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Action Recognition of Human's Lower Limbs Based on a Human Joint

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Abstract

To recognize the actions of human's lower limbs accurately and quickly, a novel action recognition method based on a human joint was proposed. Firstly, hip joint was chosen as the recognition object, its y coordinates were as recognition parameter, and human action characteristics were achieved based on Butterworth filter and wavelet transform. Secondly, an improved self-organizing competitive neural network was proposed, which could classify the action characteristics automatically according to the classification number. The classification results of motion capture data proved the validity of the neural network. Finally, an action recognition method based on hidden Markov model (HMM) was introduced to realize the recognition of classification results of human action characteristics with the change direction of y coordinates. The proposed action recognition method needs less action information and has a fast calculation speed. Experiments proved the method had a high recognition rate and a good application prospect.

Keywords: *human action characteristics, characteristic classification, improved self-organizing competitive neural network; action recognition*

1. Introduction

With the development and popularity of optical motion capture equipment, human action recognition technology has received much attention in recent years. Many scholars have studied the technology extensively and introduced many methods to recognize the human action processes in recent 20 years. Chen *et al.* [1] extracted spatio-temporal interest points and 3D-SIFT descriptors around each interest point in the videos and introduced a human behavior classification model based on dynamic Bayesian network. Barnachon *et al*. [2] extracted histograms of action poses from motion capture data to recognize ongoing activities based on dynamic time planning. Kamal *et al.* [3] received a sequence of depth maps to extract human silhouettes, from which hybrid features as optical flow motion features and distance parameters were extracted and used to work as spatio-temporal features; these features were clustered and symbolized by self-organization maps and HMMs were trained to recognize human activities. Even so, there is no mature technology which can satisfy the requirements of real-time acquisition and high accuracy in the recognition progress due to the diversity of human bodies and the complexity of action processes [4]. An important reason is action characteristics are difficult to represent. Many scholars proposed many methods, such as key frames [5, 6], spatio-temporal attitude model [7], etc. But their expression manners are always complicated and used in specific action processes. Besides, the classification methods of human action characteristics also have an impact on recognition results, and they can be divided into two classes in general. One is to classify action characteristics based on trained mathematical models, such as BP neural network [8], support vector machine (SVM) [9], relevance vector machine (RVM) [10], etc. The other is based on self-learning methods, mainly including self-organizing competitive neural network [11], K-Means [12, 13], etc. The former methods need to learn the action characteristics information which has been marked, so the expected outputs of the corresponding inputs need to be achieved in advance. Whenas, because of the limitation of human cognitive ability or environment the expected outputs are hard to achieved sometimes. The latter methods don't need to know the expected outputs, and can realize the automatic classification of action characteristics by comparing and differentiating all training samples. However, when the initial conditions of self-organizing competitive neural network are set, the

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classification number of action characteristics is hard to control; the method such as K-Means can classify action characteristics according to the set classification number, but the classification effect is influenced by the initial settings, and the method is easy to fall into local minimum value and sensitive to noise.

To realize the fast and accurate action recognition of human's lower limbs, a novel action recognition method for human's lower limbs is proposed. Only the hip joint is adopted as the recognition object and its *y* coordinates are as recognition parameter. Because the change curves of *y* coordinates in different actions can represent different graphics characteristics, wavelet transform is introduced to calculate the action characteristics after filtering the action parameter. Then, an improved self-organizing competitive neural network based on simulated annealing algorithm is proposed to classify action characteristics automatically according to the classification number set initially. Finally, an action recognition method based on HMM [14] is introduced to realize the action recognition of human's lower limbs with the change direction of *y* coordinates. Because the motion information of only a joint is adopted, the action recognition method can face the personnel of different sizes, and it has a fast calculation speed and a good recognition effect. The human action data comes from CMU human action database of Carnegie Mellon University.

2. Research Method

2.1. Action Characteristics of Human's Lower Limbs

2.1.1. The Selection of Action Parameter

In order to realize the action recognition of human's lower limbs, a simplified skeleton structure of human's lower limbs is introduced and shown in Figure 1. In the figure, WCS denotes world coordinate system and LCS denotes local coordinate system. Because the motion processes of other joints are around hip joint which can be as the root joint, we choose it to represent the action processes of human's lower limbs. When people walk or run in a room, the regulations are difficult found in the changes of the locations of hip joint in the *x* and *z* directions due to the uncertainty of motion direction. Therefore, *y* coordinates of hip joint in the WCS are chosen to recognize each action of human's lower limbs and the *y* coordinate of hip joint at time *t* is denoted as $y(t)$. In the paper, the sample frequency of motion capture data is 120 Hz and the unit of time *t* is the sample interval 1/120 s.

