Journal of Artificial Intelligence Practice (2023)
Clausius Scientific Press, Canada
DOI: 10.23977/jaip.2023.060209
ISSN 2371-8412 Vol. 6 Num. 2

Neural network and system for attitude and behavior detection based on pressure data

Jianzhong Qiu[1,2,a], Caiwei Liu[1,2,b], Jun Wu[1,2,c,*], Bingyan Zhao[1,d]

[1]*School of Mechanical and Automotive Engineering, Qilu University of Technology (Shandong Academy of Sciences), 3501, University Road, Jinan, Shandong, 250353, China*

[2]*Sichuan Machinery Research and Design Institute (Group) Co., Ltd, 48, Moxiang Road, Chengdu, Sichuan, 610094, China*

[a]*1043119044@stu.qlu.edu.cn*, [b]*1043119028@stu.qlu.edu.cn*, [c]*wujun@qlu.edu.cn*, [d]*501936@qlu.edu.cn*

[*]*Corresponding author: Jun Wu*

Keywords: Pressure Sensor, Deep Learning, Gesture Recognition, Behavior Monitoring

Abstract: In the process of monitoring the behavior of the elderly, wearable devices and visual devices are easily limited by the site and environment, resulting in poor monitoring results. This paper proposes a posture behavior detection method and system based on pressure data. The convolutional neural network algorithm is used to identify the pressure data to detect the posture, calculate the posture holding time and posture change frequency, judge the posture change action process according to the trajectory of the pressure center point, and finally record and analyze the user's behavior. The correct rate of pose classification of the model used in this paper has reached 98.69%, and the correct rate of pose retention time has reached 98.06%. Finally completed the research and development of the relevant monitoring system, which can be used in the field of medical treatment and daily care.

1. Introduction

Nowadays, the problem of population aging is becoming increasingly prominent [1]. With the rapid development of the economy and the continuous improvement of human living standards, physical health is the foundation and guarantee of everything, and its importance to people is self-evident. The health problems of the elderly should receive more attention, but children cannot guarantee enough time to take care of the elderly, and the increasingly tight medical resources cannot be able to take care of the elderly all the time. How to effectively monitor the physical state of the elderly has become a hot topic of social concern. A person's physical state can be reflected by its basic behavior: a person who is confused cannot sit in a chair normally. There are many differences in behavioral patterns between the elderly and the young. For example, the elderly are more likely to sit in a chair and maintain a certain sitting position for a long time, while maintaining a single sitting position for a long time is more likely to cause spinal diseases [2], whereas more physical activity can reduce or delay the risk of Alzheimer's disease [3].Real-time monitoring of the behavior patterns of the elderly can not only reduce the probability of accidents at home for the elderly, but also reduce the burden of hospitalized medical resources for the elderly [4-5].

Zhang Shaohua [6] and others used wearable devices to monitor human motion characteristics; Yang Weidu [7] and others realized the detection of six human behaviors of walking, going upstairs, going downstairs, running, jumping, and standing still through wearable devices; Pei Lishen [8] and others used video to identify human behavior, which improved the difficulty of visual recognition of behavior in complex scenes. Although wearable devices can effectively extract and recognize human behavior and features, it affects the comfort of users, especially some elderly users cannot wear them autonomously; The visual monitoring method does not have the above-mentioned problems, and its use is greatly restricted by external factors such as the environment and light, such as being unable to be used in strong light and far away from the house, and it is easy to violate the privacy of users.

The basis for correct judgment of behavioral patterns is accurate recognition of static postures. In recent years, there are two main researches on posture detection: posture research based on pressure sensor and posture recognition based on vision. In terms of vision, Paliyawan et al. [9] used the Kinect method to capture real-time skeletal data streams for sedentary judgment; Mallare et al. [10] proposed to obtain and evaluate sitting parameters by using computer vision;Mu et al. [11] extracted user sitting posture contour features based on pattern matching, and compared them with standard contour features to detect sitting posture. In recent years, in terms of pressure sensors, due to the advancement of machine learning algorithms, there have been studies on seat classification using machine learning algorithms. J. Yongxiang et al. [12] used the support vector machine algorithm to identify the human pose through the pressure sensor array, and the classification success rate was 83.33% [13]; adopted 12 pressure sensors and achieved a maximum accuracy of 99.48% in five poses with a supervised learning algorithm. All of the above methods can extract the user's pose in different ways. Although the visual method can judge the posture very well, its application scene is harsh, and it is greatly affected by the light intensity. When it is too dark or too bright, misrecognition often occurs. Compared with the method using pressure sensors, the data acquisition method is more direct and less affected by the environment, and is more adaptable to various scenarios.

At present, various gesture recognition systems and algorithms emerge in an endless stream, but they all detect static gestures at a certain moment, and cannot recognize and judge continuous behaviors in the time domain. This paper proposes a method to judge sitting posture, posture holding time, posture change frequency and posture change process through pressure data, and then complete the monitoring of behavior patterns.

