Extracting Features of Underwater Targets Using Kernel Fisher Discriminant Analysis

Chun-xue Shi, Zhi-jing Zhou, Hai-ming Zhao and Mu-rong Zhou

Abstract: **This study proposes a method of feature extraction based on Kernel Fisher Discriminant Analysis (KFDA) to solve problems in the classification of underwater targets, specifically the large number of original characteristic parameters and significant nonlinearity. First, a large number of features are combined through serial feature fusion to establish a new feature vector space, and KFDA is used to extract the optimal nonlinear discriminant features. Second, a test bed for an underwater experiment featuring a data processing system, echo signal acquisition, and feature extraction is described. Finally, underwater acoustic experiments are carried out, and the results of the measurement data indicate that the proposed method is superior to currently used techniques in the area.**

Index Terms: **Kernel Fisher Discriminant Analysis (KFDA), Feature Extraction, Feature Fusion, Underwater Targets, Classification**

I. INTRODUCTION

Features constitute the only source of original information needed to design a classifier. The recognition and classification of underwater targets by acoustic methods is based on the extraction of effective features from underwater echoes. The quality of the features directly influences the accuracy of recognition. Considerable progress has been made in this domain in terms of features for classification, e.g., the wavelet multi-resolution decomposition of echo signals, singular value, and echo edge features [1-4]. It is challenging to describe the characteristics of targets by using a single feature, and can even lead to loss of useful information. This in turn leads to a low rate of correct classification. Parameter indices of multiple features are usually integrated to solve this problem [5-8]. However, if many indices (large dimensions) are directly used as input to the classifier, the design of the classifier becomes complex. Moreover, these parameter indices have relatively strong correlation, and removing these correlations and reducing the number of dimensions help improve the accuracy of recognition and reduce the workload. References [6-8] used principal component analysis (PCA) for multivariate statistical analysis. PCA determines direction of injection of the maximal sample dispersion by using a sample covariance matrix without considering differences among classes. Although it can maintain an adequate number of original features, the direction obtained is not the best for classification and the features extracted are not optimal [9,10]. Fisher Discriminant Analysis (FDA) considers differences among classes, is characterized by maximizing the inter-class dispersion matrix and minimizing intraclass dispersion matrix, and can compensate for the inadequacy of PCA. Moreover, the features thus extracted are distinct. PCA is based on linear transformation for feature extraction to obtain linear features. The results are not always satisfactory when solving for highly complex nonlinear distribution structures [11]. Therefore, it is important to extract features with a high degree of distinction for the recognition and classification of underwater targets.

This paper proposes a method for underwater feature extraction from echoes using Kernel Fisher Discriminant Analysis (KFDA). By integrating the kernel method into the technique to extract features from underwater echoes, and by combining the advantages of the kernel method with those of the FDA method, multiple original features are extracted for the same sample. These features are combined using feature integration technology to form a new vector space of features. Optimal nonlinear features are extracted for identification, and classification experiments were implemented by KFDA in this space.

II. FORMATION AND INTEGRATION OF ORIGINAL FEATURES

A. *Formation of original features*

Research has shown that the shapes of the underwater echo of normal incident ultrasonic pulses are related to the roughness of the target surface, attenuation coefficients of sonic waves in sediment, structures of sound velocity, and density structures on the seabed. The shapes of the echo contain information relevant to sediment structures and their physical properties [12]. The difference in echo shapes is large for sediments with different hardness and roughness. For instance, the shapes of hard substrates are narrow and sharp with relatively large peaks, whereas those of soft substrates are relatively flat but their tails are long. Therefore, the time-domain waveform features of echo signals can be extracted as measures of features for classification, such as

Manuscript received February 8, 2018; revised February 11, 2020. This work was supported in part by the Chinese National Natural Science Fund Project under Grant 51374245, the Chinese National Natural Science Fund Project under Grant 51174087, and the Hunan Natural Science Province and City Unit Fund Project under Grant 2017JJ4038.

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the maximal peak, peak moment, effective value, absolute mean value, variance, peak factor, waveform factor, center of mass, waveform width, kurtosis, and skewness.