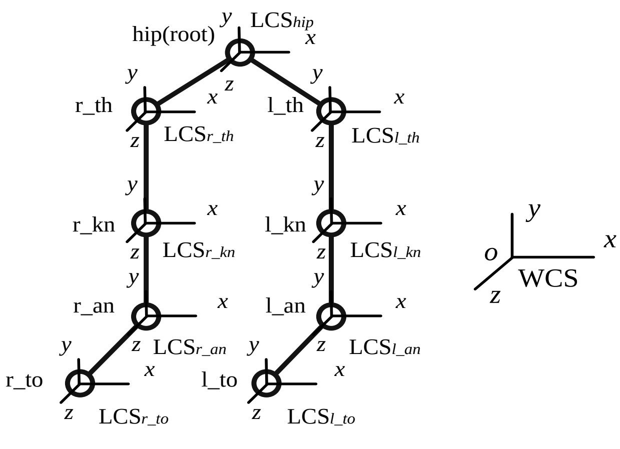

Figure 1. A simplified skeleton structure of human's lower limbs.

In order to facilitate extracting accurate action characteristics, Butterworth filter of which the cutoff frequency is set as 0.1 rad/s is adopted to filter $y(t)$, and the filtering results are denoted with $y'(t)$. Take multiple sets action data of human's lower limbs for example, such as walking, running and jumping and their filtering results are shown in Figure 2.

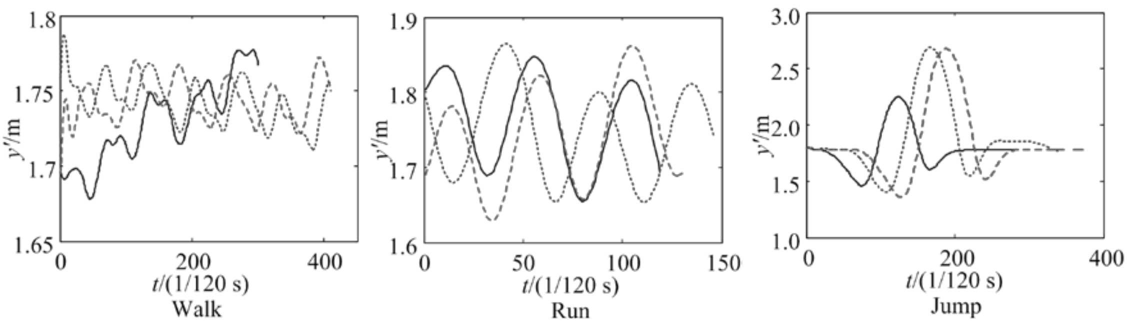

Figure 2. Change curves of $y'(t)$ in different action processes

In Figure 2, there are similar graphics characteristics of the same actions, and graphics characteristics of different actions have obvious distinction. The change direction of $y'(t)$ is calculated as follows:

$$\Delta y(t) = \frac{y'(t+1) - y'(t)}{T} \tag{1}$$

$$Dy(t) = \begin{cases} \dfrac{|\Delta y(t)|}{\Delta y(t)}, \Delta y(t) \neq 0 \\ 0, \Delta y(t) = 0 \end{cases} \tag{2}$$

Where, $\Delta y(t)$ means the velocity of hip joint in the y direction at time t; $Dy(t)$ represents the change direction of $y'(t)$.

2.1.2. The Representation of Action Characteristics

Signals' fractal characteristics represent their self-similarity. Time-frequency property of signals can be observed expediently based on wavelet transform, and the signals' self-similarity coefficients in different scales can be represented with the time-frequency property. The higher self-similarity is, the larger its coefficients are. Therefore, signals' self-similarity coefficients in different scales are introduced to represent the changes of signal morphology [15]. The formula of wavelet transform is as follows:

$$F_{a,b} = \frac{1}{\sqrt{a}} \int_Q f(t) \overline{\psi\left(\frac{t-b}{a}\right)} \mathrm{d}t \tag{3}$$

Where $f(t)$ means the action parameter $y'(t)$, $F_{a,b}$ means the wavelet transform coefficients of $f(t)$, a means the scale factor, b means the translation factor, Q means the signal space and ψ means the wavelet basis function.

