Gait Recognition Via Coalitional Game-based Feature Selection and Extreme Learning Machine

Yiming Tian[1,2], Wei Chen[1*], Lifeng Li[1], Xitai Wang[1,2], Zuojun Liu[2]

ABSTRACT

In order to achieve the goal of controlling the intelligent lower limb prosthesis effectively, it is very crucial to recognize the gait pattern of the lower limb, which usually includes walk, up and down stairs or slopes, etc. This paper proposes a gait recognition method based on coalitional game-based feature selection and extreme learning machine. Firstly, this paper extracts characteristic values of four periods in gait cycle, obtaining 24 features. Secondly, in order to improve the accuracy and reduce the computational complexity, a coalitional game-based feature selection algorithm is used to select the prominent features. Lastly, the extreme learning machine (ELM) is used to recognize the gait pattern, which can have a better result in identifying the five kinds of gait pattern in this experiment, compared with BP neural network. Compared with other feature selection algorithms, including mRMR and Relief-F, the proposed method selects fewer features and provides higher accuracy and has faster recognition speed, which proves the effectiveness and feasibility of the proposed method.

Key Words: Gait Recognition, Intelligent Artificial Limb, Feature Selection, Game Theory, Extreme Learning Machine

DOI Number: 10.14704/nq.2018.16.2.1173 **NeuroQuantology 2018; 16(2):32-39**

Introduction

Intelligent prostheses can not only help the thigh amputee patients carry out certain social activities, but also can lay a solid foundation for their reintegration into society. Gait recognition is one of the moat crucial parts of intelligent prostheses, which can identify the willing of patients (Protopapadaki & Echsler, 2007). At present, the study of gait recognition is mainly based on sensor information (Zhang *et al.,* 2007) and image information (Matovski *et al.,* 2012). The recognition part is mainly based on machine learning, including BP neural network (Zen & Wang, 2012), SVM (Gao *et al.,* 2015), HMM (Zhao *et al.,* 2015), *et al*. In (Chen *et al.,* 2008), the gait recognition of lower limb is realized by calculating the angle between knee and thigh and the pressure between toe and heel. In the paper (Milica, 2008), the patient's surface electromyographic (sEMG) signal and the support vector machine are used to recognize the gait pattern. In (Liu *et al*., 2015), principal component analysis is used to fuse the features extracted from the surface EMG signal, the hip joint angle and the hip joint acceleration, and the gait recognition is performed by using BP network which is optimized by particle swarm algorithm. In (Gao *et al.,* 2010), the information fusion method is used to fuse the preliminary results from the lower limb EMG signal, the leg angle

Corresponding author: Wei Chen

Address: [1]Key Laboratory of Rehabilitation Aids Technology and System of the Ministry of Civil Affairs, Beijing Key Laboratory of Rehabilitation Technical Aids for Old-Age Disability, National Research Center for Rehabilitation Technical Aids, Beijing, 100176, China; [2]Department of Automation Engineering, School of Control Science and Engineering, Hebei University of Technology, Tianjin, 300130, China

e-mail ✉ chenwei@nrcrta.cn

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Received: 26 December 2017; **Accepted:** 15 January 2018

signal and the plantar pressure signal and the goal of the gait recognition is realized.

High quality features are essential to improve the classification accuracy of gait recognition and reduce the computational complexity. The key of the information fusion method lies in the selection of the features under the multi-signal source. The appropriate feature selection method can avoid the dimensionality problem caused by the excessive features and the problem which is not conducive to the identification of the classifier. Furthermore, features might even confuse the classifier and reduce the classification accuracy (Nishimura & Kuroda, 2010; Trier *et al.,* 1996). Therefore, it is important to select the optimum feature subsets to achieve the best classification performance and reduce the computational cost.

Up to recent, a lot of approaches are employed in feature selection, such as Adaboost (Xie *et al.,* 2011), genetic algorithm (Ghamisi & Benediktsson, 2015), KNN (Wang *et al.,* 2015) and so on. These approaches can be divided into three groups: wrapper, embedded, and filter methods (Vergara & Estévez, 2014) according to their ways of evaluating feature subsets. The induced learning algorithm is applied by Wrapper method as a black box to evaluate each feature subsets (Kohavi & John, 1997). Embedded methods (Lal *et al*. 2006) incorporate knowledge about the specific structure of a given machine learning approach to evaluate feature subsets. Although these approaches may achieve great results, the computational costs are expensive. What's more, many classifiers are more likely to overfitting and show sensitiveness to initialization.