2. Related Work

2.1. Posture Definition

The key to pose classification and recognition is to realize the definition of human body posture, and the root cause of human body posture is that all the bones of the human body cooperate with each other. Different skeleton coordination methods will produce different postures. The human skeleton can be regarded as an open-chain space linkage mechanism (the head and tail are not closed, that is, the limbs are not closed), the bone is regarded as the connecting rod, and the joint is regarded as the rotating pair connecting each connecting rod. The various postures that the human body can make are completed by the cooperation of each link and the rotating pair. The degree of freedom of the human body is the sum of the degrees of freedom of all the moving pairs in the mechanism: $F = \sum_{i=1}^{p} f_i$.

It is known that the n umber of human bones is 206 and the number of joints is 143. It can be seen that the number of degrees of freedom of the spatial linkage mechanism formed by human bones is much larger than the dimension of the pressure data matrix, and the types of postures are far greater than the spatial linkage mechanism. the number of degrees of freedom. Therefore, under the premise that the types of postures are known to be larger than the data dimension, the mapping from the high-dimensional space to the low-dimensional space will overlap, that is, the data distribution of different postures in the pressure matrix will be the same or even exactly the same.

In the experiment, during the displacement process of the legs and the torso, the visualized pressure data matrix histogram will also change greatly, and the pressure distribution will be quite different. Based on the visualized pressure data and its corresponding sitting posture, postures can be classified into nine completely different pressure distributions. And the data results show that the pressure distribution will not change under the controllable small change of posture. Here is a summary of the nine poses:

Fig.1(a) is the bar chart of the positive sitting pressure distribution matrix and the corresponding sitting posture. It is a relatively healthy sitting posture.Fig.1(b) and Fig.1(c) are the left-leaning and right-leaning pressure distribution matrix column charts and the corresponding sitting postures. Fig.1(d) shows the corresponding sitting posture of the forward leaning pressure distribution matrix bar chart. Fig.1(e) shows the corresponding sitting posture of the bar graph of the data matrix of the backward leaning pressure. Fig.1(f) shows the corresponding sitting posture of the column chart of the pressure data matrix of the left crossed legs.Fig.1(g) shows the corresponding sitting posture of the right crossed leg pressure data matrix bar chart. The tester has two legs crossed, and the right leg is up and the left leg is down. Fig.1(h) shows the corresponding sitting posture of the bar graph of the pressure data matrix of the left forward leaning crossed leg. Fig.1(i) shows the corresponding sitting posture of the bar chart of the pressure data matrix of the right forward leaning crossed leg.