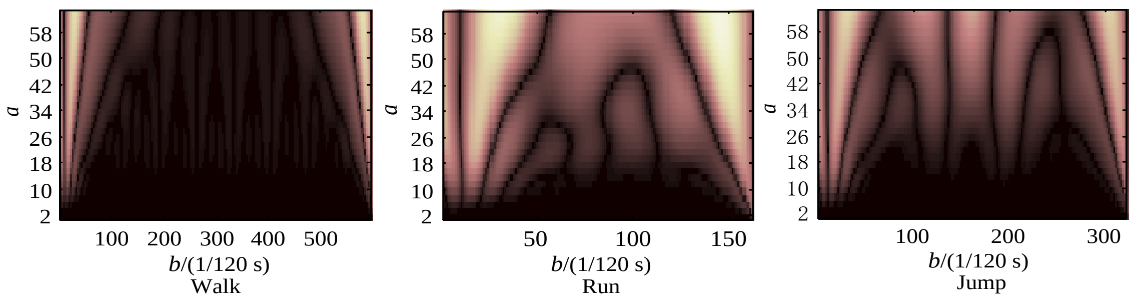

Figure 3. Wavelet coefficients of $y'(t)$ in different action processes.

Choose coif3 wavelet to transform the action parameters *y'*(*t*) in different scales of 2, 4, 6, …, 64. $(Y_{a,b}^1(t), Y_{a,b}^2(t), \cdots, Y_{a,b}^n(t))$ is used to denote the transformation results of *y'*(*t*), and *n* means the scale number which is equal to 32 in the paper. The transformation results in different action processes are shown in Figure 3. In the figure, it is found that the wavelet transform coefficients of different action processes can represent different variation rules.

2.2. The Classification Method of Action Characteristics

2.2.1. An Improved Self-Organizing Neural Network Based on Simulated Annealing Algorithm

There are two requirements in the classification process of the action characteristics of human's limbs. One is action characteristics of high similarity can be classified as the same class; another is classification results are relatively even, because it can reduce the disturbance of noise signals and ensure the representativeness of each characteristic space. Therefore, an improved self-organizing neural network based on simulated annealing algorithm is proposed to classify the action characteristics of human's limbs. First of all, set classification number *S*, then use classification space numbers $X = \{x_1, x_2, \ldots, x_S\}$ to denote classification results and classification entropy *Ec* to represent the uniformity of classification results. The calculation of *Ec* is as follows:

$$Ec = -\sum_{i=1}^{S} x_i \log_2 x_i \tag{4}$$

The training process of the neural network is following:

Step 1: Initialize network. The input layer is comprised of *R* neurons and the competitive layer is comprised of *S* neurons, the input matrix of training samples is denoted as:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1R} \\ p_{21} & p_{22} & \cdots & p_{2R} \\ \vdots & \vdots & & \vdots \\ p_{Q1} & p_{Q2} & \cdots & p_{QR} \end{bmatrix} \tag{5}$$

Where *Q* is the number of training samples; *R* equals the scale number of wavelet transform; P_{ij} denotes the *j*th input of the *i*th training sample $p_i = [p_{i1} \quad p_{i2} \quad \cdots \quad p_{iR}]$, $i = 1, 2, \cdots, Q$ and $j = 1, 2, \cdots, R$. Set initial temperature T_1, cooling temperature T_2, unit temperature variation ΔT, isothermal change number t_1, weight adjustment coefficient *N*, and the ideal information number of characteristic space $a = [Q/S]$. Let the current temperature $T = T_1$, utilize Ψ to denote the collection of all the action characteristics, denote the divided characteristic spaces $\Phi = \{\theta_1, \theta_2, \cdots, \theta_S\}$ where $\theta_i = \varnothing$ at the initial time and $i = 1, 2, \cdots, S$, and let the initial information number of each characteristic space $x_i = 0$, $i = 1, 2, \cdots, S$.

