# An Advanced Hybrid Machine Learning Approach for Assessment of the Change of Gait Symmetry

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*Abstract:* - The quantitative assessment of the change of gait symmetry has played a very important role in the clinical diagnostics. This paper investigated the application of an advanced hybrid machine learning approach such as the combining kernel-based principal component analysis (KPCA) with support vector machine (SVM) to evaluate the change of gait symmetry quantitatively based on the basic idea that the discrimination of the functional change of between human lower extremities can be hypothesized as binary classification task. To assess the change of gait symmetry accurately, more nonlinear principal components extracted by using KPCA were employed to initiate the training set of SVM, which could enhance the generalization performance of SVM. The foot-ground force gait data of 24 elderly participants were acquired using a strain gauge force platform during normal walking, and were analyzed with our proposed model. The test results demonstrated that , when compared to the SVM-based classification models, our proposed technique with superior classification performance could discriminate difference between the right and left side gait function of lower limbs accurately, and that more principal components extracted by KPCA with polynomial kernel ( $d$ =3) could capture more useful information about intrinsic nonlinear dynamics of human gait in comparison to the some key gait variables selected. The proposed hybrid model could function as an effective tool for clinical diagnostics in the future clinical circumstance.

*Key-Words:* - Gait analysis, Gait symmetry, Kernel principal component analysis, Support vector machine, Gait classification, Kinetic gait data

## 1 Introduction

In clinical diagnosis, the change of gait symmetry (i.e. asymmetry) was thought of as the indication of the pathological gait or the change of gait function because the gait symmetry has usually been considered as an identical action between the lower limbs during walking[1,2]. Therefore, the quantitative assessment of the change of gait symmetry has played a very important role in medical diagnostics, artificial limb design, gait evaluation, and early identification of at-risk gait in the elderly. The pervious literatures have reported that the quantification of the assessment of the change of gait symmetry is dealt with by using statistical models to determine similarities or dissimilarities between the lower limbs [1, 2, 3], namely, if there isn't significant difference between the gait patterns defined by using the parameters measured from biomechanical instrumentation, the gait is symmetrical. For example, the traditional statistical techniques, such as paired t-tests, principal component analysis (PCA), etc, were applied to determine similarity between right and left lower limb data for the assessment of the gait asymmetry[1,2,3]. The advantage of the use of the statistical techniques for evaluating gait symmetry or asymmetry is the introduction of objectivity, but there exist the limitation: the low sensitivity to the change of gait function. That is, the traditional statistical approaches is not capable of providing more useful information about the gait asymmetry when a large number of gait parameters should be evaluated at the same time, resulting in the failure to observe relatively small gait asymmetry. Therefore, some novel and robust algorithms are needed to be applied in lower limb data to determine the gait asymmetry accurately [4, 5].

Recently, with the emergence of some machine learning and classification algorithms with superior performance, novel and robust classification algorithm based on learning theory, these algorithms have been applied in gait data analysis for gait classification. For instance, the artificial neural network algorithms (ANN) has been employed to classify the gait patterns between the health and pathology subjects using foot-ground reaction forces gait data, and the research results have shown that, in order to obtain the better generalization ability, the ANN requires a very high number of training samples to avoid over-fitting in test[5, 6]. As we known, in the clinical surroundings, the acquired number of gait data sample is finite based on the fact that the limited access to pathological participants and limitations due to data storage, resulting in the statistical small sample size issue. For solving the small sample size issue, the support vector machine (SVM) with the better generalization ability, as one prevailing tool for machine learning, has successfully been applied to classify young and elderly gait patterns using basic, kinematics and kinetic gait data, and the results of study have demonstrated that the superior generalization performance could be obtained when the limited gait data sample available (i.e. small sample size data) were used to train and test the SVM-based gait classification model, and there exists the suitability of SVM in a binary gait classification task[7].

In order to quantify the assessment of the change of gait symmetry accurately, this study proposed the application of the SVM in the lower limb gait data for the quantitative assessment of the change of gait symmetry or asymmetry, and its basic idea is that the determination of similarity or dissimilarity between the lower limbs can be hypothesized as a binary classification task, that is, the difference of similarity between the gait patterns consisting of the corresponding lower limb gait parameters curve could be determined effectively when the SVM was adopted to classify the right and left sides gait patterns with superior generalization performance. Therefore, the quantitative assessment of the change of gait symmetry or asymmetry could be obtained accurately.

