IJICTR International Journal of Information & Communication Technology Research

Volume 4- Number 1- December 2011 (21-28)

Static Persian Sign Language Recognition Using Kernel-Based Feature Extraction

Milad Moghaddam
DSP Research Lab, Department of Electrical Engineering, University of Guilan
Rasht, Iran
moqaddam@msc.guilan.ac.ir

Manoochehr Nahvi
DSP Research Lab, Department of Electrical Engineering, University of Guilan
Rasht, Iran
Nahvi@guilan.ac.ir

Reza PR. Hasanzadeh
DSP Research Lab, Department of Electrical Engineering
University of Guilan
Rasht, Iran
hasanzadehpak@guilan.ac.ir

Received: September 3, 2011- Accepted: November 27, 2011

Abstract— **The most effective way for deaf people communication is sign language. Since most people are not familiar with this language, there is a requirement for a sign language translator system. This would be a useful tool specifically in emergency situations. A further need is facilitation of deaf people communication in cyberspace. Sign language gestures can be divided in two groups, including gestures represent the alphabets and those which are arbitrary signs representing specific concepts. The first group is usually introduced by the pose of hands and they are called postures while the second group usually includes motion of the hands. This paper evaluates the efficiency of kernel based feature extraction methods including kernel principle component analysis (KPCA) and kernel discriminant analysis (KDA) on Persian sign language (PSL) postures. To compare the impact of features on signs' recognition rate, classifiers such as minimum distance (MD), support vector machine (SVM) and Neural network (NN) is used. Experimental trials indicate higher recognition rate for the kernel-based methods in comparison with those of other techniques and also previous works on PSL recognition.**

Pattern recognition; feature extraction; kernel-based features; support vector machine; neural network; sign language recognition; PSL

I. INTRODUCTION

Sign language is the most effective way for communication of deaf people. However, most people are not familiar with this language, specifically in emergency situation. There is a further requirement which is the facilitation of deaf communication in cyberspace, for instance in chat rooms. Therefore a translator system is required to translate sign language to natural languages.

Gestures in a sign language system are introduced by pose, motion, and situation of hands regarding to the human body. Sign language gestures can be divided in two groups including gestures represents the alphabets of a natural language (hand alphabet) and those which are arbitrary signs representing specific concepts. The first group which is the foundation of sign language is usually introduced by the pose of hands and they are called postures while in the second group signs include motion of hands, head or both. Based on these two groups, in Fig.1 a conceptual block diagram for sign language recognition system is suggested. As it can be seen, in this system because of intrinsic dissimilarities within dynamic and static signs it is suggested that the gestures are separated into these two categories and then different approaches can be exploited for their recognition. The recognized signs can then be translated into voice and/or text.

Several studies of static sign language recognition have been reported in the literature for various languages, very few of which are for PSL. In [1]

