

Effect of Neural Network Algorithm Based Core Stabilization on Adverse Spinal Posts in Children Aged 3-6

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Abstract

Based on the neural network algorithm, this paper studies the influence of the neural network algorithm's core stability on the poor spinal posture of 3-6-year-old children, and mainly studies an algorithm to monitor the poor posture of the spine in children. Firstly, the basic requirements and selection methods for feature selection and extraction in sleeping position recognition are introduced. The Haar-like method is used to extract the required features. Finally, a statistic-based BP neural network algorithm is used to identify the sleeping position. Face classifier and side face classifier to be tested to detect the image, the test results show that: The recognition algorithm of the high efficiency, according to the child every time the real-time adjustment of the airbag to support the child's posture.

Keywords: Neural Network Algorithm, Spine Posture, Recognition;

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1. Introduction

Thoracic kyphosis, spinal deformity, which is clinically called kyphosis^[1]. It is well-known that sleep is essential to human health. However, people with kyphosis tend to sleep in the supine position due to the back arch of the spine, which is troublesome for such people^[2]. Especially for children with severe kyphosis deformity lying on the ordinary mattress, resulting in the extrusion of the protruding parts, often produce pressure sores, bone damage, etc., so for such people with severe deformation of the spine to monitor the posture And correction is necessary and urgent^[3].

2. State of the art

Over the years, most researches abroad have focused on the detection of human faces and fingerprints, facial expressions, matching pattern recognition algorithms of this module and have achieved remarkable results. Face recognition access control systems and fingerprint recognition have been

installed in some security- Systems, etc. However, algorithms for human sleeping position recognition are rare, and there is no complete recognition algorithm to detect human sleeping position. However, there are related algorithms for human sleeping position recognition^[4]. Some scholars detect the human body's daily basic activities and actions, the collected images are separated and processed, and the ellipse is used to replace the human head area. After calculating and processing, the human body height, arm posture and position are calculated to match the human body posture, The unobstructed part of the experimental result is used as the observation vector for human posture recognition^[5]. Some scholars have also designed an induction mattress with more than two hundred pressure sensors distributed according to a certain proportion rule, which is used to detect the sleeping position and respiratory signal of the human body. According to this principle, other scholars have made

a set of 108 pressure The Sleep Smart system, which consists of sensors and temperature sensors, collects the data back to measure the body's mass center to assess the condition of the body^[6]. Scholars judge the human body's sleep movements by measuring the pressure changes caused by the body's breathing, the body's reversal and movement during sleep^[7]. The electrostatic charge sensing bed (SCSB), which detects the state of sleep during sleep, is similar to a cell phone-like capacitive touch screen. Some scholars also detect the posture of the human body by using the conductive fiber to obtain the weak signals generated by the heartbeat and respiration of the human body^[8].

3. Methodology

3.1. Based on BP neural network attitude detection

In this paper, a statistic-based method is used to identify sleeping position images. Before sleeping position recognition, the feature of the image is extracted first. In this paper, Haar-like method is used to extract features. The image to be detected in the previous chapter geometry rotation, scaling, gray histogram equalization, image filtering, access to the image of strong, highly independent. The following is the Haar-like feature extraction principle. The classification of Haar-like features mainly uses the rectangular features as the features. In general, the selected rectangular features mainly include the following types, as shown in FIG. 1, the first and second figures show the boundary features, and the third figure shows Thin / thin rod features, and the fourth figure represents diagonal features. The absolute value of the sum of the number of pixels in the white area minus the number of pixels in the black area in the following figure indicates the feature value corresponding to each feature.

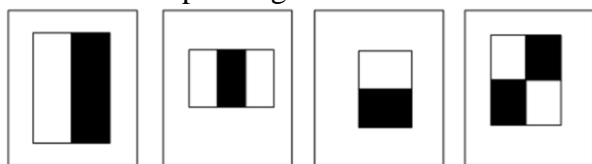


Figure 1.Rectangular features.

