# Classification of Bio-potential Surface Electrode based on FKCM and SVM

Hao Liu

School of Textile, Tianjin Polytechnic University, Tianjin, China Key Laboratory for Advanced Textile Composite of Ministry of Education, Tianjin Polytechnic University, Tianjin, China liuhao\_0760@yahoo.com.cn

hunao\_0760@yanoo.com.cn

Xiaoming Tao Institute of Textiles and Clothing, Hong Kong Polytechnic University, Hong Kong, China tctaoxm@polyu.edu.hk

> Pengjun Xu School of Textile, Donghua University, Shanghai, China tcxupj@inet.polyu.edu.hk

Guanxiong Qiu Key Laboratory for Advanced Textile Composite of Ministry of Education, Tianjin Polytechnic University, Tianjin, 300160, China qiuguanxiong@tjpu.edu.cn

Abstract—In this paper, a method which is used for evaluating the performance of bio-potential surface electrode (BSE) with multi-index is presented. The Fuzzy kernel C-means (FKCM) algorithm and *KF* statistic are employed for classifying the BSE samples and searching an optimal classification amount respectively. Subsequently, a discriminant function is constructed by support vector machines (SVM) for recognizing the new measured samples. Experimental result shows classification correction ratios of improved FKCM algorithm are 96.3% and 85% on the IRIS and BSE dataset according a priori knowledge, furthermore, the recognition correction ratios of SVM algorithm are 96.3% and 90% on the IRIS and BSE dataset.

Index Terms—FKCM, SVM, classification, recognition, biopotential surface electrode

## I. INTRODUCTION

Bio-potential surface electrode (BSE) is an importance unit in some health monitoring devices, especially in some wearable bio-potential monitoring garments [1-2]. In [3], the measurement is performed in vivo and the biopotential is utilized for evaluating the performance of BSE. In [4-7], the impedance spectra are utilized for evaluating the performance of textile-base BSE on some device by more objective methods. However, efficient evaluation methods for analyzing the performance of BSE with multi-indexes are absence so far. Improved FKCM and SVM which are the algorithms based on kernel method have better capability for solving the nonlinear problems than FCM and Fisher linear discriminant analysis method [8-11]. FKCM which is a generalization of the conventional fuzzy C-means clustering algorithm (FCM) is presented, and the concrete algorithm is shown in [12, 13]. The theory of SVM is based on the idea of structural risk minimization (SRM) [14-17], and the good generalization ability of SVM is obtained by finding a large margin between two classes. In this paper, the FKCM and SVM are employed for classifying and recognizing the BSE samples with multi-indexes, however the analysis result can provide help for design and improvement of BSE.

## II. EXPERIMENTAL MATERIAL AND MEASUREMENT INDEXES

## A. Mearsurement indexes

Five types of BSE were used in this study. A pair of 99.99% gold button electrodes (G), 4 types of fabric electrodes which are terry or plain coating silver/silver chloride (TC or PC) electrode and terry or plain coating silver (TS or PS) electrode are selected and each type of electrode with 6 pair of specimens are measured. The measurement indexes are composed of static open circuit potential (OCP) differences ( $z_1$  and  $z_2$ ), low frequency impedance at 0.01, 1, and 10Hz ( $z_3$ ,  $z_4$  and  $z_5$ ), dynamic OCP variation ( $z_6$ ). Furthermore, low frequency impedance represents the measured resistance in low frequency domain, magnitude of static OCP reflects the

Manuscript received December 24, 2010; revised February 1, 2010; accepted February 14, 2010.

Research Grants Council of the Hong Kong SAR Government (Grant No. PolyU5277/07E).

symmetry of two electrodes, and static OCP variation represents the stable of electrodes in measurement process. Dynamic OCP variation represents the noise of interface of electrode/electrolyte. However, the less are magnitude of these indexes, the better are performances of BSE. Experiments are performed at 20 degree temperature and 65% relative humidity.