Tegowski et al. have noted that seabed echoes carry fractal features of the seabed sediment. The fractal dimension of these features can be used to measure the complexity and roughness of the seabed substrate, which has provided rich information for classification [13-14]. The fractal dimension of the echo of the seabed is also used for classification. Therefore, 12 statistical features are used in this study.

B. Feature fusion

Features generated by the fusion of several features retain effective verification-related information of features participating in the fusion from all classes. To some extent, the redundancy of information among multiple features is thus eliminated [15]. Current feature fusion technologies are of two kinds: serial feature fusion and parallel feature fusion. The latter is feature fusion in unitary space, and combines two features by adopting the form of a complex vector $\lambda=\alpha+i\beta$ (i is an imaginary unit, and α and β are, respectively, feature quantities of the same sample) [16]. Parallel feature fusion can combine only two features, but serial fusion can combine several features. Assuming that $A_1,\cdots,A_{12}$ are the 12 feature quantities used in this study, the new feature quantity after fusion is $B=(A_1,\cdots,A_{12})^T$.

Although serial features can maintain complementarity among the features, the dimensions of the new features after merging is the sum of the number of dimensions of the original features, which is unfavorable for classifier design.

III. KFDA feature Extraction Algorithm

The idea of Kernel Fisher Discriminant Analysis is to transform linear, indivisible, original features to a linear, divisible, high-dimensional space and apply FDA “kernel skill” to implement nonlinear discriminant analysis relative to the original feature space [17-20].

Assume that the new feature space *X* has *D* dimensions after fusion. *X* contains *N* training samples divided into *c* classes: the number of samples of class *i* is $N_i(i=1,\cdots,c)$; x_k^i is the *k*-th sample $(k=1,\cdots,N_i)$ in class *i* and x_j is the *j*-th $(j=1,\cdots,N)$ sample. The corresponding pattern vector after nonlinear mapping is $\phi(X)\in H$. Therefore, the inter-class and intra-class dispersion matrices of the training samples in the high-dimensional feature space H are estimated as

$$S_b^\phi=\sum_{i=1}^{c}P_i(m_i^\phi-m^\phi)(m_i^\phi-m^\phi)^T \tag{1}$$

$$S_\omega^\phi=\sum_{i=1}^{c}P_i\frac{1}{N_i}\sum_{k=1}^{N_i}(\phi(x_k^i)-m_i^\phi)(\phi(x_k^i)-m_i^\phi)^T \tag{2}$$

where $\phi(x_k^i)$ is the *k*-th sample of class *i* in high-dimensional feature space; $m_i^\phi=\frac{1}{N_i}\sum_{k=1}^{N_i}\phi(x_k^i)$ is the mean value of the sample set of class *i* in H; $m^\phi=\sum_{i=1}^{c}P_im_i^\phi$ is the overall mean of various sample sets in *H*; and P_i is the prior probability of class *i*—$P_i=N_i/N$—that can be estimated from the number of training samples.

The Fisher criterion function can be defined in high-dimensional feature space H as

$$J_F^\phi(w)=\frac{w^TS_b^\phi w}{w^TS_\omega^\phi w} \tag{3}$$

where w is any nonzero vector in H. Because the number of dimensions of H is large, even infinite, the optimal Fisher discriminant vector cannot be calculated directly according to Formula (3). It is converted to include the inner product of the data after mapping, which can be expressed through the kernel function $K(x_i,x_j)=\langle\phi(x_i),\phi(x_j)\rangle$ defined in the original feature space. Common kernel functions include the Gaussian kernel function $K(x,y)=\exp(-\|x-y\|^2/2\sigma^2)$ and polynomial kernel function $K(x,y)=(\langle x\cdot y\rangle+c)^d$, where σ, c, and d are all constants.

According to the theory of reproducing the kernel [18], the solution vector w of any optimal criterion function is located in the space formed by all training samples $\phi(x_1),\cdots,\phi(x_N)$ in feature space H

$$w=\sum_{j=1}^{N}a_j\phi(x_j)=\phi a \tag{4}$$

where $a=(a_1,\cdots,a_N)^T\in R^N$ and $\phi=(\phi(x_i),\cdots,\phi(x_N))$.