To date, several filter methods have been proposed (Peng & Ding, 2005; Jiang *et al.,* 2011; Kurokawa *et al.,* 2011; Jin *et al.,* 2012). However, most of these methods tend to ignore features which as a group have strong discriminatory power but are weak as individuals, and the computational cost of some approaches is large. To tackle this problem, coalitional game theory based feature selection method is proposed in this paper to select optimum feature subsets which are succinct and efficient to the recognition of classifier. The VICON MX 3D three-dimensional gait analysis system is used to obtain the angle information of lower limbs of healthy people and the features of four periods in gait cycle of three joints of hip, knee and ankle are extracted as the basis of gait recognition. Then these features are selected by the efficient filter method based on coalitional game. In the recognition part, the ELM is used to achieve the goal of recognizing walk, up and down the stairs and slopes.

Extreme learning machine

As a single hidden layer feed-forward neuron networks (SLFNs), extreme learning machine was formally put forward in 2004 (Huang *et al.,* 2004; Huang & Wang, 2006). ELM can be used as a classifier to train neural networks through the activation function and ELM has been widely used to solve the problem of local minimum, slow convergence and complex iterative calculation.

For any N different samples ($\boldsymbol{x}_i$, $\boldsymbol{t}_j$), j=1,2,...N, where $\mathbf{x}_j=[x_{j1},x_{j2}\cdots x_{jn}]^T$ is the j_{th} sample, each sample contains n-dimensional features, and $\mathbf{t}_j=[t_{j1},t_{j2},\cdots t_{jm}]^T$ is the encoded class label. All samples belong to m different classes, and the ELM mathematical model with L hidden neurons can be expressed as:

$$\sum_{i=1}^{L}\beta_i g(\mathbf{w}_i\cdot\mathbf{x}_j+b_i)=\mathbf{t}_j,\ j=1,\cdots N \tag{1}$$

Where $g(x)$ is the excitation function, w_i, b_i, and β_i are the input weight, hidden element offset and output weights of the i_{th} hidden neuron node respectively. Equation (1) can be written in matrix form:

$$\mathbf{H}\boldsymbol{\beta}=\mathbf{T} \tag{2}$$

Where the $\boldsymbol{\beta}$ represents the output weight, **T** is the corresponding coding class label, and **H** is the hidden layer output matrix:

$$H=\begin{bmatrix} g(\mathbf{w}_1\cdot\mathbf{x}_1+b_1) & \cdots & g(\mathbf{w}_L\cdot\mathbf{x}_j+b_L) \\ \vdots & \cdots & \vdots \\ g(\mathbf{w}_1\cdot\mathbf{x}_N+b_1) & \cdots & g(\mathbf{w}_L\cdot\mathbf{x}_N+b_L) \end{bmatrix}_{N\times L} \tag{3}$$

Since the neural network system is linear, the $\boldsymbol{\beta}$ output weight is obtained by the following equation:

$$\boldsymbol{\beta}=\mathbf{H}^{\dagger}\mathbf{T} \tag{4}$$

Where **H†** is the generalized inverse matrix of **H**

33

Feature selection based on coalitional game

In the feature selection part, this paper proposes a fliter feature selection algorithm based on coalitional game. Joint mutual information is used to evaluate the degree of dependency of feature set and target class, which makes the selected feature subset not only have the highest correlation with the target class but also have relatively high internal dependency.

Feature selection and coalitional Game

Given the sample data $T=(O, F, C)$, where $O=\{o_1, o_2, \cdots, o_n\}$, $F=\{f_1, f_2, \cdots, f_m\}$ and $C=\{c_1, c_2, \cdots, c_l\}$ represents the sample set, feature set and category respectively. The feature selection problem is based on using an evaluation criterion $J(S)$ to select a subset with the highest $J(S)$ value while making $|S|$ as small as possible.