## B. Measurement data

Data of 26 samples are acquired by using electrochemical station which is composed of a computer, Electrochemical Interface 1252A (Solartron, UK) and Frequency Analyzer Response 1287 (Solartron, UK), a

TABLE I.INITIAL MEASUREMENT DATA OF 26 BSES

code	Measurement Indexes								
coue	z <sub>1</sub> (mV)	z <sub>2</sub> (mV)	Z <sub>3</sub> (ohm)	Z <sub>4</sub> (ohm)	Z <sub>5</sub> (ohm)	Z <sub>6</sub> (mV)			
G1	1.4	5.4	792320	22521	3235.8	1.34			
G2	2.5	180.7	652490	23365	3788.3	1.002			
TC1	0.1	7.6	3526	309.6	125	0.2			
TC2	1.2	23.3	1521	283.5	117.7	1.11			
TC3	0.5	2.1	1953	235.3	102.5	0.13			
TC4	1.2	12.5	871	278.9	111	0.512			
TC5	1.2	2.1	613	195.6	77.0	0.483			
TC6	0.3	2.5	685	206.2	85.4	0.494			
TS1	5.7	28.6	28007	1469.7	342.9	0.71			
TS2	0.5	12.0	55407	2707.6	597.4	0.79			
TS3	4.3	62.3	44980	2176.8	493.3	0.98			
TS4	1.1	4.3	62134	3539.1	805.7	0.829			
TS5	0.8	4.0	65408	4015.9	878.5	0.939			
TS6	4	67.3	66192	3072.3	671.8	1.059			
PC1	0	11.0	5471	626.3	259.7	0.32			
PC2	1.5	8.3	6991	679.9	265.3	0.15			
PC3	10	161	6701	641.7	228.4	0.41			
PC4	0.5	2.6	517	153.8	69.1	0.553			
PC5	0.5	3.4	720	275.7	108.6	0.38			
PC6	0.2	2.1	619	260.4	99.7	0.204			
PS1	0.2	7.3	63082	2923.3	637.8	1.92			
PS2	0.3	10.5	131000	9958	2142.7	1.94			
PS3	0.1	12.4	73751	3618.5	769.3	2.21			
PS4	1.4	0.5	114000	6358.2	1350.7	1.902			
PS5	6.0	4.3	132000	6973.8	1492.1	0.976			
PS6	0.7	7.2	127000	7307.4	1576.5	2.208			

series of signal conditioning devices and sensors.

## III. CLASSIFICATION AND RECOGNITION ALGORITHMS OF BSE

## A. Data pre-processing

To enhance the efficiency and accuracy of data analysis, it is often necessary to utilize pre-processing on the dataset before applying the improved FKCM clustering analysis algorithm. The data preprocess procedure consist of data normalization, correlative analysis of indexes, calculation of index weight, and calculation of initial clustering centers.

Let **X** be vector that is composed of measurement indexes of a sample, Dataset **X** consists of all samples and can be represented as  $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$ , where  $\mathbf{x}_i = (x_{i1}, x_{i2}, \dots, x_{ip})$ ,  $(i = 1, 2, \dots, n)$ . Vector **X** is called as pattern of input space  $\Omega^p$  also. The set **X** with *n* patterns is a subset of input space  $\Omega^p$ . The measured indexes can be represented by  $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_p\}$ 

To eliminate effect of indexes' quantity difference to final evaluation, initial measurement data should be normalized to compress the data in [0,1]. Data normalization function is

$$\mathbf{x}_{i} = \frac{\mathbf{x}_{i}' - \mathbf{x}_{min}'}{\mathbf{x}_{max}' - \mathbf{x}_{min}'}$$
(1)

Where  $\mathbf{x}_i$  and  $\mathbf{x}'_i$  denote the normalized vector and measurement vector of the *i*th sample respectively,  $\mathbf{x}'_{max}$  and  $\mathbf{x}'_{min}$  denote the maximum and minimum of measurement vectors in initial data set respectively.

The redundancy of indexes on data set exists, so correlation analysis of indexes is often necessary for reducing the dimension of data.

$$\rho(\mathbf{z}_i, \mathbf{z}_j) = \frac{cov(\mathbf{z}_i, \mathbf{z}_j)}{\sqrt{D\mathbf{z}_i}\sqrt{D\mathbf{z}_j}}, i, j = 1, 2, \cdots, p \quad (2)$$

Where  $\rho$  is the correlative coefficient between indexes,  $\mathbf{z}_i$  and  $\mathbf{z}_j$  denote the random index in index set, *cov* is the covariance function.

