method of physical training load data has received great attention. The real-time monitoring of physical training load data is based on the dynamic analysis of physical training load data and sensing monitoring, the sampling of sensing information and characteristics of physical training load data is analysed, and the correlation feature analysis method is combined to achieve real-time monitoring of physical training load data.

The increase of physical training load data needs to be combined with optimised data and information processing methods to achieve the detection and identification of physical training load data, combined with dynamic data real-time monitoring methods for dynamic analysis of physical training load to achieve real-time monitoring of physical training load data (Griffin et al., 2021; Halson, 2014). In the field of sports, athletes usually need to ensure the amount of exercise to maintain the best state, according to the traditional subjective method of judging whether the exercise is up to the standard or not, it is easy to cause under-exercise and over-exercise to happen (Boni, 2022).

Insufficient exercise will not achieve the desired effect, and excessive exercise will lead to problems such as decreased muscle strength, decreased sleep quality, insomnia and decreased resistance, which will cause great damage to one's physical health. Therefore, scientific quantitative data of exercise load is needed to reflect the physical state of athletes during training and to improve the quality of athletes' training .

At present, there are two main types of pacing algorithms in sports load monitoring: one is the dynamic threshold method, which is based on the acceleration data to dynamically calculate a certain range of thresholds, and when the acceleration data crosses the threshold, it will be recorded as a step, and this method makes use of the ascending or descending area of the acceleration curve waveform to make a judgement, and the other is the peak detection method, which looks for the peak of acceleration signals based on the acceleration signal slope, and then calculates the effective peak through the number of effective peaks, and then calculates the peaks.

Calculate the number of movement steps by the number of valid peaks, and then judge the pace from the position of the inflection point of the signal waveform (Mahajan & Banerjee, 2022). The GSP positioning system of the smartphone is used to determine the user's movement distance, and then divided by the user's step length to get the number of steps. This is obviously more troublesome and has a larger error.

Nowadays, wearable smart devices are developing in the direction of integrating multiple sensors, and technologies such as GPS positioning have also been used in the field of sports step detection to improve the accuracy of detection (Zhao, Stankovic, & Stankovic, 2016). With the development of technology, various types of chips, including electronic sensors, are developing in the direction of low power consumption, low cost, and miniaturization. In addition, the emergence of Bluetooth 4.0 technology provides a hardware platform for the development of intelligent devices.

In addition, the continuous maturity and improvement of the two major systems, Android and IOS, and the popularity of smartphones and tablets have provided growth soil for the development of portable smart devices. On September 5, 2014, Motorola released a new generation of 360 smartwatch Moto 360, which can complete functions such as heart rate monitoring, intelligent step counting, calorie recording and exercise management.

In addition, Apple announced the smart watch Apple Watch in September 2014 and Microsoft Band, a wearable device released by Microsoft on October 30, 2014. Both of these smart devices can monitor exercise conditions in real time and help users grasp their own exercise and health status in real time. Domestic manufacturers also have many excellent products.

In 2014, Xiaomi released the Mi Band, which is easy to carry and has functions such as step counting, sleep monitoring and energy consumption detection. On June 16, 2015, Tencent and Shenzhen Inqu Technology jointly launched the new smart watch product in Watch T.

The physical styles of some of the mainstream health monitoring wearable devices currently on the market are shown in Figure 1. With the development of wearable smart devices, more functions will be integrated into wearable smart devices. People can use these smart devices to better control their own health conditions and obtain a healthier and more scientific quality of life (Alexandre, Ricardo, Daniel, Dumitriu, & Salvador, 2018).

(a) (b)

Figure 1: Some wearable smart devices. (a) Apple Watch. (b) Xiaomi.

The main principle of wearable IMU based motion monitoring is as follows: firstly data is collected from multiple sensors in the IMU such as accelerometers and gyroscopes, etc., and the IMU is usually placed at the waist, thighs, ankles, wrists, etc. , and then the raw data is subjected to operations such as filtering, followed by feature extraction, and then finally recognition of daily movements and falls using methods such as machine learning (Bertholet et al., 2019; Ge, Huang, Shao, & Dong, 2018). The miniaturisation of electronics has made them easy to use and has become the method of choice for effective and cost-efficient motion monitoring techniques. Therefore, the use of wearable IMUs for motion monitoring of athletes is a future trend of great relevance. In addition, the introduction of motion image analysis technology (Hua & X, 2023) is more effective in improving the accuracy of training load monitoring in athletes. The main contributions are as follows:

(1) This paper proposes a two-level neural network motion monitoring algorithm that separately identifies periodic motion and non-periodic motion, which can effectively reduce network complexity and improve the recognition accuracy of each motion.

(2) In this paper, a data enhancement algorithm based on acceleration data is proposed, which solves the problem of fewer data samples in some datasets, greatly increases the number of samples without re-collecting data, and is more suitable for end-to-end neural network training to further improve the monitoring accuracy of the algorithm.

2. Methodology

2.1 Overall design of monitoring system

The exercise load monitoring system designed in this paper includes three parts, namely, human movement information acquisition system and

Android intelligent terminal as well as monitoring algorithm, as shown in Figure 2.

