Kernel PCA feature exaction and SVM classification algorithm for multiple statuses detection of through wall human being

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Abstract: Ultra-wideband radar with strong anti-jamming performance and high range resolution, which can be used to separate multiple human targets in a complex environment. In recent years, the through wall human being detection with UWB radar has been relatively mature. In this paper, the method of kernel PCA (kernel principal component analysis) feature exaction and SVM (support vector machines) classification algorithm are applied to identify and classify the multiple statuses of through wall human being. This method makes full use of the kernel principal component analysis of powerful nonlinear feature extraction and support vector machines, which can solve the problem of multiple statuses detection and non-linear pattern recognition. The experimental data that come from the KPCA feature exaction is used as input to the SVM classification algorithm, some of which are used to train the model and the other to test the model. Experimental results showed that the KPCA feature exaction and SVM classification algorithm effectively distinguished four statuses of through wall human being and achieved the desired results.

Keywords: Kernel principal component analysis, support vector machines, feature exaction, classification

1 Introduction

The ultra-wideband (UWB) radar can emit very short-duration pulses to penetrate walls, bulkhead, and other obstacles. Ultra-wideband radar pulse has the advantages of high accuracy, strong penetrating ability, high resolving power, good anti-stealth ability and low power consumption. It has great potential in radar detection, imaging, precise positioning and target recognition. In the fight against terrorism, disaster relief, public security riot, urban street fighting and other fields have a significant application. It mainly through the acquisition and analysis of the echo signal to carry information to detect hidden in the penetrating media such as clay walls, dielectric plates, concrete, etc. after the target, access to distance, orientation and other information. The UWB signal can realize the ranging accuracy of the order of centimeter, can identify and distinguish the different target types, and can overcome the absorbing effect of narrowband radar, and can suppress the clutter echo in complex background, and can provide non-intrusive detection. Therefore, the technology has a broad and important application prospects, as the human one of the best choice for all-round detection. The focus of this paper is using P410 UWB radar for multiple status of through-wall human detection [1].

UWB radar has a good ability to penetrate and not susceptible to weather, temperature, humidity and other practical factors, so in recent years, reaching through the wall detection has aroused more and more interest of scholars. In [2], this paper mainly introduced that the normalized difference square matrix method, and reference moving average method with Discrete Fourier Transform (DFT) as the detection techniques for periodic respiratory motion of the human target. The experimental results behind gypsum wall and concrete wall have been separately proved for human target detection. In [3], this paper mainly introduced that the through wall detection of human model based on UWB radar, deducing the wavelet packet transform of the target criterion, and constructing the procedure for the through wall human detection with statistical process control. The experimental data are collected at stationary and moving status of human being for brick wall. In [4], this paper mainly introduced an efficient method of TOA (time of arrival) estimation using UWB through-wall radar to detect and track moving target behind wall based on TWRI (through-wall radar imaging) algorithm. The processing result of the experimental data obtained through the UWB through wall radar shows its detection and tracking effects on moving targets. In [5], this paper mainly introduced residual subspace analysis addressed the anomaly detection problem in large-scale data mining applications, and suggested a framework using the compressed sensing (CS) theory. The experimental results based on the benchmark PETS 2007 and 83GB of real footage from 3 public train stations. The results show that this paper proposed method is scalable, and importantly, its performance is comparable to conventional methods for anomaly detection when the complete data is available. In [6], it processed the fuzzy pattern recognition and genetic algorithm to identify the multi-status human being after the brick wall, and recognize principle of maximum degree of membership function to establish target prediction function by fuzzy pattern. The results show that the fuzzy pattern recognition performance for the Multi-status human being behind the wall. In [7], it mainly describes a complete UWB signaling tomography system for high contrast or large object recognition, applied to breast cancer testing. This article is focused on the implementation of a two-degree free imaging set to deal with asymmetric objects with lifelike breast ghosts. In [8], it uses a radar sensor network (RSN) to arrive at a unified analytical framework that takes all factors into account and allows the uncertainty derivation of probabilities detection and location. The experimental results allow the system designer to have a clear understanding of the impact of each system parameter and the trade-off between performance and complexity. In [9], AG Yarovoy has manufactured the detection and positioning of human in complex environment with UWB radar. And it has been shown that the range to a person varies within 0.6cm because of breathing, and a novel motion or breathing detect or has been presented on the basis of the measurements of radar return spatial variations. The experimental results of human being radar return has been analyzed in the frequency band from 1GHZ to 2 GHZ. In [10], this paper describes a complex process based on the M-sequence UWB radar estimation method for wall moving target tracking, and introduces the phase task solution signal processing method. Experimental results based on the scene of concrete wall tracking through a single moving object, and the UWB radar signal is used to deal with the performance of the demonstration trajectory estimation method.