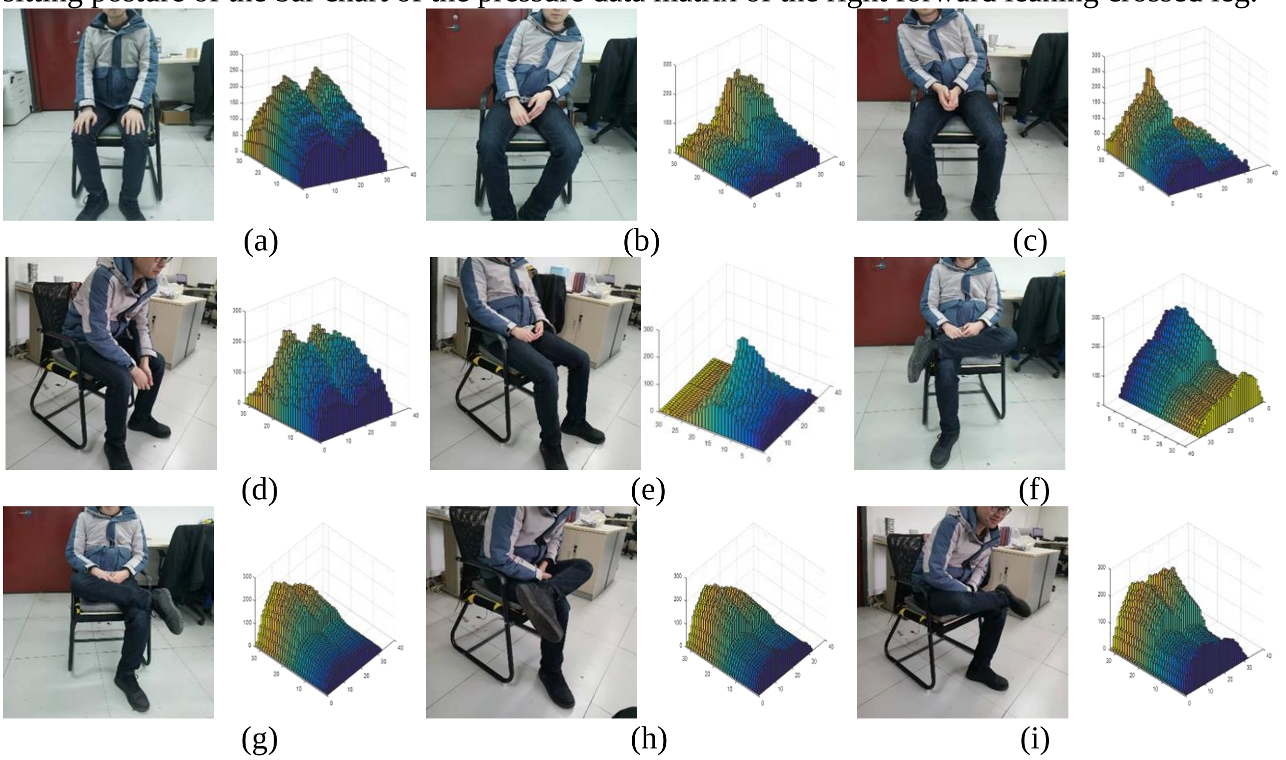


Figure 1: Posture and its corresponding pressure data matrix column chart

2.2. Convolutional Neural Networks

Deep learning algorithms have been applied to pose classification [14-16].Since different classifiers have different performances on the same dataset, Ran Xu [17] et al. used seven algorithms to identify sitting posture. Among them, the convolutional neural network has the highest recognition accuracy, which can reach 97.07%.This paper uses the convolutional neural network algorithm to build a deep learning model.

2.2.1. Principle introduction

Convolutional neural network is a feedforward neural network inspired by the natural visual cognition mechanism of biology [18].Now CNN [19] has become one of the research hotspots in many scientific fields, especially in the field of pattern classification, because the network avoids the complex pre-processing of the image and can directly input the original image, so it has been more widely used , which can be applied to image classification, object recognition, object detection, semantic segmentation, etc.

2.2.2. Convolutional Neural Network Construction

In the process of model building, this paper controls the number of convolutional layers and the size of the convolution kernel, in order to obtain the best pose classification and detection effect, and obtain the optimal network structure for processing small-resolution targets. In this paper, the number of convolutional layers is controlled as two layers, three layers, and four layers; Recognition models with different convolution layers and convolution kernel sizes. The eight recognition models built were trained using the same dataset, and the training set classified nine training labels.80% of the dataset is used as the training set to train the classification model, 10% of the dataset is used as the validation set to validate the trained classification model, and 10% of the dataset is used as the test set to evaluate the classification model.

Taking "three layers of convolution layers + 3 $\times$3 convolution kernels" (hereinafter abbreviated as "3 + 3 $\times$3") as an example, the model structure is briefly described. The pressure matrix sensor outputs a 32*32 two-dimensional data matrix input model, and goes through the first convolution layer (this convolution layer has 32 3*3 convolution kernels) for convolution operation. After the convolution, the 32*32 two-dimensional matrix becomes a 32-layer 30*30 data matrix. Then go through the pooling layer (merge the 30*30 matrix of each layer into a 15*15 matrix with a step size of 2, and take the maximum value of each small unit as the value of the new matrix during the merging process) to perform the pooling operation. Then repeat the convolution-pooling-convolution to obtain 64-layer 4*4 features. Finally, a fully connected layer is used to map the 1024 sets of features into the classification interval. Nine poses are nine groups, and the mean (mAP) of each group is the classification possibility of the corresponding category. The larger the mean, the greater the classification possibility. Fig.3 is a model structure diagram. Fig.2 is a model structure diagram.

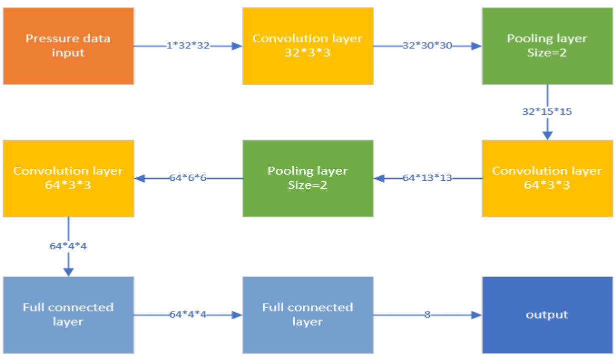


Figure 2: "3+ 3×3" model structure diagram

The built model is tested for the correctness of a single posture, and the model with the highest classification accuracy is selected as the system model. The testers sit on the test machine according to nine prescribed postures, each posture for ten seconds, and save the pressure data within ten seconds, a total of 1710 sets of data. Model classification accuracy was tested separately using the same data.

