Research on gait recognition algorithm based on multi-information perception

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Abstract: With the collected multi-information, through the information preprocessing, feature vector extraction, analysis and fusion, the recognition model based on BP neural network, genetic algorithm optimization BP neural network, the extreme learning machine and support vector machine are established. We have accurately identified five gait modes: flat walking, upstairs, downstairs, uphill, and downhill. The highest average recognition rate is 96.5%, and the recognition time is 0.156 s. By analyzing the advantages and disadvantages of the four recognition models, the optimal gait recognition algorithm can be obtained.

1. Introduction

In recent years, with the development of human-computer interaction technology, human gait information has been widely studied and applied to the fields of exoskeleton robot control, human motion function pathological detection, and identity recognition. Through the collection and processing of the key data such as human joint motion information, EEG, EMG information, and human-machine force, the current state of motion of the human body is accurately analyzed, which is the premise of sensing the human body’s motion intention, and is also the key technology of the human-computer interaction.

In the 1990s, American scholar Niyogi first proposed the concept of gait recognition, which opened the door for academic research on human gait information. They adopted a computer vision-based approach to gait recognition, analyzed and utilized some of the rules in the gait pattern for the first time [1]. The collected parameters were evaluated by simple pattern analysis of spatio-temporal images, which thus enabled accurate tracking of individuals. In 1997, Richard. F et al. [2] used ultrasonic ranging devices to extract gait information such as pace, stride, gait cycle and peak, and track gait in real time based on changes in gait information. In 2000, Sagawa et al. [3] detected the horizontal and vertical distances of human walking by installing a three-dimensional accelerometer on the toes of the subjects. In 2005, Lee et al. [4] introduced a variety of wearable motion detection sensors to propose a detection method based on spatiotemporal gait parameters. In 2006, the University of Tsukuba in Japan proposed a complete set of human body gesture recognition and prediction theory based on the muscle computer electrical signal and integrated physical sensors [5-6]. In 2010, the University of California at Berkeley established precise mathematical models based on joint motion data and human-machine forces, realizing the multi-pose recognition and control of the human body [7-8]. In 2014, Nogueira et al. of São Paulo University put forward a method of
estimating the position of lower extremity exoskeleton based on Markov jump linear system using simple exoskeleton data acquisition system [9]. In 2017, Fanello et al. [10] used the sparse representation method for real-time motion recognition and achieved good results.

At present, the gait recognition of bone robots at home and abroad is on the basis of a single sensor. There is no perfect multi-information database. The gait recognition accuracy is low and the real-time performance is not good. In this paper, we collected multivariate information for the needs of gait pattern recognition of new exoskeleton systems, and proposed a multi-person multi-mode gait classification algorithm based on data fusion of multiple physical sensors to provide technical support for human-machine coordinated control of exoskeleton robots.

2. Design of joint information collection system

Human gait information mainly includes plantar pressure, knee and hip joint angle, angular velocity and angular acceleration. In order to accurately obtain these data while eliminating the deviation caused by the sensor installation position, the system introduced a set of exoskeleton models as shown in Figure 1. In this model, the back of the simple upper limb is closely connected with the human body, and the lower limbs are fixed with straps on the thigh and the calf to ensure that the exoskeleton model has good follow abilities to the human body during the experiment. Four nine-axis sensors (MPU6050) are mounted in a coplanar manner on the outside of the thigh and calf to capture angle, angular velocity and acceleration information of the knee and hip joints. When the human body stands, the X axis of the sensor points directly in front of the human body, with the Y axis right, and the Z axis is perpendicular to the earth. The sole is bonded to an independently-developed foot pressure measuring shoe to achieve plantar pressure collection during the subject’s walking. In this paper, the multi-point membrane pressure sensor was used to collect the pressure information of the sole. The reasonable distribution of the feature points is beneficial to improve the accuracy of the plantar pressure model. In the experiment, we selected the points with significant plantar pressure changes as the collection points by reference to the plantar pressure distribution of healthy adults. As shown in Figure 3, 15 collection points for each insole can basically satisfy the collection demand of different populations. The plantar pressure collection system is composed of a pressure insole, a connecting wire, and an acquisition module. Joint data and plantar pressure collection frequencies are 40 HZ and 200 HZ, respectively. They can be acquired synchronously when wired.

Figure 1. Exoskeleton data acquisition system

Figure 2. System structure diagram
3. Data acquisition and preprocessing

3.1. Data collection

The average age of the eight healthy participants is 25.6. All participants realized the experimental procedure and considerations before they participated in the experiment. Before doing the experiment, we collected each participant’s waist circumference, thigh length and calf length as the basis to adjust the exoskeleton waist width, thigh length and calf length to suit the wearer’s needs. Once the experiment began, the participant continued to perform five gait tests: flat walking, uphill, downhill, upstairs and downstairs. Each gait test contained at least 10 gait cycles. During the experiment, there was a flatland between two deferent asynchronous states (about 3-5 meters). There should be a rest for at least 10 minutes during every 5 test periods to ensure the relaxation of the leg muscles and the authenticity and effectiveness of the walking posture data. Every participant was asked to collect ten complete sets of experimental data. The experimental process is shown in Figure 4.