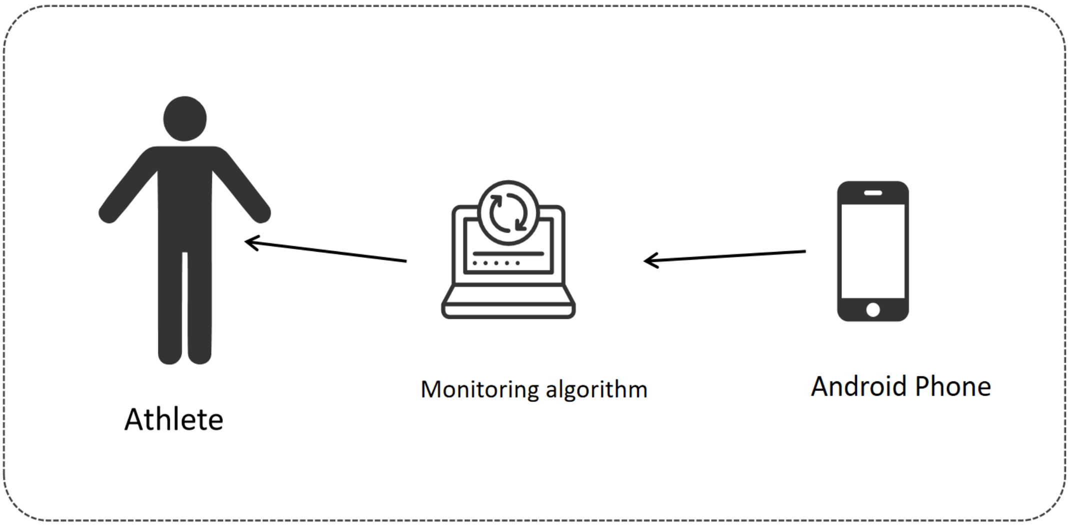

Figure 2: Schematic diagram of exercise load monitoring system

The human body movement information acquisition system includes four parts: three-axis acceleration sensor, microcontroller, data storage and wireless communication. The system collects the athlete's body movement information, processes the data in real time to get the athlete's movement load information, and finally transmits the processed results to the Android intelligent terminal through the wireless transmission module, which realises the function of displaying and recording the results of the athlete's movement information to help the athlete grasp his/her own movement load situation at any time.

The system can also save the raw acceleration data collected first, and then observe the details of human movement through specific data, the specific structure of the system's sports information collection system is shown in Figure 3.

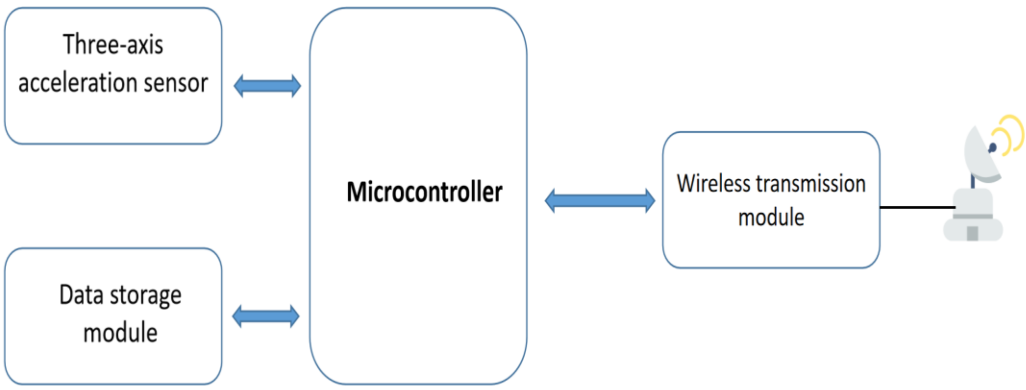

Figure 3: Schematic diagram of the structure of the sports information collection system.

2.1.1 Information collection module

During daily activities, the frequency range of the main part of the body of the human body movement is between 0Hz~20Hz, and its acceleration component generally does not exceed 6g. When a person walks, the vertical component of the frequency of the upper body part is mainly concentrated in the range of 0.8Hz~5Hz, with the amplitude range of -0.3g~0.8g, and the amplitude of the horizontal component of the torso part and the position of the head is between -0.3g~0.4g and -0.2g~0.2g, respectively. ~0.4g and -0.2g~0.2g respectively. When the human body is running, the amplitude of the vertical component is between 0.9g~5.0g and 0.8g~4g for the torso part and head position, respectively. Therefore, when measuring the acceleration of human movement, in order to obtain as much detailed information about the movement as possible, and do not have to take up too much storage space, the acceleration sensor range selected by this system needs to be more than 6g, and the sampling frequency range needs to be more than 50Hz. Currently on the market using more acceleration sensors such as STMicroelectronics LIS3DH, Bosch's BMA250, MPU6500 and ADI's ADXL362. In this paper, ADI's digital acceleration sensor ADXL345 is chosen as the system's acceleration measurement chip. ADXL345 can measure the acceleration of up to 16g with high resolution, and the output data rate ranges from 0.1Hz to 3200Hz under normal power consumption, and from 12.5Hz to 400Hz under low-power mode. small size, can be programmed to change the acceleration range and other characteristics. It can well meet the application requirements of the system in this paper.