2.2.3. Data set collection and processing

Deep learning algorithms to recognize poses require a large amount of data for model training. To collect the data, volunteers were recruited to assist in the collection of the dataset. The subjects were all young people aged 23-26, with a weight range of 60kg-80kg and a height of 165cm-185cm.The subjects all need to sit in a chair for a long time every day for office work, and there is no obvious waist and leg disease. We asked testers to test each of the above nine sitting positions for 1 minute in sequence, and collected the stress matrix generated within one minute. The horizontal and vertical positions of the pressure sensor array are 32 points, a total of 1024 collection points, each collection point outputs a voltage value, 1024 voltage values are in one frame, the voltage value is calculated through the linear relationship between voltage and pressure to obtain the pressure value, and finally, the pressure value of one frame is sent to the computer through the WIFI module for subsequent processing.

Considering the differences between different users due to gender, weight, age, etc., the pressure sensor responds differently to different people in the same posture, so the pressure data is normalized. The normalization processing step includes: retrieving the largest pressure value in the pressure data matrix, dividing all the pressure data in the matrix by the pressure value and multiplying by 255 to obtain a normalized value between 0-255:

$$f' = \frac{f}{f_{max}} * 255$$

where f is the initial pressure value, f_{max} is the maximum initial pressure value, and f' is the final normalized value from 0-255. The numerical range of 0-255 is selected not only to eliminate the influence of the shape on the correctness of the model, but also to facilitate the later visualization of data to form a pressure distribution map.

2.3. Behavior Monitoring

People have different behaviors in different environments and states, and different behaviors can often reflect people's physical states. It is very important to accurately monitor behavioral patterns or behavioral states. Behavior is the expression of an individual's posture or movement over time, such as the gradual sliding of a human body in a wheelchair, resulting in constant changes in posture and movement. Depending on the performance, this paper divides the behavior into two parts: the posture-holding phase and the posture-changing process.

Posture Hold Phase: The human body maintains one posture for a long time. At this stage, it is necessary to accurately classify and identify human postures according to the pressure data, and calculate the holding time of each posture and the frequency of posture changes.

Posture change process: The process by which the human body sits in a chair and undergoes a postural change. Although the posture-holding phase described above calculates the frequency of posture change, it cannot monitor how the posture is changed. In addition, most of the wrong classification results of the pose recognition model occur in the pose change stage, and the wrong classification results will have an impact on the frequency of pose change. At this stage, it is necessary to compare the front and rear postures of the posture maintenance stage and calculate the spatial trajectory of the pressure center point over time, and calibrate the pressure center trajectory map of common posture changes. In the posture change stage of the detection process, relying on the calibrated trajectory map to find out the change action can make up for the mistake of the posture recognition model in the process of action change, reduce the situation of misrecognition, so as to better detect the behavior of the target.

The essence of the continuous movement of the body is the continuous movement of the center of the body in space [20]. Although the two-dimensional pressure sensor cannot sense the position of the center of gravity of the human body, it can calculate the position of the center of pressure through the pressure matrix data, and then specifically describe the posture change action. The human body pressure can be regarded as a parallel force system perpendicular to the contact surface of the pressure sensor. Simplify the equivalent to any point p in the contact surface area, and a principal vector $\vec{F}$ and a principal moment $\overrightarrow{M_p}$ will be obtained. The point where the principal moment b is $\overrightarrow{M_p}$ is the center of pressure [21].

The real-time monitoring of the posture holding phase and the posture change process can monitor the entire behavior of the user. In order to verify the accuracy of the above two parts, the experiments are designed as follows: The testers sit on the test machine in the prescribed sequence of posture changes during the test time (six minutes), holding each posture for one minute. Record the tester's posture based on each frame in the time series, and assign simple codes to the postures defined in 2.2.1, for example, sitting upright is defined as 1, left leaning is defined as 2, right leaning is defined as 3... After the experiment, the correct rate of posture retention time (1-error duration/true duration) and the correct rate of posture change frequency (1-error posture changes/true posture changes) were calculated.

2.4. Monitoring system design

2.4.1. Data collection and data transmission

Compared with vision sensors, pressure sensors are less affected by the environment, easy to install and carry, less expensive and less prone to damage. Therefore, it is clearly more appropriate to use a pressure sensor array to collect the underlying data for gesture recognition.

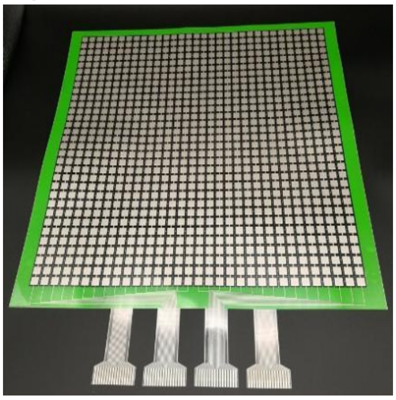
There are many types of flexible pressure sensors. According to their sensitive mechanisms, they can be divided into capacitive, resistive, piezoelectric, triboelectric and optical. The latter two are not suitable for use due to their low material applicability and high process requirements, resulting in high cost. The capacitive sensor [22] measures the pressure by changing the pressure state of the sensor, changing the distance between the plates and changing the mechanism of the intermediate dielectric layer. However, the thickness of the capacitive pressure sensor is too large and should not be used. Piezoelectric sensor [23] judges the pressure value by generating an electric potential after being subjected to a force, but the piezoelectric pressure sensor is not suitable for selection due to its low resolution and large measurement error. The resistance sensor [24-25] measures pressure by converting the pressure value into resistance change and quantifying it according to the linear relationship between pressure and resistance. The resistive pressure sensor has a smaller thickness, lower cost, and is durable, not easy to age and oxidize, and has better flexibility. Therefore, the resistive pressure sensor is selected as the carrier for data acquisition in this paper.