The contribution of indexes of samples in classification is different, and the clustering result and actual classification have the better consistent after the index weights of samples are introduced in classification. However, the methods of index weight acquisition have subjective method and objective method. In this paper, the objective method is employed for acquiring the index weight of all indexes.

$$w_{j} = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n} |z_{ij} - z_{kj}|}{\sum_{j=1}^{p} \sum_{i=1}^{n} \sum_{k=1}^{n} |z_{ij} - z_{kj}|}$$
(3)

where  $W_j$  denotes weight of the jth index,  $z_{ij} = x_{ij} / \sum_{i=1}^{n} x_{ij}$   $(i = 1, 2, \dots, n; j = 1, 2, \dots, p)$ 

To enhance the stability of clustering result, a determinate initial clustering center is desired prior to performing clustering algorithm. In this paper, the relation matrix R is constructed by employing the included angle cosine formula (4), and the samples are classified by threshold partition method. Though the classifying effect is not well, the classification result can provide a decided initial clustering center for improved FKCM clustering algorithm.

$$r_{ij} = \frac{\left|\sum_{k=1}^{p} x_{ik} x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{p} x_{ik}^{2}\right)\left(\sum_{k=1}^{p} x_{jk}^{2}\right)}} \quad (i, j = 1, 2, \cdots, n)$$
(4)

where  $r_{ij}$  denotes the similarity between the *i*th and the *j*th sample.

## B. FKCM algorithm

However, the FCM clustering analysis is somewhat limited in real world problems and nonlinear clustering analysis would be highly desirable. An efficient method of obtaining the nonlinear cluster algorithm is to first map the patterns of input space  $\Omega^p$  into some higher dimensional feature space  $\Omega^q$  using a kernel function  $\phi(\cdot)$ , the FCM can be performed in this feature space. When the kernel function is chosen, the Euclid distance between  $\mathbf{x}_i$  and  $\mathbf{x}_j$  in feature space is  $\hat{d}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = [K(\mathbf{x}_i, \mathbf{x}_i) - 2K(\mathbf{x}_i, \mathbf{x}_j) + K(\mathbf{x}_j, \mathbf{x}_j)]^{1/2}$ ,  $i, j = 1, 2, \dots, n$ .

Let **V** be clustering center matrix in input space,  $\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_c)$   $\mathbf{v}_i = (v_{i1}, v_{i2}, \dots, v_{ip}), (i = 1, 2, \dots, c)$ . Let  $\hat{\mathbf{U}}$  be membership matrix in feature,  $\hat{\mathbf{U}} = (\hat{\mathbf{u}}_1, \hat{\mathbf{u}}_2, \dots, \hat{\mathbf{u}}_n)$ ,

 $\hat{\mathbf{u}}_i = (\hat{u}_{i1}, \hat{u}_{i2}, \cdots, \hat{u}_{ic}), (i = 1, 2, \cdots, n)$ . Hence, Objective function of FKCM clustering algorithm in feature space is

$$\hat{J}_{m}(\mathbf{X}; \hat{\mathbf{U}}, \hat{\mathbf{D}}) = \sum_{j=1}^{c} \sum_{i=1}^{n} \hat{u}_{ji}^{m} \hat{d}_{ij}^{2} , \quad 2 < c < n$$
(5)

New clustering center vectors in feature space are

$$\hat{\mathbf{v}}_{j} = \phi(\mathbf{v}_{j}) = \sum_{k=1}^{n} (\hat{u}_{kj})^{m} \phi(\mathbf{x}_{i}) / \sum_{i=1}^{n} (\hat{u}_{kj})^{m} , j = 1, 2, \cdots, c$$
(6)

The  $\phi(\mathbf{x}_i)$  is dropped in (6). Unfortunately, the mapping function  $\phi(\cdot)$  may not be known explicitly and if the dimension of the feature space  $\Omega^q$  is very high or infinite, it is difficult to solve for objective function by (6). To get around this difficulty, the problem is reformulated to involve only the dot product of the patterns  $\mathbf{x}_i$  ( $i = 1, 2, \dots, n$ ) in the feature space.