As we known, the gait patterns to be classified, in SVM-based algorithms for gait classification, are commonly required to represent as points in a high-dimensional feature space mapped by using kernel function, and the generalization performance of SVM mainly depends on successfully extracting or selecting some good features containing more information about the maximal separation between classes [8]. It is well-known that the human gait is characterized by complex dynamics, and there is the nonlinear nature in the gait data containing colored noise with long-range correlation and power spectrum, which could largely deteriorate the generalization performance of a machine classifier [9]. Thus, prior to training the SVM model, we applied additional vector space transformations on the initial gait features for obtaining more useful information and reducing redundant information, that is, it is vital that the transformation of the initial gait feature set into another one to extract some good gait features for improving the generalization performance of SVM.

Recently, linear principal component analysis (PCA), as one of the effective processing technique for gait data, has successfully been applied in gait data analysis for the gait feature extraction and gait classification [4, 5]. As we know, because linear PCA algorithm only assumes linear relationships among input variables, it provides the information about the second-order correlation of data, and causes the loss of nonlinear information [10, 11]. For the sake of solving the limitation of linear PCA, based on Cover's theorem, linear PCA can be generalized into nonlinear case using the kernel method, which can capture the nonlinear information of data, that is, kernel-based PCA is able to efficiently compute principal components in a higher-dimension feature space mapped by using kernel functions, and its advantage is that the nonlinear relationship (i.e. higher-order statistical properties of the input) in the process variables could be obtained based on nonlinear interactions between input variables , and the limitation of the second-order correlations in linear PCA could be solved [12, 13].

For the improvement of the generalization performance of SVM-based classifier for discriminating gait asymmetry, this study addressed a novel scheme of training SVM, that is, the kernel-based PCA was firstly applied to extract some good gait feature from input gait variables, and than these extracted features containing additional separation information were used to initiate the training set of SVM[14]. In order to valid the proposed technique combining KPCA with SVM, the foot-ground reaction forces data of 24 elderly participants were acquired using a strain gauge force platform during normal walking. The vertical directional foot-ground forces were chose and analyzed, and each gait pattern was defined using the selected measurement values obtained from each participant during a stance phase. Besides, for the assessment of the generalization performance of the proposed models objectively, the relative operating characteristic (ROC) curves were employed to evaluate the classification performance. To demonstrate the proposed model has superior performance of classification than other gait classifiers, we compared its outcomes with those of PCA-based SVM, SVM models based on the different input feature vectors, and a traditional ANN with back propagation learning algorithm.

This paper is organized as follows: Section 2 presents the procedure of foot-ground reaction force gait data acquisition. In Section 3, we briefly explain KPCA and SVM for gait features extraction and classification. In Section 4, the evaluation of performance of the proposed technique via experiments is presented. In Section 5, the experimental result is given. Discussions and conclusions are given in the Section 6 and 7, respectively.

## 2 Kinetics Gait Data Acquisition

In this study, the bilateral kinetics gait data of twenty-four healthy elderly (mean age: 63.8±4.7 years and heights: 167±4.5cm) were collected. Each subject was asked to walk on the straight laboratory walkway of approximately 10 m at a self-determined pace. A strain gauge Bertec force platform ( Bertec Corporation, Canada), embedded in the middle of the walkway, was used to record the foot–ground reaction forces along the three orthogonal directions (vertical force $Fz$, anterior–posterior force $Fx$ and medio-lateral forces $Fy$), as shown in Fig.1, during normal walking, and the sampling frequency was set to 400 Hz. In this study, all gait parameters in the vertical directional foot-ground reaction forces during a stance phase were selected to define gait pattern since these parameters contain more useful information about normal gait function [15]. In addition, for avoiding the difference among subjects, these variables were normalized by subjects' bodyweight and gait cycle respectively. Thus, each gait pattern, as shown in Fig.2, consisted of 101 dimensions vector by sampling at each 1% in a normalized stance phase. Here, six key gait variables in the vertical directional foot-ground reaction forces, three peak forces ($Fz1$, $Fz2$ and $Fz3$) and occurrence of their respective time($Tz1$, $Tz2$ and $Tz3$) as shown in Fig. 3, were selected as gait feature and defined as gait pattern because these parameters play an important role in the evaluation of the human gait function[16].