Generally, the number of features extracted based

on the above method can reach more than 4 orders of magnitude. When such a large number of characteristic samples are input to the BP network, the speed of the characteristic is extremely slow and the real-time performance of the system is lost. Based on the above feature extraction, Viola and Jones, the calculation of the integral graph is added and the integral diagram is defined as the process of obtaining the rectangular area of the upper left of the point by $i(x, y)$ according to each point in the grayscale map of the sleeping posture picture to be detected. The results are expressed in $ii(x, y)$, where $ii(x, y)$ represents the integral value of the point, the formula is shown as follows:

$$ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y') \quad (1)$$

The integral image $ii(x, y)$ is the original image $i(x, y)$. Using formulas (2) and (3), the integral value of each integer pixel in the sleeping position image is calculated.

$$s(x, y) = s(x, y - 1) + i(x, y) \quad (2)$$

$$ii(x, y) = ii(x - 1, y) + s(x, y) \quad (3)$$

$s(x, y)$ is the cumulative line and, of which $s(x, -1) = 0$ and $ii(-1, y) = 0$. Given a point, its upper-left integral value is calculated as follows: Using the values $s(i, j)$ represent the sum of the row directions, and thinking that $s(i, -1) = 0$; $ii(i, j)$ represents an integral image, and thinking $ii(-1, j) = 0$; using mathematical recursion to calculate each row by row The integral value of pixel, the accumulated value of each line and the integral value of each point are obtained by formula (4) and formula (5).

$$s(i, j) = s(i, j - 1) + i(i, j) \quad (4)$$

$$ii(i, j) = ii(-1, j) + s(i, j) \quad (5)$$

According to the above calculation process, if we

want to extract the features in any rectangular area, that is to find the integral value corresponding to several integer points in the image, only some simple additions and subtractions of these integer points are needed.

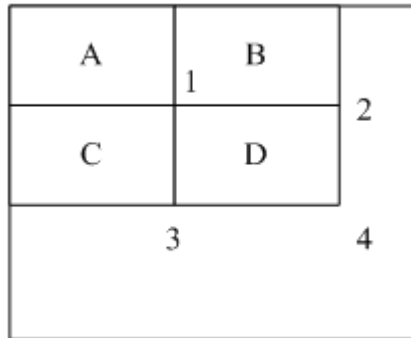


Figure2. The calculation of the integral graph of a rectangular area.

As can be seen from Figure 2 above, through the above formula can be easily calculated 1,2,3,4 points at four points, set the integral value of 1 A, points at 2 points for the A + B, 3 points The integral value is A + C, the integral value at 4:00 only needs to add the integral value at 1, 2, 3, 4, if the feature extraction only needs the D region, then it can be added or subtracted simply Realized by the formula $D = 4 + 1 - (2 + 3)$ obtained. Thus, the eigenvalue of the rectangular feature is reduced to the minimum level of computation, and the detection speed increases exponentially, which increases the real-time performance of the system.

3.2. Classifier design

Neural networks mainly include two kinds of networks. The first is a regression network. The second is the former grant network. During the operation of the two networks, the former network mainly manifests as a form of memory during the learning phase, selects the instance features that need to be memorized from the input features, and changes the connection weight values of each layer according to these memory features. The recall stage is mainly a kind of association stage, which compares the information memorized in the previous stage on the network with the information entered in the test, and

outputs the matched result. The latter type of network in the learning phase is mainly supervised learning phase. The first is to take the sample training samples and the target output values from the problem area, and then select these training sample samples as input to the network. The steepest descent method is used to repeatedly adjust the connection weights of the connections between the layers in the network. The closer the network's actual output to the expected target value during the learning phase, the better. Recall stage is the stage of classification or prediction. When you enter a sample to be detected, you want the network to guess the most likely output. BP neural network belongs to the second category, which is based on supervised learning multilayer pre-grant network. Its network architecture is similar to the network architecture of its predecessor multi-layer perceptron. Each layer of network is built by a number of neurons, neurons in the same layer are not connected to each other, independent of each other, while the layers of neurons are connected to each other. The signal is from the input node to the final output layer node, and outputs the final result by unidirectional propagation. BP neural network structure shown in Figure 3:

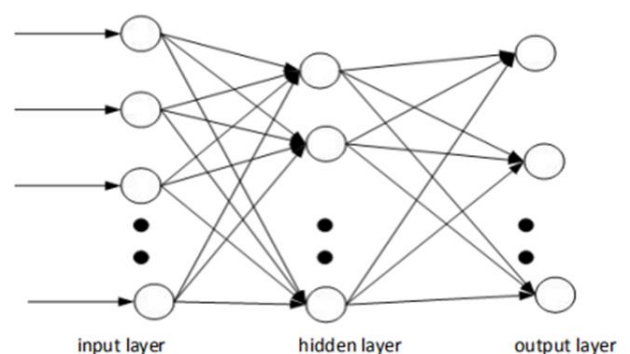


Figure3.BP neural network structure diagram.