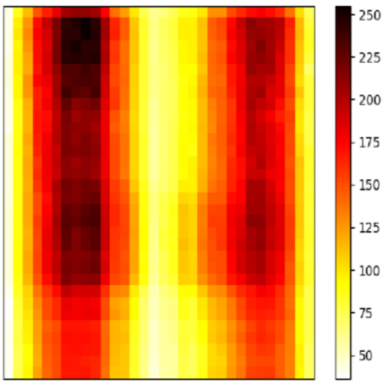
The stability of pressure data acquisition has a very important influence on the sitting posture detection, for this reason, the RX-M3232L large-format array flexible thin-film pressure sensor Fig.3 is used. The entire sensor adopts an array design of 32 rows and 32 columns. 1024 independent sensing units are distributed within a square of 400mm*400mm. The size of each sensing point is 12.5mm*12.5mm. Each sensing point of the sensor adopts an independent design to achieve Minimal disruption. The maximum range of the sensor is 20kg, the static resistance is greater than 1MG, the hysteresis is less than 6%, the drift is less than 8%, and the response time is less than 20ms.

Considering the portability of the hardware, the WIFI module ESP8266 (or changed to a 4G module) is used to transmit the underlying data. This method ensures the mobility of the device and is suitable for practical application scenarios. Considering the timeliness of pressure data, the embedded chip of STM32 series is selected as the main control chip for data acquisition and transmission.

2.4.2. Posture and behavior judgment module

In this system, the pressure data is transmitted to the computer through WIFI or 4G module for processing. In order to facilitate the integration of the gesture recognition model, PyQt5 is used to develop recognition software, which realizes the acceptance, storage and visualization of data. After the integration, the data can be classified, and the classification results can be returned to the software to realize gesture recognition, as shown in Fig.4(a). The system workflow is shown in Fig.4(b).





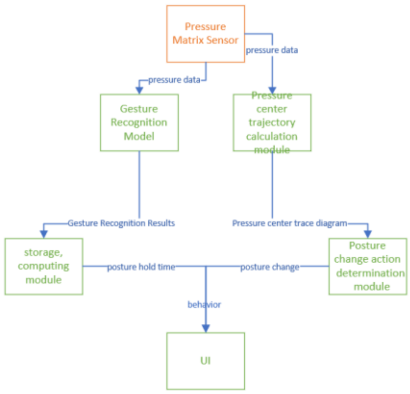


Figure 3: Pressure Sensor   Figure 4(a): Classification result graph   Figure 4(b): System Workflow

We strongly encourage authors to use this document for the preparation of the camera-ready. Please follow the instructions closely in order to make the volume look as uniform as possible.

Please remember that all the papers must be in English and without orthographic errors.

Do not add any text to the headers (do not set running heads) and footers, not even page numbers, because text will be added electronically.

For a best viewing experience the used font must be Times New Roman, on a Macintosh use the font named times, except on special occasions, such as program code.

3. Results and Analysis

3.1. Model accuracy

Tab.1 summarizes the classification accuracy of the training results of eight different structural models. Among them, the "3+3×3" model and the "5+3×3" model have higher accuracy, reaching 98.69% and 97.60% respectively. The classification accuracy of the remaining six models is not higher than that of the other six models. 95%. According to the construction methods of each model in the table and the corresponding classification accuracy, it can be seen that when the amount of data used for classification training is small (only 32×32), more convolution layers and larger convolution kernels will not to bring better results, an excessively large convolution kernel is likely to cause the model to overfit because the features cannot be extracted. Finally, this paper chooses the "3+3×3" model as the classification model of the gesture recognition system.

Table 1: Training accuracy of each model

Model	2+3×3	2+5×5	2+7×7	3+3×3	3+5×5	3+7×7	5+3×3	5+5×5
Accuracy	94.12%	57.98%	49.99%	98.69%	73.86%	57.30%	97.60%	62.26%

The recognition accuracy of each pose is shown in Tab.2. It can be seen that the left-leaning and right-leaning have the highest accuracy rates, and the accuracy rates of the eight models all exceed 90%; The accuracy rate of the left crossed leg and the right crossed leg is second, and the accuracy rate of three models is more than 85%; Some models have poor recognition accuracy for forward leaning, backward leaning, and sitting upright. Since the recognition rates of the eight models for the left-forward cross and the right-side forward cross are not as expected, even the "3+3×3" model with a correct rate of 98.69% is only 30.14% test accuracy. Too low test accuracy cannot accurately identify the posture, and it will have misleading and adverse effects on judging whether the posture changes. In the test, nearly 70% of the forward-leaning left-side crossovers were misjudged as left-side crossovers; nearly 70% of forward-leaning right-side crossovers were misjudged as right-side crossovers.

