

Serial No. 802,573  
Filing Date 19 February 1997  
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19970710 056

DISTRIBUTION STATEMENT A

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1                    WAVELET-BASED HYBRID NEUROSYSTEM FOR SIGNAL

2                    CLASSIFICATION

3  
4                    STATEMENT OF GOVERNMENT INTEREST

5                    The invention described herein may be manufactured and used  
6 by or for the Government of the United States of America for  
7 governmental purposes without the payment of any royalties  
8 thereon or therefor.

9                    CROSS REFERENCE TO RELATED PATENT APPLICATION

10                   The present invention is related to co-pending U.S. Patent  
11 Application entitled HYBRID NEURAL NETWORK FOR PATTERN  
12 RECOGNITION, (Navy Case No. 78001) having the same filing date.

13                    BACKGROUND OF THE INVENTION

14                    (1) Field of the Invention

15                    The present invention relates to a neurosystem and to a  
16 method for signal classification whose structures are a-priori  
17 known and which is especially useful in fields of utility in  
18 which economy of computational burden, accuracy of  
19 classification, or ease of accommodating additional signals to be  
20 classified are critical factors in choice of design.

21                    (2) Description of the Prior Art

22                    Signal classification involves the extraction and partition  
23 of features of targets of interest. In many situations, the

1 problem is complicated by the uncertainty of the signal origin,  
2 fluctuations in the presence of noise, the degree of data  
3 correlation in multi-sensor systems, and the interference of  
4 nonlinearities in the environment. Research and studies in the  
5 past have focused on developing robust and efficient methods and  
6 devices for recognizing patterns in signals, many of which have  
7 been developed from traditional signal processing techniques, and  
8 known artificial neural network technology.

9 FIG. 1 is a schematic representation of a conventional  
10 pattern recognition system. In this configuration, the system  
11 consists of three phases: data acquisition 10, data preprocessing  
12 12, and decision classification 14. In the data acquisition  
13 phase 10, analog data from the physical world are gathered  
14 through a transducer and converted to digital format suitable for  
15 computer processing. In this stage, the physical variables are  
16 converted into a set of measured data, indicated in FIG. 1 by  
17 electric signals,  $x(r)$ , if the physical variables are sound (or  
18 light intensity) and the transducer is a microphone (or  
19 photocells). The measured data is used as inputs to the second  
20 phase 12 (data preprocessing) and is grouped into a set of  
21 characteristic features,  $P(i)$ , as output to third phase 14. The  
22 third phase 14 is actually a classifier or pattern recognizer  
23 which is in the form of a set of decision functions. Based on  
24 the distinction of feature characteristics in  $P(i)$ , the  
25 classifier in this phase will determine the category of the  
26 underlying signals.

1           Signal classification or pattern recognition methods are  
2 often classified as either parametric or nonparametric. For some  
3 classification tasks, pattern categories are known a priori to be  
4 characterized by a set of parameters. A parametric approach is  
5 to define the discriminant function by a class of probability  
6 densities with a relatively small number of parameters. Since  
7 there exist many other classification problems in which no  
8 assumptions can be made about these parameters, nonparametric  
9 approaches are designed for those tasks. Although some  
10 parameterized discriminant functions, e.g., the coefficients of a  
11 multivariate polynomial of some degree are used in nonparametric  
12 methods, no conventional form of the distribution is assumed.

13           In recent years, one of the nonparametric approaches for  
14 pattern classification is neural network training. In neural  
15 network training for pattern classification, there are a fixed  
16 number of categories (classes) into which stimuli (activation)  
17 are to be classified. To resolve it, the neural network first  
18 undergoes a training session, during which the network is  
19 repeatedly presented a set of input patterns along with the  
20 category to which each particular pattern belongs. Then later  
21 on, a new pattern is presented to the network which has not been  
22 seen before but which belongs to the same population of patterns  
23 used to train the network. The task for the neural network is to  
24 classify this new pattern correctly. Pattern classification as  
25 described here is a supervised learning problem. The advantage  
26 of using a neural network to perform pattern classification is

1 that it can construct nonlinear decision boundaries between the  
2 different classes in nonparametric fashion, and thereby offers a  
3 practical method for solving highly complex pattern  
4 classification problems.

5 The discrete Fourier transform (DFT) has had a great impact  
6 on many applications of digital signal processing. Not only does  
7 the DFT provide data decorrelation, but it also greatly reduces  
8 the computational requirements. A standard approach for  
9 analyzing a signal is to decompose it into a sum of simple  
10 building blocks. The fast Fourier transform (FFT) and discrete  
11 cosine transform (DCT) are the most well-known examples.  
12 However, once the basis vector formed by the Fourier kernel  
13 function is a cosine basis, it does not have compact support or  
14 finite energy. Thus, a large number of transform coefficients  
15 are required to retain a significant fraction of the total signal  
16 energy.