The initial connection weights of the network are denoted as:

$$IW = [w_1 \quad w_2 \quad \cdots \quad w_R]_{S \times R} \tag{6}$$

Where $w_i = [1/(S \times R) \quad 1/(S \times R) \quad \cdots \quad 1/(S \times R)]'_{S \times 1}$, $i = 1, 2, \cdots, R$.

The initial thresholds of the network are denoted as:

$$b = [e^{1-\ln(1/S)} \quad e^{1-\ln(1/S)} \quad \cdots \quad e^{1-\ln(1/S)}]'_{S \times 1} \tag{7}$$

Set the learning speed of connection weights as α and the learning speed of thresholds as β.

Step 2: Calculate the winning neuron. Select each training sample p_m ($m = 1, 2, \cdots, Q$) orderly. According to:

$$n_i^1 = -\sqrt{\sum_{j=1}^{R}(p_{mj} - IW_{ij})^2} + b_i\ ,\ \ i = 1, 2, \cdots, S \tag{8}$$

Calculate the inputs of competitive neurons. In formula (8), n_i^1 denotes the output of the *i*th competitive neuron; p_{mj} denotes the *j*th input of the training sample p_m; IW_{ij} denotes the connection weight between the *i*th competitive neuron and the *j*th input neuron; b_i denotes the threshold of the *i*th competitive neuron.

When the *k*th competitive neuron satisfies the following:

$$n_k^1 = \max(n_i^1)\ ,\ \ i = 1, 2, \cdots, S\ ,\ \ k \in \{1, 2, \cdots, S\} \tag{9}$$

It's seen as the winning neuron. Update the related characteristic space and its information number as follows:

$$\theta_k = \theta_k \cup p_m\ ,\ \ x_k = x_k + 1 \tag{10}$$

Step 3: Update the weights and thresholds based on simulated annealing algorithm. Update the weights and threshold of the wining neuron *k* separately as follows:

$$IW_{kj} = IW_{kj} + \alpha(p_{mj} - IW_{kj}) \times rand\ ,\ \ j = 1, 2, \cdots, R \tag{11}$$

$$b_k = e^{1-\ln[(1-\beta)e - \ln(b_k) + \beta\times\alpha\times rand]} \tag{12}$$

Where *rand* is a random number, belongs to [0, 1] and follows uniform distribution. The introduction of the random number makes the variation processes of the weights can simulate the random change processes of molecules in thermal action.

After all the training samples are studied once, calculate cluster centers w_i^1 and w_i^2 of characteristic space θ_i and its complementary set $\overline{\theta_i}$ as follows:

$$\begin{cases} w_i^1 = \sum P_m / length(\theta_i), P_m \in \theta_i \\ \overline{\theta_i} = \bigcup_{j=1, j\neq i}^{S} \theta_j & , i = 1, 2, \cdots, S \\ w_i^2 = \sum P_m / length(\overline{\theta_i}), P_m \in \overline{\theta_i} \end{cases} \tag{13}$$

Then, according to the information number of each characteristic space, update all the connection weights and thresholds. The method is as follows:

a) When $length(\theta_i) > a$, $i \in \{1, 2, \cdots, S\}$

$$IW_{ij} = IW_{ij} + (e^{-\frac{1}{T}} + e^{-\frac{1}{length(\theta_1)-a}})(IW_{ij} - w_{ij}^1) \times rand / N \tag{14}$$

$$b_i = e^{1-\ln[(1-\beta)e - \ln(b_k) + \beta\times\alpha\times rand\times(length(\theta_1)-a)]} \tag{15}$$

Where w_{ij}^1 is the *j*th weight of w_i^1 and $j = 1, 2, \cdots, R$. If *T* is high or $length(\theta_i) - a$ is large, IW_{ij} will change relatively quickly in the direction away from the cluster center w_{ij}^1. With *T* drops or $length(\theta_i) - a$ decreases, the change process will become slow. The adjustment process of b_i is only related to $length(\theta_i) - a$. If the adjustment amount is too large, the change process of weights will be difficult to convergence, so weight adjustment coefficient *N* is introduced to control the adjustment speed of weights.