In recent years, multiple statuses detection of through wall human being has attracted wide attention and applied in many fields such as national economy, space technology and national defense. Kernel principal component analysis (KPCA) method can deal with the nonlinear relationship between variables, as a multi-variable statistical process monitoring effective algorithm, using this method to establish multiple statuses fault detection model. The experimental results are based on three case studies: (1) a two-dimensional toy example, (2) a realistic simulation usually used as a bench-mark example, known as the Tennessee Eastman Process, (3) real data from a methanol plant [11]. In this paper of [12], it shows that reducing the impact of channels and handsets on system performance is one of the major issues that improve the accuracy of the most state-of-the-art speaker recognition algorithms. By adapting the model between the different channel conditions to explore the SVM framework specific techniques to obtain completely non-linear channel compensation, the observed changes in the particular type of marker channel are less sensitive to the system. In [13], A Solomonoff proposed the support vector machine (SVM) method to adjust the model to improve the accuracy of the speaker recognition algorithm and reduce the impact of the channel and the mobile phone on the system performance, and discussed the SVM framework specific technology to obtain complete nonlinear channel compensation. The experimental results are based on systems that are less sensitive to the particular type of marker channel changes observed during the training. In [14], this paper mainly discusses the road detection algorithm of the front view single camera using the road probability distribution model (RPDM) and the online learning method. The combination of dynamic RPDM and fuzzy support vector machine (FSVM) makes the algorithm self-supervised and optimizes learning from the inheritance of previous results.

In this paper, we proposed an algorithm for through wall human being detection based on Kernel PCA feature exaction and SVM classification algorithm. We also used the linear PCA feature exaction and SVM classification algorithm compared with the method of this paper. The remainder of the paper is organized as follows. In section 1, we introduced the merit of UWB radar in the field of target recognition and elaborated the main research contents of this paper. In the section 2, we introduced the theory of kernel principal component analysis and support vector machines. The algorithm of construction and implementation is in section 3. Experimental results for multiple statuses human being detection will be showed in section 4. In section 5, we will introduce the conclusion and discussion.

2 Theory

2.1 KPCA nonlinear feature extraction theory [15,16]

Principal component analysis (PCA) is a linear dimensionality reduction and feature extraction method for high dimensional data. It maps the input data from the original high dimensional space to the characteristic subspace, and extracts the main feature vector of the input data, and achieves the purpose of analyzing the original data with the main component. In general, PCA (principal component analysis) can only be effectively performed on a set of observations that are best described by second-order correlations and vary linearly, or the observations are generated by a Gaussian distribution. It is well known, but, that the variations of the actual data are nonlinear and highly non-Gaussian, and that the majority of the data cannot be described by second-order correlations. Therefore, when PCA is employed, the performance is very poorest. In this paper, KPCA is a nonlinear PCA method based on kernel functions which intrinsically constructs a nonlinear mapping from the input space to the feature space F by a nonlinear transformation Φ ,and do linear PCA in F .Between two input examples x and y in the original space, one can avoid performing the nonlinear mappings and computing both the dot products in the feature space by using a kernel function of form $k(x, y) = \Phi(x) \cdot \Phi(y)$. The conceptual framework of the KPCA method is shown schematically in Fig.1