The samples of H are projected to w:

$$\begin{aligned}w^T\phi(x_j)&=a^T\phi^T\phi(x_j)\\&=a^T(\phi(x_1)^T\phi(x_j),\cdots,\phi(x_N)^T\phi(x_j))^T\\&=a^T(K(x_1,x_j),\cdots,K(x_N,x_j))^T\\&=a^T\xi_{x_j}\end{aligned} \tag{5}$$

where $\xi_{x_j}=(K(x_1,x_j),\cdots,K(x_N,x_j))^T$ is the kernel sample vector of sample x_j in the original space.

In a similar way, the mean m_i^ϕ of sample sets in H and overall mean m^ϕ are injected into w:

$$w^Tm_i^\phi=a^T\phi^T\frac{1}{N_i}\sum_{k=1}^{N_i}\phi(x_k^i)=a^T\mu_i \tag{6}$$

$$w^Tm^\phi=a^T\phi^T\frac{1}{N}\sum_{j=1}^{N}\phi(x_j)=a^T\mu \tag{7}$$

where $\mu_i=(\frac{1}{N_i}\sum_{k=1}^{N_i}K(x_1,x_k^i),\cdots,\frac{1}{N_i}\sum_{k=1}^{N_i}K(x_N,x_k^i))^T$ and $\mu=(\frac{1}{N}\sum_{j=1}^{N}K(x_1,x_j),\cdots,\frac{1}{N}\sum_{j=1}^{N}K(x_N,x_j))^T$ are, respectively, the mean of the kernel samples and the overall mean of the kernel sample set.

By using Formulae (5), (6), and (7) in Formula (4), the Fisher criterion function in H is equivalent to:

$$J_F^\phi=\frac{w^TS_b^\phi w}{w^TS_\omega^\phi w}=\frac{a^TK_ba}{a^TK_\omega a} \tag{8}$$

where $K_\omega=\frac{1}{N}\sum_{i=1}^{c}\sum_{k=1}^{N_i}(\xi_{x_k^i}-\mu_i)(\xi_{x_k^i}-\mu_i)^T$ and $K_b=\sum_{i=1}^{c}\frac{N_i}{N}(\mu_i-\mu)(\mu_i-\mu)^T$ are, respectively, the kernel's intra-class and inter-class dispersion matrices.

When K_ω is nonsingular, the optimal solution vector set of criterion (8) is maximized by generalized Rayleigh quotient theorem, which is the eigenvector $a_1,\cdots,a_d$ corresponding to the d maximum eigenvalues of generalized eigenvalue equation $K_b a = \lambda K_\omega a$. Because the generalized feature equation has $c-1$ nonzero eigenvectors at most (c is the total number of classes in the samples set), the number of optimal solution vectors of Formula (8) is $d \le c-1$.

The nonlinear optimal discriminant vector $w_d = \phi a_d$ ($d = 1,\cdots,c-1$) of the kernel Fisher can be obtained by the set of optimal solution vectors and Formula (4). The projection of arbitrary samples $y \in R^D$ on the optimal discriminant vectors w_d in H is

$$\begin{aligned} Y_d &= w_d^T \phi(y) \\ &= a_d^T \phi^T \phi(y) \\ &= a_d^T (K(x_1, y),\cdots,K(x_N, y))^T \end{aligned} \tag{9}$$

Therefore, the $c-1$ -dimensional kernel Fisher optimal discriminant feature extraction $Y = (Y_1,\cdots,Y_{c-1})^T$ of the original D-dimensional sample y can be obtained.

If K_ω is singular, the formalization method can be used. $K'_\omega = K_\omega + \varepsilon I$ (ε) (compared with the nonzero feature value of K_ω , ε is a very small constant and I is a unit matrix) is used instead of K_ω , so that K'_ω is nonsingular. Then, kernel Fisher optimal discriminant feature extraction is implemented according to the above method [17].