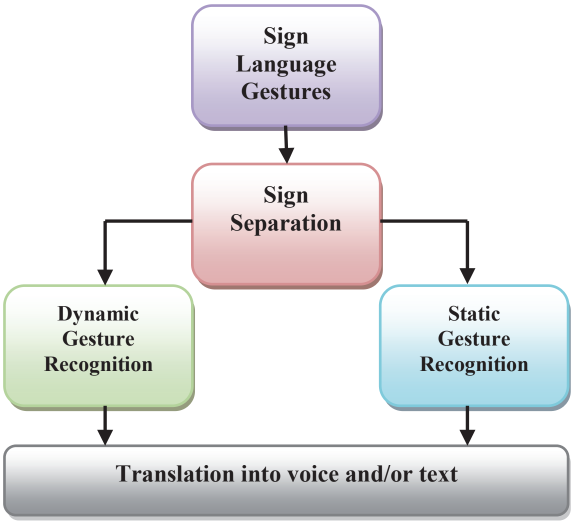

Figure 1. Conceptual block diagram of a sign language recognition system

Hough transform along with Neural Network is used to design an American static sign language recognition system. This system is based on three main stages including resizing and converting to grayscale, canny edge detection and applying the Hough transform. The resultant features are then exploited for the training of neural network. The system was implemented and tested using a data set of 300 hand sign images; 15 images for each sign. The system was able to reach a maximum recognition rate of 98.5% for training data and 80% for test data constructed with 20 different signs. In [2] a multiple discriminate analysis scheme is reported and a recognition rate of 70% achieved. In [3] a method based on the elastic graph matching is presented for the hand posture recognition system. In this research a database of 10 hand signs with light, dark and complex background is used and the recognition rate for each group was 94.3%, 93.3% and 86.2%, respectively. Although this method achieves a high recognition rate, it suffers from high computational complexity. In [4] an algorithm based on the modified census transform is reported and maximum recognition rate of 89.9% has been achieved. In [5] a system for recognition of natural hand posture is presented based on Zernike Moments and Hierarchical Classifier. In this paper, a feature selection approach based on Zernike moments and Isomap dimensionality reduction is used. Paper [6] presents a system for the recognition of sign language based on shape representation using size function. This system consists of three stages including edge detection, using moment-based size function and utilizing neural network to recognize hand gestures. The system achieved a recognition rate of 90% for 25 different signs. In [7, 8] an approach based on the wavelet transform and neural networks is exploited to classify 32 different static Persian signs. In this system in the preprocessing stage the images are cropped, resized, and converted to grayscale. Then, the discrete wavelet transform is applied on the gray scale images, and the extracted features are used to train a multi-layered perceptron neural network. The system is implemented and tested with a dataset consists of 640 samples of Persian sign images; 20 images for each sign. It is able to give a maximum classification rate of 83.03% over test set.

Due to the importance of the static signs in a PSL recognition system and also to improve their recognition rate, the focus of this paper is devoted to the static signs. In order to improve the recognition rate we developed our algorithm using efficient non-linear feature extraction based on kernel methods. The main core of kernel-based method is non-linear mapping of a set of observation vectors into a high dimensional space. In this new space, the chance of better pattern classification would be increased. Kernel based methods have been used in several multi-class problems in pattern recognition, for instance in [9-14]. In [14] a texture classification method is illustrated based on the kernel principal component analysis. In [13] an approach based on kernel principal component analysis is presented for the purpose of feature extraction in a speech recognition systems. For the same application, also in [12] the impact of kernel-based feature extraction techniques are studied in association with several classifiers including Gaussian mixture modeling (GMM), artificial neural networks (ANNs), projection pursuit learning (PPL), decision tree-based classification and support vector machines (SVMs). In [11] a kernel-based method is presented together with SVM for a iris recognition system. In [9] exploitation of KDA and KPCA in a face recognition system results in a higher recognition rate.

We examined the impact of the kernel-based features on improvement of the PSL recognition. This was evaluated in association with various classifiers including Minimum distance (MD), Neural network (NN) and support vector machine (SVM). The experiment results demonstrate a maximum rate of %95.91. This shows an improvement in comparison to those researches conducted previously for the recognition of the static PSL.

In this paper the kernel-based methods are briefly explained in the section II and then the proposed system is illustrated in section III and in the remaining sections the experimental trials, results and finally conclusions are presented.

II. KERNEL METHOD

To describe kernel method let $X = [x_1, x_2, ..., x_n]$ be a set of n observation vectors. Then, using a nonlinear mapping, X is mapped into a high dimensional space. This new space is also known as feature space. The difficulty of classification in high dimensional space may seem to be increased. But by using simple decision functions in feature space the contrary can also be true. Therefore not the dimensionality but the complexity of the function matters [15], as shown in

Fig.2. This figure shows that in two dimensions a nonlinear decision surface is necessary, while in three dimensional feature space a linear hyperplane can easily classify the points correctly. This can be achieved by the following mapping:

$$\phi : R^2 \to R^3$$

$$(\alpha_1, \alpha_2) \to (\beta_1, \beta_2, \beta_3) = (\alpha_1^2, \sqrt{2}\alpha_1\alpha_2, \alpha_2^2)$$

The essence of the kernel method is representing the nonlinear mapping by dot product. This can be achieved by special type of kernel called Mercer kernel [12, 15]. Two famous examples of the Mercer kernel are:

$$k(x, x') = \exp\left(\frac{-\|x - x'\|}{c}\right) \quad \text{(Gaussian)} \qquad (1)$$

$$k(x, x') = (x.x' + 1)^r \qquad \text{(polynomial)} \qquad (2)$$

In equations (1) and (2), $k(x, x')$ is the kernel function, x and x' are two samples of X, the parameter c is the width of the Gaussian kernel and r is order of polynomial.

Representing the nonlinear mapping by dot product for the example shown in Fig.2 is as follows:

$$(\phi(x).\phi(x')) \to (\alpha_1^2, \sqrt{2}\alpha_1\alpha_2, \alpha_2^2)(\alpha_1'^2, \sqrt{2}\alpha_1'\alpha_2', \alpha_2'^2)^T$$

$$= ((\alpha_1, \alpha_2)(\alpha_1', \alpha_2')^T)^2 = (x.x')^2 = k(x, x')$$

where $x = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}$ and $x' = \begin{bmatrix} \alpha_1' \\ \alpha_2' \end{bmatrix}$ are two data point in R^2 and k is polynomial kernel function of order 2.