b) When $length(\theta_i) < a$, $i \in \{1, 2, \cdots, S\}$

$$IW_{ij} = IW_{ij} + (e^{-\frac{1}{T}} + e^{-\frac{1}{a-length(\theta_1)}})(w_i^2 - IW_{ij}) \times rand / N \quad (16)$$

$$b_i = e^{1-\ln[(1-\beta)e-\ln(b_k)-\beta\times\alpha\times rand\times(a-length(\theta_1))]} \quad (17)$$

Where w_{ij}^2 is the *j*th weight of w_i^2 and $j = 1, 2, \cdots, R$. If *T* is high or $length(\theta_i) - a$ is large, IW_{ij} will change relatively quickly in the direction close to the cluster center w_i^2 . With the temperature drops or $length(\theta_i) - a$ decreases, the change process will become slow. The adjustment process of b_i is only related to $length(\theta_i) - a$.

c) When $length(\theta_i) = a$, $i \in \{1, 2, \cdots, S\}$

$$IW_{ij} = IW_{ij} + e^{-\frac{1}{T}} \times rand \times \mathrm{sgn}(rand - 0.5) / N \quad (18)$$

$$b_i = e^{1-\ln[(1-\beta)e-\ln(b_k)+\beta\times\alpha\times rand\times\mathrm{sgn}(rand-0.5)]} \quad (19)$$

Where $j = 1, 2, \cdots, R$. When *T* is high, IW_{ij} will change randomly and relatively quickly; when *T* drops, IW_{ij} will change slowly. The adjustment process of b_i isn't related to *T*.

Step 4: Iterate the computations of the neural network.

a) According to the isothermal change number t_1, update the neural network by executing Step 2 and 3, and calculate the changes of the classification entropy *Ec*.

b) Let $T = T - \Delta T$. If $T > T_2$, turn to a); if no, end the iterative computation process, then output weight matrix IW , thresholds b , the information number of each characteristic space and the classification entropy *Ec*.

2.2.2. The Classification of Action Characteristics

Take action characteristics of some motion capture data for example to introduce the classification method based on the improved self-organizing neural network. Training data is comprised of different kinds of human action data, and each kind consists of 3 sets of human action data. There are 1190 groups of walking characteristic data, 505 groups of running characteristic data, and 592 groups of jumping characteristic data. First of all, the training data is normalized as follows:

$$p'_{ij} = \frac{p_{ij} - \min(p^j)}{(\max(p^j) - \min(p^j)) \times b_1} \quad (20)$$

Where $p^j = [p_{1j} \quad p_{2j} \quad \cdots \quad p_{Qj}]'$, it is the *j*th column vector of the input matrix *P*, and b_1 is contraction coefficient. Let $b_1 = 1.1$ in the paper.

The initial settings are as the followings: $\alpha = 0.02$, $\beta = 0.01$, $T_1 = 1$, $T_2 = 0.95$, $\Delta T = 0.01$, $t_1 = 400$ and $S = 10$. Train the improved self-organizing neural network. The change of the classification entropy *Ec* is shown in Figure 4 and the change of the characteristic number *Ns* of a competitive neuron is shown in Figure 5.

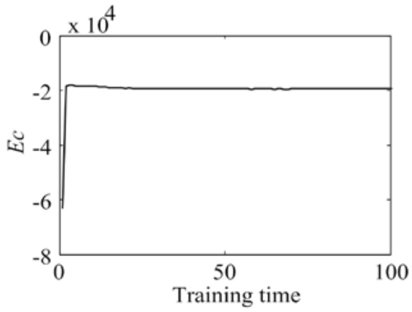

Figure 4. The change of classification entropy *Ec*

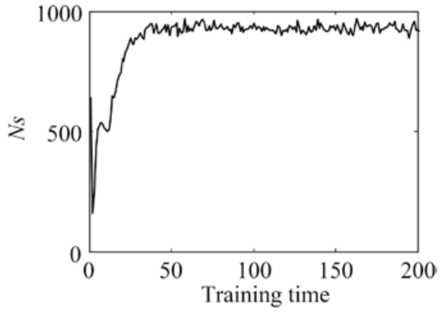

Figure 5. The change of characteristic number *Ns*

In Figure 4 and 5, some regulations can be found. Early in the iterative computations, the classification entropy *Ec* and the characteristic number *Ns* change quickly; with the increase of training time, their change processes become slow and tend to converge. After the improved self-organizing neural network is trained, the network is used to classify other action characteristics of human's lower limbs. The classification results are shown in Figure 6.

