Self Designing Intelligent Signal Processing System capable of evolutonal Learning for Classification/Recognition of One and Multidimensional Signals

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A Self-Designing Intelligent Signal Processing System Capable of Evolutional Learning for Classification/Recognition of One and Multidimensional Signals is described which classifies data by an evolutionary learning environment that develops the features and algorithms that are best suited for the recognition problem under consideration. The System adaptively learns what data need to be extracted in order to recognize the given pattern with the least amount of processing. The System decides what features need to be selected for classification and/or recognition to fit a certain structure that leads to the least amount of processing according to the nature of the given data. The System disclosed herein is capable of recognizing an enormously large number of patterns with a high accuracy.
OTHER PUBLICATIONS

Ki-Chung Chung, Seok Cheol Kee and Sang Ryong Kim, Face Recognition using Principal Component Analysis of Gabor Filter Responses, 1999 IEEE, pp. 53-57.


Weiyang Zhou, Verification of the Nonparametric Characteristics of Backpropagation Neural Networks for Image Classification, 1999 IEEE, pp. 771-779.


* cited by examiner
Clustering of coefficients computing criteria from Domain I

Extraction of coefficients from Domain 2

Decision

Input Signals

Clustering

NN 1

NN 2

NN D

Signal Index

Extraction of coefficients from Domain D

Computing Criteria from Domain D

Computing Criteria from Domain 2

Computing Criteria from Domain 1

Fig. 1
Fig. 2 Thirty-one facial images downloaded from the Internet
Fig. 3.
Fig. 4. Clusters $C_1$, $C_2$ and $C_3$ of images 1 to 31 obtained from each NN.
Fig. 5. Recognition of images using the STNN classifier.
Fig. 6 A Tree Structure for Recognition of N Signals, one signal identified at each stage
Fig. 7 A tree structure for recognition of N signals of unknown probability of occurrence
Fig. 8 The Pattern Recognition System in the Learning Mode
Unknown pattern

Project the input pattern and compute criteria as needed

(BCU-2)_{1,1}

(BCU-2)_{2,1}

(BCU-2)_{3,2}

Fig.9 The Pattern Recognition System in the Running Mode
Fig. 10 Recognition of 8 images using the system
Fig. 11 Eight facial images downloaded from the Internet
Fig. 12 Noisy facial images
Fig. 13 shows a block diagram of the Evolutionary Learning Recognition
Fig. 14
SELF-DESIGNING INTELLIGENT SIGNAL PROCESSING SYSTEM CAPABLE OF EVOLUTIONAL LEARNING FOR CLASSIFICATION/RECOGNITION OF ONE AND MULTIDIMENSIONAL SIGNALS

This invention relates to a one and multidimensional signal classification neural network system that employs a set of criteria extracted from the signal representation in different transform domains [denoted the Multicriteria Multittransform Neural Network (MCMTNN)] classifier and more particularly to the signal projection, in each appropriately selected transform domain which reveals unique signal characteristics whereby the criteria in the different domains are properly formulated and their parameters adapted to obtain classification with desirable implementation properties such as speed and accuracy and claims the benefit of U.S. Provisional Application No. 60/315,420 filed Aug. 28, 2001.

BACKGROUND AND PRIOR ART


Face recognition is one of the important research topics in this area which has been receiving the attention of many researchers due to its useful applications, such as system security and human-computer interface [Chellappa, R., Wilson, C. L. and Sirohey, S., “Human and machine recognition of faces”, a survey, Technical Report CAR-TR-731, CSEE 33339, University of Maryland, August 1994.]

In conventional pattern recognition, the task is divided into 2 parts. The first part is obtaining a feature space of reduced dimensions and complexity, and the second part is the classification of that space [Sarlashkar, M. N., Bodruzaman, M. and Malkani, M. J., “Feature extraction using wavelet transform for neural network based image classification”, Proceedings of the Thirtieth Southeastern Symposium on System Theory, 1998, pp. 412-416.]