3.2. Data preprocessing

3.2.1. Pretreatment of lower limb motion data

The joint angle is derived from the Kalman filtering, so it does not require denoising. The wavelet transform [11] is used for filtering, and the coif5 wavelet is selected as the wavelet basis function. The decomposition level is N=7. After extracting the high-frequency noise signal, the coefficients of the 1-3 layers are set to 0, and the 4-7 layers use soft threshold filtering. Take the acceleration sensor signal collected by the ground walking as an example. We compared the waveform before and after the wavelet filtering. Figure 5-7 show the hip signal filtering effect.
It can be seen from the waveforms before and after the signal processing of the nine-axis sensor that the filtering effect is obvious, and the filtered signal exhibits a significant periodicity, which provides data support for the next feature extraction.

3.2.2. Pretreatment of plantar pressure data
We used the butterworth filter [12] to denoise the two typical test points at the forefoot and the heel. The filtering effect is shown in Figure 8.

The data variance after Butterworth filtering is much smaller than the variance of the original data. The filtered curve is smoother and retains valid data in the original signal.

4. Feature extraction and fusion
In order to further extract the characteristics in the gait data, we divided a complete gait cycle into the support period and the swing period. The swing period was divided into the pre-swing period, the middle swing period and the late swing period. By calculating the average pressure of the forefoot and the heel, we used threshold analysis to accurately segment the gait phase. We compared features for complete gait cycles.

Common features of the data are generally divided into time domain features, frequency domain features and time-frequency domain features. Since the time domain features of gait information are more suitable for gait recognition, we selected the following features after analyses:

1) **Mean of angle, mean value of the plantar pressure**: reflecting the change of the average amplitude of the signal.
\[
\bar{X} = \frac{1}{N} \sum_{i=1}^{n} X_i \quad (1)
\]

Where \( \bar{X} \) is the average of the angle or foot pressure in a single cycle, and \( N \) is the number of samples in a single cycle.

(2) **Mean of angle**: reflecting the fluctuation range of the angle signal

\[
S_{\bar{X}}^2 = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2 \quad (2)
\]

(3) **Variance of angle**: correlation coefficient between acceleration X-axis and Z-axis component

\[
r_{xz}^2 = \left( \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Z_i - \bar{Z})}{\left( \sum_{i=1}^{n} (X_i - \bar{X})^2 \right)^{\frac{1}{2}} \left( \sum_{i=1}^{n} (Z_i - \bar{Z})^2 \right)^{\frac{1}{2}}} \right)^{\frac{1}{2}} \quad (3)
\]

Where \( \bar{X}, \bar{Z} \) are the average values of the X-axis and Z-axis single-cycle signals of the acceleration sensor, respectively, and \( N \) is the number of sampling points in a single cycle.

The pairs of different features are shown in Table 1.

| Features          | Angle average | Angle variance | Acceleration component correlation coefficient | Plantar pressure |
|-------------------|---------------|----------------|-----------------------------------------------|------------------|
| **Gait**          | Knee          | Hip            | Knee                                         | Hip              | Maximum | Variance | Mean |
| Flat walking      | -36.398       | -13.408        | 417.71                                       | 129.94           | 0.6370  | -0.0082  | 1.1032 | 0.1088 | 0.5028 |
| Upstairs          | -60.529       | -24.955        | 579.19                                       | 274.51           | 0.7254  | -0.6040  | 1.4107 | 0.0953 | 0.7102 |
| Downstairs        | -51.281       | -20.773        | 617.45                                       | 48.84            | 0.6850  | 0.1057   | 0.7152 | 0.0421 | 0.3762 |
| Uphill            | -42.059       | -16.452        | 270.63                                       | 139.97           | 0.7628  | 0.2729   | 1.2477 | 0.1648 | 0.6135 |
| Downhill          | -39.204       | -15.012        | 342.57                                       | 58.54            | 0.4790  | 0.1652   | 0.8792 | 0.1244 | 0.4720 |

It can be seen from the Table that these features have a high degree of discrimination in the five gaits. Since the sensor can ensure coplanar mounting on the exoskeleton, we can get the angle of each joint by the rotation angle of the Y-axis of the sensor. We selected the correlation coefficient of the X-axis and Z-axis acceleration of the four sensors in the leg, the mean value and variance of the joint angle, the maximum, mean and variance of the plantar pressure to constitute the 15-dimensional matrix about features matrix.

However, not all features have decisive information on the recognition results, many of which are irrelevant and redundant, and it is this unnecessary information that increases the search space of the classifier, thereby reducing its generalization ability [13]. In this paper, we used partial least squares (PLS) to fuse feature vector. Figure 9 shows that the contribution rate of the former 4D principal component of the PLS algorithm to the original feature vector is 93%. We could replace the original feature with the new 4D input, which can effectively shorten the training time of the model and improve the accuracy of the model.