IV. Introduction to Test System

A. Pool testbed

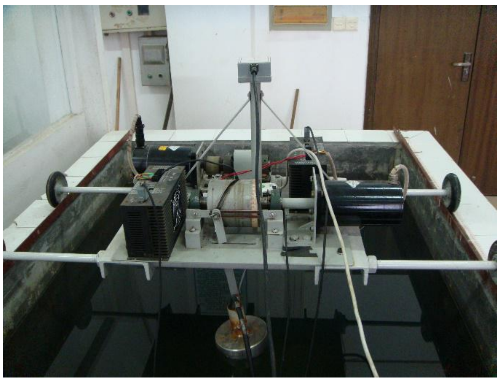

Fig. 1. Pool testbed.

A 2,000 mm × 1,600 mm × 1,800 mm rectangular pool was built in the Deep Sea Technology and Equipment Lab of Center South University with a horizontal undersurface. A guiderail with a stroke of 1,800 mm was installed along the pool's edge.

An operational mechanism with idler wheels could walk along the edge to change the position of detection. A trolley with a span of 1,600 mm was used. There was a fixing device for the ultrasonic transducer in the middle of the trolley platform that fixed it just below the middle of the trolley. The pool testbed is shown in Figs. 1.

B. Data acquisition system

The underwater acoustic signal acquisition system was constituted by the ultrasonic transducer, radiating circuit, echo-receiving circuit, master control circuit, and an industrial personal computer. As the transducer operated under the water, an integrated ultrasonic transducer for underwater reception and transmission, developed by Wuxi CSSC Acoustic Research Technology center, was selected. The transducer was composed of piezoelectric ceramics with a resonant frequency of 500 KHz, probe diameter of 140 mm, and a 3-dB direction angle of 3º.

The radiating circuit was constituted by a signal-producing circuit, power amplifier circuit, and an impedance matching circuit. The echo-receiving circuit was constituted by a pre-amplification electric circuit, TGC circuit, band-pass filtering circuit, PCI-1714 high speed acquisition card, and a computer. The master control circuit was the SCM system with AT89C52 as core. It was used to complete the generation of the ultrasonic pulse signal, synchronize the triggering of the PCI-1714 high speed acquisition card, and adjust the gain in the TGC circuit. The overall structure of the underwater acoustic signal acquisition system is shown in Fig. 2.

The working process of the system was as follows: A signal acquisition command was sent through the signal acquisition software of the computer once the system had been charged. The SCM AT89C52 immediately started the 555 oscillating circuit to generate 500 KHz of a square signal. The PCI-1714 was started for sampling. The transducer was stimulated to transmit ultrasonic waves after four cycles of the square signal had been subject to power amplification. The SCM was used to adjust the magnification of the TGC circuit according to time to guarantee that the echo signals were sufficiently amplified. The incident signals of the ultrasonic wave were reflected after touching an object and received by the ultrasonic transducer. The PCI-1714 conducted A/D conversion of the echo signals once they had been subject to pre-amplification, the TGC circuit, and analog band-pass filtering. Then, the echo signal data were stored in the computer. The internal control program of the SCM prepares the master control circuit for the next emission after signal acquisition. The control subprogram of the SCM was programmed in assembly language. The computer's data acquisition program was developed in VC++.

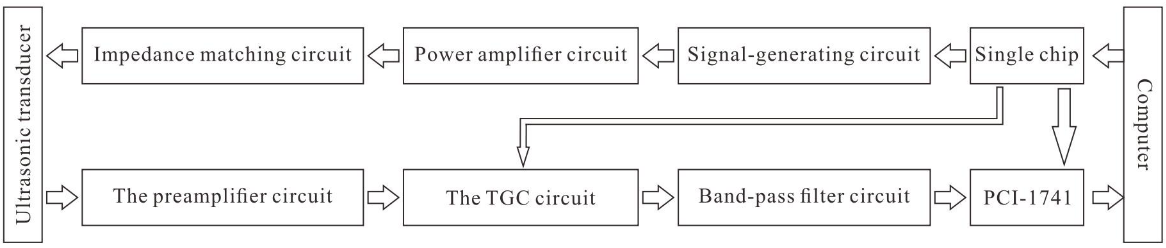

Fig. 2. Structural composition of signal acquisition system.

