Research on Gait Recognition and Prediction of Exoskeleton Robot Based on Improved DTW Algorithm

Wang Motao*, Li Zhijun, Lei Qing, Wang Meng and Zhang Rui

School of Automation, Wuhan University of Technology, Wuhan 430070, China

E-mail: *807968665@qq.com

Abstract. In order to realize the follow-up control of the exoskeleton robot better, the gait phase of the human body should be accurately identified and the human body motion intention should be matched in real time. In this paper, a set of gait data measurement system is used to collect the gait information of the human body during the movement process. Then, the gait recognition of the six models is carried out by the support vector machine through the plantar pressure information. Then the human movement intention is divided into five kinds and the improved DTW algorithm was used to complete the work of matching human motion intentions. Ultimately, the BP neural network model was designed to accurately predict the gait data. The experimental results show that the exoskeleton robot can accurately realize the three functions of recognition, matching and prediction.

1. Introduction

At present, if a robot wants to interact with another agent object, the needs to recognize the interaction between one or more of these objects and the external scene in which they are located. Then the robot needs to understand the behaviour of these objects in the corresponding external scene, and finally predict the behaviour of these intelligent objects and the corresponding inference results[1]. Although there has been in-depth research at home and abroad in gait recognition, but it is difficult to uniformly classify all gait states, due to the complexity of gait phase distinction. In this paper, the gait phase is re-divided, then matches the motion state with the improved DTW algorithm and eventually realizes the prediction of gait.

2. Gait data acquisition

The collection and analysis of data is the premise to study the whole gait recognition, matching and prediction. The sensor processes data quickly, with high sensitivity, simplicity, and easy dismantling and it is the most widely used gait information acquisition method. The system uses the controller to communicate with each sensor, collecting each sensor data in real time, and transmits the gait information data collected by the sensor to the upper computer, subsequently keeping the collected data in the text document.

After putting on the exoskeleton robot, the operator performs five states of flat walking, uphill, downhill, upstairs, and downstairs. The important features of the walking process after the operator wearing the exoskeleton robot can be accurately obtained and the gait information is measured by the system. The key is joint angle and the plantar pressure information should be least interfered. Therefore, the gait information data collected by the system can be used to analyse and predict the gait state.
3. Design and implementation of gait recognition scheme

In the gait analysis of exoskeleton robots, how to properly divide the gait phase of the lower limbs is an important research, and it is also a prerequisite for controlling the external bone robot[2]. First, smoothing the data, removing the random noise in the data and then retaining the useful signal, eliminating the small variance signal and retaining the large variance signal, and in this way the SNR can be improved well. In this paper, the gait data is smoothed by Savizky-Golay[3] convolution method. Then, the gait phase[4] is divided into four parts by the division of the gait cycle and the combination of the support state and the swing state: heel to the ground, flat standing, heel off the ground, swinging state. The support vector machine[5-6] method is used to identify the four gait phases in the process of exoskeleton robot movement. The four gait phases are divided into six one-to-one models by one-to-one method:

(1) Heel to the ground - flat standing;       (2) Heel to the ground - heel off the ground;
(3) Heel to the ground - swinging state;     (4) flat standing - heel off the ground;
(5) flat standing - swinging state;          (6) Heel off the ground - swinging state.

For the six one-to-one models, six results were identified, of which the one identified most frequently was identified, and each gait was counted separately. Figure 1 indicates the gait phase recognition in a cycle: where "0" represents the swinging state, "1" stands for flat standing, "2" stands for heel off the ground, and "3" stands for the heel to the ground.

![Figure 1. Gait phase recognition results in a single cycle.](image)

As shown in figure 1, it can be found that the use of the support vector machine to identify the phase of a gait cycle can obtain better results. Therefore, identifying the gait for a period of time, and the recognition result is shown in figure 2. After calculation, the recognition accuracy of this method is 77.39%, and the recognition effect is satisfactory.

![Figure 2. Gait recognition results for a period of time.](image)

4. Matching motion intent based on improved DTW algorithm

DTW (Dynamic Time Warping) algorithm is an algorithm based on dynamic programming (DP)[7-8]. This algorithm is a classic algorithm in the field of speech recognition. It is mostly used for isolated word recognition to solve the template matching problem caused by different lengths of pronunciation.
Because of its simplicity and effectiveness, the algorithm is still widely used. In this paper, the gait of the exoskeleton robot and the diversity of its data are similar to the different length of the speech in the isolated speech recognition. Therefore, the DTW algorithm can be used to match the gait information of the exoskeleton robot.

The DTW algorithm measures the similarity between two different time series by using the distance of a regular path. In general, the shapes of two different time series are very similar. But it is not aligned on the x-axis, therefore, it is necessary to make it reach a good state before comparing and calculating the similarity between two different time series. In order to achieve alignment of two different time series, one or two of the warping distortions must be performed on the time axis. Therefore, the DTW algorithm is a method that can effectively implement warping distortion.

