Research on Gait Detection Algorithm Based on Plantar Pressure

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Abstract. In order to identify the relationship between dynamic plantar pressure information and hallux valgus, this paper proposes a CNN model to achieve a gait detection method based on plantar pressure. The plantar pressure data during walking is converted into an image, and then the convolution neural network model in deep learning is used. Given enough input image data and expected classification results. By changing the parameters of CNN, the relationship between plantar pressure image and hallux valgus was established. Then final classification model is obtained. The result shows that the accuracy of the proposed CNN model for the diagnosis of hallux valgus achieve 90.56%, which can be used as a clinical assistant method for the diagnosis of hallux valgus. The experimental results verify the validity of the model.

1. Introduction
In the process of movement, the gait characteristics of human body have accurate records on the plantar pressure information. Plantar pressure image is an important carrier of human walking information, which can be an effective basis to judge whether the gait is normal or not [1]. Plantar pressure measurement is an advanced technique in biomechanical research, can reveal the dynamic characteristics of feet in the process of human motion. It can provide objective evaluation for the etiology analysis, condition evaluation, diagnosis, curative effect evaluation, surgical identification and functional rehabilitation of patients with clinical podiatry. It has become a research hotspot. It is of great significance to correctly recognize, continuously monitor and pathologically analyze gait based on plantar pressure [2].

Hallux valgus refers to the excessive lateral deflection of the first metatarsophalangeal joint of the great toe, which generally occurs symmetrically. It’s a common and frequently-occurring disease in orthopedics, accounting for almost half of the outpatients of foot surgery [3]. It’s a foot disease that seriously affects the masses, especially women's daily life. It not only affects the beauty of the feet and wears shoes, but more importantly, the secondary pain has a greater impact on the basic load and walking function of the foot. Long course of disease will also appear bone and joint lesions, seriously affecting physical health. In this paper, the gait of normal control group and hallux valgus patients were measured and analyzed, and can achieve identify the relationship between dynamic plantar pressure information and hallux valgus. It can assist the evaluation, diagnosis, treatment, operation and rehabilitation of hallux valgus patients, and provide data for the application of plantar pressure in various fields [4, 5].
2. Research method

In 2012, deep learning model AlexNet appears in image classification competition [6]. Subsequently, deep learning has gradually become a very important technology in the field of image classification in the continuous research, and achieved excellent results. Given the input image and expected results, deep learning can find the most direct and most relevant feature information through iterative learning, and use the feature information to perform classification and recognition [7]. Deep learning emphasizes the ability of automatically learning features from data. Even with very little data, the network can learn features well, and the deep learning model has good reusability [8]. In this paper, deep learning algorithms will be used to analyze plantar pressure data and then determine the relationship between plantar pressure information and hallux valgus. The normal and abnormal plantar pressure are classified to achieve gait detection based on plantar pressure.

The convolutional neural networks (CNN) model is mainly composed of convolution layer, activation function, pooling layer, fully connected layer and softmax. The convolution layer is composed of one or more convolution units. The parameters of each convolution core are optimized by back propagation algorithm [9]. Convolution is used to extract different features of input, and different convolution layers extract different features. Activation function is a function that runs on the neuron in the neural network model, mapping the input of the neuron to the output. After convolution operation, the input data is added to a pool layer, which aims to reduce the dimension of data, reduce the number of parameters in the fully connected layer, speed up the calculation and prevent over fitting. The fully connected layer is behind the convolution layer and the pooling layer. Each neuron in the fully connected layer is connected to all neurons in the upper layer. The output value of the last fully connected layer is transferred to the softmax classifier for feature classification [10].

The traditional logistic regression (LR) mainly solves binary classification, softmax regression is the extension of LR model in multi categories. The mathematical expression of LR model is shown in formula (1):

$$ h_{y}(x) = \frac{1}{1 + e^{-\theta^T x}} $$

The corresponding loss function is:

$$ J(\theta) = \frac{1}{m} \sum_{i=1}^{n} (-y^{(i)} \log (h_{y}(x^{(i)})) + (1 - y^{(i)}) \log (1 - h_{y}(x^{(i)}))) $$

In formulas (1) and (2), $x^{(i)}$ is the training sample; $y^{(i)} (y^{(i)} \in \{0, 1\})$ is the label corresponding to the training sample $x^{(i)}$; $m$ is the total number of sample categories, if it’s the binary classification problem, $m = 2$; $\theta$ is the model parameter of the training process.

Sigmoid function is often used as threshold function of neural network. For example, formula (3) and (4) are the expression and derivative functions of the sigmoid function. The sigmoid function maps the input data between (0,1), which can be used for binary classification.

$$ \text{Sigmoid}(x) = \frac{1}{1 + e^{-x}} $$

$$ \text{Sigmoid}'(x) = \text{Sigmoid}(x) (1 - \text{Sigmoid}(x)) $$

The activation function is the ReLU function, which is used to hide the output of layer neurons. The expression and derivative of the ReLU function are as follows in formulas (5) and (6):

$$ \text{ReLU}(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} = \max(0, x) $$
Re $LU'(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$ \hfill (6)

As a common model of deep learning, CNN has the advantages of weight value sharing, low model complexity and less weight quantity. Compared with the traditional algorithm, it can avoid the complex process of manual feature extraction and data reconstruction, and can achieve automatic feature extraction. It has great advantages in large-scale image classification and recognition. Therefore, this paper will use CNN to study the gait detection algorithm based on plantar pressure.

3. Experimental design

3.1. System structure design
Gait detection system based on plantar pressure consists of three parts: data acquisition module, data processing module and data analysis module. The system structure is shown in Figure 1. The subjects walked naturally on Tekscan sensor module, and the sensor was connected with the data collector. The data collector transmitted the measured plantar pressure data to PC through USB hub or wireless. PC preprocessed and analyzed the collected plantar pressure data and displayed the final classification results.