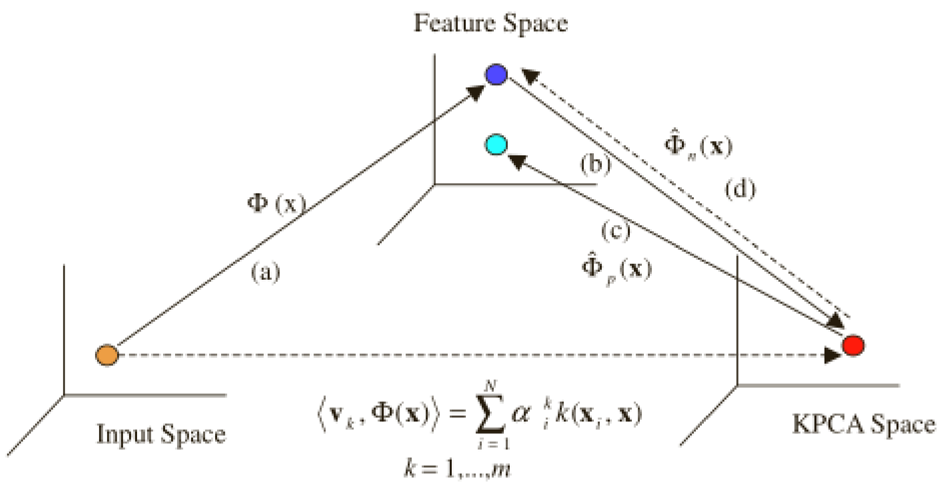


Fig.1 The conceptual framework of the KPCA method

There are many forms of kernel functions. According to Mercer's theorem of functional analysis, if the kernel function is a continuous kernel of a positive integral operator, there exists a map Φ into a dot product space F such that formula holds. As long as the requirement on the kernel function satisfying Mercer's theorem and selecting the fitting kernel function, it can achieve good dimensionality reduction effect. List some typical kernel functions, such as: Polynomial kernel $k(x,y) = \langle x,y\rangle^d$,Sigmoid kernel $k(x,y) = \tanh(\beta_0 \langle x,y\rangle + \beta_1)$,Radial basis kernel $k(x,y) = \exp(-\frac{\|x-y\|^2}{c})$. where d , β_0 , β_1 ,and c are specified a priori by the user. The poly nominal kernel and radial basis kernel always satisfy Mercer's theorem, whereas the sigmoid kernel satisfies it only for certain values of β_0 and β_1. Due to the good performance of the radial basis function, in the practical application, the radial basis function is generally chosen as the kernel function of KPCA, so, in this paper, we use the radial basis kernel as the KPCA kernel function.

Giving a set of input data(with zero mean) X ($x_1,\cdots,x_N \in R^m$ that N is the number of samples, m is the dimension of the measurement variables) through KPCA algorithm calculating their covariance matrix, the covariance can be expressed in a linear feature space F instead of the nonlinear input space.

$$C^F = \frac{1}{N}\sum_{j=1}^{N}\Phi_j(x)\Phi_j(x)^T \tag{1}$$

Where it is assumed that $\sum_{k=1}^{N}\Phi(x_k) = 0$, and the $\Phi(\cdot)$ is a nonlinear mapping function that projects the input vectors from the input space to F . Note that the dimensionality of feature space can be arbitrarily large or possibly infinite. To calculate the covariance matrix, one has to solve the eigenvalue problem in the feature space.

$$\lambda v = C^F v \tag{2}$$

Where eigenvalues $\lambda \geq 0$ and eigenvector $v \in F$, the eigenvector v for any $\lambda \neq 0$ can be linearly represented by $\Phi(x_i)$:

$$v = \sum_{i=1}^{N} \alpha(i)\Phi(x_i) \tag{3}$$

The equation (2) can be converted into the kernel eigenvalue problem:

$$N\lambda\alpha = K\alpha \tag{4}$$

Where an $N * N$ matrix K is a kernel matrix, $K = k_{ij} = (\Phi(x_i) \cdot \Phi(x_j)) = k(x_i, x_j)$,and α is the feature vector of the kernel matrix. When reconstruct input data from feature space, we use the fellow equation (5):

$$y_k = \langle v_k, \Phi(x) \rangle = \sum_{i=1}^{N} \alpha_i^k \langle \Phi(x_i), \Phi(x) \rangle \tag{5}$$

Before applying KPCA algorithm, we assume that the data has been standardized, but in the actual application, without knowing the specific form of Φ, the data is not standardized. This can be done by substituting the kernel matrix K with

$$K = K - 1_N K - K 1_N + 1_N K 1_N \tag{6}$$

Where $1_N = (\frac{1}{N})_{N \times N}$

2.2 SVM classification algorithm theory [17,18,19]

Support vector machines(SVM) are a supervised machine learning method for classification, patter recognition, regression analysis, and other learning tasks based on statistical learning theory(SLT). In this method, it uses support vectors to represent decision boundaries, then, one maps the linearly indivisible data of the low-dimensional input space into a high-dimensional feature space to make it linearly separable, and it is based on the structural risk minimization theory and then constructs an optimal separating hyper plane in this space. Basic idea for SVM as show in Fig.2.