The DTW algorithm implements the warping distortion including the following:

On the assumption that there are two different time series named Q and C, and the lengths of which are n and m. Respectively,

\[
Q = (q_1, q_2, \ldots, q_n) \\
C = (c_1, c_2, \ldots, c_m)
\]

(1)

(2)

If \( n = m \), the distance between two different time series can be directly calculated. If \( n \neq m \), it is necessary to align the Q and C. In order to better align the Q and C, a dynamic programming method can be employed. First, the matrix of \( m \times n \) is constructed, and the distance which is represented by \( d(q_i, c_j) \) between the two points of each point \( q_i \) and \( c_i \) on the Q and C is represented by (i,j). Calculated by using Euclidean distance:

\[
d(q_i, c_j) = (q_i - c_j)^2
\]

(3)

Obviously, the smaller the value of \( d(q_i, c_j) \), the higher the similarity. The DP algorithm can be seen as looking for a path through the alignment points between several Q and C in the \( m \times n \) matrix grid, which is the warping path. The warping path defining the mapping between the Q and C is \( W \), and its k-th element is denoted by \( w_k = (i - j)_k \). Among them:

\[
W = w_1, w_2, \ldots, w_k, \ldots, w_K \\
max(m, n) \leq K \leq m + n - 1
\]

(4)

\( W \) needs to meet the following three conditions:

1. Boundary conditions: \( max(m, n) \leq W \leq m + n - 1 \)
2. Continuity: In order to map any points in Q and C to the warping path, it cannot be matched across points, and can only adjacent.
3. Monotonicity: If \( w_{k-1} = (a^*, b^*) \), then the next point of the path needs to satisfy \( 0 \leq (a - a^*) \) and \( 0 \leq (b - b^*) \).

For the easiest way to find the path with the minimum distance, define:

\[
\text{DTW}(Q, C) = \min \left( \frac{\sum_{k=1}^{K} w_k^2}{K} \right)^{\frac{1}{2}}
\]

(5)

\( K \) is the compensation for the different lengths of the warping path. The most similar warping path between the Q and C, the linear minimum distance, is the final distance measuring between different Q and C.

In the implementation process of the aforementioned steps, firstly the DTW algorithm establishes an \( n \times m \)-dimensional accumulation matrix named \( D \) and an \( n \times m \)-dimensional frame matching matrix \( d \). In frame matching matrix named \( d, d = (i, j) \) is the distance between the j-th frame of the template sequence and the i-th frame of the test sequence. And \( D(N \times M) \) is the matching distances corresponding to the best matching path.

In this article, the DTW algorithm can be used to obtain good experimental results. However, the traditional DTW algorithm generally limits the slope of the bend during the matching process, which results in many points that cannot be achieved at all in reality. Therefore, it is not necessary to calculate the frame matching distance corresponding to the points other than the rectangle, and it is not necessary to save all frame matching distance matrix and the cumulative distance matrix. Further, only three grids adjacent thereto can be used for the matching calculation at each point. The calculation and
the demand for storage room in the process of DTW algorithm can be greatly reduced by taking full advantage of the previous two features. Therefore, an improved DTW algorithm comes up to reduce the amount of computation and save storage space.

As shown in Figure 3, the actual dynamic bending is divided into three segments, namely: \((1, X_a), (X_a + 1, X_b), (X_b + 1, N)\), among them:

\[
\begin{align*}
X_a &= \frac{1}{3}(2M - N) \\
X_b &= \frac{2}{3}(2N - M)
\end{align*}
\]

(6)

\(X_a\) and \(X_b\) take similar integers, then there are magnitude control factors for \(M\) and \(N\):

\[
\begin{align*}
2M - N &\geq 3 \\
2N - M &\geq 2
\end{align*}
\]

(7)

![Figure 3. Improved DTW normalization approach.](image)

When the formula (7) is not satisfied, it indicates that the difference between A and B is relatively large, and dynamic time warping cannot be performed. The second formula greatly reduces the search area of the search path, which causes it to change from the original rectangular area to a parallelogram area that is much smaller than the rectangle. Further, since the matching process follows the principle of the shortest path, it can be seen that the shortest path has a moderate slope. Therefore, the slope of the search path can be fixed within a certain range to reduce the amount of calculation and increase the matching speed. In this paper, the slope of the search path is fixed within the range of 0.5~2. Therefore, in the rectangular search area, if \((m_i, n_i)\) has passed, the point that it passed before can only come from \((m_i - 1, n_i)\) or \((m_i - 1, n_i - 1)\) or \((m_i - 1, n_i - 2)\). In the parallelogram search area, if \((m_i, n_i)\) has passed, the point it passed before may be \((m_i - 1, n_i)\), like A in Figure 3; Or one between \((m_i - 1, n_i)\) and \((m_i - 1, n_i - 1)\), like B in Figure 3; Or one among \((m_i - 1, n_i), (m_i - 1, n_i - 1)\) and \((m_i - 1, n_i - 2)\), like C in Figure 3; In this way, the cumbersome matching of the search path by three points in the whole process can be avoided, the calculation amount is greatly reduced and the matching speed is improved. Therefore, in the case of the parallelogram search area and the search path slope between 0.5 and 2, if \(D[T(m_i), R(n_i)]\) is used to indicate the distance between two frames, then:

\[
D[T(m_i), R(n_i)] = d[T(m_i), R(n_i)] + D[m_{i-1}, n_{i-1}]
\]

(8)

\[
D[m_{i-1}, n_{i-1}] = \min \left\{ \begin{array}{l} D[m_{i-1}, n_{i-1}] \\ D[m_{i-1}, n_{i-2}] \end{array} \right. \]

(9)

The path of the minimum cumulative distance calculated according to the above steps is the best path.