2.1.2 Microcontroller

The system in this paper needs to process the collected human movement information to obtain information such as the number of steps and energy consumption of athletes. This article chooses FPGA as the main controller of this system. The rapid development of microelectronics technology has enabled FPGA chips to meet the needs of all aspects of social development in terms of cost, integration and power consumption. In particular, the FPGA-based SOC concept combines the advantages of hardware and software working together to achieve the organic integration of upper-layer tasks and underlying hardware. FPGA as a semi-customized application-specific integrated circuit, as a semi-customized ASIC, FPGA makes up for the shortcomings of customized circuits and overcomes the limitations of gate resources of programmable devices. The new generation of FPGA devices integrates a CPU based on the ARM architecture, which has the characteristics of multi-threading and high speed. When designing a dedicated circuit, a hardware description language such as Verilog or VHDL is used. The netlist file after synthesis, layout and wiring is burned into the configuration memory. After each power-on, the FPGA loads the external configuration file into the internal

RAM., from implementing customized digital circuits. Commonly used MCUs are mainly oriented to transaction management and control, while DSPs are oriented to signal calculations and are mainly used for algorithms and digital signal processing. Compared with MCU and DSP, FPGA is more flexible. The FPGA is integrated with a dedicated digital processing macro unit Dsp48, which can implement digital signal processing. Compared with the software implementation of DSP, digital operations based on hardware implementation have higher speed. In addition, FPGA's large number of I/O ports can be flexibly configured to connect multiple levels of standard interfaces. In addition, FPGA has parallel processing characteristics, which makes its processing efficiency and real-time performance more prominent. This design uses Xilinx's sixth-generation Spartan series XC6SLX9 as the main control chip of the system. This series of FPGAs is the best balance of low risk, low cost and low power consumption. Compared with previous generations of devices, it not only reduces power consumption by 42%, but also improves performance by 12%. There are many packaging methods for XC6SLX9. This article uses the CPG196 packaging method. The XC6SLX9 in this package is only 8mm*8mm in size, which greatly saves the space of the system hardware circuit board. In addition, the operating voltage of XC6SLX9 is 3.3V low voltage. It has 9152 logic units and advanced memory to support 250MHz DSP Slice. It can well meet the requirements of the system design in this article.

2.1.3 Data storage module

The system in this article has the function of processing data in real time to directly obtain the movement results. It can also save the data first and then observe the details of human movement through specific data. In addition, in view of the fact that users often do not carry mobile phones during daily exercise, this system will use large-capacity storage Nand Flash chips during the design process. Nand Flash semiconductor memory has the characteristics of large capacity, small size, low power consumption, high storage rate, and impact resistance. In addition, Nand Flash chip has the characteristics of simple interface circuit and the ability to store data for a long time, and has been widely used in large-capacity storage systems. Although the Nand Flash chips have different models and different storage sizes, their operation methods are basically the same, so the interoperability of the codes is relatively strong. This article uses Samsung's K9K8G08U0A chip as the data storage module of the system.

2.1.4 Wireless transmission module

Wireless communication has the characteristics of convenience, security, and not limited by geographical conditions. It has a wide range of applications in the field of wearable smart devices. In this paper, the system selects the wireless way to communicate so that the system will not cause movement interference to the athletes because of the wired line.

At present, we commonly used short-range wireless transmission technology mainly consists of the following kinds: Wi-Fi, ZigBee, infrared, UWB and Bluetooth. Various wireless transmission methods have their own characteristics, and their respective characteristics determine their different application scenarios. ZigBee is a low-power, low-cost wireless transmission method, its transmission rate is only 10~250kbit/s, network capacity is large, an area can exist at the same time up to 100 networks. ZigBee has a very wide range of applications in the smart home, automotive electronics, industrial control, etc. Wi-Fi has a very wide range of applications in the smart home, automotive electronics, industrial control and so on. Wi-Fi is a kind of wireless extension technology of Ethernet, the transmission rate of Wi-Fi is still improving with the evolution of the technology, besides smart phones, tablet PCs, printers, washing machines and other household appliances are using Wi-Fi, Wi-Fi technology has a very strong competitiveness in the future home connectivity market. But Wi-Fi technology is still improving, such as the need to further reduce power consumption. NFC is the abbreviation of Near Field Communication (Near Field Communication), this technology evolved from the contactless radio frequency identification (RFID).

NFC is a short-range, high-frequency radio technology, in the 13.65MHz frequency operating at a distance of 20cm. Transmission rates are 106kbit/s, 212kbit/s or 424kbit/s. The biggest disadvantage of this technology is that it can be used for a wide range of applications. The biggest disadvantage of this technology is the short transmission distance, which makes it unsuitable for use in wearable devices. Bluetooth wireless technology is a radio technology that supports short-range communication of devices and allows wireless information exchange between smartphones, car audio systems, wireless headphones, game consoles and many other devices. Bluetooth has a very wide range of applications in electronic devices, smart homes, wearable smart devices and other fields. Especially the birth of Bluetooth 4.0 has expanded the application of Bluetooth technology, as shown in Table 1.

