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Intelligent Signal Processing Applied to Recognition and Classification of One and Multidimensional Signals

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Abstract: - Recently, due to emerging critical applications such as biomedical, and security applications, the area of intelligent signal processing has been receiving considerable attention. In this contribution, we present an intelligent signal processing system applied to signal recognition and classification. The system employs different structures, multicriteria and multitransform . In addition, principal component analysis in the transform domain is developed which result in further improvement in the recognition accuracy and dimensionality reduction. Experimental results are given which confirm the excellent properties of the proposed approaches.

Key-Words: - Multicriteria, Multitransform , 2DPCATD , Face recognition, Feature matrix.

1 Introduction

We propose a pattern recognition technique that can be designed to have evolutionary learning by developing the features and selecting the criteria that are best suited for the recognition problem under consideration. It is conjectured that, ultimately, it will be capable of recognizing an enormously large number of patterns by virtue of the fact that it analyzes the signals in different domains and explores the distinguishing characteristics in each of these domains. Many criteria are developed from the features extracted from the projection of the original and preprocessed signals in different domains fig.1. Based on the selected set of criteria and according to the classification technique used, the signals are grouped into a particular number of groups. Grouping of signals can be performed in parallel or in cascade. Finally,
each signal will be identified by a composite index according to the group numbers throughout the classification process.

This paper is organized as follows: Section 2 presents the parallel implementation grouping structure. Section 3 describes the cascaded grouping structure. In Section 4 sample experimental results are given to demonstrate the excellent performance of these systems. A novel technique employing two dimensional Principal Component Analysis in the Transform domain (2DPCATD) is given in Section 5. Section 6 presents the conclusions.

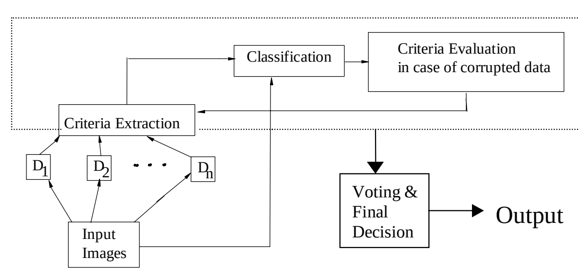

Fig. 1. The proposed Pattern Recognition System

2 The parallel implementation structure

In this implementation, shown in Fig.2, the pattern recognizer extracts the features in parallel, from more than one transform domain. Different classification criteria in each domain can be developed using the coefficients in that particular domain such as the spectral characteristics, the energy distribution in the different transform domain regions, etc. First, a criterion, with adaptable parameters, is introduced to the neural network (NN). Then, by means of supervised learning, such as the back propagation algorithm, the NN classifies the input signals into a number of groups according to that criterion over the range of the adaptable parameters. A potentially successful criterion i, with its selected values of the parameters, in a particular domain, clusters the N input signals in a number of distinct non-overlapping clusters. The cluster index, according to the i^{th} criterion, is denoted c_i, where $c_i = 1,2,3,\ldots, g_i$, and g_i is the number of groups using the i^{th} criterion. Corresponding to a number n of selected criteria, i takes the values 1,2,…, or n.
The NN Classifier learning continues, by testing all the criteria presented over the parameters range for each criterion, until a successful set of criteria is obtained. A successful classifier using n criteria, should yield a unique composite index $(c_1 c_2 c_3 \ldots c_n)$ corresponding to each of the N input signals.
$c_1 = 1,2,\ldots g_1$, $c_2 = 1,2,\ldots g_2$, … $c_n = 1,2,\ldots g_n$
$n = n_1 + n_2 + n_3 + \ldots + n_D$ where D is the number of transform domains, and n_k is the number of criteria in the k^{th} domain, (k=1,2,….D).

3 The Cascaded Structure

In this implementation shown in Fig. 3, when the classification process is completed, each signal is represented by a unique composite index, corresponding to the signal path through the decision tree, from the input to one of the terminal nodes of the tree. The proposed self-designing system is tested using two classification techniques; vector quantization and neural networks.