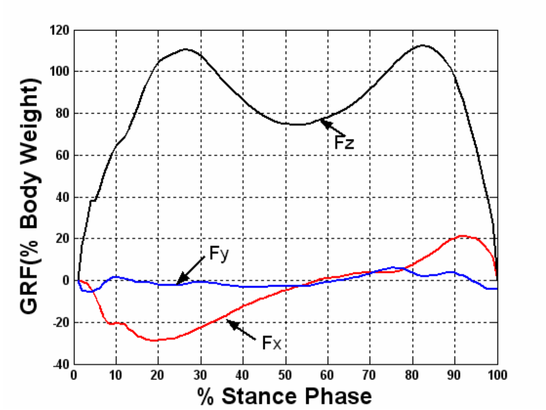


Fig.1. The foot–ground reaction forces along the three orthogonal directions during a normalized stance phase

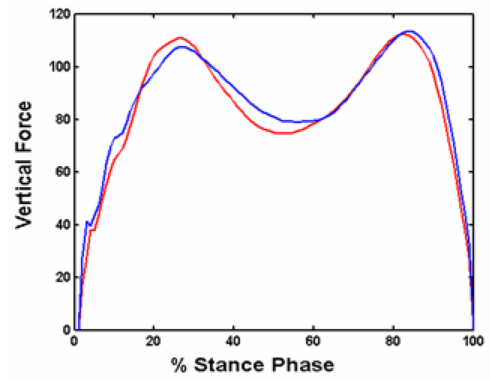


Fig.2. Vertical directional ground reaction force during a normalized stance phase (The red curve represents right-foot gait pattern and the blue curve is left-foot gait pattern)

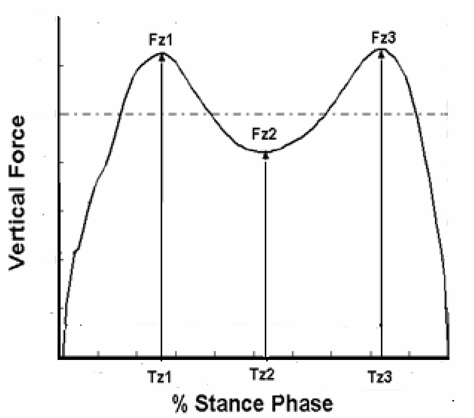


Fig.3. The selected six key gait variables from vertical directional ground reaction force during stance phase

## 3 KPCA-based SVM for Evaluating Gait Asymmetry

After the gait pattern consisting of six gait variables was defined, the first important step was that the KPCA was employed to extract more nonlinear gait features, and then the extracted gait features were used as input of SVM. We briefly introduced the kernel-based PCA as follows.

### 3.1 KPCA for Gait Features Extraction

As we known, kernel-based PCA, as a prevailing nonlinear feature extraction technique, is to generalize linear PCA into a nonlinear case via kernel function, and its basic idea is that the original input variables is firstly mapped into a higher-dimensional feature space by using kernel function, and then linear PCA is performed in that mapped space. In fact, the use of the linear PCA for feature extraction in that mapped space corresponds to the nonlinear features extraction in the input space [12, 13, 17]. Thus, KPCA can capture more nonlinear feature information about gait data. To describe the KPCA applied in foot-ground reaction force gait data for feature extraction clearly, we firstly introduce the linear PCA as follows.

#### 3.1.1 Linear PCA

In recent years, linear PCA, a traditional statistical technique, has widely been applied in gait features extraction to reduce redundant information. The aim of this algorithm is to find maximum variance in a diagonized covariance matrix [12]. Given a set of the centered gait data $D$ is $\{x_k\}$, $x_k \in R^N, k = 1,....,L$, $\sum_{k=1}^{L} x_k = 0$, where $N$ denotes the number of the selected input gait variables, and $L$ represents the numbers of the selected gait data samples. To find the maximum variance in the training set, the linear PCA can be formulated to diagonalize the following covariance matrix

$$C_1 = \frac{1}{L}\sum_{j=1}^{L} x_j x_j^T \tag{1}$$

The solved eigenvalue $\lambda > 0$ and corresponding eigenvector $V$ must satisfy