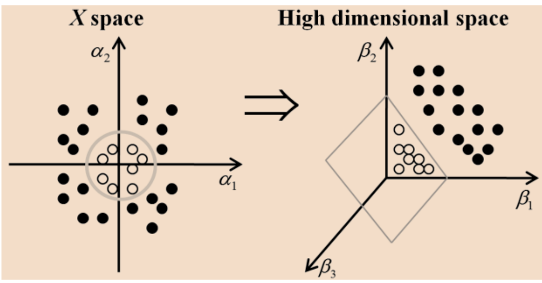

Figure 2. The mapping phenomenon

Now the conventional linear methods would be effectively able to classify the features in the new high-dimensional space. In practice, this can be conducted with application of linear methods on a kernel matrix; this will be defined in the next section. This matrix is directly calculated from data points. In this approach there is no need to explicit definition of nonlinear mapping. Therefore, performing nonlinear mapping and applying linear methods on mapped data are applied altogether by kernel functions, as shown in Fig.3.

A. Kernel principle component analysis

Principle component analysis (PCA) is a classical linear feature extraction technique widely exploited in various pattern recognition system, for instance [16]. In this method a subspace is constructed using orthogonal basis vectors corresponding to maximum-variance directions. These directions can be

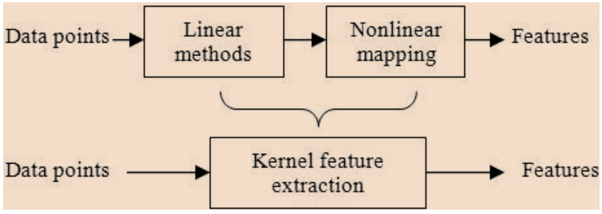

Figure 3. Nonlinear mapping and applying linear methods by kernel functions

determined by the eigenvectors of the covariance matrix of input observation samples[17].

The nonlinear extension of the PCA is called KPCA. This is performed in the feature space [12, 15]. For this, first the eigenvectors of the covariance matrix of mapped data are calculated. It can be proofed that instead of calculating this, the eigenvectors of a matrix called kernel matrix can be calculated.

$$\lambda\alpha = K\alpha \qquad (3)$$

where $\alpha = (\alpha_1, ..., \alpha_n)^T$ is the eigenvector and K is the kernel matrix and expressed by:

$$K = \begin{bmatrix} k_{11} & \cdots & k_{1n} \\ \vdots & \ddots & \vdots \\ k_{n1} & \cdots & k_{nn} \end{bmatrix} \qquad (4)$$

Each element of matrix K is $k_{ij} = k(x_i, x_j)$.

Now, all samples in the feature space are projected on the directions given by eigenvectors. It can be shown that projecting a sample x, in the direction of each eigenvector leads to a feature which is obtained by $\sum_{i=1}^{n} \alpha_i k(x_i, x)$. It is obvious that only kernel function and eigenvectors of kernel matrix, α , are required for the purpose of feature extraction. So there is no need to explicit definition of the nonlinear mapping.

The feature vector of x can be therefore obtained by its projection on the adequate number of the eigenvectors corresponding to the largest eigenvalues. This is expressed by:

$$Y = K_x A \qquad (5)$$

Where Y is the feature vector and $A = [\alpha^1, \alpha^2, ..., \alpha^d]$ is the set of eigenvectors, d is the number of required eigenvectors. In equation (5) K_x is given by:

$$K_x = [k_{x1}, ..., k_{xn}] \qquad (6)$$

$$k_{xi} = k(x, x_i) \qquad (7)$$

Then using equation (5), the feature vector Y is determined and will be utilized in the classification stage.

B. Kernel discriminant analysis

Linear discriminate analysis (LDA) is another linear method for feature extraction purpose. In this method, observation samples are projected into a new subspace such that the discrimination of classes is increased [18-20]. In fact, the samples are projected on the orthogonal basis vectors along which the classes are best separated. A non-linear extension to the LDA is KDA. Similar to the KPCA, in KDA calculations are conducted in feature space. As it is proofed in [12] , to perform KDA it is required that the following eigenvector problem is calculated.

$$N^{-1}M\alpha = \lambda\alpha \tag{8}$$

where $M = K(R-\bar{1})K$, $N = K(I-R)K$, K is the kernel matrix, $(\bar{1})_{ij} = 1/n$ and R is defined by:

$$(R)_{ij} = \begin{cases} \dfrac{1}{N_t} & if\ t = l(i) = l(j) \\ 0 & otherwise \end{cases} \tag{9}$$

The function l gives the class label and N_t is the number of samples in t^{th} class. Now, all samples in the feature space are projected on the directions given by eigenvectors. It can be shown that projecting a sample x, in the direction of each eigenvector leads to a feature which is obtained by $\sum_{i=1}^{n} \alpha_i k(x_i, x)$. Then, Similar to the KPCA, using equation (5), the feature vector can be calculated by determination of A and K_x.