Neural Networks (NN) have been employed and compared to conventional classifiers for a number of classification problems. The results have shown that the accuracy of the NN approach is equivalent to, or slightly better than, other methods. Also, due to the simplicity and generality of the NN, it leads to classifiers that are more efficient [Zhou, W., “Verification of the nonparametric characteristics of back propagation neural networks for image classification”, IEEE Transactions on Geoscience and Remote Sensing, March 1999, Vol. 37, No. 2, pp. 771-779]. As reported in the literature, NN classifiers possess unique characteristics, some of which are:

(i) NN classifiers are distribution free. NNs allow the target classes to be defined without consideration to their distribution in the corresponding domain of each data source [Benediksson, J. A., Swain, P. H. and Ersoy, O. K., “Neural Network approaches versus statistical methods in classification of multisource remote sensing data”, IEEE Transaction on Geoscience and Remote Sensing, July 1990, Vol. 28, pp. 540-551.1. In other words, using neural networks (NN) is a better choice when it is necessary to define heterogeneous classes that may cover extensive and irregularly formed areas in the spectral domain and may not be well described by statistical models;

(ii) NN classifiers are important free. When neural networks are used, data sources with different characteristics can be incorporated into the process of classification without knowing or specifying the weights on each data source. Until now, the importance-free of neural networks has mostly been demonstrated empirically [Bishop, H., Schneider, W. and Pinz, A. J., “Multispectral classification of LANDSAT-images using neural networks”, IEEE Trans. on Geoscience and Remote Sensing, May 1992, Vol. 30, pp. 482-490]. Efforts have also been made to establish the relationship between the importance-free characteristic of neural networks and their internal structure, particularly their weights after training [see Zhou above]. In addition, NN implementations lend themselves to reduced storage and computational requirements.


In the field of pattern recognition, the combination of an ensemble of neural networks has been to achieve image classification systems with higher performance in comparison with the best performance achievable employing a single neural network. This has been verified experimentally in the literature [Kittler, J., Hatef, M., Duin, R. P. W. and Matas, J., “On combining classifiers”, IEEE Transaction on Pattern Analysis and Machine Intelligence, March 1998, Vol. 20, pp. 226-239]. Also, it has been shown that additional advantages are provided by a neural network ensemble in the context of image classification applications. For example, the combination of neural networks can be used as a “data fusion” mechanism where different NN’s process data from different sources [Luo, X. and Mirchandani, G., “An integrated framework for image classification”, Proceedings of 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing, Istanbul, Turkey, Vol. 1, pp. 620-613]. A number of image classification systems based on the combination of the outputs of a set of different classifiers has been. Different structures for combining classifiers can be grouped as follows [see Lu, Y. above and Ho, T. K., Hull, J. J. and Srihari, S. N., “Decision Combination in Multiple Classifier Systems”, IEEE Trans. on Pattern
SUMMARY OF THE INVENTION

It is a primary objective of the present invention to design a high fidelity pattern recognizer.

Another object of this invention is to provide a recognition algorithm that continuously enhances itself using all the information available up to that point.

A further object of this invention is to provide an evolutionary learning environment employing a recognition algorithm.

Preferred embodiments of the invention include self-designing intelligent signal processing system comprising: means for receiving signals; and, adaptive means for recognizing a pattern from the received signals, wherein the adaptive means are constantly updated over time based on the receiving signals and the method of carrying out said system comprising the steps of: receiving signals from a source; recognizing a pattern from the received signals; and, adaptively updating the recognizing step with the received signals to enhance the signal processing method over time.

Before explaining the disclosed embodiments of the present invention in detail, it is to be understood that the invention is not limited in its application to the details of the particular arrangement shown since the invention is capable of other embodiments. Also, the terminology used herein is for the purpose of description and not of limitation.

It would be useful to discuss the meanings of some words used herein and their applications before discussing the novel self-designing intelligent signal processing system capable of evolotional learning for classification/recognition of one and multidimensional signals including:

- transform domain—mapping of data in order to extract more information from the input data by multiplying the signals by a certain mathematical formula and in order to retrieve the signal the resultant transformed signal, i.e., product, is multiplied by the inverse of this formula; these transform domains are similar to ones used in U.S. Pat. No. 6,437,972 which is incorporated herein by reference thereto;
- criterion—a method of computing some features of the signal from the available information about the signal; which features are similar to ones used in U.S. Pat. No. 5,940,815 which is incorporated herein by reference thereto;

In a neural network (NN)—some nodes are connected by links with an input and an output as shown in FIG. 14. The NN can be trained such that it gives a specific output when a particular input is introduced to it. The use of NN is similar to that used in U.S. Pat. No. 6,301,385 which is incorporated herein by reference thereto. FIG. 14 shows an example of the neural network which could have different number of nodes, different numbers of inputs and different numbers of output.