17 In the past several decades, signal characterizations have  
18 been mainly performed with traditional spectral processing such  
19 as the DFT and FFT. Signal characteristics are represented by  
20 frequency information. Based on its frequency function, or  
21 spectral information, the signal is modeled for analyzing and  
22 processing. However, Fourier transform outputs do not contain  
23 information in the time domain. Critical details of the signal  
24 as it evolves over time are lost. Therefore, difficulty arises  
25 in processing the data, especially if the data is nonstationary  
26 or nonlinear. Recently, wavelets and wavelet transforms have

1 emerged as a useful alternative for many applications in signal  
2 processing. Since their basis functions have compact support and  
3 their transforms have good localization in both time and  
4 frequency domains, wavelets have opened up new avenues for  
5 improving signal processing. By a wavelet transform of a given  
6 function  $g(t)$ , one can represent the function as follows:

$$g(t) = \sum_n \sum_k c_{nk} v_{nk}(t). \quad (1)$$

7 where  $n$  and  $k$  are integer indexes and the  $v_{nk}$  are the  
8 coefficients. Each of the functions  $v_{nk}(t)$  belongs to one of a  
9 finite number of families  $\{v_{nk}(t)\}$ , and the parameters  $n$  and  $k$  are  
10 related to the frequency scale and time location of this  
11 function.

12 Despite these advances, there still remains a need however  
13 for systems and methods of pattern classification which perform  
14 at a high level.

#### 15 SUMMARY OF THE INVENTION

16 Accordingly, it is an object of the present invention to  
17 provide an artificial neural network-based system and method for  
18 signal classification, or pixel-based image classification, which  
19 is economical in computation burden.

20 It is another object of the present invention to provide a  
21 system and method as above which is highly accurate in its  
22 performance of signal classification.

1           It is still another object to provide a system and method  
2 above whose capacity for number of distinct signals undergoing  
3 classification may be simply and inexpensively increased.

4           The foregoing objects are attained by the system and the  
5 method of the present invention.

6           In accordance with the present invention, a system for  
7 signal classification broadly comprises: one or more sensors for  
8 receiving signals (including pixel-based image signals); means  
9 for transforming the input signals so that characteristics or  
10 features of the signals are represented in the form of wavelet  
11 transform coefficients; and means for classifying said signals  
12 into multiple distinct categories and generating a classification  
13 output signal. The transforming means comprises a wavelet  
14 transform module for which an operator can specify the number of  
15 selected coefficients for processing and the basis kernel  
16 function for the wavelet transformation. The classifying means  
17 in a preferred embodiment comprises an array of hybrid neural  
18 networks with each network having a location neural network, a  
19 magnitude neural network, and a classification neural network.  
20 Preferably, the location and magnitude neural networks are one-  
21 layer neural networks which are trained using an unsupervised  
22 training algorithm. The classification networks are preferably a  
23 two-layer neural network which are trained using a supervised  
24 training algorithm.

25           The method of the present invention broadly comprises  
26 receiving a series of input signals, transforming the input

1 signals so that characteristics of the signals are represented in  
2 the form of wavelet transform coefficients, and classifying the  
3 signals into multiple distinct categories and generating a  
4 classification output signal.

5 The system and method of the present invention represent a  
6 novel system and method for efficient signal classification based  
7 upon wavelet transform characteristics of the acoustic signals  
8 using an artificial neural system with a hybrid architecture that  
9 employs components utilizing different types of neural networks  
10 training algorithms.

11 Other details of the system and method of the present  
12 invention, as well as other objects and advantages, are set forth  
13 in the following detailed description and the accompanying  
14 drawings wherein like reference numerals depict like elements.

#### 15 BRIEF DESCRIPTION OF THE DRAWINGS

16 FIG. 1 is a schematic representation of a prior art pattern  
17 recognition system;

18 FIG. 2 is a schematic representation of a wavelet-based  
19 hybrid neurosystem signal classifier system in accordance with  
20 the present invention;

21 FIGS. 2A, 2B and 2C are schematics illustrating a diversity  
22 of forms of receiving means 22, FIG. 2.

23 FIG. 3 is a schematic representation of the architecture of  
24 the location/magnitude neural networks used in the system of the  
25 present invention;



1 signals. The acoustic signals received by the sensors are  
2 digitized in a known manner preferably in the module 22. The  
3 digitized signals are then forwarded to the data preprocessing  
4 module 24.

5 As stated above, receiver module may take a diversity of  
6 forms. However, it is to be appreciated that in accordance with  
7 the present invention each of of these diverse forms is adapted  
8 to provide the information which it gathers in the form of serial  
9 train of spatially coordinated information components. Referring  
10 to FIG. 2A, which represents the case of the sensor of signal  
11 receiving means 22 being (FIG. 1) being embodied as a singly  
12 acting hydrophone 22a, the signal which the receiving means  
13 provides would simply be a train of sampled and digitized  
14 representations of the amplitude of the acoustic signal that  
15 impinge upon the hydrophone. Referring to FIG. 2B, the input of  
16 the of a receiving means 22b may alternative be embodied as an  
17 array 23b of spatially separated hydrophones, such as a towed  
18 array of hydrophones used in undersea warfare sonar systems. The  
19 signals for the individual hydrophones of the array are  
20 conventionally processed by sonar beamformers or sonar trackers  
21 which provide either a signal train having 1-dimension (e.g.,  
22 towed array output representing the conical angle bearing of the  
23 contact relative to the axis of the towed array) or a signal  
24 train having 2-dimensions (e.g., the density function of a  
25 conical scan stepped through  $180^\circ$  about the towed array axis in  
26 small increments). In the latter 2-dimensional case, a