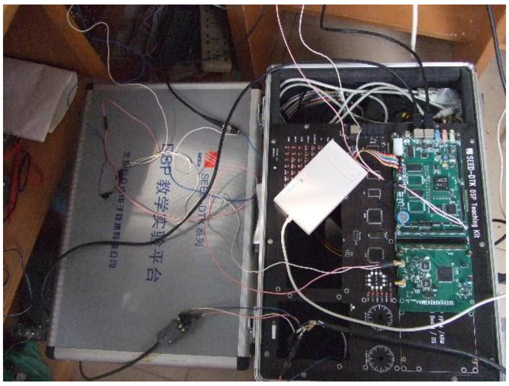

Fig. 3. DSP and A/D sampling card module

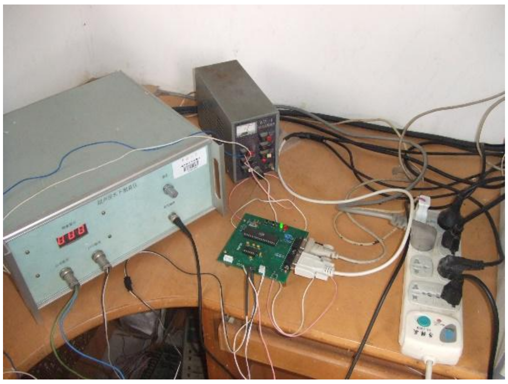

Fig. 4. Microcontroller module

Figs. 3 and 4 show the DSP and A/D sampling card modules, and the microcontroller module of the detection system, respectively.

C. Echo signal acquisition

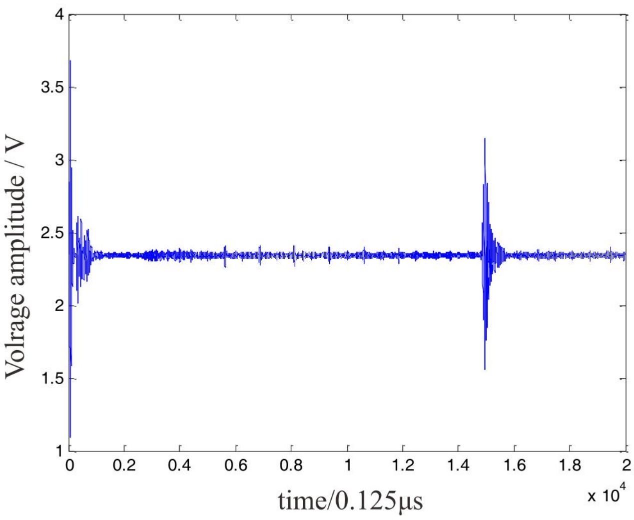

Fig. 5. Waveform of sampled signal.

The waveform of a sampled signal is shown in Fig. 6. The 20,000 sampling points included both the transmitting signal and the true echo signal of the sediment. The waveform before the 2,000th point was the incident signal and that around the 16,000th point was the echo signal. The echo signal of the 20,000 points and their incident signal was subjected to cross-correlation to find the starting point of the true echo. A total of 1,024 points were intercepted at the starting point of the echo as true echo. This number of sampling points was sufficient to contain the true echo through several experimental observations. A sample was randomly extracted from 160 true echo signal sets for each kind of sediment. The waveform of a sampled signal is shown in Fig. 5.

D. Feature extraction of generalized dimensions

The procedure for the calculation of generalized dimensions was used to extract features of generalized dimensions for the collected echo signals of the sediments. The range of values of q was $[-100,100]$ at intervals of two. The result is shown in Fig. 6.