BP neural network has a significant advantage in sleeping position recognition. Therefore, it has been widely used in many face recognition and target recognition fields. This article also uses BP neural network algorithm for sleeping position recognition process. The test results show that the recognition

rate is about 93% on average, the recognition rate is very good, you can invest a lot of product development. Then we proceed to layer node design. The first is input and output layer node design. The number of input layer nodes in the network is ultimately determined by the size of the system and the efficiency of identification. The relationship between the input layer and the hidden layer connection weights is:

$$net = x_1\omega_1 + x_2\omega_2 + \dots + x_n\omega_n \quad (6)$$

Among them, x_1, x_2, \dots, x_n represents the network acceptance of the input information and $\omega_1, \omega_2, \dots, \omega_n$ represents the connection between the input layer and hidden layer connection weights. The sleeping position image undergoes the integral value of each point after the extended Harr-Like feature in the previous section. As the picture is 20×20 , setting the point (x, y) for each point to indicate the location. In this paper, we choose multiple sets of matrix features to test, to see which points of the final value of the pixel error convergence faster, and then select the point as the input. As shown in Figure 4, the rectangle represents the sleeping image. The sum of the matrixes of points D, 6, and 7, the sums of the sums of 11 and 12 matrixes, and the matrixes of 14 and 15, as well as the subdivided, extracted features of each of the matrixes 1-16, may be selected as well as the rectangle size. In this paper, the output is 4 kinds, so we can define the output node number is 2, so we can construct four states, namely the four basic sleeping positions.

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

Figure4.Gray pixel integral graph.

The following uses the sleeping posture features selected in the previous section as the input layer of the neural network to build a two-output BP neural network classifier model for sleeping position recognition as shown in Figure 5 below:

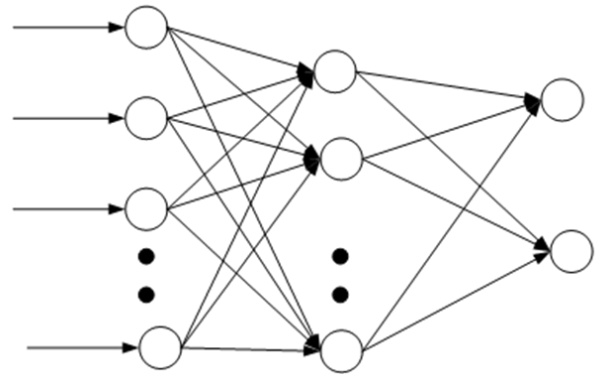


Figure5.Two output BP neural network classifier model.

There are no specific rules on the number of nodes in a hidden layer. However, if there are too few nodes in a hidden layer, the network may not converge, resulting in no result or not "robust". If too many hidden layer nodes are selected, the redundancy of the network becomes larger and the training time of each network will be very long. Although the number of network convergence training can be greatly reduced, each identification process takes a long time, Can not guarantee the system's real-time requirements. Therefore, the number of hidden layer nodes in this paper is determined as follows: First, the maximum and minimum number of hidden layer nodes are determined by empirical formulas $n_1 = \sqrt{x + y + a}$ and $n_1 = \log_2 x$, where x represents the number of input layers, y represents the number of output layers, a denotes the arbitrary constant between 1 and 10, and then selects multiple sets of values in the interval to test based on the same training set to check the convergence speed of the last network. After the network is converged, the infrared images to be identified are selected for preprocessing and characteristics After extraction, enter the trainer,

check its recognition rate, the final results shown in Table 1.

Table1.Tidden layer number selection results.

layer	node	Recognition rate result	step
		92.21%	10
		94.65%	10
		95.21%	10
		95.35%	10
		98.31%	10
		95.36%	10
		96.12%	10
		96.78%	10
		96.58%	1

Therefore, the number of hidden layer nodes selected in this paper is 40. When the network input layer data, output layer data, the hidden layer of the final determination of the data, the excitation function selection to determine the final total error function. Therefore, the choice of excitation function plays an important role in the convergence of the network. According to BP neural network algorithm, it is required that the selected excitation function must be permeable everywhere in each point of the function, and two types of functions are usually selected as the excitation function of the network as follows:

$$F^{(1)}(n) = \frac{1}{1 + \exp(-n)} \quad (7)$$

$$F^{(2)}(n) = n \quad (8)$$

The first one is an S-shaped excitation function and the second one is a linear excitation function. The BP neural network mainly realizes the desired effect through reverse propagation of errors and repeats this process, finally completes the network training and forms the classifier. The BP neural network algorithm minimizes the mean variance of the expected output value and the actual output value by continuously adjusting the weight of the connection during the

learning phase. Which y^i represents the actual output, w^i represents the hope that the output and w_{ij} represents the weight of the connection. Then the BP neural network training error function as shown in Equation 9 below:

$$E = \sum_i \sum_j (y^i_j - \omega^i_j)^2 \quad (9)$$

The whole algorithm update process is expressed as:

$$w_{ij}(k+1) = w_{ij}(k) - \varepsilon \frac{\partial E}{\partial w_{ij}} \quad (10)$$