$$K(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) = \phi(\mathbf{x}_{i}) \cdot \phi(\mathbf{v}_{j}) = \frac{\sum_{k=1}^{n} (\hat{u}_{kj})^{m} K(\mathbf{x}_{k}, \mathbf{x}_{i})}{\sum_{k=1}^{n} (\hat{u}_{kj})^{m}}$$
(7)  

$$K(\hat{\mathbf{v}}_{j}, \hat{\mathbf{v}}_{j}) = \phi(\mathbf{v}_{j}) \cdot \phi(\mathbf{v}_{j}) = \frac{\sum_{k=1}^{n} \sum_{t=1}^{n} (\hat{u}_{kj})^{m} (\hat{u}_{ij})^{m} K(\mathbf{x}_{k}, \mathbf{x}_{t})}{\left(\sum_{k=1}^{n} (\hat{u}_{kj})^{m}\right)^{2}}$$
(8)  

$$\hat{u}_{ij} = \frac{(1/\hat{d}_{ij}^{2}(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}))^{1/(m-1)}}{\sum_{j=1}^{c} (1/\hat{d}_{ij}^{2}(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}))^{1/(m-1)}}$$
(9)  

$$= \frac{(1/(K(\mathbf{x}_{i}, \mathbf{x}_{i}) - 2K(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) + K(\hat{\mathbf{v}}_{j}, \hat{\mathbf{v}}_{j})))^{1/(m-1)}}{\sum_{j=1}^{c} (1/(K(\mathbf{x}_{i}, \mathbf{x}_{i}) - 2K(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) + K(\hat{\mathbf{v}}_{j}, \hat{\mathbf{v}}_{j})))^{1/(m-1)}}$$
(9)  
When  $\hat{d}_{ij}^{2}(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) = 0$ ,  $\hat{u}_{ij} = 1, \hat{u}_{ii} = 0, (t \in [1, j) \cup (j, c])$ .  
 $\hat{d}_{ij}(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) = [K(\mathbf{x}_{i}, \mathbf{x}_{i}) - 2K(\mathbf{x}_{i}, \hat{\mathbf{v}}_{j}) + K(\hat{\mathbf{v}}_{j}, \hat{\mathbf{v}}_{j})]^{1/2}, (10)$ 

To acquire the optimization membership degree matrix  $\hat{\mathbf{U}}^*$  and corresponding distance matrix  $\hat{\mathbf{D}}^*$  , the equation of  $|\hat{J}^{(l)} - \hat{J}^{(l-1)}|$  must be convergent, that is, equation of  $\lim \hat{J}_m(\mathbf{X}; \hat{\mathbf{U}}, \hat{\mathbf{D}})$  comes into existence [18]. Hence, the variance  $\varepsilon$  can be set at a random small value, the initial distance matrix and the initial membership matrix are known, then the iterative algorithm can be performed by (5), (7), (8), (9), and (10), if  $|\hat{J}^{(l)} - \hat{J}^{(l-1)}| < \varepsilon$ , the iterative algorithm ceases, and the constraint optimization membership matrix  $\hat{\mathbf{U}}^{(l)}$  and the constraint optimization distance matrix  $\hat{\mathbf{D}}^{(l)}$  can be acquired, finally, samples is classified in terms of maximum membership principle. When dot product operation is performed between pattern and indexes weight vector in kernel function of the FKCM clustering algorithm, the improved FKCM clustering algorithm can be obtained. Furthermore, the statistic F in (11) can be utilized for acquiring the optimal classification amount. Statistic F is a conventional index for evaluating the clustering validity and the nonlinear factors of data set are not considered, hence the KF index is constructed by using kernel function and shown in (12) for evaluating more efficiently the clustering validity.

$$F = \frac{SSA/(c-1)}{SSE/(n-c)} = \frac{(n-c)\sum_{i=1}^{c} n_i \| \overline{\mathbf{x}}_i - \overline{\mathbf{x}} \|^2}{(c-1)\sum_{i=1}^{c} \sum_{t=1}^{n_i} \| \overline{\mathbf{x}}_{it} - \overline{\mathbf{x}}_i \|^2}$$
(11)

$$KF = \frac{SSA/(c-1)}{SSE/(n-c)} = \frac{(n-c)\sum_{i=1}^{c} n_i \hat{d}^2(\overline{\mathbf{x}}_i, \overline{\mathbf{x}})}{(c-1)\sum_{i=1}^{c}\sum_{t=1}^{n_i} \hat{d}^2(\overline{\mathbf{x}}_{it}, \overline{\mathbf{x}}_i)}$$
(12)

Where: *KF* is statistic of samples vectors in feature space, SSA is between class variance, SSE is inner-class variance,  $\overline{\mathbf{x}}_i$  is the mean vector of the *i*th class samples vectors,  $\overline{\mathbf{x}}$  is the mean vector of the whole samples vectors,  $\overline{\mathbf{x}}_{it}$  is the *i*th class and the *t*th sample vector,  $n_i$  is amount of samples of the *i*th class.