According to the simulation results, it can be seen that when the sequence of the test data is walking on the ground, the shortest distances after matching the five states of the flat walking state,
the upstairs, the downstairs, the uphill, and the downhill are 678, 1586.66, 1546.59, 1902.15, 1712.92, As shown in Figure 4, where: (a) flat walking state-flat walking state; (b) flat walking state-upstairs; (c) flat walking state-downstairs; (d) flat walking state-uphill; (e) flat walking state-downhill.

![Graphs](image)

Figure 4. Matching graph based on improved DTW algorithm.

The DTW algorithm and the improved DTW algorithm are respectively matched to the human motion intention, and the matching accuracy is shown in Table 1.

Table 1. Identification accuracy of DTW algorithm and improved DTW algorithm.

| Algorithm        | Recognition accuracy |
|------------------|----------------------|
|                  | flat walking state   | upstairs | downstairs | uphill | downhill |
| DTW              | 0.87                 | 0.85     | 0.83       | 0.84   | 0.85      |
| Improved DTW     | 0.91                 | 0.88     | 0.84       | 0.87   | 0.86      |

It is not difficult to see from the above comparison that not only the improved DTW algorithm improves the certain accuracy rate to a certain extent, but also runs faster than the general DTW algorithm in time.

5. Gait prediction and implementation

Since the response of the sensor and the control of the system are slightly delayed, the gait of the external bone robot must be predicted in real time in order to follow the external bone robot in real time better. In this way, the force between the human and the machine can be reduced, so that the human and the machine can cooperate with each other and get real-time control. Therefore, the BP neural network model is used to predict the gait foot pressure information, and the simulation results are shown in figure 5.
Figure 5. BP neural network prediction map.

As can be seen from figure 5, when the BP neural network model is used for gait prediction, results obtained can be satisfactory. Therefore, even when the system has a certain delay, the exoskeleton robot can accurately predict the gait. And the system can complete the follow-up control in real time.

6. Conclusions
In order to study the gait movement state of the exoskeleton robot in more detail, the operator must wear the exoskeleton robot to conduct experiments, collect and obtain various available data information in the experiment and use the information to analyse the various properties of the exoskeleton robot. Firstly, a large number of reliable gait data is collected and preprocessed by a set of gait data measurement systems; Secondly, the support vector machine is used to perform gait recognition on six models by one-to-one method; Then the gait data was used to establish a database, and the improved DTW algorithm was used to match the motion intent; Finally, the BP neural network was used to predict the plantar pressure signal. Although this paper proves the effectiveness of the gait recognition algorithm through verification experiments, there are still some aspects that need to be further modified and improved.

Acknowledgement
The completion of this article is inseparable from the strong support of the exoskeleton robot project (Item Number: 2017YFB1300502). Here, I would like to sincerely thank Dr. Yu Fangli and Dr. Guo Chaoyue for their guidance and help on gait recognition. Thanks to Zhang Yong of the Tenth Research Institute of China Aerospace Science and Industry Corporation for their effective research work on communication protocols and sensor nodes. Thanks to all the project team members for their great help. Finally, I would like to thank all the scholars involved in this article. The writing of this thesis is inseparable from your excellent achievements.

References
[1] Abowd G D and Mynatt E D 2004 Designing for the human experience in smart environments[M]// Smart Environments: Technologies, Protocols, and Applications.
[2] Bar A, Ishai G, Meretsky P, et al 1983 Adaptive microcomputer control of an artificial knee in level walking[J]. Journal of Biomedical Engineering,5(2):145-50.
[3] Chen J, JCnsson P, Tamura M, Gu Z, Matsushita B, et al 2004 A simple method for reconstructing a high-quality NDVI time-series dataset based on the Savitzky-Golay filter[J]. Remote Sensing of Environment,91:332-44.
[4] Jun-Young J, Wonho H and Hyundae Y, et al 2015 A neural network-based gait phase classification method using sensors equipped on lower limb exoskeleton robots[J]. Sensors,15(11):27738-59.
[5] Zhang X-G 2000 Introduction to statistical learning theory and support vector machines[J]. Acta Automatica Sinica,26(1):32~42.
[6] Cristianini N and Taylor J S 2000 An introduction to support vector machines and other kernel-based learning methods[M]. Cambridge University Press, Cambridge.
[7] Sideratos G and Hatziargyriou N D 2007 An Advanced Statistical Method for Wind Power Forecasting[J]. IEEE Transactions on Power Systems, 22(1):0-265.

[8] Wang Y, Lei P, Zhou H, et al 2014 Using DTW to measure trajectory distance in grid space[C]//IEEE International Conference on Information Science & Technology. IEEE.