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Gait recognition via multi-source information and d-s evidence theory

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Abstract. In order to solve the problem of high failure rates in using the single feature and the complexity of the feature space in using the multiple features of gait recognition. This paper proposes a method which uses multi source information and D-S evidence theory. Firstly, features of different attributes from the surface electromyography (sEMG) signal and hip joint signal are extracted. Secondly, the preliminary recognition results are obtained by using the feature level fusion of neural network from characteristics of different signal sources. Lastly, a final recognition result is obtained through the decision level fusion by using the D-S evidential fusion algorithm. The proposed method is tested by using five common gait patterns of lower limbs, the experimental results showed that the proposed method can obtain higher reliability and accuracy rate.

Key words. Gait patterns, data fusion, multiple-source information, neural network, d-s evidential theory, feature extraction.

1. Introduction

Wearing prostheses is one of the important ways in which thigh amputees can regain their basic behavioral capacity. As the intelligent prosthesis can identify the wearer's movement intention, realize the exchange and control of information between human, prosthetic and environment effectively, it has been widely valued in recent years[1]. The intelligent prosthesis can be controlled effectively only on the basis of correct recognition of the wearer's intension of gait pattern. Therefore, the recognition method of gait pattern of lower limbs is significantly important for

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intelligent prosthesis to achieve a variety of gait patterns to adapt to the patient's intention and external environment.

Surface electromyogram (sEMG) signals have a good predictive effect on the mode of action, some scholars use it as a signal source for recognizing the movement pattern of lower limbs and other activities. Miller et al. [2] acquired EMG signal of four muscles and used SVM and LDA to recognize seven lower limbs movement patterns. The time domain features of sEMG and hidden markov model have been utilized by Meng Ming et al. [3] for identifying five periods of lower limbs movement. The optimal result of 91% accuracy rate has been obtained from their experiment. Young et al. [4] analyzed the role and significance of sEMG data in the recognition of gait patterns when using inertial sensors. In [5], the features of the extracted sEMG signal, hip angle signal and hip joint acceleration signal were analyzed by principal component method to solve the problem of feature dimension and difficulty of classifier identification.This paper fuses the initial identification results from the multi-source information signal at the decision level through the fusion algorithm.

2. Multi-signal acquisition and feature extraction of lower limbs

The movement of lower limb is complex and regular, and the multi-source information can better describe the movement pattern of the lower limbs. In this paper, we selected sEMG signal of lower limb, acceleration signal and angle signal of hip joint as the multi-signal source of the experiment.

2.1. sEMG signal

We selected four muscles such as semitendinosus as sEMG signal resources. The specific choice of the muscles are semitendinosus thigh biceps lumbar fascia and rectus femoris. The sEMG signal produced by the four selected muscles have better specificity and differentiation, which are easy to identify the movement patterns of lower limb.

2.1.1. Features of sEMG signal In order to obtain more effective features of sEMG signals, this paper adopts the combination of time features and frequency features. Specifically: the integral sEMG [3] in the time domain method (I) the absolute value [3] of the time domain method (V) and power spectrum ratio [6] of frequency domain method (K). The three characteristic parameters are selected for the sEMG signals collected from the four muscles. Therefore, the eigenvector of the sEMG resource can be expressed as:

F_1=[$I_1, V_1, K_1, I_2, V_2, K_2, I_3, V_3, K_3, I_4, V_4, K_4$] (1)

2.1.2. Acceleration feature of hip joint Due to the magnitude of acceleration with no directional information, the acceleration magnitude-based gait recognition algorithm is orientation independent. The magnitude of synthesized acceleration can be formulated as follows:

$$ai = \sqrt{X^2 + Y^2 + Z^2} \tag{1}$$

Where X, Y, Z, stands for the acceleration sensor in the x, y, z three axes of the accelerometer respectively.

In order to realize the distinction between different gait patterns, this paper selects the angle feature of hip joint X, standard deviation σ, skewness S and correlation coefficient C_{xy}as the acceleration features[7], [8]. Thus, the eigenvector of the hip joint signal source of gait patterns can be expressed as:

F_2=[X, σ, S, C_{xy}] (3)

3. D-S evidence theory

Defining an identification framework Θ which represents a set of all possible situations for a decision or recognition problem M. Evidence theory which is also known as trust function theory is an extension of classical probability theory[9]. D-S evidence theory can leave the rest of the trust to the recognition frame, which has the ability to express uncertainty. The D-S evidence fusion rule is:

$$\begin{aligned} &m\left(u\right) = \tfrac{1}{1-k} \textstyle\sum_{Ai1 \bigcap Ai2 \bigcap \cdots \bigcap Ain = A} m1(Ai1) \cdot m2(Ai2) \cdot \cdots \cdot mn(Ain) \quad (\forall A \subseteq \Theta) \\ &k = \textstyle\sum_{Ai1 \bigcap Ai2 \bigcap \cdots \bigcap Ain = \Phi} m1(Ai1) \cdot m2(Ai2) \cdot \cdots \cdot mn(Ain) \end{aligned} \tag{2}$$

4. Gait recognition based on D-S evidence theory

The sEMG features and hip joint features are independent of each other and there are no correlations between them, so we can utilize different information sources to train the neural network, whose recognition results are translated into the confidence distribution. Then the D-S evidence theory is utilized to fuse the credibility of the two independent evidence distribution. Finally, the final recognition results are obtained . The overall recognition flow is shown in Figure 1.