Table1: Comparison of short-range wireless communication methods

TYPE	WIFI	ZIGBEE	IRDA	UWB	BLUETOOTH
COMMUNICATION SPEED	54Mb/s	<1Mb/s	4Mb/s	100Mb/s	1Mb/s
COMMUNICATION DISTANCE	>100m	50m	2m	50m	10m
POWER CONSUMPTION	High	Middle	Middle	High	Low
COSTS	Middle	Low	Low	Low	Middle

Considering that the system in this article needs to transmit the processed data to Android smart terminals, the two wireless methods of WiFi and Bluetooth are first considered. Among these two methods, WiFi consumes relatively large amounts of power and is not suitable for the low power consumption requirements of the system. Therefore, this article finally chooses Bluetooth technology as the wireless transmission method of the system.

2.2 Training load monitoring algorithm based on two-level neural network

In the motion monitoring recognition algorithm based on wearable IMUs, traditional methods tend to extract a large number of features from the data, and then the feature vector composed of these features is used as the input to the neural network (Chen, Li, et al., 2023), but the extraction of the features often requires specialised domain knowledge, and if the extracted features are not appropriate they will directly affect the final classification results, leading to difficulties in improving the accuracy of the model.

At the same time, if the feature dimension is continuously increased, it also leads to an increase in the amount of computation. With the deepening of deep learning research (Chen, Han, Zhang, You, & Zheng, 2023; Ye, Wang, Sun, Zhang, & Li, 2024), many researchers have proposed end-to-end neural networks, which do not involve artificial feature extraction and can obtain classification results by directly inputting the original data. End-to-end neural networks can automatically learn the features in the data, thus avoiding the trouble of feature extraction and also improving the accuracy of recognition.

A large number of researchers have started using end-to-end neural networks for motion recognition, but due to the diversity and complexity of motion, there are some problems with single-level neural networks. Although the overall accuracy is high, the recognition rate for some complex motions is still low, and the false positive rate is also high.

In addition, the depth of the neural network has to be increased in order to recognise more motions, leading to an increase in computational effort, which makes it unsuitable for running on wearable devices. In order to solve the above problems, this paper proposes a motion monitoring algorithm based on a two-level convolutional neural network. Taking the classification in UMAF all data as an example, this paper divides all the motions into two categories of periodic and non-periodic for identification, the first level neural network mainly identifies walking, jogging, jumping and climbing stairs, and the second level neural network mainly identifies falling, bending, lying down and sitting down.

Compared with the single-level neural network, this paper divides the complex, multi-species motions into two categories for recognition, which can effectively reduce the network complexity, and also save the time of certain motion recognition, and at the same time improve the recognition accuracy of individual motions.

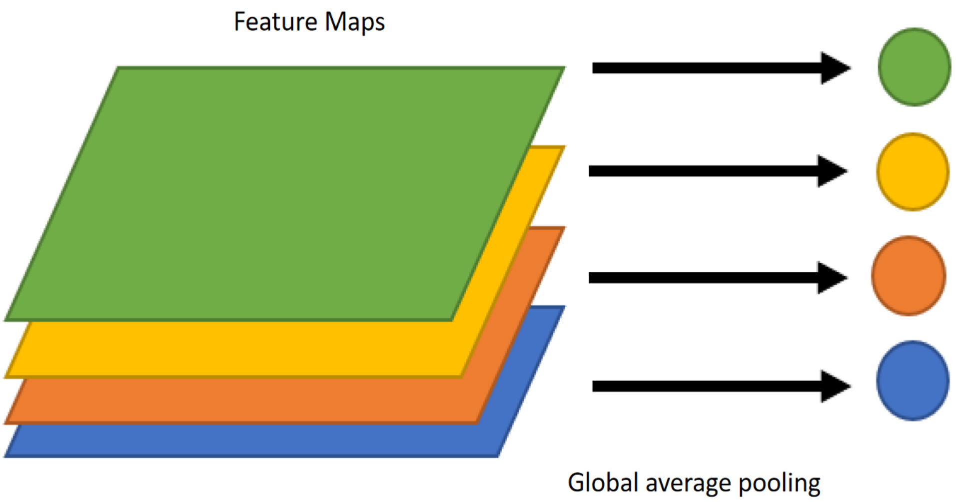

Figure 4: Schematic diagram of global average pooling

The first level neural network mainly identifies motions with periodicity, such as walking, jogging, jumping and stair climbing, while other non-periodic motions are classified into another category, i.e., the first level neural network classifies the results into 5 categories: walking, jogging, jumping, stair climbing, and other motions, and then proceeds to the second level neural network if it identifies other motions. In the first level neural network, two convolutional layers and two pooling layers are mainly used, each convolutional layer is immediately followed by a pooling layer, the first pooling layer uses maximum pooling, and the second pooling layer uses global average pooling, which has a variety of roles, and is usually used as a substitute for the fully connected layer.