Back propagation—a learning algorithm that is used to train the neural network to obtain a particular output when
a certain input is introduced to the neural network which training is similar to that system used in U.S. Pat. No. 6,418,378 which is incorporated herein by reference thereto; cluster—group which is similar to the ones used in U.S. Pat. Nos. 6,336,108 and 6,337,980 which are incorporated herein by reference thereto; cluster index—group number which is similar to the ones used in U.S. Pat. No. 5,598,507 which is incorporated herein by reference thereto;

Discrete Cosine Transform (DCT), HAAR Transform (HAAR) and Singular Values Decomposition Transform (SV)—various types of known transforms with each one having a particular mathematical formula. When one multiplies the signals by each of these formulas certain features can be easily extracted from the signals. Each one of the formulas has its own advantages, disadvantages and problems to be used in. As discussed in the transfer domain, the multiplication of the transformed signal by the inverse of the transform generates the original signal again. The (DCT) is similar to the ones used in U.S. Pat. No. 4,791,598, U.S. Pat. Nos. 4,837,724 and 5,539,836 which are incorporated herein by reference thereto. The (HAAR) is similar to the one used in U.S. Pat. No. 4,224,678 which is incorporated herein by reference thereto. The (SV) is similar to the one used in U.S. Pat. No. 5,010,504 which is incorporated herein by reference thereto;

Single Transform Neural Network (STNN)—a single transform neural network converts the information resulting from transforming the signals into one transform domain into an input to the neural network which STNN is similar to that used in U.S. Pat. No. 6,437,743 which is incorporated herein by reference thereto;

neuron—a node in neural network wherein the nodes are connected together by links from the input to the output wherein NN are utilized in evolutionary learning and their use is similar to that used in U.S. Pat. No. 5,619,617 which is incorporated herein by reference thereto; and,

AND operation—a logic operation represented by ones and zeros, i.e., 1 AND 1 gives 1, 1 AND 0 gives 0, 0 AND 0 gives zero, in other words, in order to achieve a certain goal all parts should be accomplished (check several facts and all of them come out to be true).

According to this invention, the above objects are achieved by an evolutionary recognition classifier. The advantages and features of this inventive pattern recognition technique are realized by a design which has evolutionary learning by developing the features and selecting the criteria that are best suited for the recognition problem under consideration. The evolutionary learning is similar to one used in U.S. Pat. No. 6,263,325 B1 which is incorporated herein by reference thereto. This technique is capable of recognizing an enormously large number of patterns by virtue of the fact that it basically analyzes the signal in different domains and explores the distinguishing characteristics in each of these domains. In other words, this approach uses available information and extracts more characteristics for classification purposes by projecting the signal in different domains. A large number of classification criteria can be developed to greatly enhance the performance of the classifier by exploiting: (a) Structure type; and, (b) Criteria selection and formulation from the information in the different domains.

In the following section (Section 2), a particular structure illustrates the inventive technique, namely, a parallel implementation approach using the novel Multicriteria Multitransform Neural Network (MCMTNN) classifier for image classification. Then in (Section 3) the experimental results of the parallel MCMTNN classifier is compared with the implementation and experimental results employing a Single Transform Neural Network (STNN) classifier. This comparison between the MCMTNN and the STNN classifiers confirms the improved performance of the classifier of the invention. Also, in (Section 3) experimental results are given demonstrating the improved classification/recognition performance, in the presence of additive noise, of the inventive MCMTNN classifier. Finally, conclusions are presented in (Section 4).

Section 2. Multicriteria Multitransform Neural Network (MCMT): A Parallel Implementation

In this implementation, shown in FIG. 1, the pattern recognizer extracts the features in parallel, from more than one transform domain, i.e., Domain 1 is 10, Domain 2 is 12, ... Domain D is 14. These features are obtained from the transform coefficients representing the input signals 16 into the different Domains 10, 12, 14. Different classification criteria in each Domain 18, 20, 22 (shown as a separate box for each respective domain) are developed using the coefficients in that particular domain such as the spectral characteristics, energy distribution in each of the different transform domains several regions, etc. First, a criterion, with adaptable parameters, is introduced to the several neural networks (NN) which are identified as NN1 is 24, NN2 is 26 and NN3 is 28. Then, by means of supervised learning, such as the respective back propagation algorithms of the several NNs, such 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 ith criterion, is denoted Ci where Ci=1, 2, 3, ..., Cn. Corresponding to a number n of selected criteria, i takes the values 1, 2, ..., or n. It is worthwhile to note that more than one criterion can be derived from a given domain. Also, Ci is in general, different for the different i’s.