III. PROPOSED SYSTEM

As it was mentioned, in this paper a static gestures recognition system for the PSL is presented using non-linear feature extraction based on the KPCA and KDA. A brief conceptual block diagram of this system is illustrated in Fig.4. It shows two main blocks consist of training and test in the left and right of figure, respectively. In the system, it is initially required that the training part is performed. This results in the projection matrix A and the trained classifier which is required in the test process.

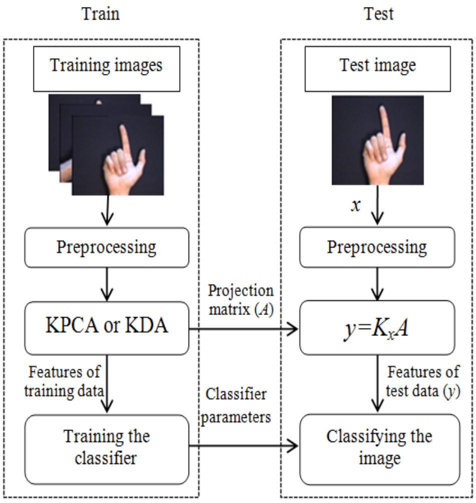

Figure 4. The system's block diagram

In Fig. 4, the pre-processing stage briefly includes image rescaling, converting the images into the greyscale and hand region cropping. In the feature extraction blocks the non-linear features can be extracted using either KPCA or KDA techniques. Corresponding features in the training stage are used for the purpose of determination of A and classifier training and in the test stage they are utilized for the classification of the test images. In the classification stage, various methods were exploited.

IV. EXPRIMENTAL TRIALS

To evaluate the performance of the presented method several experimental trials were performed. As it was mentioned, for the classification several methods were examined. They are MD with the Euclidean and cosine distance function, feed forward NN and SVM. For the NN classifier, one hidden layer was considered and the number of hidden neurons was set to 222 and 58 for KPCA and KDA features, respectively. All these experiments were performed with the two types of kernel functions mentioned in section II.

In the training and test stages a database of 35 different Persian hand alphabet signs were utilized, shown in Fig. 5. In total this database consists of 700 images, 455 of which were for the training and the rest of images were used in the test stage. This database is provided by authors of [3].

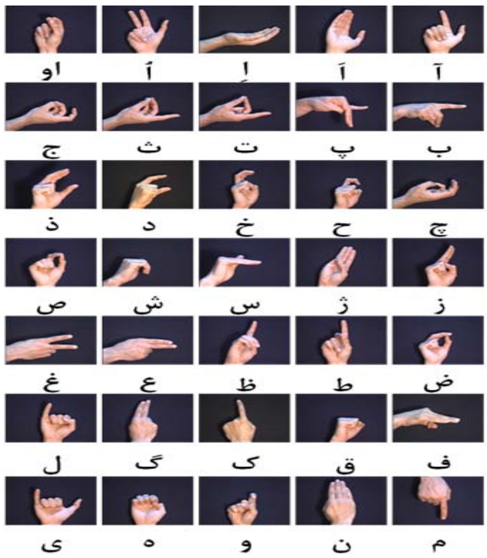

Figure 5. Static sign of Persian hand alphabet

For further verification and also comparing the performance of our algorithm with other researches, it was examined on the Jochen–Triesch static hand posture database [3] , shown in Fig. 6, which was used by other researchers, for instances [21, 22]. This database consists of 10 hand signs performed by 24 different persons against different backgrounds. The backgrounds are uniform (light and dark) and complex. The results of performing kernel methods on the database with uniform background are briefly given in Table II.

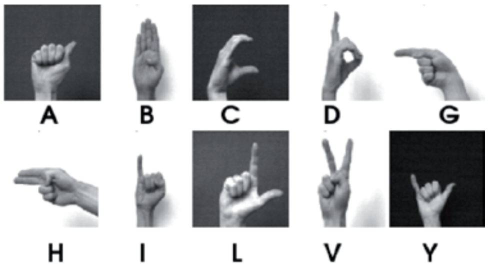

Figure 6.Jochen–Triesch static hand posture database

Fig.7 demonstrates the experiment results for the KPCA using polynomial kernel function. It shows the recognition rate versus the order of polynomial, *r*. The results shows that to achieve maximum recognition rate the order must be within the range of *r*=2 to 4.