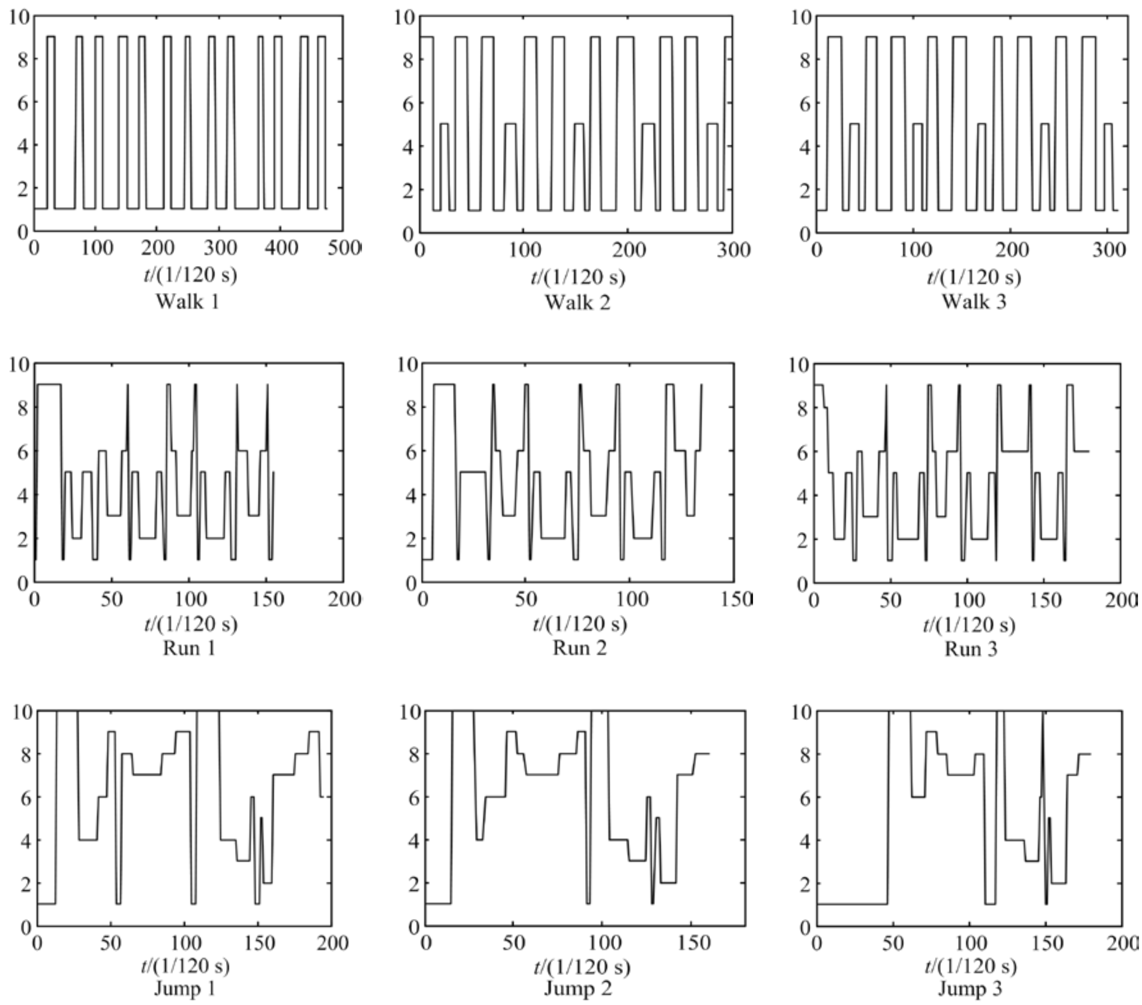

Figure 6. Some classification results

Some conclusions can be achieved in Figure 6. The classification results of same actions have similar change characteristic, but the change processes of the classification results for different actions are quite different.