$$\lambda V = C_1 V \tag{2}$$

According to equations (1) and (2), we can obtain

$$C_1 V = \frac{1}{L}\sum_{j=1}^{L}\left(x_j \cdot V\right) x_j \tag{3}$$

where $(\cdot)$ denotes the dot product between input variables. All solution $V$ must lie in the span of $x_1,.......,x_L$, that is, in a new basis defined by mutually orthogonal eigenvectors, these eigenvectors are ranked in a descending order based on the value of the corresponding eigenvalues. Therefore, we only chose a few principal components to obtain useful linear information between gait variables and to lose more nonlinear feature information related to the change of gait symmetry.

#### 3.1.2 Kernel-based PCA

Unlike linear PCA, kernel-based PCA can efficiently calculate principal components in higher-dimensional feature space mapped by kernel function[12, 13, 17]. Given a set of the centered gait data $D$ is $\{x_k\}$, $x_k \in R^N, k = 1,....,L$, $\sum_{k=1}^{L} x_k = 0$, where $N$ denotes the number of the selected input gait features, and $L$ represents the numbers of the selected gait data samples. The first step is to map the original input gait data into a higher-dimensional feature space $H$ via the non-linear function

$$\phi : R^N \to H \tag{5}$$

The second step is that linear PCA is performed in that space $H$, and the covariance matrix of the input gait variables can be estimated as follows[12]

$$C_2 = \frac{1}{L}\sum_{j=1}^{L}\phi\left(\mathrm{x}_j\right)\phi\left(\mathrm{x}_j\right)^T \tag{6}$$

where $\phi\left(\mathrm{x}_j\right)$ are centered nonlinear mapping of the input gait variables, and $\phi\left(\mathrm{x}_j\right)\phi\left(\mathrm{x}_j\right)^T$ is a dot product in the mapped space $H$. Similarly, to find maximum variance, the covariance matrix $C_2$ need to be diagonalized. Thus, the solved eigenvalue $\lambda_2 > 0$ and corresponding eigenvector $V_2$ must satisfy [12]

$$\lambda_2 V_2 = C_2 V_2 \qquad (7)$$

As all solutions $V_2$ with $\lambda_2 \neq 0$ lie in the span of $\phi(x_1),...,\phi(x_L)$, equation (7) is equivalent to the following equation

$$\lambda_2\left(\phi(x_k)\cdot V_2\right) = \left(\phi(x_k)\cdot C_2 V_2\right) \qquad (8)$$

Beside, according to the expansion coefficients $\beta_j$ ( $j = 1,......,L$ ), $V_2$ could be represented as

$$V_2 = \sum_{i=1}^{L}\beta_j\phi(x_j) \qquad (9)$$

According to equations (6) and (9), equation (8) could be written as

$$\lambda_2\sum_{j=1}^{L}\beta_j\left(\phi(x_k)\cdot\phi(x_j)\right) =$$

$$\frac{1}{L}\sum_{j=1}^{L}\beta_j\left(\phi(x_k)\cdot\sum_{j=1}^{L}\phi(x_j)\right)\left(\phi(x_j)\cdot\phi(x_i)\right) \qquad (10)$$

where $\left(\phi(x_j)\cdot\phi(x_i)\right)$ is the dot product in the mapped space $H$ . Here, noted that the kernel function $K$ is introduced to implicitly determine the mapping $\phi$ and the space $H$ , that is, the eigenvalue problem in equation (10) only involves dot products of mapped shape vectors in the space $H$ . The mapping $\phi$ need not be explicitly computed, and the dot products of two input vectors in the feature space $H$ are calculated by

$$K(x_i, x_j) = \phi(x_i)\cdot\phi(x_j) \qquad (11)$$

Thus, the equation (10) can be expressed as

$$L\lambda_2\beta = K\beta \qquad (12)$$

where $\beta = (\beta_1,......,\beta_L)$ . Therefore, the linear PCA is performed in the space $H$ is to solve the eigenvalue problem for nonzero eigenvalues of equation (11). The eigenvectors $\beta_1,......,\beta_L$ corresponding to eigenvalue $\lambda_{21} \geq \lambda_{22} \geq \cdots \geq \lambda_{2L}$ are calculated. After selecting the first $p$ nonzero eigenvectors, the selected eigenvectors $\beta_1, \beta_2......,\beta_p$ are normalized in the light of the requirement of the corresponding vectors in the space $H$ normalized, that is,

$$\left(V_{2k}\cdot V_{2k}\right) = 1 \quad \text{for all } k = 1,..., p \qquad (13)$$