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, i.e. decision, should yield a unique composite index (c1, c2, c3, ..., cn) corresponding to each of the N input signals.

Also, it is easy to show that

\[ N \leq \prod_{i=1}^{n} C_i \]

\[ C_i=1, 2, \ldots, C_i; C_i=1, 2, \ldots, C_n \]

where D is the number of transform domains, and n is the number of criteria in the kth domain, (k=1, 2, ..., D).

Section 3. Experimental Results

Sample experimental results are given to illustrate the performance of the technique. In this example, thirty-one, 8 bit gray level, facial images are downloaded from the Internet as shown in FIG. 2 and identified numerically therein. These images are presented to the classifier. The results obtained using the MCMTNN technique, are pre-
presented and compared with those obtained from a NN employing a Single Transform, STNN.

3-i MCMTNN Classifier

A resulting successful structure is shown in FIG. 3. It uses three NN’s in parallel and projects the images in three domains, namely, Discrete Cosine Transform (DCT) 30, HAAR Transform (HAAR) 32, and Singular Values Decomposition (SV) 34, as shown in FIG. 3. Each NN has one neuron in the input layer, 10 neurons in the first hidden layer, 15 neurons in the second hidden layer, and one neuron in the output layer. The first criterion 35, selected by the first NN 36, is the sum of the 4x4 spatial low frequency components, which is the sum of the 4x4 low sequency HAAR coefficients for each image. The second criterion 37 which is the sum of the 4x4 low sequency HAAR coefficients for each image was chosen by the second NN 38. When using the third criterion 39 (SV), a simple AND operation of their respective numbers in four groups, i.e., C1-C4 for each NN, and i=1, 2 and 3. The back propagation algorithm was used for training, yielding a mean square error (MSE) of $10^{-3}$. The MCMTNN classifier, denoted Classifier 1, successfully yields a unique composite index, $c_1 c_2 c_3$, for each image, as shown in FIG. 4, i.e., the classification accuracy is 100%.

The inventive technique, when presented with a given classification task, can yield more than one classifier. For example, in this experiment another classifier, denoted Classifier 2, is obtained which yields 100% classification accuracy. It uses the same structure as Classifier 1 except the third NN, where the learning results in a criterion that employs the sum of the second ten largest singular values instead of the first ten largest singular values. The performance of different classifiers can be evaluated and/or the redundancy can be used to devise a voting scheme to enhance the accuracy of classification of incomplete or corrupted data.

Alternatively, a design criterion is incorporated in the design of the classifiers such that the fused data from the different classifiers yields acceptable performance under nonideal conditions, i.e., much distortion, corrupted signals, noise, etc. An example of the non-ideal conditions is given in the following section, 3-iii.

3-ii MCMTNN Classifier of Corrupted Images

White noise up to 10 gray levels is added to each facial image shown in FIG. 2 and then presented to Classifier 1 and Classifier 2 as described in Seq 3-i. The following results are obtained as follows in 3-ii-a and 3-ii-b:

3-ii-a Classification of noisy images by Classifier 1

From the thirty-one images in FIG. 2, thirty images are clustered correctly when using the first criterion 35 (DCT), all images are clustered correctly when using the second criterion 37 (HAAR) and 24 images are clustered correctly when using the third criterion 39 (SV). By combining the outputs of the 3 NNs, 24 images out of the 31 are recognized successfully when Classifier 2 is used.

It is significant to note that Classifier 2 is designed such that the images that Classifier 1 fails to recognize are recognized successfully by Classifier 2, and vice versa, when an additional deciding appropriate criterion is introduced. This is illustrated in the following Section 3-ii-c:

3-ii-c Classification enhancement by combining Classifier 1 and Classifier 2:

By using a simple detector and another feature of the image, energy in this example, it is determined which of the two results, from classifiers 1 and 2, when they disagree, is correct. This additional voting step resulted in recognizing all of the 31 images successfully.