In the above equation, we denote the transformation of iterations in the update process with k, and ε represents the invariant circulation of the entire algorithm learning rate using the above formula until the variance of the mean of the expected output and the actual output tends to be minimum, stable and no longer change. In fact, when deciding which kind of function to use as the activation function of the BP neural network algorithm, the selected function can be used as the activation function of the network as long as the selected function is ubiquitous. This system selects

the S type function: $f(x) = \frac{1}{1 + e^{-kx}}$ as the incentive function of this system. In this function, the bigger the value of constant k is, the slower the function is, the faster the convergence speed of the network is, but the slower the convergence speed is. When the value of k is smaller, the faster convergence of the network, but the probability of shocks has increased. After many experiments and analysis, we find that when we choose $k = 1$, the error convergence rate is the fastest, so we choose $k = 1$ in this paper.

4. Result analysis and discussion

The BP neural network algorithm for sleeping position recognition detection system mainly includes two modules: a sample training and learning module and a face detection module. The training

part extracts the rectangle features of the face samples and the side face samples, selects the appropriate rectangle features to select and segment the face features, and sends the obtained feature information to the BP neural network for training, continuously changing the weights until the output result Match with the expected result, thus construct BP neural network classifier. The detection part first extracts the to-be-detected sub-window from the image, and pre-processes the image to be identified and the feature selection and face segmentation, and identifies the feature information through the BP neural network classifier. According to the needs of the system, the collected samples of the human body pose should not be a single, facial expression, angle, attitude should be varied, shooting environment. Light should also consider a variety of situations. Therefore, in order to meet the requirements of this system, this paper chooses Zhang Lei from Hong Kong Polytechnic University to construct the ORL human pose database image, which is used to train BP neural network Finally make the network convergence, forming a classifier, the specific data as shown below:

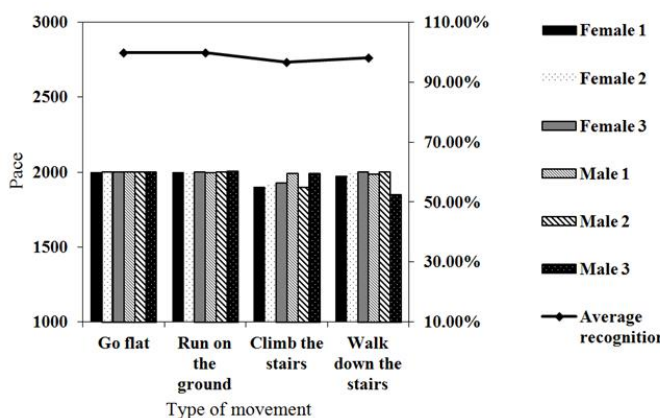


Figure6. Human posture data.

Table 2.Detection results.

Face posture	Total number of images	Correct test results	Misdiagnosis result	Leak detection result	accuracy rate
Positive	28	27	1	0	96.4%

So that it can identify a certain type of sleeping position, the use of their own people's sleeping position images taken sleeping posture recognition process, the experiment found that the network recognition efficiency is very good. These images taken from the ORL library must be preprocessed. The preprocessing process is the same as that of the sleeping image. The process is as follows: the image geometry is preprocessed to a uniform size of 20 * 20; the gray level of the image is normalized to gray Degree histogram equalization, image filtering. According to the above process BP network training, when the network eventually converges, the training is completed, then you can be detected to identify the operation of the picture, from a near infrared camera to capture a sleeping image of children, respectively, geometric normalization, the image Rotation, scaling, and gray normalization, histogram equalization and image filtering, and then extract the integral value of the extracted pixel matrix through the Haar-like feature extraction into the already trained BP network classifier , The test result is correct.