In order to ensure the accuracy of gesture recognition, we divide the forward-leaning left cross into the left cross, and divide the forward-leaning right cross into the right cross, and the nine postures are finally defined as seven postures. The recognition accuracy rate of the seven poses tested in practice reached 99.01%.

Table 2: Model single gesture recognition accuracy

Posture Model	2+3×3	2+5×5	2+7×7	3+3×3	3+5×5	3+7×7	5+3×3	5+5×5
Sitting	88.94%	56.84%	48.94%	97.89%	74.73%	56.31%	96.31%	62.1%
Left tilt	94.73%	92.1%	90%	98.94%	93.15%	92.63%	97.36%	92.63%
Right tilt	95.26%	92.1%	92.63%	99.47%	93.68%	91.05%	96.84%	93.15%
Lean forward	86.84%	46.31%	29.47%	99.47%	73.86%	44.73%	99.47%	50.52%
Backward tilt	92.63%	46.84%	32.1%	98.42%	71.05%	43.68%	98.94%	48.42%
Left cross leg	89.47%	57.36%	50.52%	99.47%	73.15%	55.26%	97.36%	62.1%
Right cross leg	92.63%	57.36%	52.1%	99.47%	74.21%	52.63%	96.84%	61.05%
F-L- cross leg	23.15%	22.1%	26.31%	30.14%	28.94%	26.31%	27.89%	26.84%
R-L- cross leg	27.36%	28.94%	26.84%	29.79%	28.42%	25.72%	29.47%	26.31%

3.2. Posture and behavior

In the experiments of monitoring the posture hold time and recording the frequency of posture changes, the recorded time-based postures can be converted into time-based code sequences. Each set of arrays represents a tester's change in posture during the test time. The frequency of posture change can be obtained from the number of digital changes; the posture holding time can be determined by multiplying the number of consecutive times by the sampling frequency. The frequency of posture change is recorded in Tab.3. The results show that the response error between the time point of the test result and the actual time point of the change of posture is less than one second. The test results of two groups A and E are the best, and nine groups are in full agreement with the actual situation. In the 50 test experiments, 40 groups were in full agreement, and 10 groups were wrongly judged. Among the ten groups of misjudged data, there are four groups that are less than the actual number of posture changes, and the remaining six groups are that the system determines that the posture has changed but the change method is inconsistent with the actual situation. The reason is that the pressure data is likely to be wrongly classified by the model during the action Therefore, the accuracy of the system determination of the frequency of posture change is greater than 90%. Tab.4 shows the percentage of the measured posture holding time and the actual posture holding time. The correct rate of the five testers' posture holding time is above 98%.

Table 3: Behavioral Experiment Results

	A	B	C	D	E
1	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
2	1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-4-1-5-1-2-1-6	1-3-1-2-1-6
3	1-3-1-2-1-6	1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
4	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
5	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-5-1-4-1-6	1-3-1-2-1-6
6	1-3-1-2-1-6	1-3-1-6-1-2-1-6	1-3-1-2-1-6	1-5-1-3-1-2-1-6	1-3-1-2-1-6
7	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-4-1-6	1-3-5-1-4-1-6	1-3-1-2-1-6
8	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
9	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	5-1-2-1-6	1-3-1-2-1-6
10	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-6
Time	<1	<1	<1	<1	<1

Table 4: Time Accuracy

personnel	A	B	C	D	E
time accuracy	98.33%	98.66%	98.43%	98.06%	98.23%

The above-mentioned experiments in the posture holding phase show that the system has a good recording effect on the calculation of posture holding time, and the five groups of experimenters have a time accuracy of more than 98% in ten tests. However, there is still this deficiency in the frequency of posture changes, and the accuracy rate is only 86%. This is because in the posture change stage, the pressure data generated by the body under dynamic changes cannot be effectively and accurately converted into posture results, resulting in misjudgment. affected the experimental results. To address this error, we interpret the postural changes using real-time monitoring of the pressure center.

The pressure sensor area where the pressure center point is located is a two-dimensional plane, as shown in Fig.5(a). The testers made common posture changes and recorded the pressure center trajectory curve. By using MATLAB to analyze and calculate the pressure data. At the initial stage of the tester's departure action, the pressure center point moves in the positive direction of y, and as the center of gravity of the body moves forward, y moves to the negative direction after reaching the maximum value. It can be seen that the action of getting up has obvious characteristics: The displacement of the pressure center point along the x-direction is extremely small, and the movement of getting up has nothing to do with the x-direction, which can be digitally represented by the y-direction displacement.