3-iii Single Transform Neural Network (STNN) Classifier:

This structure uses one NN and one transform as shown in FIG. 5. The STNN classifier is trained with different criteria in different domains. The neural network that successfully classifies the images in FIG. 2 has one neuron in the input layer, 20 neurons in the first hidden layer, 30 neurons in the second hidden layer, 40 neurons in the third hidden layer, 50 neurons in the fourth hidden layer and one neuron in the output layer. A Backpropagation algorithm is used for training with MSE of $10^{-5}$. It is worthwhile to note that the number of outputs of the STNN classifier is much more than that of the approach. Thus, the time taken in training the STNN classifier is expected, and confirmed experimentally, to be more than that of the time taken to train the MCMTNN (approximately five times in this example).

Then, the classifiers are tested with images corrupted with noise. The criterion in a particular domain that gives the best results is retained. After many trials, the best results obtained using one of the 3 transforms, DCT, HAAR and SVD, are as follows:

In the DCT domain, six images out of the thirty-one are recognized successfully and the criterion selected by the STNN is the sum of the 4x4 low frequency components; In the HAAR domain, eight images out of the thirty-one are recognized successfully and the criterion selected by the STNN is the sum of the 4x4 spatial low sequency components, for each image; and;

by the use of SVD, eight images out of the thirty-one are recognized successfully when using the sum of the 4 largest Singular values for each image.

Section 4. Different structure of the proposed technique (Multi-Stage Binary Classifier)

The pattern recognition technique is capable of recognizing a large number of patterns by analyzing the projected patterns (signals) in different domains, explores the distinguishing characteristics, and formulates the corresponding criteria, in each of these domains. The optimum set of criteria is selected by the classifier to satisfy certain constraints. According to these criteria, at each node in each stage, the signals presented are binary clustered, i.e., divided into two groups, according to an appropriately selected criterion. The members of the same group are assigned an index of 0 or 1. Similarly, the signals of each group are binary clustered repeatedly. The process is continued until each signal, or group of signals, is identified by a unique composite index.

A useful structure and the corresponding classification algorithm are hereafter described. Sample experimental
A Useful Structure of MSB Classifier

In this Section, a useful multistage structure, with binary classification at each node in each stage, is described, the algorithm employed is presented and the algorithm’s evolutionary learning is also shown.

As will become clear in the following sections, for unique classification of N patterns, the number of Binary Classification Units (BCU’s) needed equals N-1, irrespective of the number in each subgroup after each BCU. The number of stages each pattern has to go through to be identified depends on the subgrouping strategy. Two extreme situations are given in the following sections.

In FIG. 6, the pattern with the highest probability of occurrence is identified in one stage, while the pattern with the lowest probability is identified after N-1 stages. For the 25 patterns. The corresponding structure is shown in FIG. 7. At the jth stage, there are q nodes where q=2^j-1. The number of stages required to uniquely identify each of the N=2^q input patterns is r. The total number of (BCU-2)'s equals N-1, at the kth node, (k=1, 2, ..., q), in the jth stage. (BCU-2)_jk employs criterion Cjk to group its input set of patterns, Sjk, into two groups, g_{Sjk} and g_{~Sjk}, where w_r are j bit binary words equal to 2k-2 and 2k-1, respectively.

B. MSB Structure and Algorithm

The structure is shown in FIG. 7. The system operates in two modes, namely, the learning (training) mode, and the running mode.

1. The MSB system in the Learning Mode:

Referring to FIG. 8, the algorithm, in the learning mode, is summarized as follows: The training signals are projected into the appropriately selected domains in the training mode; Corresponding to each feature, a criterion is developed that computes a quantitative measure of the feature parameter and, for each (BCU-2)_jk in FIG. 7, starting from j=1 and progressing towards the output, different criteria are evaluated. A successful criterion Cjk is selected and its parameters are adapted to optimize performance. The quantitative measure using Cjk divides the input signals set Sjk to (BCU-2)_jk into two subgroups, g_{Sjk} and g_{~Sjk}, each containing (almost) the same number of elements. A signal in the input group Sjk belongs to subgroup g_{Sjk} if the signal falls in a certain range, say r_{min} and belongs to subgroup g_{~Sjk} if it is in the range r_{max}. The distance from r_{min} to r_{max} is the range corresponding to unsuccessful classification. It is worthwhile to note that the system’s reliability particularly under nonideal conditions such as noisy or corrupt data, several (BCU-2)'s each operating with its appropriately selected criterion, are in a voting scheme to replace a critical (BCU-2)_jk. The prespecified optimality constraints for adapting a criterion Cjk include computational complexity, distance between the subgroups (guard range), classification accuracy with noisy/distorted data, etc. The steps above are followed until each member of the N input patterns in case of recognition (N district groups in case of classification) is uniquely classified, FIG. 7, by the r bits binary word subscript of g_{Sjk} at the output stage.