## C. SVM Algorithm

According to the above classification result, we can acquire a training set  $S = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\}$  of N data points, where  $\mathbf{x}_i \in \Omega^p$  is the *i*th input pattern and  $y_i \in R$  is the *i*th output pattern. In most cases, the searching of a suitable hyperplane in an input space is too restrictive to be of practical use. Hence, suppose  $\{\varphi_j(x)\}_{j=1}^m$  represents the nonlinear transfer set from the input space to feature space, where *m* is the dimension of feature space. Hence, a decision hyperplane in feature can be defined as

$$y_i[w^T \varphi(x_i) + b] \ge 1, \quad i = 1, \dots, N,$$
 (13)

Where  $\varphi(\cdot)$  is a kernel function which maps the input space into a higher dimensional space, *m* and *n* are, respectively, the dimensions of the input space and feature space. However, this function is not explicitly constructed. In order to have the possibility to violate (15), in case a separating hyperplane in this higher dimensional space does not exist, slack variables  $\xi_k$  are introduced such that

$$\begin{cases} y_i[w^T \varphi(x_i) + b] \ge 1 - \xi_i, i = 1, \cdots, N\\ \xi_i \ge 0, i = 1, \cdots, N \end{cases}$$
(14)

Subsequently, according to the structural risk minimization principle, the risk bound is minimized by considering the optimization problem

Minimize 
$$\frac{1}{2}w^T \cdot w + C\sum_{i=1}^N \xi_i$$
 (15)

subject to (14). Where C is a constant and can be regarded as a regularization parameter. Tuning this parameter can obtain a balance between margin maximization and classification violation. In order to

solve the constraint optimal problem, one constructs the Lagrangian and transformed into the dual

$$\begin{cases}
Maximize \\
W(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_i y_j y_j K(x_i, x_j) & i = 1, \dots, N \\
Subject to \sum_{i=1}^{N} y_i \alpha_i = 0, \quad 0 \le \alpha_i \le C, i = 1, \dots, N
\end{cases}$$
(16)

Searching the optimal hyperplane in (15) is a quadratic programming (QP) problem, according to the Kuhn-Tucker theorem, the solution of the optimal problem must satisfies the equality

$$\begin{cases} \alpha_i (y_i(x_i w_i + b) - 1 + \xi_i) = 0\\ (C - \alpha_i)\xi_i = 0 \end{cases}, \quad i = 1, \dots, N$$
(17)

In (12),  $\alpha_i$  is zero for most of samples, when the nonzero values  $\alpha_i$  are satisfied with the equality sign in (14), the pattern  $x_i$  corresponding with  $\alpha_i$  is called support vector.

If  $\alpha^*$  is the optimal solution in (16), then

$$w^{*} = \sum_{i=1}^{N} \alpha_{i}^{*} y_{i} x_{i}$$
(18)

That is the weight coefficient vector of optimal classification hyperplane is linear combination of training pattern vectors. After solving the above problems, the optimal classification function can be acquired as

$$f(x) = sign\left(\sum_{i=1}^{N} y_i \alpha_i^* K(x_i \cdot x) + b^*\right)$$
(19)

#### IV. RESULET AND DISCUSSION

In order to evaluate the performance of BSE and verify effect of these algorithms, the improved FKCM and SVM were performed on IRIS dataset and measurement dataset respectively. Matlab7.01 software was utilized for data processing and analyzing.

## A. Pre-processing of measurement dataset

After data normalization, procedures of correlation analysis, weight computation, and initial clustering center were performed on IRIS dataset and measurement dataset in turn. Correlation coefficients of IRIS dataset were shown in Tab. II and Tab. III by using (2). However, some indexes with strong correlation can be eliminated by Pearson Correlation coefficient analysis method. Because of strong correlation in indexes,  $z_4$ ,  $z_5$  and  $z'_4$  can be deleted in data analysis process. Furthermore, index weight coefficient of measurement dataset and IRIS dataset was, respectively, WM = (0.2399 0.2858 0.2967 0.1776) and WIRIS = (0.2374 0.1785 0.2785 0.30) by using (3).