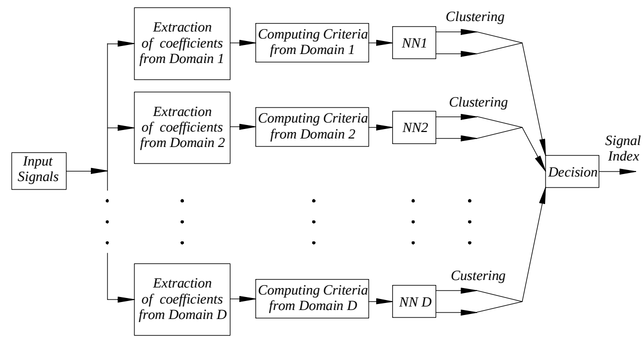

Fig. 2. A parallel implementation of the proposed classification technique

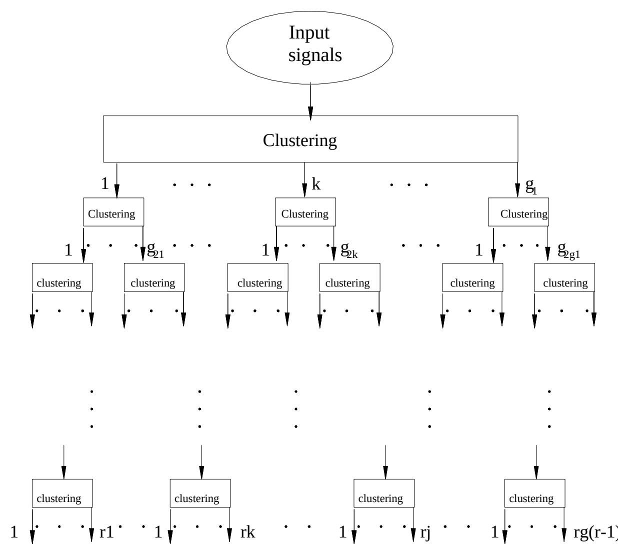

Fig. 3. The cascaded structure of the classifier employed by the system

4 Experimental Results

In these experiments, 32 eight bit gray level, facial images from the ORL database are used. Up to 80 gray level white Gaussian additive noise was introduced to the 32 images.
After testing all available criteria, the optimum set of criteria that was least susceptible to noise was as follows:

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• DCT transform: sum of the 3 x 3 low-frequency components, sum of the 4 x 4 low-frequency components, sum of the 3 x 3 high-frequency components, the maximum DCT coefficient, the ratio between the maximum and minimum coefficients, etc.
• Haar transform: summation of mid 5 x 5 spatial low sequency, summation of mid 3x3 spatial low sequency, summation of high 4 x4 spatial low sequency, etc.
• Singular value decomposition: summation of the largest 10 values, summation of the largest 5 singular values, the largest singular value of the binary image that represents the edges of the image to be recognized, etc.
• Energy of signal.

4.1 Experimental Results and Analysis employing the Parallel Structure System

In this experiment, two classifiers have been used to recognize these images [1]. The 2 classifiers have the same structure but they employ different set of criteria. 26 images out of the 32 are recognized successfully when using the first classifier. 24 images out of the 32 are recognized successfully when classifier 2 is used. Classifier 2 is designed such that the images that Classifier 1 fails to recognize are recognized successfully by Classifier 2, and vice versa. When both classifiers are used, all the 32 images are recognized successfully

4.2 Experimental Results and Analysis employing the Cascaded Structure System

In this experiment, two classification techniques, vector quantization and neural networks, were used for testing [2].

4.2.1 Results using Vector Quantization

The signals presented at each node, in each stage, of the classification decision tree are binary clustered using vector quantization techniques.
When the system was tested by noisy images, the classification accuracy was 100%.