1 conventional beamformer/tracker, 23b' provides the signal to  
2 preprocessing module 24, and in turn to wavelet transform module  
3 26, in the form of a serial signal train in which the increments  
4 scan information components are spatially coordinated. Referring  
5 now to FIG. 2C, in another alternative embodiment the input of a  
6 receiving means may be a pixel-based photoelectrical camera 23c,  
7 which in viewing an image 23c' accumulates and stores the image  
8 as a series of pixels whose 2-dimensional locations are  
9 determined by Cartesian x and y scan circuits 23c'' and 23c'''.  
10 By means of a suitable multiplexing type circuit 23c'''' the x-y  
11 position information is translated into a serial signal train in  
12 which the x and y pixel location information is spatially  
13 coordinated before passing to the wavelet transform module 26 (in  
14 this case the noise/segmentation circuitry 24 may be omitted).

15 Data preprocessing module 24 may comprise any suitable means  
16 known in the art for carrying out noise reduction and data  
17 segmentation. The data preprocessing module 24 may be formed by  
18 a computer, or a portion of a computer, which has been  
19 preprogrammed to carry out the desired processing of the  
20 digitized acoustic signals. Any suitable algorithms known in the  
21 art may be used to process the digitized signals in a desired  
22 manner. The output from the data preprocessing module 24 is then  
23 fed to the wavelet transform module 26.

24 The wavelet transform module 26 transforms the preprocessed  
25 signals so that the signal characteristics or features in each  
26 segment of the underlying signal are represented in the forms

1 wavelet transform coefficients. It has been found that the  
2 information contained in the wavelet coefficients reflects the  
3 signal's features in both time and frequency domains. The  
4 wavelet transform module preferably comprises a processor  
5 programmed to transform the preprocessed digitized signals into a  
6 set of wavelet transform coefficients, which typically will be a  
7 parallel type processor. The particular programming used in the  
8 processor does not form part of the present invention. In fact,  
9 any suitable wavelet transformation algorithms known in the art  
10 may be used in the module 26. Standard wavelet functions, such  
11 as the Daubechie series of functions are available with a  
12 repertoire of so-called "basis kernel functions" which are  
13 matchable to corresponding harmonic characteristics of the input.  
14 When performing the wavelet transform, the operator specifies an  
15 appropriate kernel function via a wavelet library 34. The  
16 operator also specifies the number of selected coefficients for  
17 processing via a coefficient selector module 36. Coefficient  
18 selector 36 enables the operator to select a portion of the  
19 waveform transform processor's total coefficient producing  
20 capacity (ranked starting with the largest magnitude of  
21 coefficient appearing in the output and decreasing in a  
22 monotonical sequence with respect to coefficient magnitude  
23 therefrom) to represent a signal. This in turn enables tailoring  
24 operation of module 26 to operate with an economy of processing  
25 resources matched to the needs of the characteristics of input  
26 signals. In accordance with well known principles, a wavelet

1 transform processor 26, FIGS. 2 and 5 produces a data output  
2 representing the portion of wavelet coefficients chosen per the  
3 operator's selection made using selector 36. This output takes  
4 the form of a cluster of data representing the selected  
5 coefficients having the frequency versus time location, and the  
6 magnitude information, associated with each wavelet coefficient  
7 embedded in the data cluster. A location information databus 38  
8 and a magnitude information databus 40 are operatively connect to  
9 the output of the processor 26 such that they respectively tap  
10 the location and magnitude information regarding the selected  
11 coefficients. The location of the coefficients in time and  
12 frequency domain is may be directly tapped by databus 38.  
13 Reindexing, may be necessary in tapping the magnitude of each  
14 coefficient. The properties of the coefficients, namely, the  
15 location and magnitude of each wavelet are coupled to array 28 of  
16 hybrid multi-component neural network systems 30 via location  
17 databus 38 and magnitude databus 40, respectively. More  
18 particularly databus 38 and 40 separately pass the location and  
19 magnitude coefficients to the location and magnitude artificial  
20 neural networks 42 and 44, in each hybrid multi-component neural  
21 network system 30. It is to be appreciated that the above  
22 described production of location and magnitude properties and the  
23 technology of applying them to succeeding stages in a processing  
24 system via a data bus are well known.

25 The hybrid neurosystem 28 comprises an array of multiple  
26 hybrid multi-component neural network systems 30. Any desired

1 number of neural network systems 30 may be used in the array. In  
2 the hybrid neurosystem 28, signals are classified into multiple  
3 distinct categories corresponding to their wavelet transform  
4 characteristics. Each hybrid multi-component neural network  
5 systems 30, as shown in FIG. 2, consists of a location artificial  
6 neural network 42, a magnitude artificial neural network 44, and  
7 a classification artificial neural network 46. As will be  
8 discussed in more detail hereinafter, the location and magnitude  
9 neural networks 42 and 44 are each one-layer networks known as  
10 feature extraction networks and the classification neural network  
11 46 is a two layer network. The networks 42 and 44 in effect each  
12 generate "topological" maps of the signal feature(s) being  
13 processed, which topological maps are in effect supplied to  
14 classification network 46. Categorization of the signal is  
15 performed by each hybrid neural network 30 based on a certain set  
16 of wavelet transform features recognized by the distribution of  
17 synaptic weights or "topological maps". Stated another way,  
18 wavelet transform features intrinsic to each category of signal  
19 being classified are recognized by distribution of the synaptic  
20 weights in artificial neural networks 42 and 44 of each hybrid  
21 neural networks 30. This distribution of weights arises as the  
22 result of the unsupervised learning process to which network 42  
23 and 44 are subjected. The distribution of the synaptic weights  
24 within networks 42 and 44 are the physical manifestations of the  
25 aforesaid topological maps.