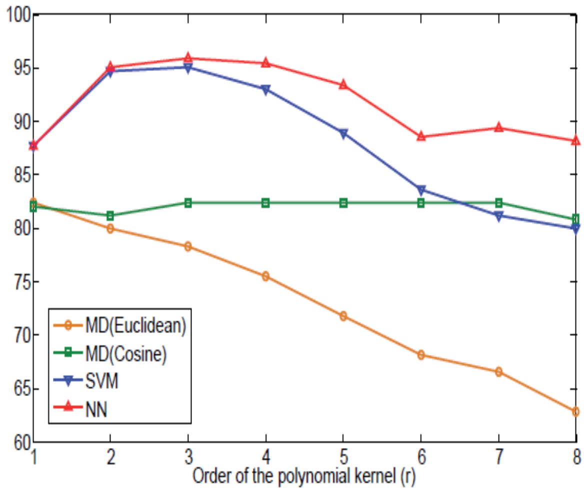

Figure 7. KPCA with polynomial kernel

It is also obvious that NN and SVM outperform MD classifiers. The result shows the maximum rate of 95.91% can be obtained using *r*=3 and NN classifier.

The performance of the KPCA using Gaussian kernel, versus parameter *c*, is shown in Fig. 8. In this figure it can be understood that the SVM and NN classifiers can provide higher rate in comparison with other techniques. However, the result of SVM is slightly better than those of NN. The highest rate in this case is 95.51% achieved by *c*=250 and SVM technique.

The results of experiments with KDA are demonstrated in Fig. 9 and 10. These figures show the result of the polynomial and Gaussian kernel functions, respectively. They illustrate that the type of classifiers have less impact on the recognition rates in comparison with those of KPCA in the Fig. 7 and 8. In Fig.9, the highest rate of 95.10% is gained with *r*=4 and MD classifier using cosine distance.

In the case of Gaussian kernel, Fig.10, the maximum rate of 95.51% can be achieved with c=350 and MD classifier. By comparison of the results it can be concluded that KDA technique gives maximum rates with MD classifiers while KPCA exhibits its best performance with NN and SVM.

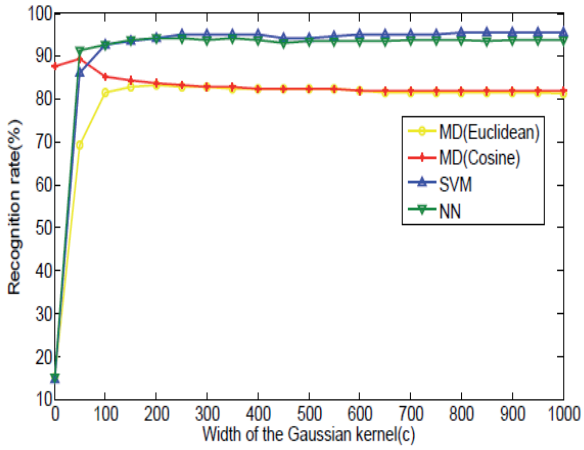

Fig.8: KPCA with Gaussian kernel

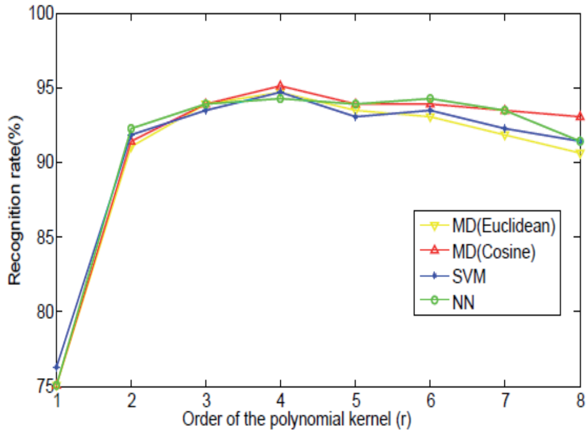

Figure 9. KDA with polynomial kernel

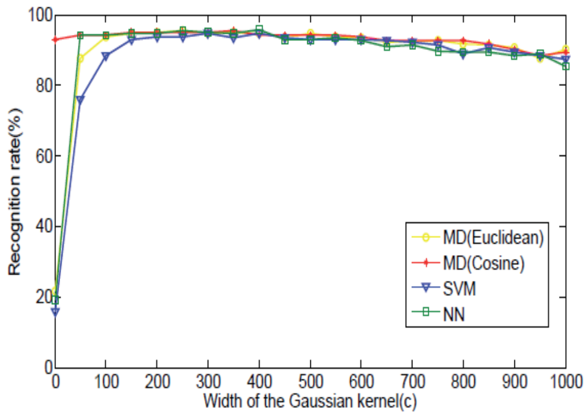

Figure 10. KDA with Gaussian kernel

In this paper, the reason of including the wavelet method is for the purpose of comparison of our results with the previous work conducted using wavelet transform reported in[7], using same PSL database. The results in the Table I indicate the maximum recognition rate of 95.91% demonstrating very good improvement in our method, comparing with the recognition rate of 83.03% reported in [7].