Global average pooling is generally used in place of the fully connected layer. Usually in classification neural networks, the last layer or layers are fully connected, increasing the number of fully connected layers can improve the accuracy to a certain extent, but the more fully connected layers, the larger the number of parameters of the neural network, which increases the amount of computation, and may also lead to overfitting. To prevent overfitting, a dropout operation is usually added after the fully connected layers to increase the generalisation of the model.

Global average pooling, on the other hand, pools all the features in the feature map to obtain a value, and then inputs them into the softmax layer for classification, as shown in Figure 4 for the global average pooling schematic. Global average pooling greatly reduces the number of parameters in the neural network and reduces overfitting because it reduces the number of parameters in the network. The reduction in the number of parameters is necessary for neural networks running on wearable devices to reduce the amount of computation in the wearable device and reduce the recognition time of the motion.

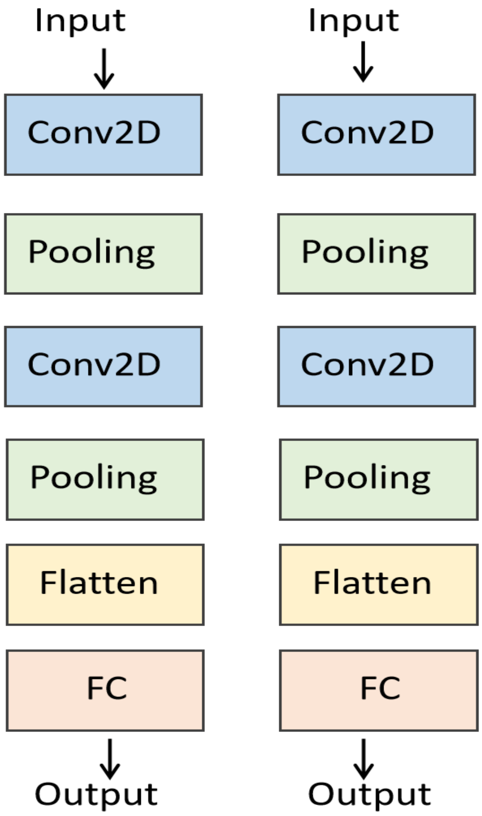

Figure 5: Schematic diagram of the detailed structure of the neural network model.

The second level neural network mainly recognizes non-periodic motions, such as falling, bending, lying down and sitting down, and activates the second level neural network when the first level neural network recognizes it as other motions, the input data of the second level neural network and the first level neural network are the same, and the output results are falling, bending, lying down and sitting down. The second level neural network has the same structure as the first level neural network, both contain two convolutional layers and two pooling layers, relative to the first level neural network, the size of the first convolutional kernel of the second level neural network is larger than that of the first level neural network, in non-periodic movements, some movements last longer, so larger convolutional kernel can sense the presence of the wilds better, and at the same time, can acquire the features better. The detailed structure of the two-level neural network is shown in Figure 5.

While training the neural network, the first level neural network and the second level neural network are trained separately. In the first level of neural network training, the falling, bending, lying down and sitting in the UMAFall dataset is grouped into one category, and the other movement samples make up the training data for the first level of neural network, i.e., the samples in the dataset are classified into five categories, namely, walking, jogging, jumping, climbing stairs and other movements. When the second level neural network is trained, the walking, jogging, jumping and stair climbing samples in the dataset are removed, and only the data samples of falling, bending, lying down and sitting are used for training. For the whole model, the segmented data samples are fed into the first level network, if the sample is judged to be one of walking, jogging, jumping and stair climbing then the results are directly output, if it is other movements then the sample continues to be fed into the second level network for further recognition.

2.3 Data augmentation algorithm based on acceleration data

Currently, one of the major problems facing wearable sensor-based motion monitoring recognition is the insufficient amount of data, although there are some publicly available datasets, the amount of data contained in these datasets is small. For example, the UMAFall dataset contains 7 daily movements and 3 types of falls, but there are only 530 valid samples, which averages out to 53 valid samples for each movement, which is not conducive to the training of neural networks. On the one hand, due to the special characteristics of the acceleration sensors in IMU, the different placement of the sensors will lead to completely different tri-axial data collected, so different datasets cannot be shared for neural network training even though they all contain acceleration sensor data. On the other hand, for the motion situation, each person's motion posture is different, for example, walking posture, some people may walk fast, some may walk slowly, if we can obtain a large amount of data from the same person, it will greatly improve the accuracy of motion recognition. However, in the actual experimental process, it is not possible to collect and label the data of the person under test in a fixed posture for a long period of time, so it often leads to a small dataset of the wearable sensor. In order to solve these problems, this paper proposes a data enhancement algorithm based on acceleration data, which can increase the number of effective samples without re-collecting data, and can enhance the neural network training effect and improve the neural network recognition accuracy.