Different posture changes have different pressure center trajectories. We extract the experimental data for continuous movement changes, calculate the pressure center point, and find that no matter what safe posture the body is in, the coordinates of the pressure center point are always at (12, 22) , (29, 22), (12, 34), (29, 34) in the closed rectangle, as shown in Fig.5(b). When the position of the pressure center point exceeds the range of the matrix shown in Fig.5(b), it can be determined that the behavior has a tendency to develop into a dangerous action or a dangerous posture.

After adding the method of "calculating the trajectory of the pressure center to judge the posture change process", the experimental results are shown in Tab.5. The frequency of pose changes is 98% accurate. It can be seen that identifying the posture change action by calibrating the pressure center trajectory curve can effectively reduce the calculation error of the posture change frequency caused by the misrecognition of the posture recognition model.

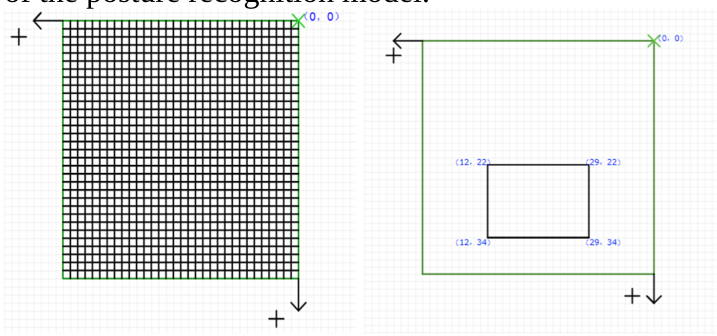


Figure 5(a): The 2D plane where the pressure center point is located   Figure 5(b): Pressure Center Trajectory Range Plot

Table 5: Modified Behavioral Experiments

	A	B	C	D	E
1	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
2	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
3	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
4	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
5	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-5-1-4-1-6	1-3-1-2-1-6
6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
7	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
8	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
9	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6
10	1-3-1-2-1-6	1-3-1-2-1-6	1-3-1-2-1-6	1-5-1-3-1-2-1-6	1-3-1-2-1-6
Time	<1	<1	<1	<1	<1

3.3. Simulation Application Scenario

This section simulates the actual application scenario, and Tab.6 shows the experimental results:

Table 6: Application Scenario Experimental Results

Attributes time	posture	hold time	Posture changes	behavior
0	sitting	90s	3	Sit upright
1:30				
1:33	sitting	3s		Lean forward
1:35	Lean forward	2s		
1:37	Lean forward	2s		Slip
3:00	Left tilt	81s		Sit upright
3:03	sitting	0		get up

Experimental process: The tester is sitting for one minute and thirty seconds, and then leans forward until the body has a tendency to fall, then the posture is changed from forward leaning to left leaning, and then the body gets up. Tab.6 shows the experimental results. The posture classification recognition model is monitored as sitting upright at 0~1:33, forward leaning at 1:33~1:37, left leaning at 1:37~3:00, and left at 3:00~ 3:03 Monitoring is sitting upright; The holding time of the posture is basically correct, and there is a two-second error in the holding time of the left leaning sitting posture; the number of posture changes is correct; the behavior and actions conform to the actual experimental process.

4. Conclusions

This paper proposes a method to monitor behavior patterns through stress data, and designs a corresponding behavior monitoring system. Use the pressure matrix sensor to detect the pressure data, compare the classification accuracy of several gesture recognition models through experiments, and finally use the "three-layer convolution + 3*3 convolution kernel" model for gesture recognition. It realizes the recording of posture holding time and posture change frequency, and uses the method of calculating the trajectory of the pressure center and calibrating the posture change action to correct the error in the posture change stage, which can effectively monitor the user's behavior. The correct rate of posture classification and recognition of the method in this paper is 98.69%, and the correct rate of posture retention time recording is greater than 98.06%. The system has the characteristics of high precision, low energy consumption and low cost, and has a wide range of application prospects in medical care and old and young people. The method and system can monitor the user's posture change process all the time without affecting the user's privacy. Medical staff can rely on the method and system in this paper to judge the behavior status of users. In the future, the research direction of this paper mainly focuses on the corresponding calibration of emotions, physical conditions and behavior patterns, enriching the monitoring functions and expanding its application fields.

Acknowledgements

This research was supported by the Major Science and Technology Project of Sichuan Provincial Department of Science and Technology (No. 2020YFS0366).