According to equations (9) and (12), the normalization condition for $\beta_1, \beta_2......,\beta_p$ is as follows

$$\lambda_{2k}\left(\beta_k\cdot\beta_k\right) = 1 \qquad (14)$$

Consequently, for a test gait data $x$ , the extracted principal components can be obtained by calculating the projection of $\phi(x)$ onto the eigenvectors $V_2$ in the space $H$ [12,17].

$$\left(V_k\cdot\beta(x)\right) = \sum_{j=1}^{L}\beta_j^k\left(\phi(x_j)\cdot\phi(x)\right), \; j = 1,..., p \qquad (15)$$

From equation (15), we can observe that kernel-based PCA can obtain more principal components than linear PCA when the numbers of gait data sample are more than that of the selected input gait variables.

### 3.2 SVM for Discriminating the Gait Patterns Between Lower Limb

After the nonlinear principal components were extracted, these extracted principal components were used as the inputs of SVM to train and test the gait classifier. As we known, SVM, based on the Vapnik-Chervonenkis (VC) theory and structural risk minimization (SRM)[18], is one powerful tool for binary classification task, and its main idea is to first map input data into a higher dimensional feature space by using kernel function, and then to construct an optimal separating hyperplane between the two classes in that mapped space. In this study, we selected the gait data set $D_1$ of points $M$ ( $M < L$ ) as the training set where all points belong to two different classes +1 and –1 in which +1 represents the right-foot gait pattern and –1 is the left-foot gait pattern.

$$D_1 = \{(x_l, y_l), y_l \in (+1, -1)\} \quad (16)$$

where $l \in \{1, \ldots.., M\}$, $x_l \in R^n$, $n$ are the numbers of the choice of principal components, and $y_l \in (+1, -1)$ represents the corresponding label space.

The whole gait data of the training set were firstly mapped into the higher-dimensional feature space by using kernel function, and then the aim of SVM-based gait classifier in that mapped space was to find a decision function (i.e. optimal separating hyper-plane) that maps the points from their data space to their label space [18].

$$F : R^n \to \{+1, -1\}, x_l \to y_l \quad (17)$$

Usually, the optimal separating hyper-plane in SVM is expressed as follows:

$$F(x) = sign\left(\sum_{j \in SV} \alpha_j y_j K(x_j, x) + b\right) \quad (18)$$

where SV denotes support vectors; $K(x, y)$ is kernel function satisfying Mercer's conditions ; $b$ is a bias estimated on the training set; $\alpha_j$ ,as the coefficients of the generalized optimal separating hyper-plane, are obtained by solving the following quadratic programming (QP ) problem:

$$\min W(\alpha) = -\alpha^T I + \frac{1}{2}\alpha^T M \alpha \quad (19)$$

subject to $\alpha^T y = 0$ , $\alpha_j \in [0, C]$ and $I$ is $M$ - dimensional identity matrix.

In order to minimize classification error, some non-negative slack variables, $\xi_j \geq 0$ , and a penalty function, $f(\xi) = \sum_j \xi_j^y \gamma \geq 0$ are introduced in SVM, where the $\xi_j$ are a measure of misclassification errors. The generalized optimal separating hyperplane is determined by solving the following optimization problem [18]

$$\min \frac{1}{2}\|w\|^2 + C\sum_j^M \xi_j \quad (20)$$

subject to $y_j(w^T x + b) \geq 1 - \xi_j$, $j = 1, \ldots.., M$ .

where $w$ is the weight vector in the generalized optimal separating hyperplane. Minimizing $\frac{1}{2}\|w\|^2$ corresponds to minimizing the bound on the VC dimension of the classifier (i.e. maximizing the margin), and minimizing $C\sum_j^M \xi_j$ corresponds to minimizing the classification error. $C$ , as the misclassification penalty parameter, can control the trade-off between the maximum margin and the minimum error. Usually, it must be set to a given value[18].

