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An Automated Approach to Passive Sonar Classification Using Binary Image Features

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Abstract: This paper proposes a new method for ship recognition and classification using sound produced and radiated underwater. To do so, a three-step procedure is proposed. First, the preprocessing operations are utilized to reduce noise effects and provide signal for feature extraction. Second, a binary image, made from frequency spectrum of signal segmentation, is formed to extract effective features. Third, a neural classifier is designed to classify the signals. Two approaches, the proposed method and the fractal-based method are compared and tested on real data. The comparative results indicated better recognition ability and more robust performance of the proposed method than the fractal-based method. Therefore, the proposed method could improve the recognition accuracy of underwater acoustic targets.

Keywords: binary image; passive sonar; neural classifier; ship recognition; short-time Fourier transform; fractal-based method

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1 Introduction

For passive sonar, radiated noise has considerable significance. It is designed to utilize the features of this form of noise and to distinguish it from background of self-noise or ambient noise (Urick, 2008). Detecting the target in considerable background noise environments is the major difficulty in passive sonar systems. What makes this important task particularly hard to fulfill in practice is the complexity of underwater sound signals, which are highly noisy and typically include multiple components of a variety of sources such as underwater propeller cavitation, vessel shell vibration and machine rotation. Due to a wide range of applications, both in military and civilian purposes the research on underwater acoustic has particular importance. This includes identification and tracking of ships or submarines via the noise radiated by their machinery components (Urick, 2008; Chen *et al*., 2000; Soares-Filho *et al*., 2001; Yang *et al*., 2002; Lennartsson *et al*., 2006; Rajagopal *et al*., 1990) and underwater acoustic communication (Luo *et al*., 2012; Diamant and Lampe, 2013). This also includes identifying marine mammals (Zimmer *et al*., 2008) and oceanography (Howell and Wood, 2003). For decades, the trained people got used to classify and recognize the class of marine vessels by listening to their radiated noise. Therefore, classical methods involve the operator's ability in these purposes, i.e. the classification and identification of underwater targets, to classify and identify significant features (Rogoyski *et al*., 1994). Substituting these people with intelligent systems is one of the hot topics in signal processing and artificial intelligence. So, employed in sonar signal classification, automatic methods can accelerate the process of decision-making and assist the operators. Moreover, automatic classification of underwater signals is necessary to reduce the operator's load.

Some studies on this special topic of sonar systems used real data of passive sonar to evaluate the performance of their suggested systems while the sonar data acquisition is a time and money-consuming project, so most of the works used the simulated data. The selection of discriminating features and classifiers are two important issues, as well. Implementation issues for hidden Markov models (HMM) can be found in Becchetti and Ricotti (1999), where implementation issues of Markov chains were considered. To develop a sensor-adaptive autonomous underwater vehicle (AUV) technology specifically directed toward rapid environmental assessment and mine countermeasures in coastal environments, a low-frequency sonar system was introduced in Generic Ocean Array Technology Sonar (GOATS) joint research program at MIT (Eickstedt and Schmidt, 2003).

The discriminating features introduced by Lourens (1988) are locations of poles of the second order autoregressive (AR) model. These were used for classifying the noises of three propulsion systems (High-speed diesel, Low speed diesel and Turbine). Sadjadi and Chun (2001) defined four classes of marine vessels. These classes can be recognized by the vessels speed, the blade rate of propeller, the location of tonal components of machinery, the gear noise, the injector noise and the low frequency radiation from hull of marine vessels. All of these features could be extracted from power spectral density (PSD) (Stoica and Moses, 2005) of radiated noise. Li *et al*. (1995) uses six parameters extracted from power spectrum. In this method, a standard feature vector is obtained for each category of ships. Then, the weighted distance between each standard vector and the extracted feature vector from test data is calculated. This distance determines the category to which the test data belongs. There are nine unknown parameters in the feature extraction process and

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nothing is suggested about selection of these parameters in Li *et al*. (1995). Therefore, implementation of this method is difficult or even impossible. The discriminating features suggested in Soares-Filho *et al*. (2000) are based on power spectral density of radiated noise of four different classes of ships. The method in Ward and Stevenson (2000) is based on the short time Fourier transform (STFT) as features and finite impulse response neural network (FIRNN) as classifier. The recorded data by Defense Research Establishment Atlantic were utilized for performance evaluation, using underwater sonobuoys in the Bedford Basin off Nova Scotia, Canada. Farrokhrooz and Karimi (2005) represented the acoustic radiated noise of ships by an AR model with appropriate order and coefficients of this model are used for classification of ships. A probabilistic neural network (PNN) (Duda *et al*., 2000) is used as the classifier and the AR model coefficients are used as the feature vector to this classifier. The performance of this method is examined by using a bank of real data files.