FKCM and SVM Performed on IRIS Dataset

TABLE II.	
PEARSON CORRELATION COEFFICIENT OF ALL MEASURED INDEXES	
IN IRIS DATASET	

code	$z'_1$	$z'_2$	$z'_3$	$z'_4$
$z'_1$	1	-0.12	0.87	0.82
$z'_2$	-0.12	1	-0.42	0.37
$z'_3$	0.87	-0.42	1	0.96
$z'_4$	0.82	-0.37	0.96	1

TABLE IV. Comparison of Wrong Classification Amount of Samples by Using Three Clustering Methods

Clustering	Amount in	Amount in	Amount in	Total	Correction
Algorithm	1st Class	2 <sup>nd</sup> Class	3rd Class	amount	Ratio (%)
FCM	0	12	4	16	89.33
FKCM	0	9	3	12	92.00
Improved	0	4	3	7	95.33
FKCM					

TABLE III. STATISTIC F and KF of IRIS DATASET USING IMPROVED FKCM

Preset Class Amount	2	3	4	5	6	7
Actual Class Amount	2	3	4	5	6	7
F validity index	339	342	284	233	197	192
KF validity index	430	485	409	346	289	273

IRIS dataset contains 150 examples with 4 dimensions and 3 classes. One class is linearly separable from the two other; the latter are not linearly separable from each other. Iterative accurate degree and class number are, respectively, 10e-5 and 3, and the kernel function of improved FKCM clustering algorithm chooses  $k(\mathbf{x}, \mathbf{y}) = \exp(\sum_{i=1}^{p} (w_i * (x_i - y_i))^2 / \sigma)$ 

where  $\sigma = 0.8$ .

Tab. IV showed the F and KF value were all maximal when samples in IRIS were classified into three classes, and the result was consistent with the actual classification of samples. Furthermore, wrong classification amount of samples and classification correction ratios using FCM, FKCM, improved FKCM in IRIS dataset were shown in Tab. V, samples in the 1st class was classified correctly which shows three clustering algorithms can solve efficiently the linear classification problems, however, the improved FKCM is obviously better than FCM and KFCM for solving the nonlinear problems.

In order to compare the performance of four discriminant methods: the SVM, Kernel Fisher Discriminant Analysis (KFDA), back promulgation neural network (BPNN), and radial basis function neural

TABLE V. Pearson Correlation Coefficient of All Measured Indexes in Measurement Dataset

Index code	$Z_1$	$Z_2$	<i>Z</i> <sub>3</sub>	$Z_4$	$Z_5$	$Z_6$
$z_1$	1	0.63	0.03	0.03	0.04	-0.12
$Z_2$	0.63	1	0.35	0.36	0.35	-0.05
$Z_3$	0.03	0.35	1	0.97	0.92	0.31
$Z_4$	0.03	0.36	0.97	1	0.99	0.43
$Z_5$	0.04	0.35	0.92	0.99	1	0.51
$Z_6$	-0.12	-0.05	0.31	0.43	0.51	1

network (RBFNN), We performed these algorithms on IRIS dataset, the training samples were utilized for training the networks, then employing the trained networks to recognize the testing samples. The parameters of BPNN were set as follow: the neurons of input layer were the amount of the training samples, the neurons of hidden layer were obtained according the equation  $n_1 = \sqrt{i+o} + a$  where  $n_1$ , *i* and *o* were the neurons amount of hidden layer, input layer and output layer respectively, parameter a were taken in the integer domain [1,10]. The transfer function of hidden layer was set for "tansig", the transfer function of output layer was set for "purelin", training algorithm selected "Levenberg-Marquardt" method, the output tolerance was 0.05, training error was set for 0.001, the transfer coefficient of RBFNN was 1.0. In KFDA algorithm, Gauss kernel function  $k(\mathbf{x}, \mathbf{y}) = \exp(-\|\mathbf{x} - \mathbf{y}\|^2 / \sigma)$  was selected and parameter  $\sigma$  was 0.7. In SVM algorithm, the kernel function was 'gaussian' and parameter of 'kerneloption' was 2, and bound on the lagrangian multipliers was 1000. Then above four methods were performed on IRIS dataset, and the effects of every method were evaluated by the correction recognition ratios to testing samples.

The four fifth of each class of IRIS were using as training samples, and the other samples were using as testing samples, the discriminant functions were constructed by above described four methods. And experimental results showed the correction recognition ratios of BPNN, RBFNN, KFDA, and SVM methods in Tab. VI. Obviously, the effects of SVM method and KFDA were better than other two methods. Therefore, the SVM method was chosen for constructing the discriminant function of measurement dataset.