5. **Research on gait recognition algorithm**

5.1. **Algorithm design**
This paper used machine learning algorithms to identify five gait modes: flat walking (labeled 1), upstairs (labeled 2), downstairs (labeled 3), uphill (labeled 4), and downhill (labeled 5). We compared the advantages and disadvantages of BP Neural Network, Optimized BP Neural Network by Genetic Algorithm, Extreme Learning Machine (ELM) and Support Vector Machine (SVM) in real time and accuracy. The algorithm design block diagram is shown in Figure 10.

![Algorithm flow diagram](image)

Figure 10. Algorithm flow diagram

We used the eight people’s data for modelling and simulation. The fused feature vector in a single gait cycle was used as the algorithm input, and the gait tag was used as the output. We selected 100 samples for each gait, 75 of which were training samples, and 25 were used for testing. The training set totalled 3,000 samples and the test set totalled 1,000 samples.

5.2. Calculation and Simulation

In order to improve the learning rate of the BP Neural Network and the performance of the recognition model, Genetic Algorithm (GA) was introduced to optimize the initial weights and thresholds of the neural network. In this study, the BP Neural Network adopted a three-layer structure in which the hidden layer was provided with 24 nodes. The initial population of the genetic algorithm was set to 50, and the number of iterations was set to 100. The fitness function was derived from the following formula.

\[ SE = \sum_{i=1}^{n} (A_i - A'_i)^2 \]  
\[ val = SE^{-1} \]

Where \( A_i \) is the true value of the \( i \) th sample, and \( A'_i \) is the predicted value of the \( i \) th sample. \( SE \) is the sum of the squares of the errors, and \( val \) is the fitness value of the genetic algorithm. The relationship between the fitness value and the number of iterations is shown in Figure 11. It can be seen that the solution after 50 times is very close to the optimal initial weight and threshold.

The number of hidden layer nodes of ELM [14] has an important influence on the performance of the algorithm model. Figure 12 reflects the influence of the number of nodes on the accuracy of the model. When the number of nodes is 857, the model has the highest accuracy, reaching 93.1%. The Sigmoid function was selected as the activation function of ELM.
In the research, we used the radial basis function kernel. In the SVM [15] training, the kernel function coefficient $g > 0$, and the penalty factor $C$ determined the convergence speed and generalization ability of the SVM. The selection of the $C$ and $g$ parameters directly affected the performance of the SVM. In the study, the grid method was adopted in the parameter selection. Firstly, the range of values of $C$ and $g$ was set. In MATLAB, the for loop was used to calculate the classification accuracy of the training set under the $C$ and $g$ parameters of a single traversal. At the same time, cross validation was used to ensure the validity of the results. Finally, when $C=16$ and $g=0.00097$, we got the highest classification accuracy rate. The performance of different algorithms is shown in Table 2.

| Gait          | BP (%) | GA-BP (%) | ELM (%) | SVM (%) |
|---------------|--------|-----------|---------|---------|
| flat walking  | 89     | 92        | 89      | 100     |
| upstairs      | 74     | 87        | 98      | 96.5    |
| downstairs    | 95.5   | 91        | 96.5    | 94.5    |
| uphill        | 83     | 86        | 91      | 94.5    |
| downhill      | 67.5   | 81        | 91      | 92.5    |
| average recognition rate (%) | 81.8  | 87.4  | 93.1  | 96.5  |
| average time (s) | 0.2188 | 0.125 | 0.3572 | 0.0156 |

5.3. Analysis and comparison of results

In the process of verification, it is found that the BP Neural Network cannot obtain the global optimal solution. This is mainly because the weight used is optimized by the gradient descent method. This optimization process can only optimize it on one point. GA-BP uses genetic algorithms to optimize the initial weights and thresholds of BP Neural Networks, so it exists the same problem. The real time and accuracy and performance of the ELM algorithm are largely affected by the number of neurons in the hidden layer, and the results of each training process are deviations. In general, SVM is better than BP, GA-BP and ELM algorithms. And it has a great improvement in the recognition time. The misidentified data is mainly the uphill and downhill data. This is due to the small slope used in this study, which is similar to the flat walking in some features, leading to the identification error of individual samples.

6. Conclusions

This paper proposes a gait recognition method based on multi-information perception. Firstly, the multi-information of human motion is obtained through the data acquisition experiments, and then the data is smoothed and denoised. The gait cycle is divided according to the plantar pressure and we
analyze the gait characteristics in a single cycle, further extract and fuse the effective eigenvalues. Finally, based on the eigenvectors after fusion, the gait recognition model is used to realize the recognition of five kinds of asynchronous states: flat walking, upstairs, downstairs, uphill and downhill. The highest average recognition rate reaches 96.5%. This shows that the SVM algorithm has better generalization performance and recognition accuracy, and the recognition time is short, which provides a theoretical basis for further study of gait information.

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