The wavelet transform may also be utilized in association with the KPCA and KDA. In this approach, the initial feature space was created by applying the 2-D wavelet transform on the input signs. Then, for the purpose of facilitation and improvement of the classification procedures, the initial feature space was converted to a new space using KPCA and KDA; the results are presented in Table I. The results obviously indicate the improvement of these methods in comparison to the wavelet itself, but comparing with the KPCA and KDA they don't demonstrate better performance.

TABLE I. COMPARISON OF KERNEL METHODS WITH WAVELET

	MD (EUC.)	MD (Cos.)	SVM	NN
KPCA, r=3	78.36	82.44	95.10	95.91
KPCA, c=1000	81.22	82.04	95.51	93.87
KDA, r=4	94.69	95.10	93.46	94.28
KDA, c=350	95.10	95.51	93.46	94.69
Wavelet	71.01	69.38	91.42	80.81
Wavelet+KPCA	71.42	76.32	95.10	92.62
Wavelet+KDA	93.06	94.69	93.87	93.87

To study the impact of the nonlinear kernel mapping, in Fig. 11, their maximum recognition rates were compared with those of conventional PCA and LDA.

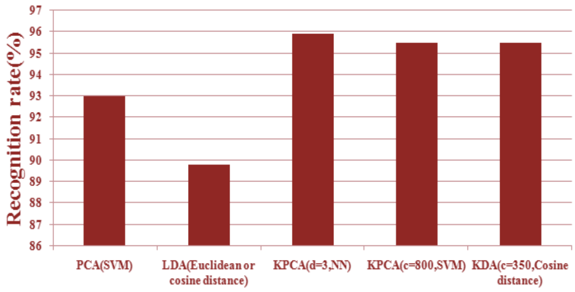

Figure 11. Comparison of Kernel methods with PCA and LDA

Fig.11 shows that nonlinear mapping used in the kernel-based methods has significant impact on the improvement of the recognition rate of liner methods. This is achieved due to the nonlinear mapping of data points to a higher dimensional feature space in the kernel methods. This space can make data points which is not linearly separable in low dimensional space more linear separable. Furthermore because the feature space is nonlinearly related to the input space, the nonlinearities in the data points are taken into account by kernel function[23].

Table II briefly demonstrates the results of performing the presented method on the Jochen–Triesch database (with uniform background). For the purpose of comparison, the maximum rate reported in [3, 21, 22] are also included in the table. As it is shown, kernel-based methods outperformed other works. In the case of Ref.[3], although the improvement is lower, but in terms of computational speed the presented method in this paper is much faster than that in [3]. The method in [3] requires several seconds to analyze a single image [22].

Table III illustrates a comparison between computational costs of the methods with highest rates. The LDA has the lowest computational time, but it has the lowest rate in comparison to the other techniques. Kernel-based methods can improve the recognition rate but their computational time is higher than the others. As can be seen in the table III, kernel methods need the highest time in the feature extraction stage. This is because of the time consumed for the calculating of the vector K_x for each test sample. According to the equation (6), the kernel function must be calculated as many as the training samples. This results in high overall computational cost and that it is inefficient in the case of big training sets. Further, in the classification stage, In the Case of classification time, as illustrated in the table III, the methods KDA and LDA have lowest computational cost when they have been applied together with MD classifier. It must be stressed here these methods give their highest recognition rates with MD classifier. This may be related to the way that LDA and that KDA intrinsically reduce the proximity of the classes using scatter matrixes. Therefore, the MD is simply able to discriminate the classes.

All algorithms were coded in Matlab 2008b, 32 bits[24] and performed on a PC (Intel processor, Core2 Duo, 2.80 GHz, 4 GB RAM).