At present, researches have put forward many excellent evaluation criteria $J(S)$, such as IG, MIFS, mRMR, CMIM and so on. However, these feature subset evaluation criteria still have the disadvantage of the Filter method, that is, a subset with stronger distinguishing features is easily overlooked.

The coalitional game is an effective mathematical model which is used to solve the distribution of rights or contributions between individuals. The purpose is to find a reasonable way of allocating rights so that the rights obtained by the individual are equivalent to their contribution.

Definition: given a finite participant set N, the characteristic of the coalitional game is the ordinal number pair (N, v), where the characteristic function v is the mapping from $2^N = \{S|S\subseteq N\}$ to the real set R^N.

Evaluation of feature influence

In coalitional game theory, Shapley value is used to measure the powers of game players. In this paper, Shapley value is introduced to evaluate each feature weight. Considering the relevance, redundance and interdependence of features, the Shapley value as an efficient approach is utilized to evaluate the contribution of features, which is formulated as following:

$$\Psi_i(v) = \sum_{K\subset N\backslash\{i\}} \Delta_i(K)\frac{|K|!(n-|K|-1)!}{n!}. \tag{5}$$

And the win function is formulated as following:

$$\Delta_i(K) = v(K\cup\{i\}) - v(K) \tag{6}$$

where n means the number of players and the sum extends over all subsets K of N not including player i.

Coalitional win criteria based on joint mutual information

Mutual information is an important concept in Shannon's information theory (Shannon, 2001; Thomas & Cover, 2006), which is widely used as a measure of relevance in the selection of features, it is calculated as:

$$I(X,Y)=\sum_{x,y} p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \tag{7}$$

Joint mutual information can effectively measure the degree of dependence between multiple variables X_1, X_2,..., X_n and variable Y, which is calculated as:

$$I(X_1,X_2,\cdots,X_n;Y)=$$
$$\sum_{x_1x_2\cdots x_ny} p(x_1,x_2,\cdots,x_n,y)\log\frac{p(x_1,x_2,\cdots,x_n,y)}{p(x_1,x_2,\cdots,x_n)p(y)} \tag{8}$$

In this paper, the joint mutual information between union K and target class is expressed as following:

$$I(K;c)=I(f_1,f_2,\cdots,f_{|K|};c) \tag{9}$$

In the process of feature selection, the feature f_i joins in union K. If the joint mutual information of newly formed union $K\cup\{f_i\}$ and the target class c is greater than the joint mutual information of original union K and the target class, then f_i wins in the league K. Thus, in the feature selection the winning function in (5) is defined as:

$$\Delta_i(K)=\begin{cases}1 & I(K\cup\{f_i\};c)>I(K;c)\\ 0 & \text{else}\end{cases} \tag{10}$$

Feature selection algorithm

The steps of the Filter feature selection algorithm based on the coalitional game are as follows:
Input: Training sample set $T=(O, F, C)$.
Output: Optimal feature subset S.
Step1: Initialize $S = \emptyset$.

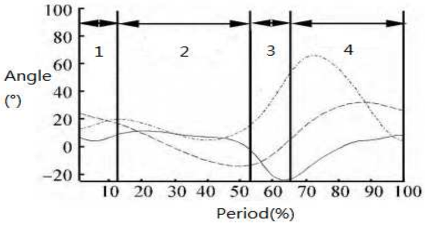
Step2: Calculate the number of winners of each feature f_i in the feature set F based on the joint mutual information.
Step3: Calculate the Shapley value $\psi_f(v)$ for each feature f in the feature set F according to equation (5).
Step4: Each feature priority in F is its Shapley value, $Pri(f)=\psi_f(v)$.
Step5: All the features in F are sorted in descending order of priority.
Step6: The k features with the highest priority are put the optimal subset S, which is the output.