2.3. Action Recognition of Human's Lower Limbs
2.3.1. Action Recognition Based on HMM

Because HMM has a strong ability of building sequential model and it is a kind of dynamic information processing method based on sequential accumulative probability, it is introduced to recognize the action processes of human's lower limbs.

a) The states of HMM are denotes as $\theta_1, \theta_2, \cdots, \theta_N$, where *N* is the number of the states. The state of the model at time *t* is denoted as q_t , and $q_t \in (\theta_1, \theta_2, \cdots, \theta_N)$.

b) The observations which each state is related to are denoted as $V_1, V_2, \cdots, V_M$, where *M* is the number of the observations. The observation at time *t* is denoted as O_t , and $O_t \in (V_1, V_2, \cdots, V_M)$.

c) The probability distribution of the initial states is represented with $\pi = (\pi_1, \pi_2, \cdots, \pi_N)$, where $\pi_i = P(q_1 = \theta_i)$ ($i = 1, 2, \cdots, N$), and q_1 is the state at the initial time.

d) The state transition probability matrix is denoted as $A = (a_{ij})_{N*N}$, where $a_{ij} = P(q_{t+1} = \theta_j | q_t = \theta_i)$.

e) The probability distribution matrix of observations is denoted as $B = (b_{jk})_{N*M}$, where $b_{jk} = P(O_t = \theta_k | q_t = \theta_j)$.

Therefore, HMM can be denoted as $\lambda = (N, M, \pi, A, B)$. There are two basic algorithms when using HMM: Baum-Welch algorithm and Viterbi algorithm. Baum-Welch algorithm is used to study the existing observation data and train the relevant HMM. Viterbi algorithm is used to calculate the most probable sequence of hidden states and the probability given an observation sequence based on the trained HMM. In the paper, the classification results of action characteristics are as the observations, Baum-Welch algorithm is used to train the HMM of each action kind and Viterbi algorithm is used to calculate the action kind of the most probability given an observation sequence. Because there may be a amount of similarity among different actions and the motion directions of many actions are opposite such as sitting and standing, the recognition result based on HMM and *Dy*(*t*) are used to judge action kind comprehensively and the action recognition method of human's lower limbs is shown in Figure 7.

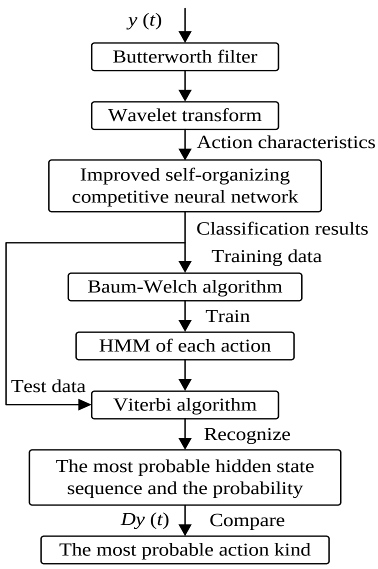

Figure 7. The action recognition method of human's lower limbs

2.3.2. Experiments

Some typical actions of human's lower limbs are chosen to validate the action recognition method, such as walking, running, jumping, sitting, standing, climbing up and climbing down. The action processes are shown in Figure 8.

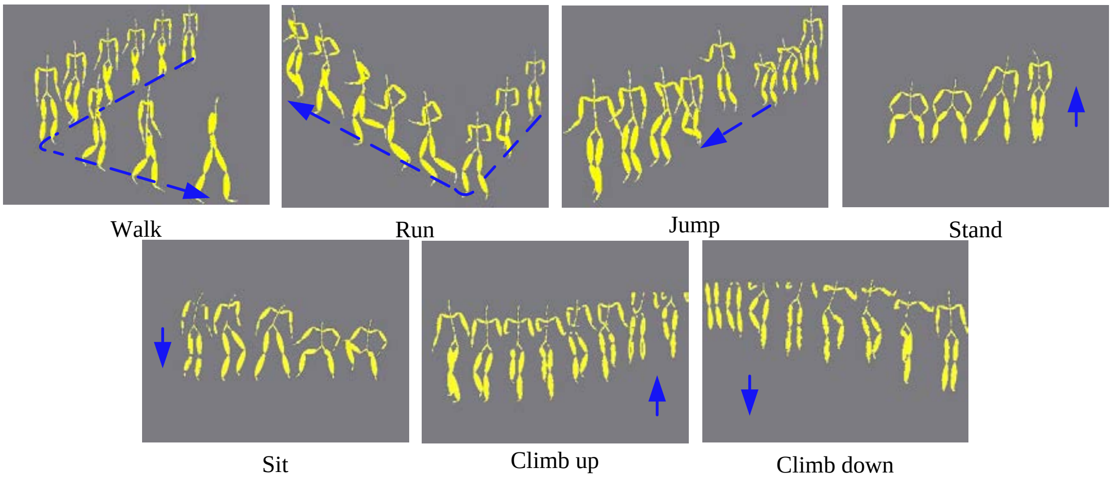

Figure 8. Action processes of human's lower limbs

The experimental data is listed in Table 1, and figures in brackets represent the number of action processes in the set of human action data.