## B. SVM and FKCM Performed on Measured Dataset

26 samples were measured on electrochemical station and 6 indexes are obtained. G, TS and PS are polarization electrodes but TC and PC are non-polarization electrodes, the priori knowledge showed the non-polarization electrodes had the better performance than polarization electrodes [19]. Improved KFCM was performed on measurement dataset. Tab. VII showed *KF* value was maximal when samples were classified into

TABLE VI. Comparison of Correction Recognition Ratios Using above Four Methods on IRIS Dataset

Discriminant Methods	BPNN	RBFNN	KFDA	SVM
Correction Recognition Ratio (%)	93.33	86.67	96.67	96.67

two classes. Obviously, two classes was best classification amount, and the class amount of classification result was consistent with the priori knowledge.

Tab. VIII showed the first class has 14 samples and the second class has 12 samples by using improved FKCM algorithm. The four samples of TS2, TS4, TS5 and PC3 are disagreement with the priori knowledge, and approximate 85% samples agree with the priori knowledge. Subsequently, the front eight of each class measured samples were selected as training samples, and the other measured samples were selected as testing samples. According to the previous describe, SVM was performed on training samples and acquires a discriminant function and some support vectors, and 90% recognition correction ratio can be acquired by applying discriminant function on the testing samples.

 TABLE VII.

 STATISTIC KF OF MEASUREMENT DATASET USING IMPROVED FKCM

Preset Class Amount	2	3	4
Actual Class Amount	2	3	-
KF validity index	15	10	-

 TABLE VIII.

 CLASSIFICATION NUMBER AND QUALITY GRADE OF SAMPLES

code	Membership degree	Number of class	grade	code	Membership degree	Number of class	grade
G1	0.53	2	2	G2	0.54	2	2
TC1	0.69	1	1	PC1	0.71	1	1
TC2	0.65	1	1	PC2	0.69	1	1
TC3	0.68	1	1	PC3*	0.54	2	2
TC4	0.77	1	1	PC4	0.75	1	1
TC5	0.74	1	1	PC5	0.72	1	1
TC6	0.73	1	1	PC6	0.69	1	1
TS1	0.54	2	2	PS1	0.51	2	2
TS2*	0.82	1	1	PS2	0.54	2	2
TS3	0.62	2	2	PS3	0.53	2	2
TS4*	0.82	1	1	PS4	0.55	2	2
TS5*	0.77	1	1	PS5	0.55	2	2
TS6	0.63	2	2	PS6	0.55	2	2

a.\* express class number of the sample is different according the priori knowledge and improved FKCM algorithm

## V. CONCLUSION

In this paper, a generalization evaluation method is proposed and employed in quality evaluation of BSE. By classifying the IRIS dataset using FCM, FKCM and improved FKCM clustering algorithm, experimental result shows improved FKCM is more efficient than other two algorithms for solving the nonlinear problem. The constructed *KF* statistic can help find the optimal classification amount of measured samples, and the classification result is consistent with a priori knowledge. Subsequently, we construct the discriminant function for recognizing the new measured samples by SVM algorithm, and a well recognition effect can be acquired. In all, the improved FKCM and SVM algorithms can compose a complete evaluation method for the performance of BSE.

## ACKNOWLEDGMENT

The authors would like to thank Research Grants Council of the Hong Kong SAR Government (Grant No. PolyU5277/07E). This work was supported in part by a grant from The Hong Kong Polytechnic University.