1           The classification outputs from the classification neural  
2 network 46 are put into a global context for an end user in the  
3 classification output comparator gate module 32. Module 32 is  
4 operative to compare the magnitudes of outputs at the  
5 classification neural network 46 of each hybrid multi-component  
6 neural network systems 30 one to another, and to pass only the  
7 output of the single system 30 whose output is largest. The  
8 implementation of this function (i.e., of module 32) in software  
9 or hardware is within the skill of the art. At this final  
10 stage, the classification output is compared against a preset  
11 threshold value, for example a value of 0.5. If the output is  
12 greater than the threshold level, classification is declared;  
13 otherwise no classification is made. These results may be  
14 displayed to the operator in any suitable fashion.

15           FIG. 5 is a flow chart illustrating the operation of the  
16 wavelet-based hybrid neurosystem of the present invention. The  
17 foregoing method of operation is illustrated in this figure.

18           Referring now to FIG. 3, one can see the architecture of the  
19 location artificial neural network 42, which architecture is  
20 identical to that of the magnitude artificial neural network 44.  
21 As shown in this figure, the location artificial neural network  
22 42 has an input layer 132 formed by a plurality of input layer  
23 neurons 138 and an output layer 134 formed by a plurality of  
24 output layer neurons 140 with synaptic feedforward (excitatory)  
25 connections 136 from the input layer neurons 138 to the output  
26 layer neurons 140 and lateral (inhibitory) connections 142 among

1 neurons 140 in the output layer 134. The stream of location  
2 information data flowing along location databus 38 is applied to  
3 in parallel to all the input neurons 138. Preferably, each  
4 output neuron 140 is fully connected to all of the input neurons  
5 138. The input neurons 138 in the input layer 132 receive input  
6 signals  $x_1 - x_i$  (i.e., all receive the same input signal at a  
7 given instants, which is the location information fed from  
8 location databus 38, where  $i$  equals the number of input neurons  
9 138. The output neurons 140 generate outputs  $y_1$  through  $y_i$ ,  
10 where  $i$  equals the number of output neurons. In the network 42,  
11 as well as the network 44, the neuron cells at the output layer  
12 compete in their activities by means of mutual lateral  
13 interactions and develop adaptively into specific detectors of  
14 different signal patterns through an unsupervised learning  
15 process. In one embodiment of the present invention, each  
16 network 42 and 44 consist of 100 neurons (50 input neurons and 50  
17 output neurons).

18 Each of the neural networks 42 and 44 is designed so that at  
19 a given time only one cell or a local group of cells gives an  
20 active response to the current input. As a result, the locations  
21 of the responses tend to become ordered as if meaningful  
22 coordinate systems for different input features were being  
23 created over the network. The spatial location of a cell in the  
24 network corresponding to a particular domain of signal patterns  
25 provides an interpretation of the input information.

1           A set of competitive learning rules based on the Kohonen  
2 algorithm may be used to train each of the neural networks 42 and  
3 44. Such a training scheme is described in the above-identified  
4 co-pending patent application, filed on an even date herewith  
5 (Navy Case No. 78001), which is hereby incorporated by reference.

6           Training data for the unsupervised training of the location  
7 and magnitude artificial neural networks 42 and 44 is introduced  
8 at the acoustic signal input of the sensor module 22. The  
9 training data may consist of location data and magnitude data  
10 derived from samples of raw, noisy, acoustic signals for a  
11 variety of speed, direction and sea noise conditions, for a given  
12 target type of the target types that the system is being trained  
13 to recognize. Thus, the training process uses the full structure  
14 of the system shown in FIG. 2. The number of samples used to  
15 train an early version of the system was 744. Any number between  
16 500 and 1000 is believed to be sufficient. The number of samples  
17 used for testing was 380. Any number of test samples between 200  
18 and 500 is believed to be sufficient.

19           The architecture of the classification neural network 46 is  
20 shown in FIG. 4. As shown therein, the neural network 46 may be  
21 a standard two-layer, fully connected feedforward network whose  
22 architecture may be termed a multilayer perceptron configuration.  
23 There are three layers: an input layer 144 formed by a plurality  
24 of input neurons 150, a hidden layer 146 formed by a plurality of  
25 neurons 152 and output layer 148 formed by one output neuron 154.  
26 In one embodiment the input layer 144 is constructed with 100

1 input neurons with each input neuron 150 receiving information  
2 from a corresponding output neuron 140 of the networks 42 and 44.  
3 The number of input neurons 150 which are provided equals the  
4 number of output neurons of the associated location neural  
5 network 42 plus the number of output neurons of the associated  
6 magnitude neural network 44 (e.g., 50 plus 50 = 100). Each  
7 output neuron of neural networks 42 (i.e., having output neurons  
8 140) and 44 (output neurons not shown) is coupled to a respective  
9 one of the input neurons 150 of classification neural network.  
10 The hidden layer is preferably constructed of 20 neurons. The  
11 classification neural network 46 is a dedicated input neural  
12 network as opposed to the conventional Lippman fully connected  
13 neural network.