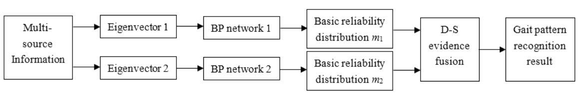

Fig. 1. Recognition model of multi-source information and evidence theory

The proposed method can be implemented as following procedure:

1) Build the overall identification framework Θ={A_1, A_2, , A_k}and the evidence body E_i(i=1, 2, , n).

2) Determine the basic probability distribution function of each evidence body. In this paper, we use the improved output of the BP neural network mentioned in [10] as the evidence to construct the probability distribution function. According to the formula (1), the structure of the BP network 1 is determined as 12-5-5 structure.

According to the formula (3), the structure of the BP network 2 is 4-8-5. The target vector of BP network 1, 2 is T= [10000; 01000; 00100; 00010; 00001], which represent five kinds of gait patterns respectively. The training target error of BP neural network is required to be 0.001.

5. Experimental results and analysis

5.1. Experimental setup and data sets

This study is conducted on an experimental platform in Figure 2. The platform consisted of a 3.5-meter slope of 15 and six steps. The experimental data on the ground is acquisition at a speed of 4 km/h on a treadmill. On the basis of this, seven healthy students (3 males and 3 females) and are selected as the experimental subjects. The experimental data are divided into training samples and test samples according to the ratio of 6:4. The information acquisition units contain two parts, the information acquisition part and the sensor part. In this experiment, Q-PID data acquisition card produced by Quanser is utilized to achieve the collection of gait information, the sampling frequency is 1KHz.

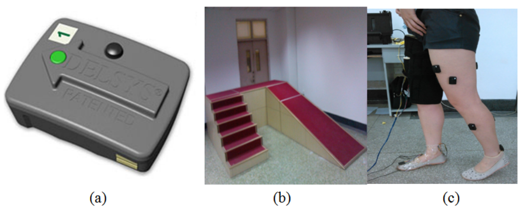

Fig. 2. Experimental equipment

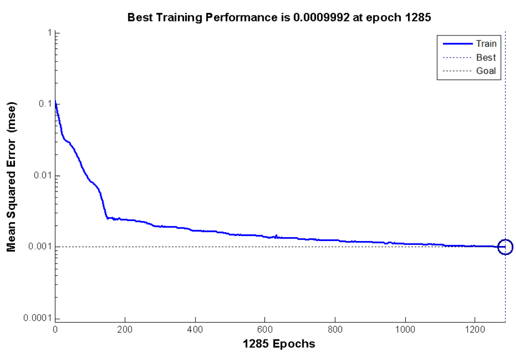

Fig. 3. BP network training curve.(a) network training curve of BP1; (b) network training curve of BP2

5.2. Experimental results

The BP neural network is trained by the experimental data collected. The training error is shown in Fig. 3. The neural networks 1 and 2 are trained by 1285 and 706 iterations respectively. The training accuracy of the two neural networks is 0.0009992 and 0.00099723 respectively, which can meet the error requirement of 0.001.

Tab 2. Believe value of discernment frame

Gait pattern	Network	Walking $m(u_1)$	Up stairs $m(u_2)$	Down stairs $m(u_3)$	Up slopes $m(u_4)$	Down slopes $m(u_5)$	$m(\Theta)$
Walking	BP1	**0.665**	0.109	0.085	0.064	0.052	0.025
	BP2	**0.621**	0.177	0.083	0.076	0.04	0.003
	BP1+BP2	**0.907**	0.051	0.012	0.015	0.007	0.008
Up stairs	BP1	0.036	**0.711**	0.136	0.075	0.022	0.020
	BP2	0.071	**0.561**	0.076	0.178	0.096	0.018
	BP1+BP2	0.001	**0.909**	0.031	0.039	0.009	0.011
Down slopes	BP1	0.026	0.021	0.082	0.059	**0.790**	0.022
	BP2	0.052	0.043	**0.593**	0.090	0.204	0.018
	BP1+BP2	0.014	0.008	0.135	0.032	**0.810**	0.001

Tab 3. The recognition rate of test samples

Network Combination	Walking (u_1)	Up stairs (u_2)	Down stairs (u_3)	Up slopes (u_4)	Down slopes (u_5)	Average
BP1	92.5%	86.8%	87.6%	90.3%	87.3%	88.9%
BP2	90.7%	83.1%	89.4%	87.2%	88.6%	87.8%
BP1+BP2	92.5%	90.2%	89.4%	91.8%	90.1%	90.8%

The recognition results of single-source information and recognition results of mutiple-source information using D-S evidence theory of 400 test samples are shown in Tab. 3. Observed from Tab.3, the accuracy rates of the gait recognition based on the features of the sEMG signal source and features of the hip joint signal are different, but the average recognition rate of the sEMG is slightly higher. As features of gait information from single source are not comprehensive enough, which results that recognition rate is generally low. The proposed method combines the decision information from two signal sources, which can avoid the imperfectness of the single signal source. Therefore, the result of using D-S theory fusion is more advantageous, and the average recognition rate of five kinds of gait patterns is 90.8%.

6. Conclusion

In this paper, the neural network classifiers based on sEMG features of lower limb and features of hip joints are established. The output of the neural network is constructed as independent evidence of the basic reliability distribution on the two signal sources. The D-S evidence theory is used to effectively integrate the preliminary decision information which come from different signal sources in the decision level. Lastly, the final recognition is obtained by using threshold rule. Experiments show that the proposed method can not only avoid the problem of low recognition rate due to the one-sidedness of the features of single signal, but also can solve the problem that the multi-signal feature is too high. At the same time, combining the feature level fusion of neural network with the decision-level fusion of D-S evidence theory can reduce the basic probability assignment of uncertainty and improve the accuracy and robustness in gait recognition.

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