## REFERENCES

- Jerald Yoo, Long Yan, Seulki Lee, Hyejung Kim, and Hoi-Jun Yoo, "A wearable ECG acquisition system with compact planar-Fashionable circuit board-based shirt," *IEEE Trans. Inform. Tech. Biomed.*, vol. 13, pp. 897–902, November 2009.
- [2] Tae-Ho Kang, Carey R. Merritt, Edward Grant, Behnam Pourdeyhimi, and H. Troy Nagle, "Nonwoven fabric active electrodes for biopotential measurement during normal daily activity," *IEEE Trans. Biomed. Eng.*, vol. 55, pp. 188–195, January 2008.
- [3] Enzo Pasquale Scilingo, Gemignani A, Paradiso R, Taccini N, Ghelarducci B, and De Rossi D, "Performance evaluation of sensing fabrics for monitoring physiological and biomechanical variables," *IEEE Trans. Inform. Tech. Biomed.*, vol. 9, pp. 345–352, September 2005.
- [4] Rattfalt L, Linden M, Hult P, Berglin L and Ask P, "Electrical characteristics of conductive yarns and textile electrodes for medical applications," *Med. Biol. Eng. Comput.*, vol. 12, pp. 1251–1257, December 2007.
- [5] Westbroek P, Priniotakis G, Palovuori E, De Clerck K, Van Langenhove L and Kiekens P, "Quality control of textile electrodes by electrochemical impedance spectroscopy," *Text. Res. J.*, vol. 2, pp. 152–159, February 2006.
- [6] Priniotakis G., Westbroek P., Van Langenhove L. and Kiekens P., "An experimental simulation of human body behaviour during sweat production measured at textile electrodes," *Int. J. Cloth. Sci. Technol.*, vol. 3–4, pp. 232-241, October 2005.
- [7] L Beckmann, C Neuhaus, G Medrano, N Jungbecker, M Walter, T Gries, et, al., "Characterization of textile electrodes and conductors using standardized measurement setups," *Physiol. Meas.*, vol. 31, pp. 233–247, February 2010.
- [8] GROLAMI M., "Mercer kernel based clustering in feature space," *IEEE Trans. Neural Netw.*, vol.13, pp.780–784, May 2002.
- [9] Bernhard Scholkopf, Sebastian Mika, Chris J. C. Burges, Philipp Knirsch, Klaus-Robert M<sup>-</sup>uller, Gunnar Ratsch, et,

al., "Input space versus feature space in kernel-based methods," *IEEE Trans. Neural Netw.*, vol.10, pp. 1000–1017, September 1999.

- [10] Chua, K.S., "Efficient computations for large least square support vector machine classifiers," *Pattern Recogn. Lett.*, vol. 24, pp. 75–80, January 2003.
- [11] Vapnik, V., Statistical Learning Theory, Wiley, New York, 1998.
- [12] ZHANG Li, ZHOU Weida and JIAO Licheng, "Kernel clustering algorithm," *Chinese Journal of Computers*, vol. 25, pp. 587–590, June 2002.
- [13] ZHAO Yugao and PENG Hong, "An improved fuzzy kernel clustering algorithm," *Journal of Xihua University: Natural Science Edition*, vol. 26, pp. 48–50,69, March 2007.
- [14] Shawe-Taylor, J. and Bartlett, P.L., "structural risk minimization over data-dependent hierarchies," *IEEE Trans. Inform. Theor.*, vol. 44, pp. 1926–1940, September 1998.
- [15] Chih-Wei Hsu and Chih-Jen Lin, "A comparison of methods for multi-class support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, pp. 415–425, March 2002.
- [16] Qin Yuping, Wang Xiukun, Li Xiangna and Wang Chunli, "Study on multi-class text classification algorithm based on hyper-sphere support vector machines," *Computer Engineering and Applications*, vol.44, pp. 166–168, July 2008.
- [17] K. Crammer and Y. Singer, "On the learnability and design of output codes for multiclass problems," *Mach. Learn.*, vol. 47, pp. 201–233, February/March 2002.
- [18] BEZDEK J C., "Convergence theory for fuzzy c-Means: counterexamples and repaires," *IEEE Trans on SMC*, vol. 17, pp. 873–877, September/October 1987.
- [19] John G. Webster, *Medical instrumentation : application and design*, 3<sup>rd</sup> ed., New York : Wiley, 1998, pp. 183-232.

**Hao Liu** received the B.Eng. and M.Eng. degrees in textile material and design from Tianjin Polytechnic University, Tianjin, China, in 2001 and 2004. He is currently working towards the PhD degree in textile engineering at Tianjin Polytechnic University, Tianjin, China. His research interests are data analysis and image processing in textile and clothing Engineering, smart textiles and apparel and wearable electronics.

**Xiaoming Tao** is Chair Professor and Head of Institute of Textiles and Clothing. Prof. Tao graduated with a B.Eng. in Textile Engineering and a first class prize for undergraduate students from East China Institute of Textile Science and Technology in 1982. She gained her PhD in Textile Physics from University of New South Wales, Australia in 1987.Her research interests are fibrous materials, textile Science and technology, smart textiles and apparel and wearable electronics and photonics.

**Pengjun Xu** is currently working towards the PhD degree in textile engineering at Donghua University, Shanghai, China. His research interests are fibrous materials, smart textiles and apparel.

**Guanxiong Qiu** is professor of Tianjin Polytechnic University. His research interests are textile material and knitted engineering.