In fact, the solution of SVM are represented sparsely, that is, its solution can be determined by a few support vectors that are a subset of total training gait data points.

# 4 The Technique and Criterion of Assessment for KPCA-based SVM Model

In order to evaluate the accuracy of the our proposed model objectively, the total gait data samples were divided into two parts, that is, the KPCA-based SVM gait classifier was developed using the training gait data, and the remaining gait data were used as the test set to evaluate the performance of the proposed gait classification. The technique and criterion of assessment for KPCA-based SVM model were as follows, respectively.

## 4.1 Cross-validation Technique for Assessment of The KPCA-based SVM Model

In this study, due to the small size sample data, the cross-validation techniques [7, 19], as a standard test technique commonly used for classification task, was adopted to assess the gait classification performance and to choose the optimal parameters of the classifier. Its basic idea is to ensure that as much as information as possible is employed in the training and testing process by using different combinations of the training and testing data sets, that is, the total data sample sets is equally divided into $m$ subsets. First, the selected $m-1$ subsets are combined to construct the training sets, and the remaining one is used as the testing set. After a training process is finished, a testing result is able to be obtained. The above process is then repeated

$m-1$ times while each of the $m-1$ subsets can be used as the test set in turn. Consequently, the final result is obtained by averaging $m$ testing results. Here, a six-fold cross-validation was schemed, that is, the whole 48 sample data consisting of 24 right-foot gait data and 24 left-foot gait data were divided into six segments equally, each containing 4 right-foot and 4 left-foot gait patterns. Firstly, 5 out of the 6 segments were used to train and construct the SVM decision surface while the remaining one was used in testing. The above procedures were then repeated for 6 times. Therefore, the finally averaged result can be obtained.

### 4.2 The Criterion of Assessment of The KPCA-based SVM Model

In addition, in order to effectively evaluate the generalization ability of KPCA-based SVM model, the area under relative operating characteristic (ROC) curves were adopted as the quantitative criterion of validation [19]. In fact, the ROC curve is the graph where the true-positive rate (sensitive) is plotted against the false-positive rate (1–specificity). Here, sensitivity (i.e. a true positive rate) is that the KPCA-based SVM model identifies a right-foot gait pattern truly, and specificity (i.e. a true negative rate) is that proposed model recognizes a left-foot gait pattern accurately. Thus, the ROC curve could be used to illustrate the accuracy of the SVM-based gait classifier and the area under ROC calculated could be employ to assess the generalization performance of the proposed classifier.

## 5 Experimental Result

In order to demonstrate the extracted principal components containing nonlinear feature information about the intrinsic change of human gait function by using KPCA technique, Polynomial kernel function was adopted for KPCA, and is expressed as follows:

$K\left(\mathrm{x}_i, \mathrm{x}_j\right) = \left(\left(\mathrm{x}_i \cdot \mathrm{x}_j\right) + 1\right)^d$ , where $d$ is the degree of polynomial. In this experiment, KPCA with different polynomial degrees ($d$ =1, $d$ =2 and $d$ =3) to extract nonlinear principal components respectively.

To test the effect of the extracted principal components on the generalization performance of SVM, we trained a SVM with linear kernel to perform the binary gait classification task. As we known, the all extracted principal components contain more redundant information, and they don't offer all the necessarily separate information for SVM. To obtain the best generalization performance of SVM, it is vital to find the optimal numbers of principal components as the SVM inputs. Therefore, in this experiment, all principal components extracted were investigated, that is, the number of principal component is increased one by one at each step based on the order rank from the maximum eigenvalue to the minimum eigenvalue. According to the proposed methods and quantitative criterion of validation, the best classification performance of KPCA-based SVM model was obtained. According to the equation (15), the maximal numbers of principal components extracted by using polynomial kernel degree $d$ =2 or 3 is 48, whereas the maximal numbers of principal components extracted by using polynomial kernel degree $d$ =1 is 6. Here, the classification performance against the first 16 number of principal components extracted was presented in Fig.4. From Fig.4, we could observe that the classification performance of our proposed model varied with the selected number of principal component $n$ and the polynomial degree $d$ . When the selected number of polynomial degree $d$ is more than 1(i.e. $d$ =3 or $d$ =2), the superior generalization performance of our proposed model could be obtained on the test set. Also, it was obvious that the more principal components were obtained by using polynomial kernel with its degree $d$ =3 or $d$ =2 than polynomial kernel with its degree $d$ =1(i.e. linear PCA). When the number of chosen principal components (i.e. as the inputs of SVM) extracted by using polynomial degree $d$ =1 was 5, the best ROC area was almost 0.85. However, when the number of chosen principal components extracted by using polynomial degree $d$ =3 was around 10, the maximal ROC area was almost 0.89. Once the numbers of principal components selected was more than 10, the maximal value of ROC area decreased, suggesting that inclusion of further principal component containing more redundant information deteriorated the generalization performance of SVM. These results demonstrated that the kernel-based PCA could obtain more principal components and provide additional separation information related to human movement with SVM-based classifier than linear PCA, and that the classification performance of SVM depended on the number of selected principal components.