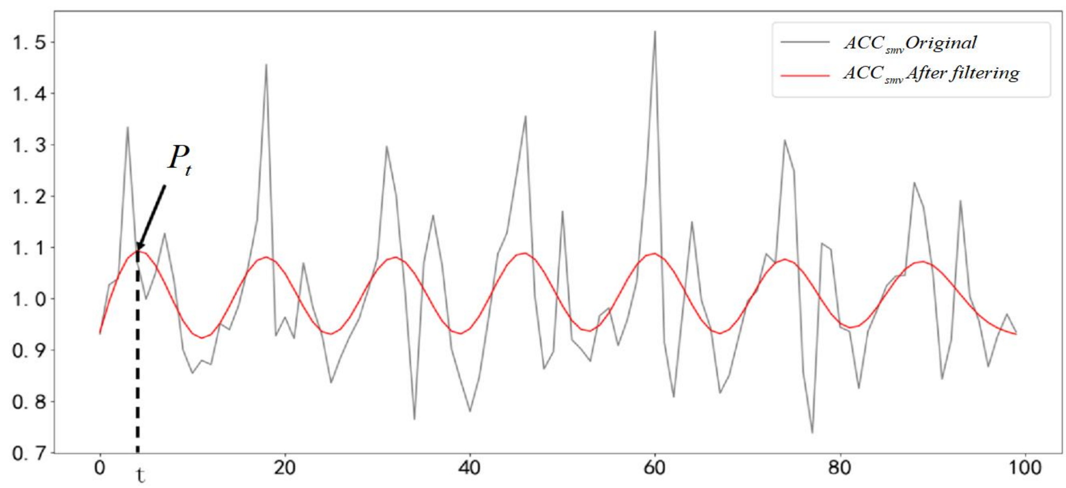

Figure 6: Schematic representation of a self-supervised pre-training agent task

In this article, motion monitoring includes daily motion and falls, which can be roughly divided into periodic motion and non-periodic motion.

(1) Periodic motion key point detection: Many daily movements are periodic, such as walking, jogging, etc. Generally speaking, in periodic movements, the data of the sample will also show periodicity. There are many methods to detect the period. properties, for example, you can find peaks or troughs in the data as the beginning or end of a cycle. This article uses the crest as the beginning of a cycle. Since three-axis acceleration has data in three directions, it can be judged by the acceleration signal amplitude vector ACC_{smv}. The calculation equation of the acceleration signal amplitude vector of a person at a certain moment of movement is as follows:

$$ACC_{smv} = \sqrt{acc_x^2 + acc_y^2 + acc_z^2} \tag{1}$$

Of course, the sensor cannot avoid the influence of noise, which leads to the lack of regularity in the collected data, so ACC_{smv} can be low-pass filtered, as shown in Figure 6. The figure shows the curve of the acceleration signal amplitude vector during walking, in which gray is the original unfiltered waveform of the curve, it is difficult to see the periodicity during walking due to the presence of noise.

The red curve in the figure represents the waveform after low-pass filtering of the data. It can be seen that the periodicity of the processed waveform is more obvious. For the filtered data, you can use the peak detection algorithm to find the peak value. For the data ACC_{smv}. at any sampling point, if:

$$\begin{cases} ACC_{smv}(t) > ACC_{smv}(t) - 1 \\ ACC_{smv}(t) > ACC_{smv}(t) + 1 \end{cases} \tag{2}$$

Then the sampling point is the peak value, which is the key point P_t, and its sampling point position is *t*.

(2) Non-periodic motion key point detection: For non-periodic motion, key points need to be selected based on its motion characteristics. A falling action contains a trough and a peak. After analyzing a large amount of data, the duration of a falling action is about 1.5 seconds to 2 seconds. Therefore, assuming that the trough is the key point P_t, for a fall, the sampling point of the key point is:

$$t = t_1 - 20 \tag{3}$$

After obtaining the sampling point positions *t* of the two sample key points, perform the following calculations on all subsequent data points of *t*:

$$\begin{cases} ACC(X) = \lambda * ACCX_1 + (1-\lambda) * ACCX_2 \\ ACC(Y) = \lambda * ACCY_1 + (1-\lambda) * ACCY_2 \\ ACC(Z) = \lambda * ACCZ_1 + (1-\lambda) * ACCZ_3 \end{cases} \quad (4)$$

3. Experiment and Results

3.1 Datasets

(1) UMAFall: In the UMAFall dataset, a large sample of 17 healthy experimental subjects was tested: 6 females and 11 males, aged between 14 and 55 years, weighing between 50 and 93 kg, and with heights ranging from 155 to 195 cm.

Each subject performed a set of 7 predetermined general ADLs: walking, jogging, bending, jumping, climbing stairs (up and down), lying (and getting up) in bed, and sitting in a chair. In addition, all subjects except two (those older than 50 years) mimicked 3 different categories of falls on the mattress: sideways falls, forward falls, and backward falls, as shown in Figure 7.