![Figure 1. The system of plantar pressure detection](image)

3.2. Data acquisition module
In this project, Tekscan sensor of F-Scan system is used to collect experimental data. Before data acquisition, simple calibration should be completed and subjects should warm up properly. During the test, the subjects walked at an appropriate speed, and the pressure test sensor module saved the plantar pressure data of the subjects as file, and then used PC to receive the corresponding plantar pressure data file.

3.3. Data processing
The data processing is preprocess the collected plantar pressure data. Convert the plantar pressure data derived from the system to plantar pressure image. There were 50 healthy subjects and 43 hallux valgus patients in this study. Each subject collected 10 groups of data. The plantar pressure data derived from the acquisition system corresponds to a complete process of foot contact with the ground, which is divided into left and right feet. Each foot corresponds to about 100 two-dimensional tables. The two-dimensional table corresponding to each frame of each foot is shown in Figure 2(a). Each number in the two-dimensional table represents the plantar pressure value at the corresponding position at this time.

According to the two-dimensional table of plantar pressure data, the plantar pressure image can be obtained by converting the data into the corresponding image data. In Figure 2(b), the larger the value in the two-dimensional table, the greater the plantar pressure value in the corresponding position, the closer the color is to red, and the smaller the value is, the closer it is to blue. The part with a value of 0 indicates that the position is an area not to be considered. Data preprocessing transforms the effective plantar pressure value into plantar pressure image, which is used for gait analysis.
In the F-Scan system, the three-dimensional image of plantar pressure can be generated according to the collected plantar pressure data. Figure 3 is the peak three-dimensional figure of plantar pressure data under a certain attitude. From the figure, we can know that the higher the plantar pressure data value, the higher the corresponding peak value, and the closer the color is to red. The lower the plantar pressure data, the closer the color is to blue. The enlarged image of plantar pressure image conversion is shown in Figure 4.
3.4. Experimental analysis

According to the plantar pressure image obtained by data processing, a plantar pressure image dataset can be obtained and used for gait classification and recognition. In this paper, we use the method of deep learning to carry out experiments, using convolutional neural network. Convolutional neural network is a very complex function with variable parameters, which is recorded as $y = f(x | \theta)$. Among them, $x$ is the input data, that is the plantar pressure image. $y$ is the expected output classification result. $f(x | \theta)$ is a function corresponding to convolution neural network, and $\theta$ is the parameter to adjust the numerical value in training. When there is a certain relationship between the input image and the expected output result, and the amount of data in the training set is enough, the trained convolutional neural network model can get the correct analysis and prediction results after given the input.

The plantar pressure image data set is divided into training set and testing set. The training set is used to adjust the parameters of the model, and the most direct relationship between the plantar pressure information and hallux valgus is obtained from the continuous iterative updating. The testing set is used to simulate diagnosis, evaluate the accuracy, compare with the real situation, and evaluate the performance of the model. When the amount of data in the training set is enough and there is a certain relationship between the input image and the expected output result. The trained CNN model can get the correct analysis and prediction results after given the input.

The convolution neural network used in this paper consists of five convolution layers and two fully connected layers, the convolution kernels in the convolution layer are all 3 x 3 in size, and the number of each is 32, 64, 64, 128 and 128. Use the ReLU function as the activation function. Max pooling core size is 2x2. Two fully connected layers at last. After the first fully connected layer, the activation function uses the ReLU function, which has a Dropout layer with a parameter of 0.5 to avoid over fitting. The second activation function used by the fully connected layer is the sigmoid function. The ending model is activated by a single neuron and a Sigmoid, which produces the result of binary classification. The structure of convolution neural network is shown in Figure 5.

**Figure 5.** Structure of convolutional neural network

In the experiment, 2 convolutions, 3 convolutions, 4 convolutions and 5 convolutions were used. Among them, the fully connected layers are all 2 layers, and they are all located behind the convolution layer. Through the experiment, it can be found that the experimental results obtained by using 5 convolution layers are better, and the accuracy can reach 90.56%. It can be used to classify whether the plantar pressure is normal or not. The experimental results are shown in Table 1.

| Number Of Convolution Layers | Accuracy Rate |
|-----------------------------|---------------|
| 2 Convolution Layers         | 82.13%        |
| 3 Convolution Layers         | 85.75%        |
| 4 Convolution Layers         | 86.89%        |
| 5 Convolution Layers         | 90.56%        |
The full name of SVM is Support Vector Machine, which is mainly used to solve the problem of data classification in the field of pattern recognition. It is a binary classification model, which belongs to a supervised learning algorithm. During the experiment, the CNN algorithm used in this paper is also compared with SVM algorithm. The result is shown in Table 2. Using CNN can effectively improve the accuracy.

Table 2. Classification Accuracy of Different Algorithm Models

| Algorithm Model | Accuracy Rate |
|-----------------|---------------|
| SVM             | 85.17%        |
| CNN             | 90.56%        |

4. Conclusion
In this paper, the collected plantar pressure data is converted into plantar pressure image. Using CNN model in deep learning, a classification model for identifying the relationship between dynamic plantar pressure information and hallux valgus was obtained. It can be used to classify normal and abnormal gait with an accuracy of 90.56%. It can be used as a clinical assistant diagnosis method of hallux valgus. From the experimental results, it can be seen that the deep learning method can get better results in a short time, and the classification performance is good. According to the information of plantar pressure, judge whether the gait is abnormal, and achieve gait detection based on plantar pressure. As a method of clinical assistant diagnosis, the operation is simple and convenient. It can improve diagnosis efficiency effectively.

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