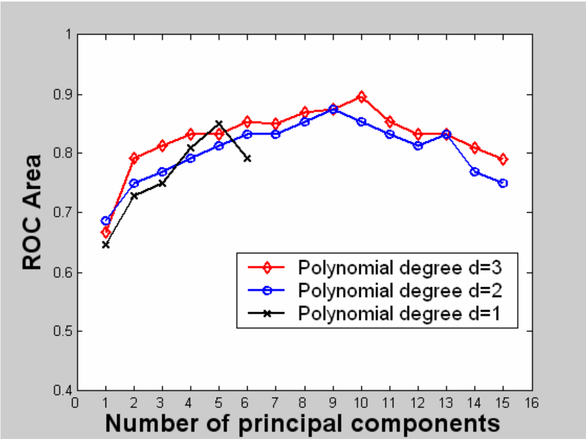


Fig.4 The comparison of classification performance between the different polynomial degrees $d$

To further validate the generalization performance of our proposed model, by using the same gait data, the evaluation criterion and technique, we compared our proposed model with the other SVM-based gait classification model such as SVM model in which the selected six gait variables (i.e. a gait pattern was represented as 6 dimensions vector, as shown in Fig.3) were used as the SVM inputs. Here, the following kernel functions were used in the other SVM-based model respectively.

(1) Linear: $K\left(x_i, x_j\right) = x_i \cdot x_j$ .

(2) Polynomial : $K\left(\mathrm{x}_i, \mathrm{x}_j\right) = \left(\left(\mathrm{x}_i \cdot \mathrm{x}_j\right) + 1\right)^d$ ,

where $d$ represents the polynomial's degree

(3) Gaussian radial basis function (RBF): $K\left(\mathrm{x}_i, \mathrm{x}_j\right) = \exp\left(\dfrac{\left\|\mathrm{x}_i - \mathrm{x}_j\right\|^2}{2\sigma^2}\right)$ ,

where $\sigma$ denotes the width of RBF.

The comparative result of the different classifiers was presented in Table 1. As shown in Table 1, the generalization performance of the KPCA-based SVM is obviously superior to the other gait classification models, suggesting that the principal components extracted by KPCA could offer more additional discriminatory information with SVM than the selected six important gait variables.

Table 1. The comparative results of the different gait classifiers

| Classifiers | Kernel functions | Optimal parameters ( $C$ $d$ $\sigma$ $n$ ) | ROC Area |
|---|---|---|---|
| KPCA-based SVM | Polynomial, Linear | 0.75 3 ---- 10 | 0.89 |
| SVM based on six important gait variables | Linear | 0.45 ---- ---- 6 | 0.83 |
| | Polynomial | 0.85 3 ---- 6 | 0.85 |
| | Gaussian RBF | 0.65 --- 900 6 | 0.85 |
| ANN with BP | ------ | ---- | 0.77 |

Note: polynomial and linear kernel were adopted for KPCA and SVM in KPCA-based SVM respectively

For comparison with the KPCA-based SVM, an ANN-based gait classification model was also applied to recognize right and left sides gait patterns using the same gait data and the evaluation criterion and method. In this experiment, a three-layer ANN model, which consisted of an input layer comprising 6 neurons corresponding to input gait variables, one hidden and an output layer corresponding to the gait pattern to be classified, was used to discriminate the left and right side gait pattern, and the standard backpropagation (BP) learning algorithm was employed in the proposed ANN-based model [5, 6, 20]. The comparative result was also presented in Table 1. From Table 1, it was obvious that the best ROC area of ANN-based model were smaller than those of KPCA-based SVM model, suggesting that our proposed technique had better generalization ability for gait classification than ANN-based model.