Extracting and filtering of feature

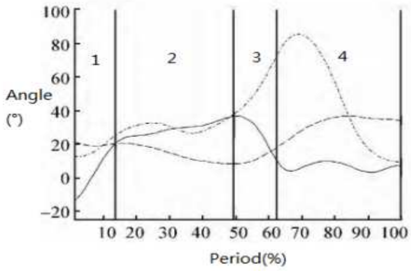
Data collection and processing

The experiment platform is the VICON MX 3D system in the biomechanics laboratory of national rehabilitation aids research center. The experiments include walk, up and down stairs and slopes. The step staircase is up to 10 cm of the upper and lower platform, and the slope of the up/down slope is 15°. The VICON MX 3D gait system is used to collect the joint angle values of hip, knee, ankle in these five gaits.

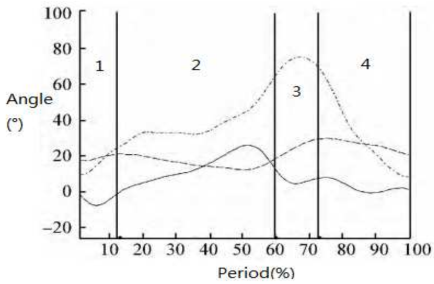
According to the observation and contrast to the information of foot pressure plate, this paper chooses the minimum value of knee joint angle and maximum value of hip joint angle as the start point of walking gait cycle; chooses the maximum value of hip joint angle as the start point of going up stairs or slopes; chooses the minimum value of knee joint angle as the start point of going down stairs or slopes. Fig. 1 shows the angle value of hip, knee, ankle under five kinds of gait. The long dashed line stands for the hip angle, dotted line stands for the knee angle, solid line stands for the ankle angle. According to the actual walking of the image information and analysis of plantar pressure signal, this paper divides the gait cycle, which includes initial stance (IS), middle stance (MS), terminal stance (TS) and swing phase (SP). As shown in Fig. 1, 1 represents initial stance, 2 represents middle stance, 3 represents terminal stance and 4 represents swing phase.



(a)

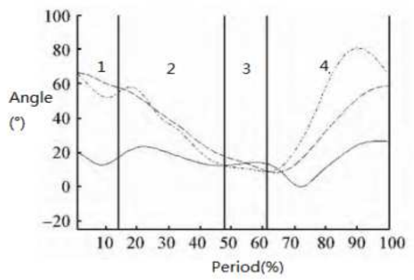


(b)

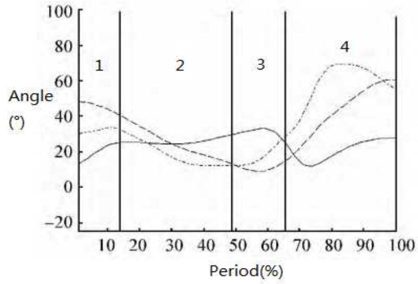


(c)

eISSN 1303-5150



(d)



(e)

Figure 1. Joint angles during five gaits: (a) joint angles during walking; (b) joint angles during going down stairs; (c) joint angles during going down slopes; (d) joint angles during going up stairs; (e) joint angles during going down slopes

Feature extraction

Feature extraction methods include time domain, frequency domain and time-frequency. Considering the complexity of computation, this paper only considers the mean value and standard variance of time domain. In this paper, we extract the mean value and standard deviation of angle value of hip, knee and ankle in the four periods of gait cycle and the functions of mean value and standard deviation are (11) and (12). Table 1 shows the features of mean value and their notations and Table 2 shows the features of standard deviation and their notations.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{11}$$

$$std = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{12}$$

Table 1. Features of mean value and their notations

Position / Features of phase	Hip	Knee	Ankle
Mean value of IS	averISh	averISk	averISa
Mean value of MS	averMSh	averMSh	averMSa
Mean value of TS	averTSh	averTSk	averTSa
Mean value of SP	averSPh	averSPk	averSPa

Table 2. Features of standard deviation and their notations

Position / Features of phase	Hip	Knee	Ankle
Standard deviation of IS	stISh	stISk	stISa
Standard deviation of MS	stMSh	stMSh	stMSa
Standard deviation of TS	stTSh	stTSk	stTSa
Standard deviation of SP	stSPh	stSPk	stSPa

Selection of features

In this paper, the features are selected by the coalitional game-based features selection algorithm and the Shapley value of each feature is shown in Table 3. For the above selected features, the proposed features selection method is repeated 5 times to calculate the average Shapley value. The features are represented by the above notations. Through the Shapley value, the degree of influence of features on gait recognition is reflected, and the higher the Shapley value, the more the component of the extracted variable is and the greater the effect on the recognition gait.