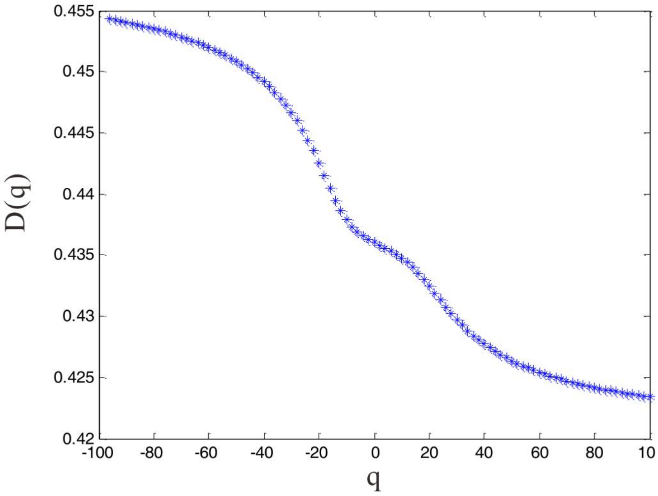

Fig. 6. One kind of generalized dimension spectrum.

V. Experimental Analysis

We considered reflected echoes of four kinds of sediments, rock, gravel, sand, and mud, as research targets, and each had 80 samples. Preprocessing was first applied to the echo data by extracting the statistical features introduced at II.B. Then, serial feature fusion technology was used to combine the features. Different feature extraction methods were then used for analysis and comparison.

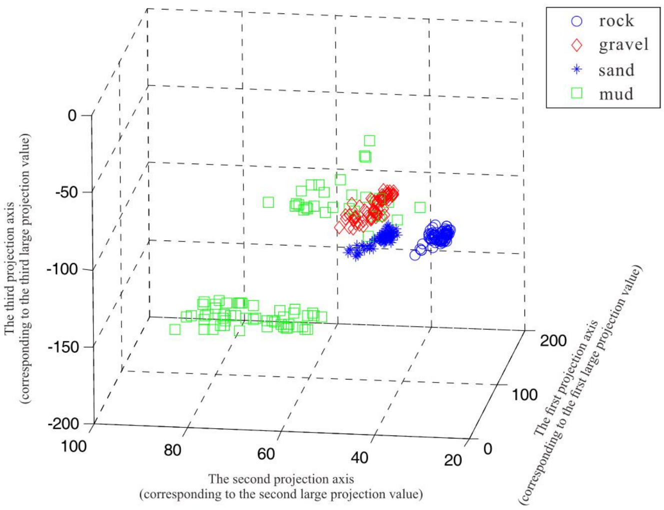

Fig. 7. Four kinds of target features extracted by PCA.

Fig. 7 show the features extracted by PCA. Because it did not consider the differences among classes, the extracted features were not optimal classification features, and there were overlaps among different targets.

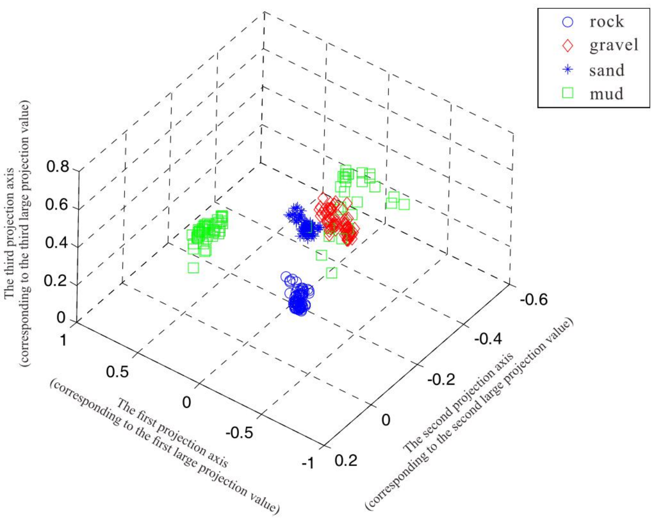

Fig. 8. Four kinds of target features extracted by KPCA.

Fig. 8 shows features extracted by PCA based on the kernel method, where the Gaussian kernel function with $\sigma = 165$ was selected. Although the method made use of the kernel, the features extracted did not have the desirable effect because the method inherited the inadequacy of PCA.