## 6 Discussions

The experiment results demonstrated that our proposed technique is able to map the foot-ground reaction force gait data structure associated with elderly lower limb during walking into a linearly separable space with higher-dimension. Especially, the principal components extracted by KPCA could offer more useful information about the change of human gait function, and be used to develop SVM for classifying the gait patterns between the right and left sides related to lower limb with superior generalization performance. Currently, the quantitative assessment of gait symmetry or asymmetry, in clinical application, is a challenging endeavor. Based on the consideration of the quantitative assessment of gait symmetry or asymmetry as a binary gait classification task, the aim of the presented research is search for an advanced gait classification model for assessment of gait symmetry or asymmetry. As we known, the human gait reflects the intrinsic nonlinear dynamics of human movement, and all the ‘interesting’ characteristic information about the gait function change resides in gait variables that generally interact in a complex nonlinear fashion [4, 5]. This motivate the application of the combining KPCA with SVM technique for the quantitative assessment of gait symmetry or asymmetry, that is, kernel-based PCA technique was used to capture more useful information about the human movement for SVM, which could discriminate gait asymmetry accurately. As we known, the advantage of the kernel-based PCA algorithm is that it is able to extract more non-linear principal components from underlying data structure in higher-dimension feature space via non-linear mapping. The extracted nonlinear principal components usually consist in nonlinear interactions between the data points, and the higher-order statistical properties of the input variables reveal the nonlinear features information about data. In this study, we adopted KPCA with polynomial kernel to extract more principal components from foot-ground reaction force gait data, because polynomial kernels of degree $d$ could contain relevant information about the intrinsic nonlinear dynamics of human movement based on nonlinear interactions between input gait variables with a monomial degree $d$ . As shown in Fig.4, more principal components could be obtained by using KPCA with polynomial degree $d$ =2 or $d$ =3 than $d$ =1. Especially, when the number of polynomial degree $d$ and the number of principal components selected is 3 and 10 respectively, we could obtain the best generalization performance of our proposed model. This is because, compared to linear PCA, kernel-based PCA can extract more nonlinear principal components in the mapped higher-dimension feature space, more important, it can allow the information about the change of human gait symmetry to be spread into more nonlinear principal components, which the noisy part of gait data resided could be discarded[12].

To further illustrate the superior performance of our proposed model, we compare the KPCA-based SVM model with the other common SVM-based gait classification based on foot-ground reaction force gait data. The comparative results were appeared in Table 1, these results demonstrated that gait input features defined by the six important gait variables selected from the normalized stance phase didn’t offer more separate information for the training set of SVM. However, with our proposed model, when the training set of SVM is initialized by the selected nonlinear principal components, it make representative, that is, the selected nonlinear principal components could provide SVM with more additional separate information related to the change of human gait symmetry. In addition, we also compared our proposed model with ANN-based gait classification model, the comparative result in Table 1 showed that it is obvious that the generalization performance of our proposed model was superior to that of ANN-based model. This possible reason is that ANN algorithm for classification doesn't obtain globally optimal solution and is over fitting [18, 20, 21].

Besides, the selection of the kernel functions and its corresponding optimal parameters, such as misclassification penalty parameter $C$ and the kernel parameters ($d$ ,$\sigma$) of SVM, is vital in SVM-based gait classification algorithm because these parameters chosen had an effect on the generalization performance of SVM. For obtaining the best generalization performance, the above optimal parameters, as shown in Table 1, need to be selected carefully according to the combination of experience and trial-and-error method [4, 5].

## 7 Conclusion

In conclusion, the result of present study demonstrated the KPCA-based SVM could classify the right and left gait patterns related to foot-ground reaction force gait data with superior generalization performance, and has the good suitability in the quantitative assessment of gait symmetry or asymmetry. The KPCA-based SVM model can be served as a powerful tool for the future clinic applications of early diagnosis of the change of gait symmetry.

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