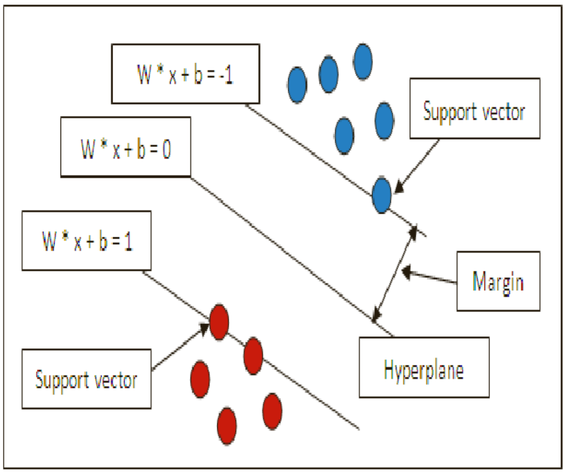


Fig.2 Basic idea for SVM

Given a training set of N data points $(y_j, x_j),\ j = 1, 2, 3, \ldots, N$ where $x_j \in R^n$ is the input pattern and $y_j \in \{1, -1\}$ is the output pattern. The SVM method approach aims at constructing a classifier of the form:

$$y(x) = sign[\sum_{j=1}^{N} \alpha_j y_j \Psi(x, x_j) + b] \tag{7}$$

Where $sign(\cdot)$ is a symbolic function used to classify, α_j are positive real constants and b is a real constant. For $\Psi(\cdot,\cdot)$ is a kernel function similar to KPCA, here, we also select the radial basis kernel as the SVM kernel function.

The classifier is constructed as follows. One assumes that

$$\omega^T \varphi(x_i) + b \geq 1, \quad if \quad y_i = +1 \tag{8}$$

$$\omega^T \varphi(x_i) + b \leq -1, \quad if \quad y_i = -1 \tag{9}$$

Which is equivalent to

$$y_j[\omega^T \varphi(x_j) + b] \geq 1, \quad j = 1, 2, 3, \ldots, N \tag{10}$$

Where $\varphi(\cdot)$ is a nonlinear function which maps the input space into a higher dimensional feature space. But, in order to have the possibility to violate formula (10), the function is not clearly constructed. We introduce the variables ξ_j to solve the following primal optimization problem and to obtain the separating hyper plane in the higher dimensional space.

$$\min_{\omega,\xi_j} \quad \frac{1}{2}\omega^T\omega + C\sum_{j=i}^{N}\xi_j \tag{11}$$

$$\text{Subject to} \quad y_j(\omega^T\varphi(x_i)+b) \ge 1-\xi_j \tag{12}$$

$$\xi_j \ge 0,\ j=1,2,\ldots,N$$

3 Algorithm and Implementation

In order to better understand the feature extraction algorithm of this paper, we give the training steps of the network in the following:

Algorithm 1 Kernel Principal Component Analysis algorithm

Input: training set data, testing set data

Output: feature exaction data

1: standardize the input sample data to generate samples matrix X

2: select the radial basis function, select the appropriate c value and calculate the matrix K ,according to equation (6) to obtain the matrix K

3: find the eigenvector and eigenvalues of K according to equation (4), and select the eigenvectors corresponding to the largest eigenvalues.

4: calculate the projection of selected sample data according to equation (5), as input data for supporting vector machine recognition, classification for multiple statuses detection of through wall human being.