Gait recognition result and analysis

Training data and parameter settings

In this paper, five healthy people are selected to take part in the experiments with the VICON MX 3D system. All these participants are voluntarily participating in the experiment. 500 experimental data samples are obtained (each participant includes 100 samples of walking, 100 samples of down stairs, 100 samples of down slope, 100 samples of up stairs, and 100 samples of up slope). These samples are divided into training samples and testing samples according to the ratio of 6:4. In the parameter settings, the number of hidden layer of the ELM model is 20, the incentive function is "Sigmoid", and the other parameters are randomly selected, which may not influence the performance of ELM.

Analysis of the method proposed

The features in Table 3 are arranged in descending order of Shapley value, which can help us analyze the relevance and impact of different numbers of feature to the recognition effect. In order to test the effect of the number of selected features on gait recognition, this paper chooses different numbers of feature to find out the most suitable feature combination. The validation is repeated five times with each union used exactly once for testing and the final results are their average values. The curve of relationship between number of features and recognition rate recognition results are shown in Fig. 2.

It can be seen from Fig. 2 that the highest recognition rate is 91.5% when the number of feature is 16. The recognition rate increases with the increase of number of feature, because few features cannot contain whole information of features. When the number of selected features is too large, the recognition result is not the best, partly because huge feature vector is unbeneficial to the recognition of ELM.

When the number of feature is 16, 200 testing samples are recognized by the proposed method by this paper and the results obtained are shown in Table 4.

Table 3. Shapley value of selected features

Feature	**averISh**	**averISk**	**averISa**	**averMSh**	**averMSh**	**averMSa**
Shapley value	0.352	0.273	0.162	0.283	0.419	0.363
Feature	averTSh	averTSk	averTSa	averSPh	averSPk	averSPa
Shapley value	0.382	0.439	0.373	0.437	0.129	0.216
Feature	stISh	stISk	stISa	stMSh	stMSh	stMSa
Shapley value	0.283	0.183	0.271	0.462	0.271	0.154
Feature	stTSh	stTSk	stTSa	stSPh	stSPk	stSPa
Shapley value	0.282	0.427	0.274	0.185	0.362	0.295

Table 4. Recognition results by using proposed method

Mode of action	**Testing sample number**	**Correct identification number**	**Recognition rate (%)**
Walking	40	38	95
Up stairs	40	36	90
Down stairs	40	35	87.5
Up slope	40	37	92.5
Down slope	40	37	92.5
Total	200	183	91.5

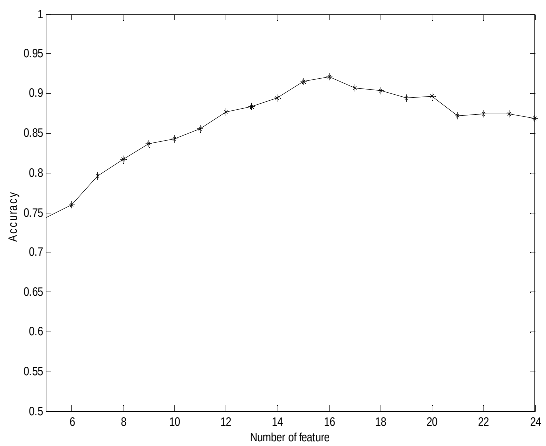


Figure 2. Curve of relationship between number of features and recognition rate

Performance analysis of different filter algorithms

In order to test the proposed method empirically, several experiments have been carried out to evaluate the proposed approach comparing with the original feature selection methods Relief-F and mRMR. Relief-F is previously proved as one of the most successful filter feature selection method, is chosen as the baseline algorithm for comparison. Fig. 3 shows the comparison of the classification accuracy against the number of selected features. In Fig. 3, the number *x* on the X-axis refers to the top *x* features with the selected descending order using different approaches of feature selecting, and accordingly the performance of classifier is represented on Y-axis. The validation is repeated five times and the final results are average values.