TABLE II. RESULT OF EXPRIMENT ON JOCHEN-TRIESCH DATABASE

Method	Number of Training Samples	Recognition Rate over test set
Ref. [22]	60	85.1
Ref. [3]	60	93.7
KPCA,SVM	60	89.5
KDA,SVM	60	89.7
Ref. [22]	160	91.8
Ref. [21]	160	89.9
KPCA,SVM	160	95.3
KDA,SVM	160	92.8

TABLE III. COMPUTATIONAL COST

	Feature Extraction		Classification	
	Training	Testing	Training	Testing
PCA(SVM)	542(ms)	26(ms)	2.40(s)	278(ms)
LDA (Euc. distance)	1.28(s)	8(ms)	1(ms)	11(ms)
KPCA(NN)	431(ms)	63(ms)	22(s)	18(ms)
KPCA(SVM)	481(ms)	79(ms)	3.56(s)	280(ms)
KDA (Cos. distance)	457(ms)	78(ms)	1(ms)	11(ms)

The results in this paper exhibit that the kernel-based methods efficiently improve the ability of the conventional PCA and LDA in the recognition of the static signs in the PSL. The results also shows good improvement in comparison to the previous rates reported in the literatures. As discussed earlier in this paper the only drawback of the kernel methods, however, is high computational cost and therefore they are not suitable to be utilised for the real-time applications. To overcome this weakness, fast kernel-based methods have been presented in [25, 26] which is able to deduce the computational cost. These methods are based on the approximation of the kernel methods by a portion of the training samples so-called nodes. Therefore, the kernel function is calculated as many as the nodes are adequate for the purpose of the feature extraction. This can significantly decrease the time of calculating kernel functions. But, in practice, exploiting small number of nodes leads to the loosing of the system accuracy and that lower recognition rates. Thus, the time of feature extraction cannot be effectively reduced. Therefore more researches are needed to be conducted in order to deduce the computational time of the kernel-based methods.

V. CONCLUSION

The paper described a recognition system for the static PSL based on the nonlinear kernel feature extraction consist of KPCA and KDA methods. These methods were examined in association with various classification methods. The results of the experimental trials on the two different databases indicated that the kernel feature extraction has significant impact on the improvement of the recognition rates. The maximum rate of 95.91% was achieved by KPCA with NN classification. The paper concluded that the kernel methods give better recognition rates but with higher computational cost and that it would not be suitable for the real-time applications. As explained in the paper, a solution to this problem is fast kernel methods. But, these methods may also lead to reduce the accuracy of recognition rate. Therefore further researches are needed to overcome the problem.

ACKNOWLEDGMENT

The authors would like to express their sincere thanks to Dr. Ali Karami for the providing of the PSL database.

REFERENCES

[1] Q. Munib, M. Habeeb, B. Takruri, and H. A. Al-Malik, "American sign language (ASL) recognition based on Hough transform and neural networks," *Expert Systems with Applications,* vol. 32, pp. 24-37, 2007.

[2] D. Jiangwen and H. T. Tsui, "A PCA/MDA scheme for hand posture recognition," in *Proc. 5th IEEE Int'l Conf. Automatic Face and Gesture Recognition*, 2002, pp. 294-299.

[3] J. Triesch and C. von der Malsburg, "Classification of hand postures against complex backgrounds using elastic graph matching," *Image and Vision Computing,* vol. 20, pp. 937-943, 2002.

[4] A. Just, Y. Rodriguez, and S. Marcel, "Hand Posture Classification and Recognition using the Modified Census Transform," in *7th Int'l Conf. Automatic Face and Gesture Recognition, FGR 2006*, 2006, pp. 351-356.

[5] G. Lizhong and S. Jianbo, "Natural hand posture recognition based on Zernike moments and hierarchical classifier," in *IEEE Int'l Conf. Robotics and Automation, ICRA 2008*, 2008, pp. 3088-3093.

[6] M. Handouyahia, D. Ziou, and S. Wang, "Sign Language Recognition using Moment-Based Size Functions," in *Proc. Intl. Conf. on Vision Interface*, pp. 210–216.

[7] A. Karami, B. Zanj, and A. K. Sarkaleh, "Persian sign language (PSL) recognition using wavelet transform and neural networks," *Expert Systems with Applications,* vol. 38, pp. 2661-2667, 2011.

[8] A. Kiani Sarkaleh, F. Poorahangaryan, B. Zanj, and A. Karami, "A Neural Network based system for Persian sign language recognition," in *IEEE Int'l Conf. Signal and Image Processing Applications (ICSIPA)* 2009, pp. 145-149.

[9] Q. Liu, R. Huang, H. Lu, and S. Ma, "Face Recognition Using Kernel Based Fisher Discriminant Analysis," in *Proc. Fifth Int'l Conf. Automatic Face and Gesture Recognition*, 2002.

[10] S. Mika, G. Ratsch, B. Scholkopf, A. Smola, J. Weston, and K. R. Muller, "Invariant Feature Extraction and Classification in Kernel Spaces," *Advances in Neural Information Processing Systems 12, Cambridge, Mass.: MIT Press,* 1999.