In this paper, we used the ROC (receiver operating characteristic) curve to estimate the performance of the classification algorithm more comprehensively. The ROC curve has the advantages of high credibility, accurate description of the target, not affected by the data environment. It is based on a series of different two classification methods (cutoff or decision threshold). In ROC curve, FPR (False Positive Rate) is used as the abscissa and TPR (True Positive Rate) is used as the ordinate. Compared with the traditional evaluation methods, the ROC curve analysis method performance is better and there is no excessive restrictions. Therefore, the ROC curve analysis method is applicable to a wider range. The evaluation index of ROC are shown in the following [20]:

Table 1: The evaluation index of ROC

		Predicted		
		1	0	SUM
Actual	1	True Positive(TP)	False Negative(FN)	Actual Positive(TP+FN)
	0	False Positive(FP)	True Negative(TN)	Actual Negative(FP+TN)
SUM		Predicted Positive(TP+FP)	Predicted Negative(FN+TN)	TP+FP+FN+TN

TP is the positive sample which is predicted to be true by the model, FN is the positive sample which is predicted to be false by the model, FP is the false sample which is predicted to be true by the model, and TN is the false sample which is predicted to be false by the model. The calculation formulas of FPR and TPR are as follows:

$$FPR = \frac{FP}{TN + FP}, TPR = \frac{TP}{TP + FN} \tag{13}$$

4 Experimental process and results

In this experimental, the UWB radar is P410 of time domain company. The P410 equipment development board mainly composed of FPGA, DSP, network port, UWB transceiver, fan and many more and connected with the computer by net mouth using the UDP protocol to set the signal pulse length, the number of times and others. The center frequency of P410 UWB radar is 4.3GHZ. The wall material is thick 23.5cm brick. The P410 UWB radar is placed at a distance of 20cm from the brick wall and the distance between the UWB radar and the ground is the half of the brick wall. In this experiment environment, there are four statuses for through-wall human being detection. The first is no person behind the brick wall, the second is two persons walking 1m away from the brick wall, the third is three persons normal breathing 2m away from the brick wall, the last is two persons rapid breathing 1m away from the brick wall. Each data in the four statues consist of 500 groups of pulses and a pulse sampling points set for 1000.

Based on the computer of P42.5GHZ,512M RAM and matlab R2009a simulation experiment, We respectively from four kinds of state of the selected 300 groups of data by feature extraction as a training set, and the rest as the testing set. In order to compare the effect of feature extraction, the feature extraction method of this paper is compared with the PCA feature extraction method about the classification result. And the experiments were performed on the same training data and testing data using the two feature extraction algorithms combined with support vector machines. Through the theoretical knowledge of the second section, we know that the KPCA method has the same mathematical and statistical properties as the linear PCA in the feature space, such as the uncorrelated of the principal components; the principal component can represent the maximum variance of the sample data; the sample is reconstructed with the least squares error; in addition, it can extract more sample information than the linear PCA. Under the premise of the same classification performance, KPCA requires less number of principal elements than PCA, and it does not need to solve the nonlinear optimization problem and only the eigenvalue decomposition of the matrix compared with other nonlinear feature extraction methods.

In the simulation results, the eigenvalues by descending order of PCA and KPCA are shown in the following. The Fig.3 is the matrix eigenvalues of PCA and the Fig.4 is the matrix eigenvalues of KPCA. In this picture, the horizontal axis represents the number of sample eigenvalues, and the vertical axis represents the eigenvalues. Compared with the two graphs, we can see that the KPCA tends to zero at the 300th eigenvalue, but the PCA starts to trend zero at the 500th eigenvalue. If the variance contribution rate that the sum of the selected eigenvalues divided the sum of the entire eigenvalues of the eigenvalues reaches 90%, the PCA needs the first 100 eigenvalues representation, that is, the 1000-dimensional column vector can be compressed into a vector of only 100-dimension. However, the KPCA only needs the first 70 eigenvalues to make the contribution rate of 90%, in other words, 1000-dimensional column vector can be compressed into a vector of only 70-dimension. Under the same classification performance, the kernel principal component analysis requires less principal elements, less mean square error, and the effect of reducing the dimension is more obvious.