4.2.2 Results using Neural Networks

The signals at each node, in each stage, are split into 2 groups such that the statistical properties are the same in the two groups. NN are used to split images, at each node, into 2 groups. The structure of the NN used in this example has the following specifications: 7 neurons in the first hidden layer, 10 neurons in the second hidden layer and one neuron in the output layer. Back propagation algorithm, with 10^-5 MSE, is used in training the NN. When the system was presented by noisy images, the recognition accuracy was 96.8%.

5 The 2DPCATD Algorithm

In 1991 the eigenfaces method for face recognition based on principal component analysis (PCA) was presented [3]. Recently Yang et al [4] proposed the two dimensional PCA (2DPCA) algorithm, which has many advantages over PCA method. It is simpler for image feature extraction, better in recognition rate and more efficient in computation. However it is not as efficient as PCA in terms of storage requirements, as it requires more coefficients for image representation. In this contribution we propose a fast Transform domain algorithm based on the 2DPCA method employing vector quantization (VQ) that minimizes the storage requirements, by reducing the number of coefficients representing the images without sacrificing the recognition rate and accelerating the recognition process in the testing mode.
The proposed algorithm represents the images and their covariance matrix in the Transform domain where, the energy in facial images is concentrated in small number of coefficients. This results in considerable reduction in the coefficients required to represent the images. Consequently, the computational and storage requirements are greatly simplified as will be shown. The algorithm is described as follows

A. Training mode

In the training mode, the features of the data base are extracted, stored, and grouped as described by steps 1 through 7.
<u>Step 1:</u> The suitable transform (*Tr*) is applied to each $m \times n$ image A_i of the N training images, yielding T_i ($i=1$ to N).

$$T_i = Tr\{A_i - \bar{A}\} \qquad (1)$$

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Where $\bar{A}$ is the mean matrix, of all the N training images.

Step 2: The transform is chosen such that the significant coefficients of T_i are contained in a submatrix, T_i', (upper left part of T_i) of dimension $n' \times n'$. Thus T_i' is used to replace A_i in our algorithm.

Step 3: The covariance matrix S for the N training images is calculated using (2).

$$S = \frac{1}{N}\sum_{i=1}^{N}(T_i')^T (T_i') \tag{2}$$

Step 4: A set of k eigenvectors, V= $[V_1, V_2 \ldots V_k]$ of size n' corresponding to the largest k eigenvalues is obtained for S.

Step 5: The feature matrices of the training images B_i are calculated in (3) and (4),

$$Y_{j,i} = T_i' V_j \qquad j = 1,2,\ldots k \;\; and \;\; i = 1,2,..N \tag{3}$$

$$B_i = [Y_{1,i}, Y_{2,i}, \ldots Y_{k,i}] \tag{4}$$

It is worthwhile to note that the feature matrix representing the training image has dimensions much lower than those obtained using the spatial 2DPCA method (*$n' << n$, and now k is smaller).*

Step 6: Vector quantization is employed to group the feature vectors, $Y_{j,i}$, representing the training images.

Step 7: The vectors representing the centroids of all groups are stored.

B. Testing mode

In the testing mode a facial image A_t is presented to the system to be identified. The following steps are followed

Step 1 The same transform used in the training mode is applied to A_t which yield T_t.

Step 2 The sub matrix T_t' containing the significant coefficients is obtained (dimension $n' \times n'$)

Step 3 The feature matrix B_t for the testing image is calculated from

$$B_t = [Y_{1,t}, Y_{2,t}, \ldots Y_{k,t}] \tag{5}$$

$$Where\ Y_{j,t} = T_t' V_j \qquad j = 1,2,\ldots k \tag{6}$$

Step 4 Distance measures, such as the Euclidean distances, between the feature vectors of the testing image $Y_{j,t}$ and the centroids, are computed. The group corresponding to the minimum distance is determined. The tested image is assigned to that group.