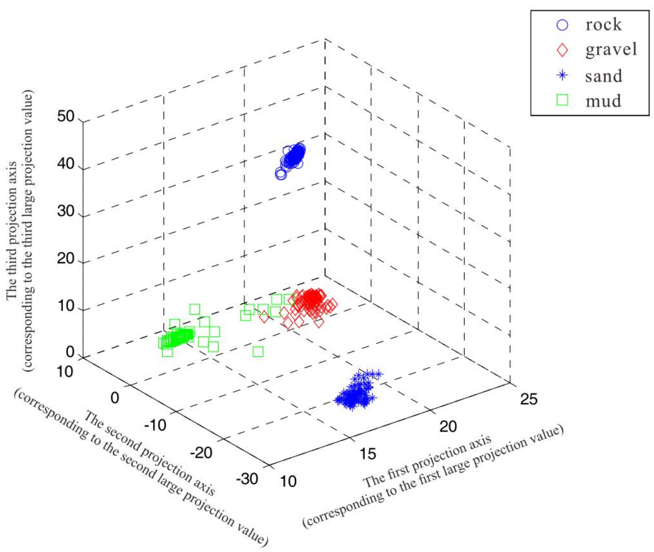

Fig. 9. Four kinds of target features extracted by FDA

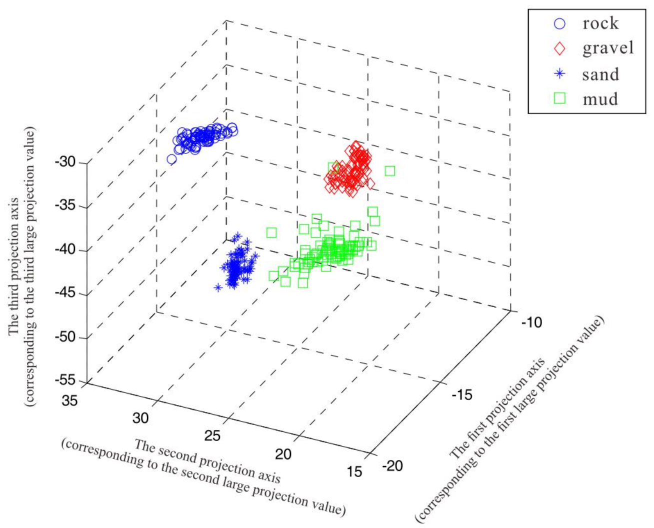

Fig. 10 The four kinds of target characteristics extracted by KFDA

Fig. 9 shows features extracted by the FDA method. The method ensured maximal interclass distance and minimal intra-class distance so that the features extracted were more easily distinguishable, but it failed to solve for nonlinear relations among the features. Because of this, there was a partial overlap among the targets.

Fig. 10 shows the features extracted by the proposed method, where the Gaussian kernel function with $\sigma = 15$ was used, and $\varepsilon = 0.00001$. The method combined the advantages of the kernel method and FDA, because of which the features extracted were easily distinguishable.

The features extracted previously were classified by the k-means clustering algorithm, as shown in Table 1, to obtain the results.

TABLE 1
CLASSIFICATION RESULTS OF FOUR FEATURE EXTRACTION METHODS

Method	PCA	KPCA	FDA	KFDA
Average rate of correct classification	86.6 %	90.3 %	95.0 %	99.4 %

Table 1 shows that the proposed method delivered a higher correct classification rate than all the other methods tested. The results show that the nonlinear optimal judgment vector extracted from the fusion feature space by using kernel Fisher judgment analysis can better solve problems of the classification of highly complex substrates .

VI. CONCLUSION

1) By fusing multiple features, the benefits of complementary features can be reaped to obtain richer identification information.
2) The extraction of nonlinear optimal features of identification by using Fisher judgment analysis eliminated redundant information and reduced the number of dimensions while yielding more distinct features.
3) Tests showed that the proposed feature extraction method based on KFDA yielded a higher rate of correct classification than other methods.

ACKNOWLEDGEMENT

The authors are grateful to the editor and unknown referees who helped improve the quality of this paper.

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