14 The system of the present invention uses conventional back  
15 propagation artificial neural network (ANN) training to train the  
16 classification neural network 46. One back propagation training  
17 algorithm which may be used to train the classification neural  
18 network 46 is described in the above-identified co-pending U.S.  
19 patent application, filed on an even date herewith, (N.C. 78001),  
20 which is incorporated by reference in its entirety herein.

21 During training, samples of acoustic data from a recording  
22 of a particular target type are repeatedly fed to the sensor  
23 system 22, causing characteristic magnitude and location patterns  
24 to appear at the inputs of the classification neural network 46.

25 In the system and method of the present invention, any  
26 suitable wavelet function may be used to transform the underlying

1 signal in the module 26. In a preferred embodiment, wavelet  
2 functions Daubechies 2, 4, 6, 8, and 12 are used.

3 The cluster of Wavelet coefficient data from may be stored  
4 from wavelet transform processor may be stored in a storage  
5 device (no shown) for use in the artificial neural networks.  
6 More specifically they may be stored in the 2-dimensional  
7 time versus frequency domain matrix 156, FIG. 6 (in which the  
8 ordinate is frequency and the absissa is time) well known to  
9 those of skill in the wavelet function art. As noted above, the  
10 tapping of the embedded location information by time-positions of  
11 databus 38, FIGS. 2 and 38 for feeding location information to  
12 artificial neural networks 42, is straight forward. One  
13 illustrative technique for tapping the magnitude information from  
14 this matrix includes forming a ordered concatenated string 158 of  
15 the magnitude information, and then reindexing this into the  
16 uniform time-positions of databus 40, which reindexing is  
17 diagrammatically represented by the arrows indicating assignment  
18 of databus position index integers contained in box 160 to the  
19 concatenation positions in string 158. Any other suitable  
20 mechanism for effecting a translation of a 2-dimensional data  
21 matrix to two 1-dimensional databus position may be used as an  
22 alternative.

23 The location neural network 42 combines what otherwise would  
24 be a frequency neural network and a time neural network and  
25 thereby improves efficiency. Although three items of data  
26 (frequency, time and magnitude) are being processed, only two

1 artificial neural networks are used to accomplish the feature  
2 extraction. This configuration in combination with the use of  
3 wavelet transforms approaches the efficiency of a Quad Mirror  
4 Filter (QMF) as shown in FIG. 7.

5 The combination of wavelet and wavelet transform, hybrid  
6 neural network architecture, and advanced training algorithms in  
7 the design makes the system of the present invention unique and  
8 provides high classification performance. In particular, signal  
9 transformation with wavelet, and principal component analysis for  
10 selecting wavelet coefficients, provide efficiency in feature  
11 extraction with relatively less computational expenses. Further,  
12 hybrid neural networks with their feature of a self-organizing  
13 feature topological map produces a high classification accuracy.  
14 In self-organizing systems, the use of computational maps offer a  
15 number of advantages as follows.

16 The present invention affords an advantage of high  
17 information processing efficiency. The hybrid neurosystem is  
18 required to analyze and classify complex signals arising in a  
19 dynamic environment on a continuous basis. This, in turn,  
20 requires the use of processing strategies that permit the rapid  
21 handling of large amount of information. Computational  
22 topological maps provided by the self-organizing systems are  
23 ideally suited for this task. In particular, computational maps  
24 represent the results obtained from complex stimuli in a simple  
25 and systematic form.

1 Further the present invention afford an advantage of  
2 simplicity of access to process information. That is to say the  
3 use of computational maps simplifies the schemes of connectivity  
4 required to utilize the information by the classification  
5 network. An important by-product of this advantage is that the  
6 capacity of system 20, in terms of the number of distinct signals  
7 it will handle, may be simply and inexpensively increased. a  
8 channel for a new signal to undergo classification may be added  
9 by simply adding another hybrid multi-component neural network  
10 system 30 in parallel with the already provided array 28 of  
11 systems 30. Training the new system (unsupervised training of its  
12 location and magnitude neural networks 42 and 44 and supervised  
13 training of its classification neural network 46) to provide a  
14 classification output response for the new signal requires only  
15 the same increment of effort as had been required for the  
16 existing signal observation channels.

17 Still further, the present invention affords an advantage of  
18 a common form of representation. More specifically, the common,  
19 mapped representation to the results of different kinds of  
20 computations permits the classification network to employ a  
21 single strategy for pattern recognition.

22 While the invention has been described in combination with  
23 specific embodiments thereof, it is evident that many  
24 alternatives, modifications, and variations will be apparent to  
25 those skilled in the art in light of the foregoing description.  
26 For example, if recognition of only a single known structure of

1       input signal is desired, the location and magnitude information  
2       need only be fed (via data buses 38 and 40) to a single hybrid  
3       multi-component neural network systems 30)and system 20 will only  
4       perform a function of indicating presence of the single input  
5       signal structure. Accordingly, it is intended to embrace all  
6       such alternatives, modifications, and variations.