Table 1. Experimental data

Action	Training data	Test data
Walk	02_01, 02_02, 05_01	06_01, 07_01, 07_02, 08_01, 08_02, 16_12, 16_13, 16_14, 16_15, 16_16, 16_17
Run	16_35, 16_36, 16_37	02_03, 09_01, 09_02, 09_03, 35_17, 35_18, 35_19, 35_20, 16_38, 16_39, 16_40, 16_41, 16_42, 16_43
Jump	16_01, 16_02, 16_03	01_01(2), 02_04, 13_11, 13_13, 13_39, 13_40, 13_41, 16_04, 16_05, 16_06, 16_07, 16_09
Sit	13_01(2), 13_02	13_03(3), 13_04(4), 13_05(2), 13_06(3), 14_27, 14_28, 14_29(3), 14_30(2), 14_31(2), 14_32(3)
Stand	13_01(2), 13_02	13_03(2), 13_04(4), 13_05(2), 13_06(3), 14_27, 14_28, 14_29(2), 14_30, 14_31(2), 14_32(2)
Climb up	01_02(3)	01_03(2), 01_04(2), 01_05(2), 01_06(2), 01_07(3), 13_35, 13_36, 13_37, 13_38, 14_21, 14_22, 13_23
Climb down	01_02(3)	01_03(2), 01_04(2), 01_05(2), 01_06, 01_07, 13_35, 13_36, 13_37, 13_38, 14_21, 14_22, 14_23

The HMM training parameters in the action recognition process of $y'(t)$ are as follows: the number of states $K_1 = 7$, the number of observations $K_2 = 10$, and the maximum number of cycles $C_1 = 40$. After the HMMs are trained with the training data, test data is recognized based on the proposed action recognition method and the final recognition results are listed in Table 2.

Table 2. The final recognition results

	Walk	Run	Jump	Sit	Stand	Climb up	Climb down
Walk	11	0	0	0	0	0	0
Run	1	13	0	0	0	0	0
Jump	0	1	11	0	0	0	0
Sit	0	0	0	20	0	4	0
Stand	1	0	1	0	14	0	4
Climb up	0	0	0	1	0	17	0
Climb down	0	0	0	0	1	0	14

3. Discussion

Calculations in the experiment were performed using a computer with a guad-core Intel E5 2.80GHz CPU. The average calculation time of recognition processes of CMU human action database is about 0.82s. Compared with other action recognition methods, the recognition results are listed in Table 3.

Table 3. The Comparison of Recognition Results.

Method	Accuracy
Dynamic temporal warping [2]	0.8421
Trajectory Projection [7]	0.8684
Learning action ensemble [16]	0.9035
Proposed method	0.8772

It can be found that the proposed method has a high recognition rate in Table 3. Compared to the other action recognition methods, the proposed method needs less motion information; it doesnot need to adjust the motion trajectories of multiple human joints at the same time and can obtain the action characteristics quickly based on wavelet transform. Therefore, the proposed method can perform a fast calculation speed.

4. Conclusion

To realize the fast and accurate action recognition of human's lower limbs captured by optical motion capture equipment, a novel action recognition method of human's lower limbs is proposed. After filtered, the *y* coordinates of hip joint in the WCS are used to calculate action characteristics and they are classified based on an improved self-organizing neural network proposed in the paper. An action recognition method based on HMM is introduced to realize the recognition of the actions of human's lower limbs in conjunction with the change direction of *y* coordinates. The action recognition method of human's lower limbs only utilizes the *y* coordinates of hip joint to calculate other action information; it has a fast calculation speed and can satisfy the action recognition needs of different personnel. Experiments prove the method has a good recognition effect and a good application prospect.

Acknowledgements

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