The experimental results obtained by Poser in the three mannequins 10 supine and side-lying pictures and the use of infrared cameras to capture the surrounding people's 40 sleeping pictures, a total of 50 pictures, the test results in Table 2.

side	22	21	1	0	95.4%
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In this paper, four children were selected, respectively, 2 men and 2 women, respectively, for each child's mattress installed specifically designed for children's devices were recorded for each child sleeping in the day and night supine and lying on the

side of each 10 times, The system identification rate was verified by the number of bleed air bleeds for each balloon. The test results are shown in Table 3 and Figure 7 below:

Table 3.Test results.

Testers	Gender	Time	Supine total number	Supine recognition times	Supine recognition rate	Total number of lateral decubitus	Number of lateral decubitus recognition	Lateral decubitus recognition rate
A	male	Day	10	10	100%	10	9	90%
A	male	Night	10	9	90%	10	9	90%
B	male	Day	10	9	90%	10	9	90%
B	male	Night	10	9	80%	10	8	80%
C	male	Day	10	10	100%	10	9	90%
C	male	Night	10	9	90%	10	10	100%
D	female	Day	10	9	90%	10	8	80%
D	female	Night	10	8	80%	10	9	90%

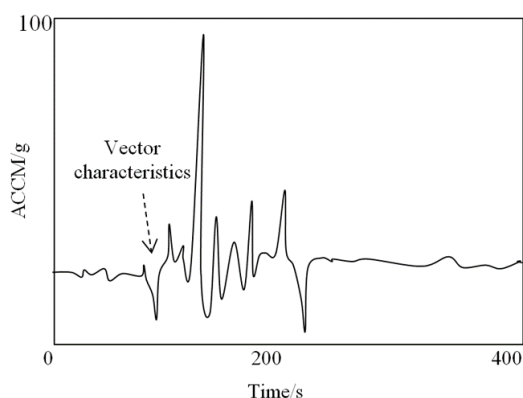


Figure7. Abnormal condition of spinal column.

Through the above sleeping posture test results show that the recognition rate of the system is high, according to each child's real-time display of changing gestures to remind the child's gestures.

5. Conclusion

In this paper, the neural network algorithm is used to study the effect of core stability on the poor spine posture of 3-6 year-old children. Firstly, the neural network algorithm is used to judge the sleeping

position of children, and the characteristic information is sent to BP neural network for training. Change weights until the output matches the expected result to construct a P BP neural network classifier. Then the children's sleeping position images are obtained from the near infrared camera, and the preprocessing operations such as geometric normalization, gray histogram equalization and image filtering are performed on the acquired sleeping image, and then the sleeping posture is extracted using the e-Haar-like method. Then, these matrix features are introduced into the trained method to extract the pixel integral matrix features of the sleeping image, and the matrix features are introduced into the trained P BP neural network classifier. Finally, after testing, this algorithm has high recognition efficiency, which can remind children to change their posture according to the real-time monitoring and display of each changing posture of children.

References

- [1] Imhof K, Faude O, Strebel V, et al. Examining the association between physical fitness, spinal flexibility, spinal posture and reported back pain in 6 to 8 year old children[J]. *Journal of Novel Physiotherapies*, 2015, 161(2):521-534.
- [2] Panova G, Jovevska S, Gazepov S, et al. Rehabilitation and correction of spine in children[J]. *Social & Personality Psychology Compass*, 2015, 9(6):239-254.
- [3] Nuzzo J, Trajano G S, Barry B K, et al. Arm-posture-dependent changes in corticospinal excitability are largely spinal in origin.[J]. *Journal of Neurophysiology*, 2016, 115(4): 885.
- [4] Lafage R, Challier V, Liabaud B, et al. Natural head posture in the setting of sagittal spinal deformity: validation of chin-brow vertical angle, slope of line of sight, and mcgregor's slope with health-related quality of life[J]. *Neurosurgery*, 2016, 79(1):108.
- [5] Jia W, Zhao D, Shen T, et al. An optimized classification algorithm by BP neural network based on PLS and HCA[J]. *Applied Intelligence*, 2015, 43(1):1-16.
- [6] Li X, Xiang S, Zhu P, et al. Establishing a dynamic self-adaptation learning algorithm of the bp neural network and its applications[J]. *International Journal of Bifurcation & Chaos*, 2016, 25(14):1540.
- [7] Bai L, Guo X X. The model of evaluating teaching quality based on bp neural network algorithm[J]. *Applied Mechanics & Materials*, 2015, 719-720(12): 1297-1301.
- [8] Di L I, Cheng G, Zhang J, et al. Research on sitting posture spinal mechanism and device design[J]. *Research & Exploration in Laboratory*, 2017, 49(19):102