The main idea of feature selection is to select a smaller number of optional features from the full huge feature set. From Fig. 3 we can see that too small number of features cannot achieve the goal of improving recognition accuracy, which is not expected. If the number of the selected top features less than a certain amount in the three approaches, the accuracies are generally less than 80%. In fact, the accuracy can reach 91.5% by proposed method with 16 features, 89.5% by mRMR with 14 features and 88% by Relief-F with 20 features, which is also greatly smaller than the number of the original features. On the other hand, too many features selected provide no meaning for recognition accuracy of ELM and may also increase computational cost. Therefore, the number of selected features should stay in an accepted range. The recognition results of different approaches of filter algorithms are shown in Table 5 when the proposed method with 16 features, mRMR with 14 features and Relief-F with 20 features.

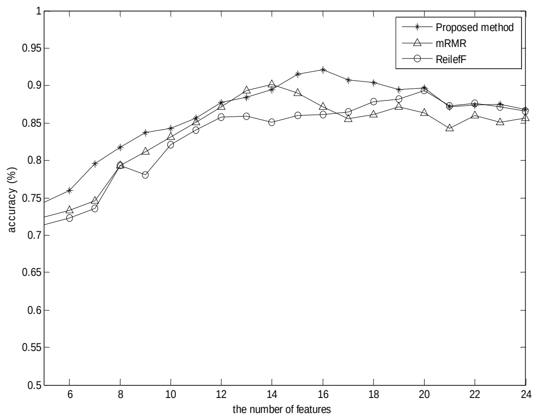


Figure 3. Accuracies versus different number of features

Table 5. Comparison of different filter algorithms

Pattern of gait	Recognition rate (%)		
	Proposed method	RMR	Relief-F
Walking	95	2.5	95
Up stairs	90	0	90
Down stairs	87.5	7.5	87.5
Up slope	92.5	7.5	85
Down slope	92.5	0	82.5
Total	91.5	9.5	88

Performance analysis of different methods

To better illustrate the proposed method, several experiments based on other methods have been carried out to compare with the result of the proposed method. In the feature selection part, this paper compares the results of method without feature selection, method with mRMR, method with Reilef-F. In the classifier part, this paper introduces BP network as the comparison. The recognition results and their time costs of these methods are shown in Table 6. All the experiments are conducted on a computer of Window 7, with an Intel(R) Core(TM) i3, 3.6GHZ and 4GB RAM. The algorithms are all implemented in Matlab.

Table 6. Comparison of different methods

Method	Total accuracy (%)	Time cost (second)
Without feature selection+BP	87.8%	8.657
mRMR + BP	85.4%	5.562
ReilefF + BP	83.2%	6.834
Coalitional game + BP	86.3%	7.542
proposed method	91.5%	5.372

It can be seen from Table 6 that the proposed method which use coalitional game-based feature selection method and ELM has the highest accuracy rate and least time cost. The time cost of proposed method is very similar with that of mRMR+BP. Comparing the method of ours and the calitional game+BP, we can know that BP costs more time than ELM, and its accuracy is inferior with ELM. Moreover, from the results of mRMR+BP, Reilef-F+BP and coalitional game+BP, we can also draw the conclusion that our proposed features selection method has the highest accuracy rate between three these three selection methods, although its time cost is relatively high, it can select features with acceptable computational complexity.

Conclusion

In order to recognize the gait patterns of lower limb effectively, coalitional game-based feature selection method and ELM have been proposed for gaits of the lower limb of recognition in this paper. Comparing with Relief-F and mRMR in the experiments, results show that better classification has been obtained by the proposed method. Classifiers of BP network has been utilized to evaluate the effect of our proposed features selection method combined with ELM. In future, more subjects and more activities will be required to test the proposed method.

Acknowledgement

This work was supported by the National Key Technology Research and Development Program of the Ministry of Science and Technology of China NO. 2015BAI06B03.

References

Chen L, Yang P, Xu X, Zu L, Guo X. Above-knee prosthesis control based on posture recognition by support vector machine. In Robotics, Automation and Mechatronics IEEE Conference 2008: 307-312.

Gao FR, Wang JJ, Xi XG, She QS, Luo ZZ. Gait recognition for lower extremity electromyographic signals based on PSO-SVM method. Journal of Electronics & Information Technology, 2015; 37: 1154-59.