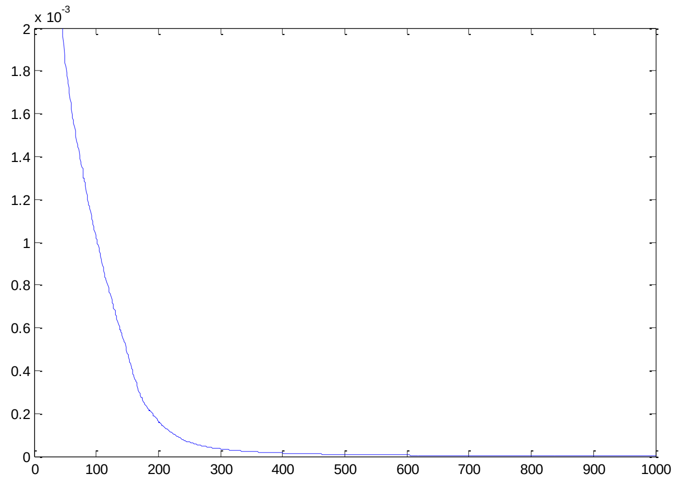


Fig.3 Matrix eigenvalues of PCA

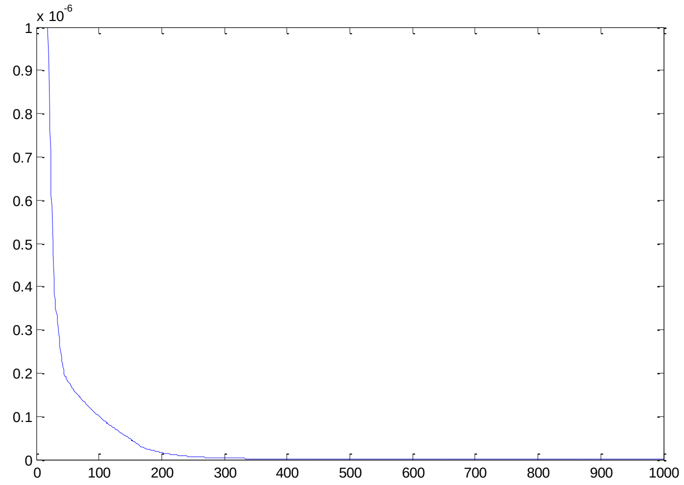


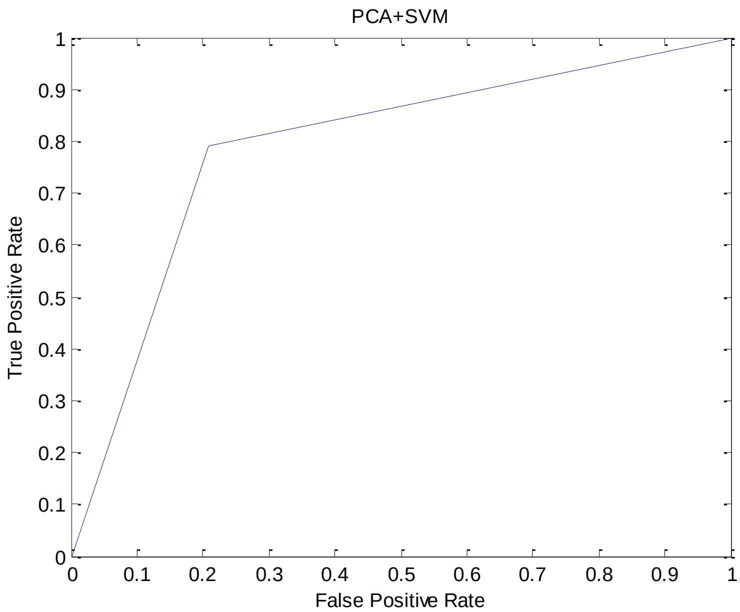
Fig.4 Matrix eigenvalues of KPCA

In this paper, the data by feature extract of the training set is input into the support vector machines for training model. After the model training is finished, the test set data is input to the trained model for testing, and the experimental results are showed in Table 2. In the table, nine indicators are listed, and the feature extraction performance of the two algorithms is compared by each indicator. The accuracy of the KPCA algorithm is significantly higher than that of the PCA algorithm. The Kappa Statics is an important indicator of the degree of consistency in the evaluation. If kappa value is greater than 0.75, the consistency is good, indicating consistency between 0.75 and 0.4, Less than 0.4 indicates poor consistency. From the table, we can see the kappa value of KPCA algorithm is greater than 0.75 consistency is better and the kappa value of PCA algorithm is less than 0.75 consistency. The mean absolute error and root mean squared error are used to measure the difference between the predicted value of the classifier and the actual result and the value smaller the classification performance better. So, it is obvious that the KPCA is superior to PCA. When the absolute error cannot reflect the error of the true size, the relative absolute error and root relative squared error can reflect the size of the error by the proportion of the error to the true value. And the smaller the relative absolute error is, the better the classification performance of the feature exaction algorithm is. To sum up, the KPCA and SVM combination algorithms are better than those of PCA and SVM in comparison with each index of the two algorithms.