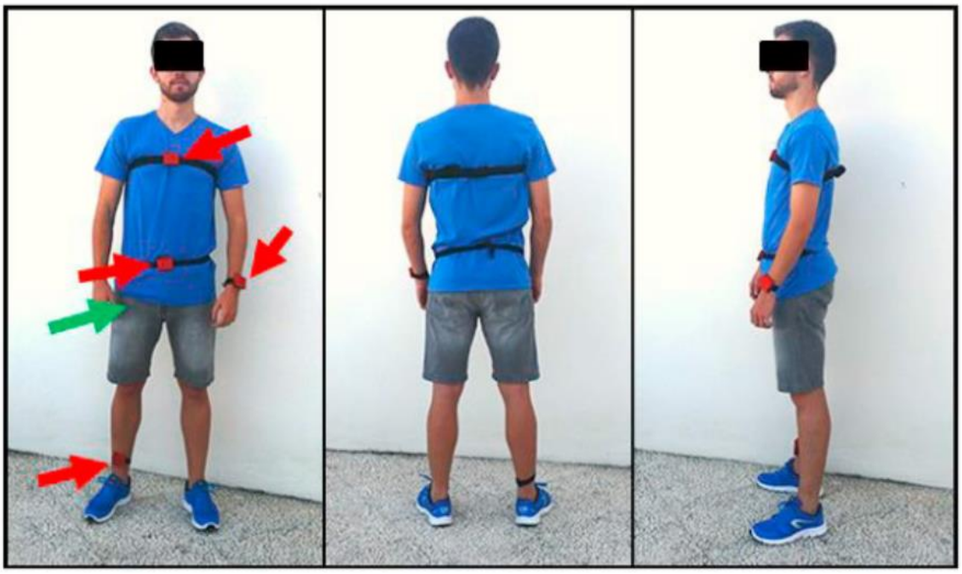

Figure 7: Testers wearing sensors

(2) DUMD: The DUMD dataset is a sensor-based human motion recognition dataset. In this data set, 25 subjects participated in the test, and approximately 2500 valid samples were obtained, which were recorded using a wrist acceleration sensor. The data set contains 10 categories of movements, which can be divided into two categories: falls and daily movements.

As shown in Figure 8, during the test, each subject was equipped with only basic protective equipment (to maintain a sense of reality), including cycling gloves (to prevent palm abrasions), kneepads (to prevent abrasions), and elbow pads (to prevent abrasions). The sensor is worn on the dominant wrist. During the experiment, the sensor data is saved in a text file in the SD card through the SD card module.

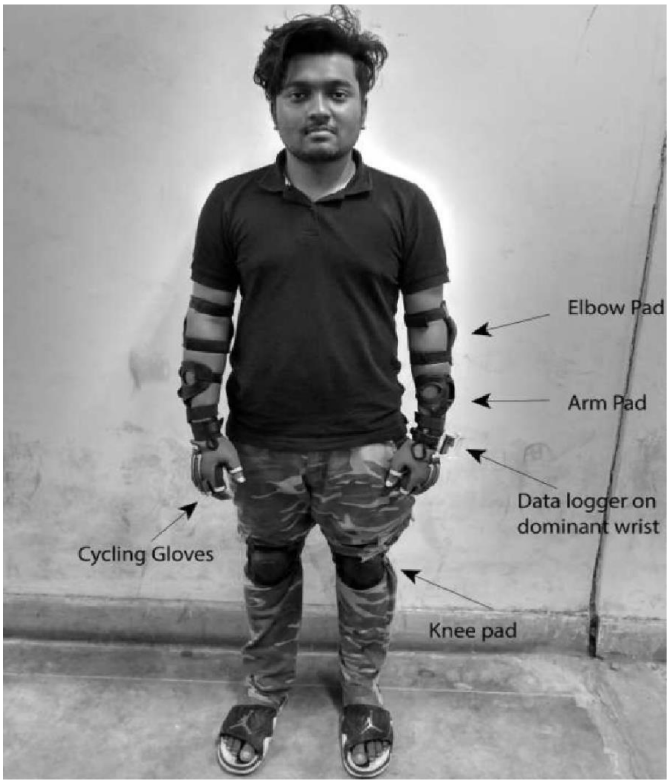

Figure 8: Testers wearing protective equipment and sensors

3.2 Evaluation method

Accuracy is one of the most common evaluation indicators. The definition of accuracy is the percentage of correctly predicted samples to the total number of samples. The calculation equation of accuracy is as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \tag{5}$$

3.3 Experimental results and analysis

In this paper, we firstly use the accuracy rate to judge the classification effect of the model, for each class, and also compare and analyse with the methods in other articles. The first level neural network mainly performs periodic motion recognition, in the UMAFall dataset, the classification of the first level neural network includes walking, jogging, jumping, stair climbing and other motions, where other motions are falling, bending, lying down and sitting down.

As shown in Fig. 9, the accuracy acc and loss curves of the first level neural network trained with the UMAFall dataset are shown, and the model achieves up to 98.06% accuracy in the test set.