Gao Y, She Q, Meng M, Luo Z. Recognition method based on multi-information fusion for gait patterns of above-knee prosthesis, Chinese Journal of Scientific Instrument, 2010; 31: 2683-88.

Ghamisi P, Benediktsson JA. Feature selection based on hybridization of genetic algorithm and particle swarm optimization. IEEE Geoscience and Remote Sensing Letters 2015;12(2):309-13.

Huang GB, Zhu QY and Siew CK. Extreme learning machine: a new learning scheme of feedforward neural networks, IEEE International Joint Conference on Neural Networks, 2004; 2: 985-90.

Huang GB, Zhu QY, Siew CK. Extreme learning machine: theory and applications. Neurocomputing 2006;70(1):489-501.

Jiang M, Shang H, Wang Z, Li H, Wang Y. A method to deal with installation errors of wearable accelerometers for human activity recognition. Physiological Measurement 2011;32(3):347-58.

Jin X, Ma EW, Cheng LL, Pecht M. Health monitoring of cooling fans based on Mahalanobis distance with mRMR feature selection. IEEE Transactions on Instrumentation and Measurement 2012;61(8):2222-29.

Kohavi R, John GH. Wrappers for feature subset selection. Artificial intelligence 1997;97(1-2):273-324.

Kurokawa U, Choi BI, Chang CC. Filter-based miniature spectrometers: spectrum reconstruction using adaptive regularization. IEEE Sensors Journal 2011;11(7):1556-63.

Lal TN, Chapelle O, Weston J, Elisseeff A. Embedded methods, in Feature Extraction, Springer-Verlag, 2006: 137-65.

Liu L, Yang P, Liu Z. Lower limb locomotion-mode identification based on multi-source information and particle swarm optimization algorithm, Journal of Zhejiang University (Engineering Science) 2015; 49: 439-47.

Matovski DS, Nixon MS, Mahmoodi S, Carter JN. The effect of time on gait recognition performance. IEEE Transactions on İnformation Forensics and Security 2012;7(2):543-52.

Milica D. Automatic recognition of gait phases from accelerations of leg segments, 9th Symposium on Neural Network Applications in Electrical Engineering 2008: 121-24.

Nishimura J, Kuroda T. Versatile recognition using Haar-like feature and cascaded classifier. IEEE Sensors Journal 2010;10(5):942-51.

Peng H, Ding C. Minimum redundancy and maximum relevance feature selection and recent advances in cancer classification. Feature Selection for Data Mining 2005;52-59.

Protopapadaki A, Drechsler WI, Cramp MC, Coutts FJ, Scott OM. Hip, knee, ankle kinematics and kinetics during stair ascent and descent in healthy young individuals. Clinical Biomechanics 2007;22(2):203-10.

Shannon CE. A mathematical theory of communication. ACM SIGMOBILE Mobile Computing and Communications Review 2001;5(1):3-55.

Thomas JA, Cover TM. Elements of Information Theory, Wiley Press, 2006.

Trier ØD, Jain AK, Taxt T. Feature extraction methods for character recognition-a survey. Pattern Recognition 1996;29(4):641-62.

Vergara JR, Estévez PA. A review of feature selection methods based on mutual information. Neural Computing and Applications 2014;24(1):175-86.

Wang A, An N, Chen G, Li L, Alterovitz G. Accelerating wrapper-based feature selection with K-nearest-neighbor. Knowledge-Based Systems 2015;83:81-91.

Wu F, Zhang X. Feature-extraction-based inspection algorithm for IC solder joints. IEEE Transactions on Components, Packaging and Manufacturing Technology 2011;1(5):689-94.

Zeng W, Wang C. Human gait recognition via deterministic learning. Neural Networks 2012;35:92-102.

Zhang JY, Wang L, Zhang LX. Research on real-time gait phase measuring based on multi-sensor. Journal of Harbin Engineering University 2007;28(2):218-21.

Zhao LN, Liu ZJ, Gou B, Yang P. Gait recognition pre-judgment of dynamic lower limb prosthesis based on Hidden Markov model. Robot 2014; 36(3):337-41.