5.1 Experimental Results and Analysis

The proposed algorithm was applied to the ORL database [5]. The ORL database consists of 400 images of 40 individuals (10 images each), where pose and facial expressions are varying, Fig.4. Results are compared with those obtained using 2DPCATD without employing VQ and existing techniques, namely, the 2DPCA, and PCA .

Two experiments have been applied to the ORL database, where all the images are grayscale with 112 x 92 pixels each.

In the first experiment, 40 images of 40 different individuals are used for training and the remaining 360 images are used for testing. A two-dimensional discrete cosine transform (DCT) is applied to the N training images. The dimensions of T'_i and the covariance matrix S are 20×20. The 5 largest eigenvectors of S corresponding to the 5 largest eigenvalues are obtained. In our approach k of only 5 was needed relative to $k = 10$ in other approaches, while even achieving better recognition accuracy.

The feature matrices for all the training images are obtained using (3) and (4).

A tree of VQ codebooks, using $Y_{1,i}$, *(i= 1 to N)*, are constructed as shown in Fig.5 , where $Y_{1,i}$, are used to represent the images

The procedure in section 5.*B* is followed for the 360 testing images. Results are listed in Tables I and II.

Fig.4. Five samples for 3 individuals in the ORL database.

In the second experiment 5 images per class are used for training and the remaining 200 images are used for testing. The Dimensions of T'_i and S are the same as in the first experiment. Results are listed in Tables I and II

Table I shows that the proposed algorithm yields better recognition accuracy using VQ than without using it and even better results, compared with one of the best existing methods , than the 2DPCA .

Table II illustrates the storage requirements, in terms of the dimensions of the feature matrix. It is seen that, for the 2DPCATD/VQ and 2DPCATD, the amount of storage is drastically reduced (by approximately 90%), compared with the 2DPCA algorithm. In addition the new technique drastically improves the recognition speed in the testing mode. It can be easily shown that in contrast with other techniques, the number of steps required to uniquely identify an unknown facial image is considerably reduced. Consequently, 2DPCATD /VQ lends itself to facial recognition of large databases.

Table I
Recognition accuracy for experiment I and II on ORL database using 2DPCATD/VQ , 2DPCATD, 2DPCA and PCA methods.

Method	Recognition accuracy for experiment I	Recognition accuracy for experiment II
2DPCATD/VQ	79.25 %	95.8 %
2DPCATD	73.61 %	92.0 %
2DPCA	72.77 %	91.0 %
PCA	62.80 %	83.5 %

Table II
Dimensions of feature matrix and number of computations required for the testing mode on ORL database, for experiments I, II.

	2DPCATD/VQ	2DPCA
Dimensions of feature matrix per image	(20x5)	(112x10)
Storage requirements for N images	(20x5)xN	(112x10)xN
# of multiplicatn for testing mode	57344	103040
# of comparisons for the testing mode	10 (experimental)	40

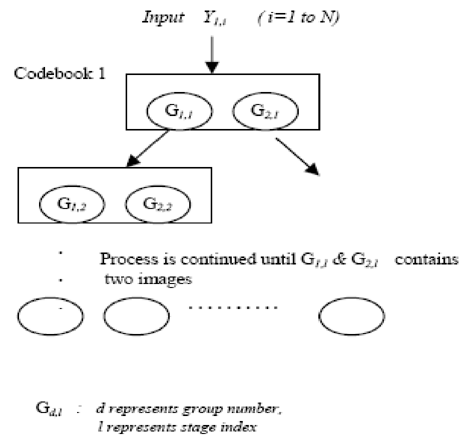

Fig.5. A tree of VQ codebooks employing $Y_{1,i}$

6 Conclusions

In this contribution, a comprehensive coverage of a powerful Intelligent Signal Processing system applied to recognition and classification of signals is presented. This includes the different aspects of the recognition system: multicriteria, multitransform, principal component analysis and Vector Quantization. Sample results are given which confirm the excellent performance of the techniques presented in terms of recognition accuracy, speed, and storage requirements, etc. Research work is in progress.

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