The MSB System in the Running Mode

Referring to FIG. 9, the steps can be described as follows:

The unknown pattern P is projected into the appropriately selected domains in the training mode:

According to the path P, takes in FIG. 7, say it reaches the input of (BCU-2)_jk, the appropriate criterion Cjk is computed, and the correct group (path) g_{Sjk} or g_{~Sjk} is identified;

The process is repeated for j=1, 2, ..., r, where the unknown pattern is recognized by the r bits binary word subscript of g_{Sjk} and,
Corresponding to the figure, the example shown for unknown pattern in group g

\[ \text{I. Implementation Examples} \]

Two simple examples are given to illustrate the performance of the technique. The results obtained using the MSB technique in case of noisy or corrupted data are compared to those obtained using Single Transform Neural Network (STNN), as well as Multi-Input Neural Networks.

A. First Example

In this example, eight, 8 bit gray level, facial images are downloaded from the Internet (Olevitt Research Laboratory ORL), as shown in FIG. 10. Up to 80 gray level additive noise was introduced to the 8 images resulting in those shown in FIG. 11.

1. Results using the MSB Classifier:

The technique is employed for the images of FIG. 12. The results obtained are summarized as follows in that each of the input images were uniquely recognized using 4 criteria and the total number of criteria used to recognize the 8 input images equaled 7. The following criteria have been employed by the BCU’s used in this example:

- Summation of the largest 10 singular values representing each input image, sum of the 3x3 spatial low frequency components in the DCT domain for each image, the sum of the 3x3 low frequency HAAR coefficients and the ratio between the maximum gray level and the mean value of each image;
- There is a unique one to one correspondence between the identified patterns s₁ to s₈ and the input patterns s₁ to s₈ in the input set S; and,
- All 8 images were recognized successfully.

2. Results using Single Transform Neural Network Classifier.

This structure uses one NN and one transform as in FIG. 5. The STNN classifier is trained with different criteria developed from different transform domains. The neural network of FIG. 5 which successfully recognized the images, has one neuron in the input layer, 10 neurons in the first hidden layer, 15 neurons in the second hidden layer and one neuron in the output layer. A Backpropagation algorithm with different MSE (10⁻², 10⁻³, 10⁻⁵) is used in training the neural network. The classifier is tested with images corrupted with up to 80 gray level additive noise. The best results are obtained when the sum of the 3x3 spatial low frequency components in the DCT domain for each image is introduced to the input of the neural network. 3 images out of 8 images were recognized correctly.


A Multi-Input Neural Network has been trained to recognize the 8 facial images. Different combinations of 3 criteria have been used in training the Multi-Input Neural Network with different mean square error (MSE). In the best result obtained, 4 images out of 8 images were recognized correctly.

In order to facilitate a better understanding of the invention, it is useful to discuss the relation between: FIG. 1 and FIG. 8 as seen hereafter:

**PREFERRED EXAMPLE**

In order to fully understand the invention described herein, it would be useful to describe the best mode of carrying it out by referring again to FIG. 3 which shows an implementation example of the MCMTNN classifier.

In the implementation of FIG. 3, one must recognize the following parameters which include a Matlab software package which has been used in digital programming of the invention. There are different ways to classify signals. For example, one inherently classifies facial images based on their eyes, hair, type of face, race, etc. which has been used in the algorithms employed in classifier of the invention. The teachings of this application introduces herein an example of the features that could be used in classifying the signals. These features are extracted from the transform domains into which the signals are projected; as is seen the DCT, HAAR and SVD transform domains have been used. They were used because it is shown in literature that these transforms can compact most of the information about the signal in small number of coefficients. From these coefficients, one can compute different criteria which are introduced to the input of neural networks in order to classify any input signal to the appropriate group.

Referring specifically to FIG. 3, the input images are downloaded from the internet in bitmap format at input 29. These digitized images are transformed to different domains.