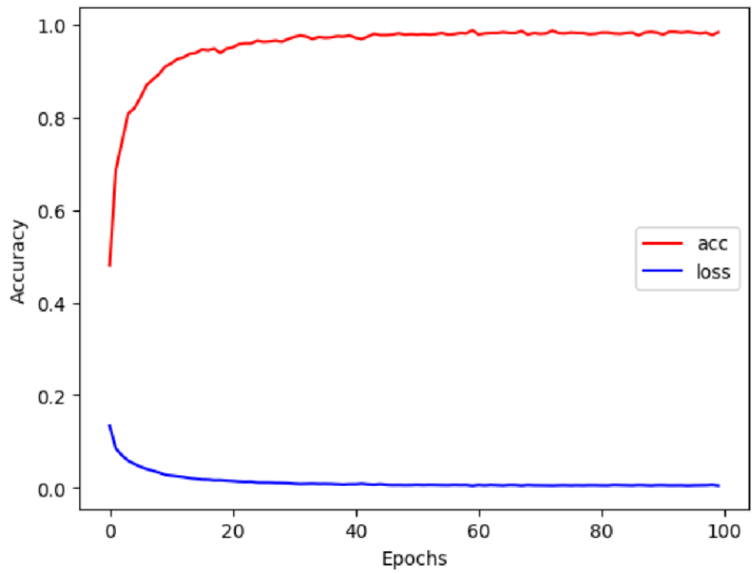

Figure 9: Acc and loss curves for the first level of the UMAFall dataset.

The second-stage neural network mainly performs non-periodic motion recognition, and in the UMAFall dataset, the second-stage neural network is classified as: falling, bending, lying down and sitting down.

In a large number of studies, falls are usually not meticulously classified, so the falls in this paper include all three types of falls in the UMAFall dataset. As shown in Fig. 10, the graph shows the acc and loss curves of the second level neural network trained using the UMAFall dataset, and the model can achieve up to 98.72% accuracy in the test set.

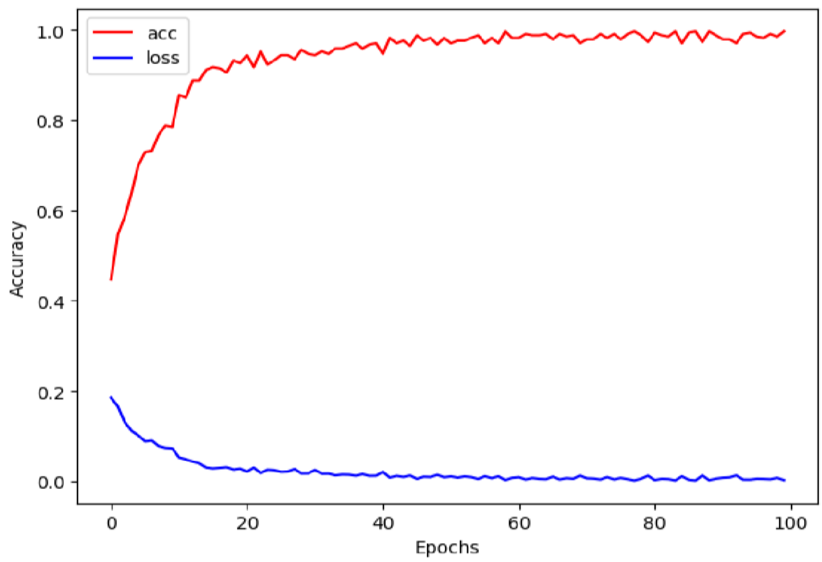

Figure 10: Acc and loss curves for the second level of the UMAFall dataset

Table 2: Comparison results with other algorithms

METHODS	ACC/BICLASSIFICATION	ACC/MULTICLASSIFICATION
CNN	0.9606	0.9356
KNN	0.9383	0.9258
LSTM	0.9236	0.9411
BILSTM	0.9525	0.9525
GRU	0.9758	0.9756
Ours	0.9802	0.9903

Compared with the algorithms in other articles, the two-level neural network proposed in this article can effectively identify various movements. In the case of original data, the data is divided according to the requirements of the two categories for identification. The identification accuracy of this article can reach 96%. %, the accuracy rate in multi-class recognition can reach 92.1%. At the same time, after using the data enhancement algorithm proposed in this article, the effective samples of the data set are increased, which is more conducive to end-to-end neural network training. In the case of two classifications, the recognition accuracy is 99.03%, and in the case of multiple classifications, the recognition accuracy is 99.03%. 98.2%.

4. Conclusion

Traditional motion monitoring algorithms based on wearable IMU usually need to extract a large number of features for identification. However, feature extraction often requires knowledge in professional fields. If the extracted features are inappropriate, it will be difficult to improve the accuracy of the algorithm. Therefore, in this article, we propose a two-level neural network motion monitoring algorithm to separately identify periodic motion and non-periodic motion, which can effectively reduce network complexity and improve the recognition accuracy of each motion. In addition, this paper proposes a data enhancement algorithm based on acceleration data. This algorithm solves the problem of few data samples in some data sets. It greatly increases the number of samples without re-collecting data, and is more suitable for terminal applications. The training of the end-to-end neural network further improves the accuracy of algorithm recognition, and the simulation experiment results show that it can be applied to actual situations.

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