7

2  
3 WAVELET-BASED HYBRID NEUROSYSTEM FOR SIGNAL

4 CLASSIFICATION

5  
6 ABSTRACT OF THE DISCLOSURE

7 The present invention relates to a system and a method for  
8 signal classification. The system comprises a sensor array for  
9 receiving a series of input signals such as acoustic signals,  
10 pixel-based image signal (such as from infrared images  
11 detectors), light signals, temperature signals, etc., a wavelet  
12 transform module for transforming the input signals so that  
13 characteristics of the signals are represented in the form of  
14 wavelet transform coefficients and an array of hybrid neural  
15 networks for classifying the signals into multiple distinct  
16 categories and generating a classification output signal. The  
17 hybrid neural networks each comprise a location neural network  
18 for processing data embedded in the frequency versus time  
19 location segment of the output of the transform module, a  
20 magnitude neural network for processing magnitude information  
21 embedded in the magnitude segment of the output of the transform  
22 module, and a classification neural network for processing the  
23 outputs from the location and magnitude neural networks. A  
24 method for processing the signal using the system of the present  
25 invention is also described.





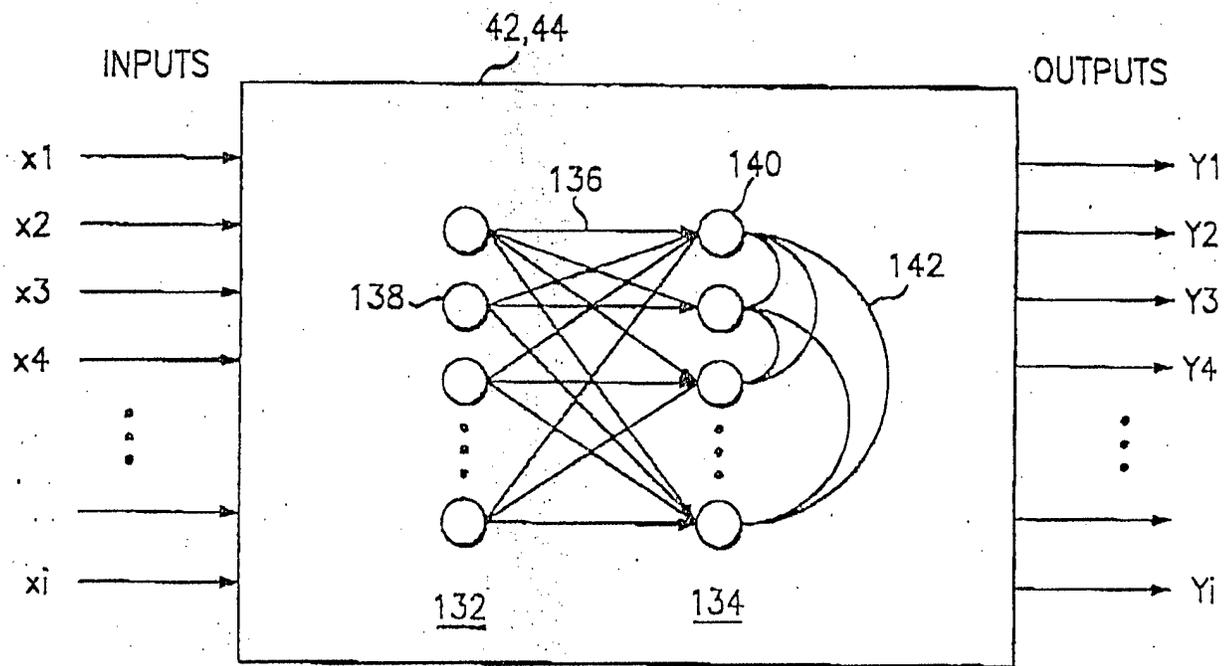


FIG. 3

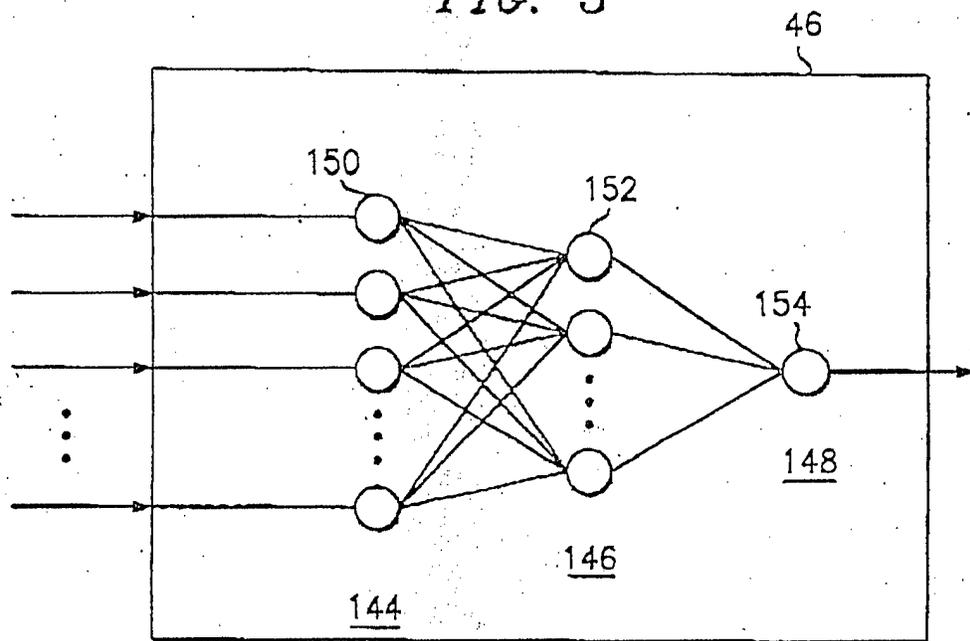
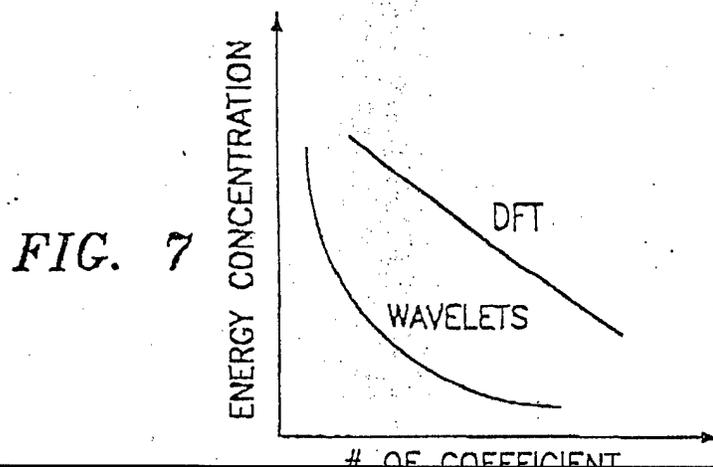
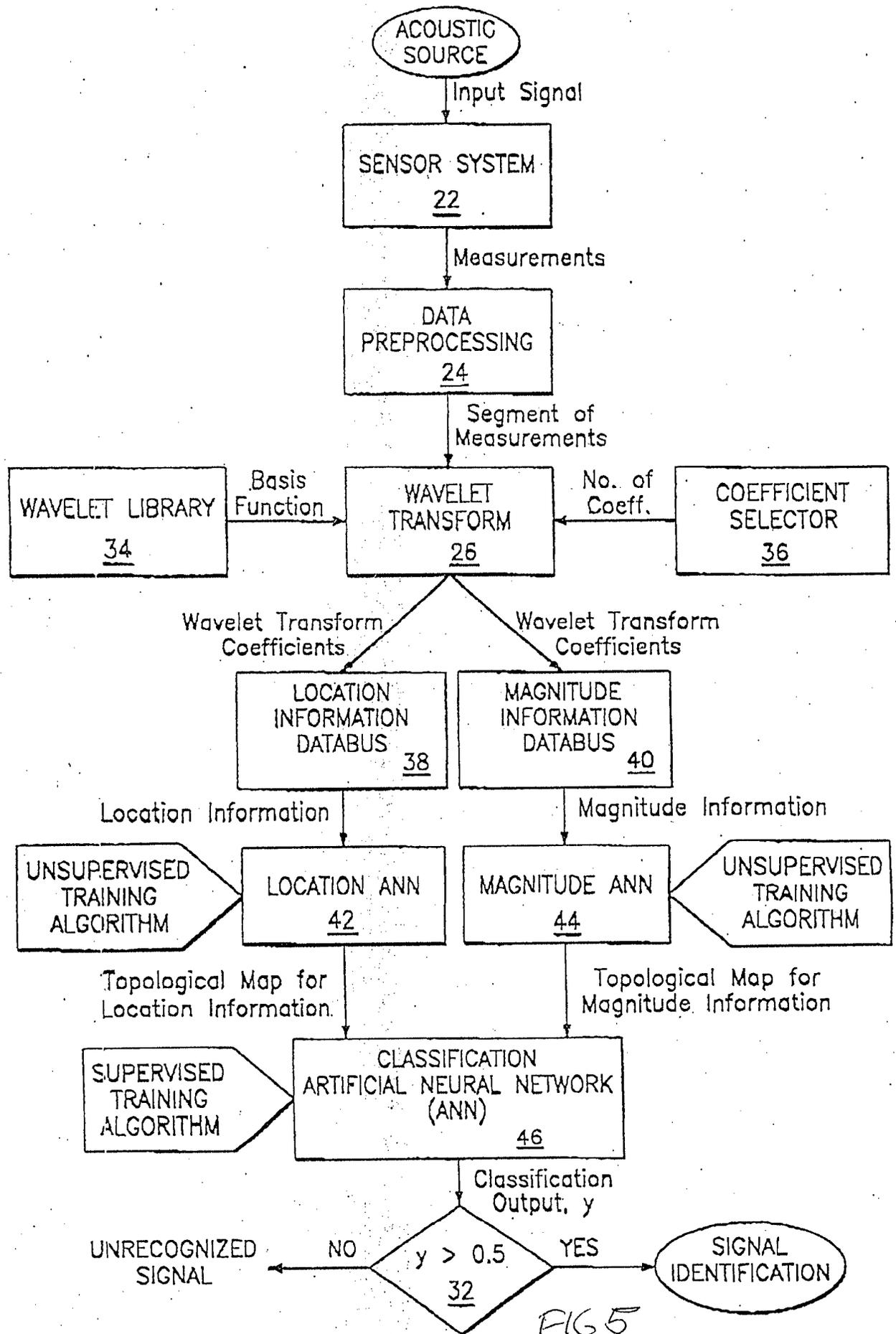
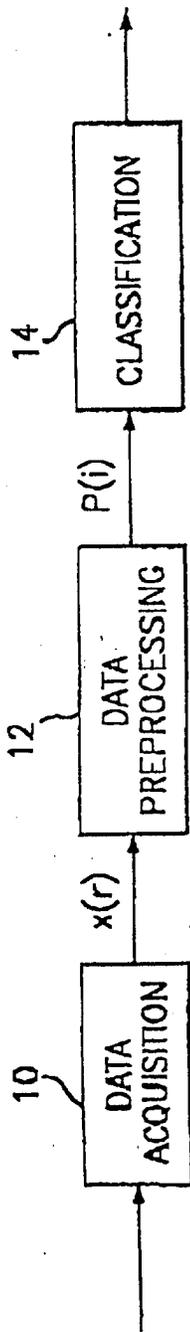