In the first branch of FIG. 3 they are mapped into the DCT domain 30 where the requisite images are extracted by multiplication by the mathematical formula:

\[
    f_y = \begin{cases} 
    \frac{1}{\sqrt{N}}, & i = 0, \quad 0 \leq j \leq N - 1 \\
    \frac{2}{N} \cos \left( \frac{\pi (2j + 1) i}{2N} \right), & 1 \leq i \leq N - 1, \quad 0 \leq j \leq N - 1 
    \end{cases}
\]
For 2-D (2 dimensions):
The transformation matrix $Y = GXG^T$

The result is a certain matrix, which represents the specified image in the DCT. This matrix has low frequency coefficients and the high frequency coefficients and some frequencies in between. The criterion $35$, used in this system is the sum of the $4 \times 4$ spatial low frequency components in the DCT domain 30 for each image. Each image will be represented by a certain component according to the DCT. The component representing each image will be introduced to the neural network 36. The neural network 36 will group the 31 images into 4 groups according to the values of these components. Each image will have a group number as shown in FIG. 4.

In the second branch of FIG. 3 they are mapped into the HAAR domain 32 where the requisite images are extracted by multiplication by the mathematical formula

The 1-D Haar transform is most easily expressed in matrix notation. If one lets the elements of G equal

Where $r = \log_2 i$ and $m = i - 2r + 1$, $0 \leq i \leq N - 1$

For two dimensions signal
The transformation matrix $Y = GXG^T$

The result is that each of the digitized images has three 3 group numbers resulting from the groupings by NN 36, NN 38 and NN 40. The result is that the clusters C1, C2 and C3 of FIG. 4 relate directly to the clusters 42, 44 and 46 of FIG. 3 and FIG. 4 is the total output represented by 48 and 50.

Each image is represented by a composite index representing the group number to which it belongs with respect to each criterion. This is a unique index for each image. It differs from one image to the other. The final result has been represented by a simple example. These results come out from the learning as different criteria have tried for this problem and the criteria that give the best result in case of noisy images have been selected.

It is a feature of this invention that its advantage is in the evolutionary learning that the value of the invention is realized. Refer now to FIG. 8 which with block diagrams indicate the pattern recognition system in the learning mode which provides the full benefits of the invention. FIG. 8 illustrates the evolutionary learning system of the Pattern Recognition System in the Learning Mode. An enormous set of criteria have been formulated and then evaluated in case of noisy or corrupted data until the optimum criteria are selected which give the highest classification accuracy.

Reference shall now be made to FIG. 13 which shows in a further block diagram the evolutionary learning recognition system of the invention. The training signals (input images 132) are projected and analyzed in a multiplicity of different domains indicated therein as D1 as 134, D2 as 136 and DN as 138. Distinguishing characteristics are extracted by the appropriate criteria in the block indicated as Criteria Extraction 140 in each of these domains. Corresponding to each feature, a criterion is developed that computes a quantitative measure of the feature parameters. The signals are then classified into the required set of groups based on the criteria developed in the block identified as Classification 142.

The pattern recognition system will be tested by noisy images and the selected criteria will be evaluated. In other words, the selected criteria will be tested to find out if they can still classify signals successfully when they are corrupted with noise. The Criteria Evaluation 144 is made and for those of low classification accuracy the signals will be returned for criteria extraction at 140 with other criteria.

If the criteria give high classification accuracy in case of noisy data, they will be retained. In case of non-accurate classification, other criteria will be tested until the optimum criteria are selected which give the highest classification accuracy in case of noisy signals.

SECTION 5. CONCLUSIONS

A novel MCMTNN for one and multidimensional signal classification using multicriteria processing and data fusion has been described. The multicriteria are extracted from the projections of the signals, to be classified, in multiple transform domains. The implementation example demonstrates the utility of the MCMTNN classifier for image classification. It employs NN's in parallel and three classification criteria obtained from the image projections in three transform domains. These results are compared with a traditional STNN classifier. The comparison between the MCMTNN and the STNN classifiers illustrates the improved performance of the MCMTNN classifier in terms of appreciable reduction in the overall computational complexity and increased speed.

Additional results, some of which are given in Section 3, confirm the superior performance of the MCMTNN classifier relative to the STNN approach for image classification in the presence of additive noise. Since the inventive MCMTNN classifier is capable of evolutionary learning by selecting the criteria as well as optimizing each criterion for best overall performance, it yields enhanced performance and classification accuracy for different classification environments such as noisy and incomplete data.