[11] S. Shuai and X. Mei, "Kernel-based Classifier for Iris Recognition," in *8th Int'l Conf. Signal Processing*, 2006.

[12] A. Kocsor and L. Toth, "Kernel-based feature extraction with a speech technology application," *Signal Processing, IEEE Transactions on,* vol. 52, pp. 2250-2263, 2004.

[13] M. Lima, H. Zen, Y. Nankaku, C. Miyajima, K. Tokuda, and T. Kitamura, "On the use of kernel PCA for feature extraction in speech recognition," in *Proc. Eurospeech*, Geneva, Switzerland, 2003, pp. 2625–2628.

[14] K. I. Kim, S. H. Park, and H. J. Kim, "Kernel principal component analysis for texture classification," *Signal Processing Letters, IEEE,* vol. 8, pp. 39-41, 2001.

[15] K. R. Muller, S. Mika, G. Ratsch, K. Tsuda, and B. Scholkopf, "An introduction to kernel-based learning algorithms," *IEEE Trans. Neural Networks,* vol. 12, pp. 181-201, 2001.

[16] M. Kirby and L. Sirovich, "Application of the Karhunen-Loeve procedure for the characterization of human faces," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 12, pp. 103-108, 1990.

[17] K. Fukunaga, *Introduction to Statistical Pattern Recognition*: Academic Press, 1991.

[18] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 19, pp. 711-720, 1997.

[19] W. Liwei, W. Xiao, and F. Jufu, "On image matrix based feature extraction algorithms," *IEEE Trans. Systems, Man, and Cybernetics, Part B: Cybernetics,* vol. 36, pp. 194-197, 2006.

[20] W. Xiao-ming, H. Chang, F. Xiao-ying, and L. Jin-gao, "2DPCA vs. 2DLDA: Face Recognition Using Two-Dimensional Method," in *Int'l Conf. Artificial Intelligence and Computational Intelligence, AICI '09*, 2009, pp. 357-360.

[21] A. Just, Y. Rodriguez, and S. Marcel, "Hand Posture Classification and Recognition using the Modified Census Transform," in *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*, 2006, pp. 351-356.

[22] D. Kelly, J. McDonald, and C. Markham, "A person independent system for recognition of hand postures used in sign language," *Pattern Recognition Letters,* vol. 31, pp. 1359-1368, 2010.

[23] D. Widjaja, C. Varon, A. Dorado, J. A. K. Suykens, and S. Van Huffel, "Application of Kernel Principal Component Analysis for Single-Lead-ECG-Derived Respiration," *IEEE Trans. Biomedical Engineeringi,* vol. 59, pp. 1169-1176, 2012.

[24] *Mathworks, Inc.* Available: http://www.mathworks.com

[25] J. Wang, Q. Li, J. You, and Q. Zhoao, "Fast kernel Fisher discriminant analysis via approximating the

kernel principal component analysis," *Neurocomputing,* vol. 74, pp. 3313-3322, 2011.

[26] Y. Xu, D. Zhang, F. Song, J. Yang, Z. Jing, and M. Li, "A method for speeding up feature extraction based on KPCA," *Neurocomputing,* vol. 70, pp. 1056-1061, 2007.

Milad Moghaddam received his B.Sc. degree in 2009 and his M.Sc. degree in 2012 from the University of Guilan, Rasht, Iran, both in electronics engineering. His research interests mainly include image processing, pattern recognition, kernel-based machine learning and artificial intelligence.

Manoochehr Nahvi received his B.Sc. degree in communication engineering from K.N.T University of Technology, Tehran, Iran, his M.Sc. degree in electronics engineering from Tarbiat Modarres University, Tehran, Iran, and his Ph.D. degree in electronic engineering from the School of Electronics & Electrical Engineering, University of Leeds, Leeds, U.K. He is an assistant professor in the Department of Electrical Engineering at the University of Guilan, Iran. His research interests mainly lie in the areas of image processing, pattern recognition, industrial process imaging and signal processing for electronic sensors.

Reza PR Hasanzadeh is an Assistant Professor in the Department of Electrical Engineering at the University of Guilan, Rasht, Iran, since 2008. He completed his B.Sc. at University of Guilan and his M.Sc. and Ph.D. at Amirkabir University of Technology (Tehran Polytechnic) with honor degrees respectively. His research interests lie in the area of digital signal and image processing, and fuzzy logic & its applications for processing of industrial and medical images. Dr. Hasanzadeh has several publications in both national and international journals and conferences.