FIG. 4



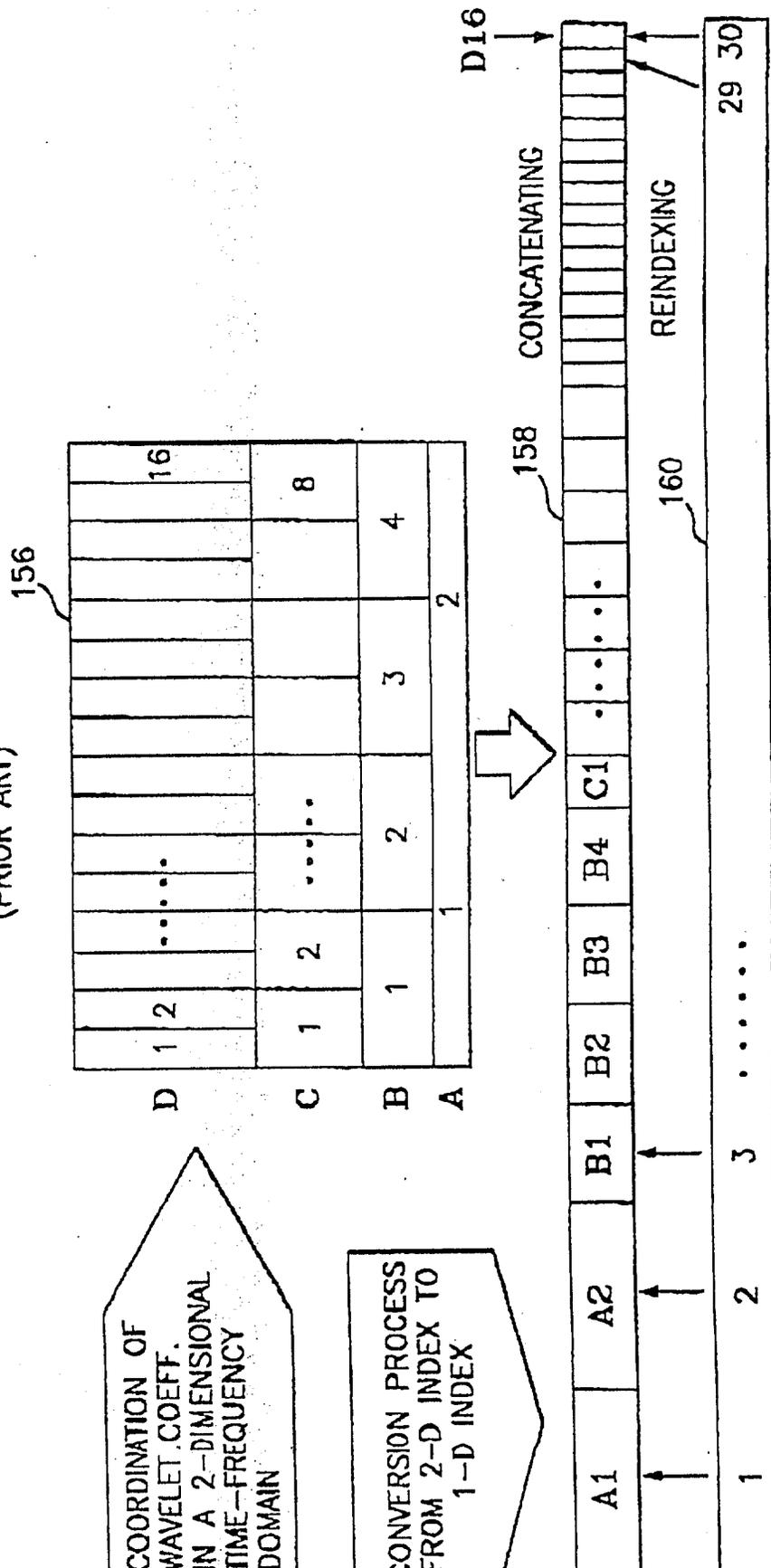




**FIG. 1**  
(PRIOR ART)

COORDINATION OF  
WAVELET COEFF.  
IN A 2-DIMENSIONAL  
TIME-FREQUENCY  
DOMAIN

CONVERSION PROCESS  
FROM 2-D INDEX TO  
1-D INDEX



NEW LOCATION INDICES TO USE IN TRAINING

**FIG. 6**