References

[1] Wang Lei. Analysis of pension risks and avoidance of elderly living alone [J]. Journal of Chongqing University of Technology (Social Sciences), 2020, 34(12):64-70.
[2] Sun Jieying, Zhang Xuetong, Wang Zhuying. The relationship between the accumulation pattern of meditation and the risk of common chronic diseases among the urban elderly [J]. Journal of Capital Institute of Physical Education, 2022, 34(01):63-70+108.
[3] Li Qian, Li Yanling, Zhang Miao, Lu Yatian, Zhang Hong. The relationship between physical activity and mental health of the elderly [J]. Modern Health, 2019(14):171-172.
[4] Mh A, Mia B, Ds C. Learning architecture for the recognition of walking and prediction of gait period using wearable sensors. 2022.
[5] Jegham I, Khalifa A B, Alouani I, et al. Vision-based human action recognition: An overview and real world challenges [J]. Digital Investigation, 2020, 32:200901.
[6] Zhang Shaohua. Research on wearable devices and data transmission technology for monitoring human physiological characteristics [D]. Beijing University of Technology, 2015.
[7] Yang Weidu. Research on human behavior recognition and state monitoring method based on wearable devices [D]. Harbin Institute of Technology, 2016.
[8] Pei Lishen, Zhao Xuezhuan, Zhang Guohua. Research on group behavior analysis model based on multi-level deep network architecture [J/OL]. Computer Application Research. 2020: 1-8.
[9] Paliyawan P, Nukoolkit C, Mongkolnam P. Prolonged sitting detection for office workers syndrome prevention using Kinect [C]., International Conference on Electrical Engineering/electronics. IEEE, 2014:1-6.
[10] Mallare, John Cloie T., Pineda, Dianne Faye G., et al. Sitting Posture Assessment using Computer Vision [J]. IEEE HNICEM, 2017,
[11] Lan Mu, Ke Li, Chunhong Wu. A Sitting Posture Surveillance System Based on Image Processing Technology [A]. 2010 2nd International Conference on Computer Engineering and Technology ICCET 2010 [C]. 2010
[12] Jiang Yongxiang, Duan Jingle, et al. Sitting posture recognition by body pressure distribution and airbag regulation strategy based on seat comfort evaluation [J]. .The Journal of Engineering, 2019, Vol. 2019(23): 8910-8914

[13] Ma C, Li W, Gravina R, et al. Posture Detection Based on Smart Cushion for Wheelchair Users[J]. Sensors, 2017, Vol. 17
[14] C. Ma, W. Li, R. Gravina, G. Fortino, Activity recognition and monitoring for smart wheelchair users, in: 2016 IEEE 20th Int. Conf. Comput. Support. Coop. Work Des. CSCWD, IEEE, Nanchang, China, 2016, pp. 664–669
[15] Guanqing Liang, Jiannong Cao, Xuefeng Liu, Smart cushion: a practical system for fine-grained sitting posture recognition, in: 2017 IEEE Int. Conf. Pervasive Comput. Commun. Workshop PerCom Workshop, IEEE, Kona, HI, 2017, pp. 419 424.
[16] J. Roh, H. Park, K. Lee, J. Hyeong, S. Kim, B. Lee, Sitting posture monitoring system based on a low-cost load cell using machine learning, Sensors 18 (2018) 208.
[17] Xu Ran, Cong Wang, Yao Xiao, Xuliang Gao, Zhiyuan Zhu, Bin Chen. A portable sitting posture monitoring sysrem based on a pressure sensor array and machine learning, Sensors and Actuators A: Physical, 2021, vol. 331.
[18] Dean T, Cox, et al. Neural Networks and Neuroscience-Inspired Computer Vision [J]. Current Biology: CB, 2014.
[19] Iu A, Mw B. Quality assessment of compressed and resized medical images based on pattern recognition using a convolutional neural network—Science Direct [J]. Communications in Nonlinear Science and Numerical Simulation, 2020, 95.
[20] Zhou Liping, Liu Jinghao. A gait analysis method based on the trajectory of human center of gravity [J]. Information Technology, 2016(08):147-150+154.
[21] Liu Gang, Lu Ying, Shen Ying. Numerical simulation study of static body surface pressure distribution in human sitting posture [J]. Computer Engineering and Design, 2009, 30(10):2486-2488+2492.
[22] Joo Y, Byun J, Seong N, et al. Silver nanowire-embedded PDMS with a multiscale structure for a highly sensitive and robust flexible pressure sensor [J]. Nanoscale, 2015, 7(14):6208-6215.
[23] Kumar S, Bijender, Yadav S, et al. Flexible microhyperboloids facets giant sensitive ultra-low-pressure sensor[J]. Sensors and Actuators A Physical, 2021:112767.
[24] Yu Jiangtao, Sun Lei, Xiao Yao, Jiang Shuwen, Zhang Wanli. Research progress of piezoresistive flexible pressure sensors [J]. Electronic Components and Materials, 2019, 38(06):1-11.
[25] Jianzhong Qiu, Guoyong Wan, Jun Wu, et al. A Target Detection and Evaluation Method for Safety Protection Equipment [J]. Journal of Physics, 2021, 1966(1): 012035.*