Another structure was discussed in Section 4. A Multi-Stage Binary pattern classification/recognition system (MSB) is presented to classify N patterns (or groups), where N=2^r. Two cases are presented. In the first case, no apriori information regarding the statistical properties of occurrence of the patterns is available. The MSB structure used (N−1) Binary Classification units. The number of stages required to identify an unknown pattern (or group) is equal to r. In the second case, the probability of occurrence of signals differs from one signal to the other. Signals are extracted in a descending order of their probability. The system is capable of evolutionary learning to extract and optimize the classification criteria employed by the Binary Classification Units.
While the invention has been described, disclosed, illustrated and shown in various terms of certain embodiments or modifications which it has presumed in practice, the scope of the invention is not intended to be, nor should it be deemed to be, limited thereby and such other modifications or embodiments as may be suggested by the teachings herein are particularly reserved especially as they fall within the breadth and scope of the claims here appended.

We claim:

1. A self-designing intelligent signal processing system, comprising:
   (a) means for receiving signals corresponding to plural images, wherein each of the plural images are not related to other ones of the plural images;
   (b) means for extracting coefficients from the received signals in more than one transform domain, wherein the coefficients correspond to the plural images;
   (c) means for determining corresponding criteria in each of the more than one transform domain using the extracted coefficients;
   (d) an adaptive learning means that determines a best characteristics and corresponding criteria to be extracted by each of the more than one transform domain in order to recognize the plural images with the least amount of processing;
   (e) means for classifying the plural images from each more than one transform domain into selected groups according to the criteria corresponding to that one of the more than one transform domain over a range of adaptable parameters; and
   (f) means for recognizing each of the plural images from the selected groups from the more than one transform domain, wherein the self-designing intelligent signal processing system is capable of recognizing different number of different images with a high level of accuracy.

2. The self-designing intelligent signal processing system of claim 1, further comprising:
   (a) a discrete cosine transform (DCT);
   (b) a singular values (SV) decomposition transform domain which cooperate to provide an output of digitized images, wherein said DCT, HAAR and SV transforms are arranged in parallel.

3. The self-designing intelligent signal processing system of claim 1, further comprising:
   (a) a criteria selector for selecting classification criteria over a range of parameters; and
   (b) means for selecting an optimum criteria for use in classification of the plural images from noisy signals.

4. The self-designing intelligent signal processing method, comprising the steps of:
   (a) receiving signals from a source, the signals including plural unrelated images;
   (b) recognizing a pattern from the received signals using plural transforms domains to select from each one of the plural transforms domains unique features and corresponding criteria.

(c) classifying the unique features into selected groups for each of the plural transform domains based on the corresponding criteria;
(d) determining fidelity of said selected groups; and
(e) updating each of the selected groups from said plural transform domains by an evolutionary recognition classifier that selects a different optimum feature and corresponding criteria for use by each of the plural transforms domains, whereby the fidelity of said selected groups is constantly improved over time based on the receiving signals to recognize each of the plural unrelated images with a high level of accuracy.

5. The self-designing intelligent signal processing method of claim 4, wherein the signals include:
   (a) one of a one-dimensional signals and a multi-dimensional signal.

6. The self-designing intelligent signal processing method of claim 4, wherein the patterns include digitized images.

7. The self-designing intelligent signal processing method of claim 4, wherein the patterns are developed by a back propagation of respective neural networks of each one of the plural transform domains.

8. The self-designing intelligent signal processing method of claim 4, wherein the patterns include noise signals.

9. The self-designing intelligent signal processing method of claim 4, further comprising the step of:
   (a) filtering out noise from the received signals.

10. The self-designing intelligent signal processing method of claim 4, wherein the patterns are clustered into digitized groups of common facial characteristics.

11. A multi-criteria multi-transform neural network (MCMTNN) classifier for image classification comprising:
   (a) an input device for receiving input signals having plural different digitized images;
   (b) plural transform domains in parallel for receiving the input signals from the input device, each of the plural transform domains comprising:
      (a) a pattern recognizer for receiving the input signals and developing transform coefficients for a particular domain and extracting plural features from the transform coefficients;
      (b) a criteria selector for selecting classification criteria from the transform coefficients for the particular domain; and
      (c) a neural network for classifying the plural digitized images into plural groups according to the selected criteria over a range of parameters; and
   wherein the MCMTNN classifier adaptively determines the best features and criteria for use in each of the plural transform domains for the recognition problem under consideration with the least amount of processing to recognize the plural different digitized images.

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