Table 2: Experimental results compared with PCA+SVM, KPCA+SVM

Classification algorithm parameters	PCA+SVM		KPCA+SVM	
Correctly Classified Instances	633	79.125%	654	81.75%
Incorrectly Classified Instance	167	20.875	146	18.25%
Kappa statistic	0.7217		0.7567	
Mean absolute error	0.2827		0.2794	
Root mean squared error	0.3604		0.3558	
Relative absolute error	75.3889%		74.5%	
Root relative squared error	83.2388%		82.1584%	
Total Number of Instances	800		800	

This paper also used the ROC curve to analyze the experimental results. The ROC curve is closer to the upper left corner, it represents that the algorithm has a higher accuracy. As shown in Fig.5, the ROC curve of the through wall human being detection by the two algorithms, using the KPCA algorithm is significantly better than that of the PCA algorithm. The ROC curve of the through wall human being detection is shown as follows：



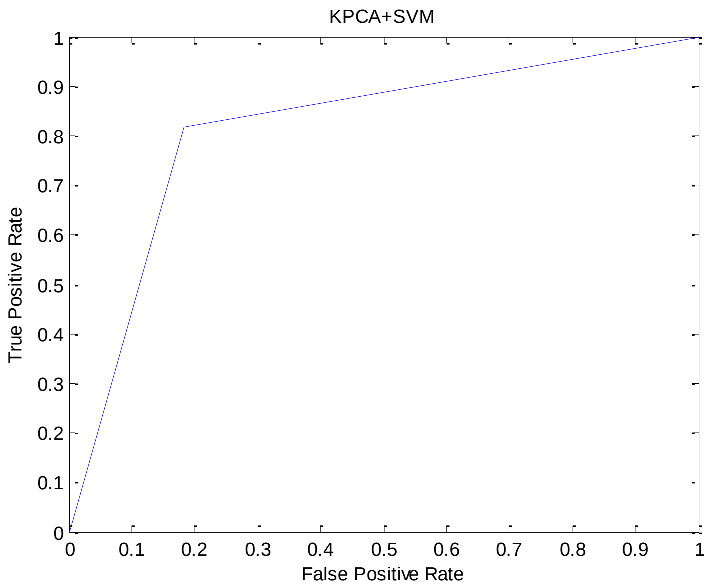


Fig.5 ROC of the through wall human being detection

5 Conclusion

We have presented a framework for through wall human being detection under four statuses with P410 UWB radar on SVM classification algorithm. In the classification algorithm before, we need to extract the feature of the data to reduce the dimension and the time complexity. Compared to other feature extract methods, KPCA has the following main advantages:(1) the nonlinear data effectively is dealt; (2) no nonlinear optimization is involved; (3) the calculations in KPCA are as simple as in standard PCA, and (4) the number of PCs need not be specified prior to modeling. So, in this paper, the combination of kernel principal component analysis and support vector machine with this method combines their advantages of kernel principal component analysis and the support vector machine in the application of pattern recognition, so the practical application can be better than the two methods alone performance. Experimental results show that the algorithm can effectively distinguish the no person behind the brick wall, the two persons walking 1m away from the brick wall, the three persons normal breathing 2m away from the brick wall, the two persons rapid breathing 1m away from the brick wall and have the important theoretical significance and practical application value. Compared with the traditional principal component analysis method, the simulation results show that the proposed method has better stability and reliability, can improve the recognition rate effectively, and can effectively optimize the extraction of the radar target principal feature, accelerate the identification of speed, improve the recognition performance of the target, then also has a good ability to promote. Further research work is focused at a small sample of the multiple statuses human being detection and improve the recognition rate with different kernel functions.

Competing interests

The authors declare that they have no competing interests.

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