He *et al.* (2010) analyzed the advantages and disadvantages between discriminating features extracted from power spectral density and higher order spectrum, and then they were combined to extract the distinguishable characteristics synthetically. The proposed classifier is a kind of back propagation (BP) neural network (Duda *et al*., 2000) with some modifications. Two sets of discriminating features were proposed in (Farrokhrooz and Karimi, 2011). The first set of features is extracted from AR model of radiated noise and the other is directly extracted from power spectral density of radiated noise. The proposed classifier is the modified probabilistic neural network, which is referred to multi-spread PNN (MS-PNN) and a method for estimating the parameters of classifier. Moreover, other considerable efforts were made to classify and identify ships or underwater targets based on spectral scrutinization approaches (Soares-Filho *et al*., 2000; Zak, 2008; Shi and Hu, 2007), recently on fractal-based approaches (Yang *et al*., 2000; 2002), chaotic features (Yang and Li, 2003) and nonlinear features (Bao *et al*., 2010). Major concern about studies based on fractal approaches is whether ship sounds are fractal signals or not.

These approaches include analysis based on fractional Brownian motion, fractal dimension analysis, and wavelet analysis (Yang *et al*., 2002). Noise sensitivity, excessive extracted features, and complexities of analysis are some demerits of the cited methods. In this paper, an appropriate algorithm is proposed using narrowband and broadband processing, obtained from short-time Fourier transform (STFT). The idea of our method, is relatively simple, and can be divided into 4 steps, including 1) preprocessing, 2) forming the matrix of binary image, 3) extraction features, and 4) neural classification. In addition, a low-pass digital filter processes the digitized incoming signal.

This low-pass filter is an eighth order Chebyshev, ensuring that there are no aliasing effect in the pass-band. Two approaches, the proposed method and the fractal-based method, are compared and tested on real data. The comparative results indicate better recognition ability and more robust performance of the proposed method than the fractal-based method.

The remainder of this paper is organized as follows: Section 2 presents statement of the problem. Section 3 discusses the proposed algorithm. Classification experiments are conducted with fractal based approach in Section 4, showing a remarkable success of our method to extract efficient features and to aim our purpose for ship classification. Finally, our conclusions are drawn in Section 5.

2 Problem formulation

The acoustic radiated noise produced by the vessel's machinery and its motion in sea consists of broadband and narrowband components. The propeller and the hydrodynamic turbulence produce a broadband noise. The propeller, propulsion system and auxiliary machinery produce the narrowband components. Generally, the spectrum of acoustic radiated noise varies with the change of speed (Urick, 2008). Noise spectra are basically of two types. These two spectral types are illustrated diagrammatically in Fig. 1. One type is broadband noise having a continuous spectrum. The other basic type of noise is tonal noise having a discontinuous spectrum. This form of noise consists of tones or sinusoidal components having a spectrum containing line components that occurs at discrete frequencies. The radiated noise of vessels consists of a mixture of these two types of noise over much of the frequency range and may be characterized as having a continuous spectrum containing superposed line components (Urick, 2008).

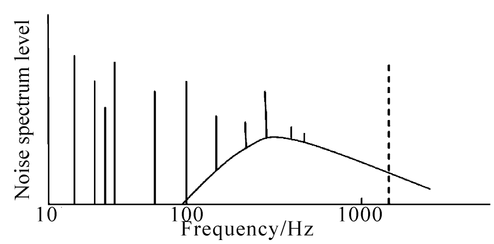


Fig. 1 Typical frequency spectrum of a sample vesel (Bao *et al*., 2010)

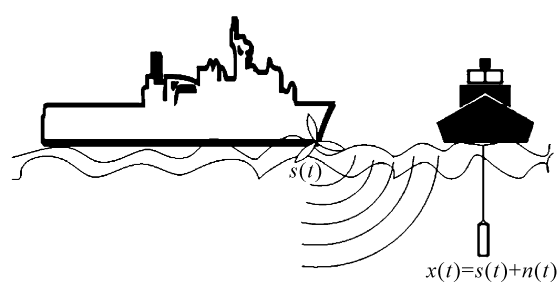


Fig. 2 Possible scenario for sonar operation

Consider the following practical problem. Fig. 2 shows a possible scenario for a sonar operation, in which there is one target: the ship that has a surface contact. In this case, the hydrophone is receiving the signals from the target and the purpose is to identify the class of the target. The noise radiated by vessels is nearly always measured by running the vessel past a stationary distant measurement hydrophone. Various types of hydrophones and hydrophone arrays have been employed for this purpose. The simplest arrangement uses a single hydrophone hung from a small measurement vessel (Urick, 2008).

The system is to be designed with the purpose of examining the underwater acoustic waves received by hydrophone and determining whether an important target is within the reach of the system in order to classify it. To do so, a three-step procedure has been devised. First, the preprocessing operations are utilized to reduce noise effects and provide signal for feature extraction. Second, a binary image, made from frequency spectrum of signal segmentation, is formed to extract effective features. Third, a neural classifier is designed to classify the signals. Considering this, these steps will be dealt with in details in the next section. Before proceeding further, it is necessary to define our model and assumptions as follows:

Assumption

i. The output of the hydrophone will be modeled as $x(t)=s(t)+n(t),$ where $s(t)$ and $n(t)$ are signal and noise waveforms, respectively.
ii. Background noise $n(t)$ is modeled by a spatially and temporally white, zero mean Gaussian random process.
iii. Signal and noise are independent stationary Gaussian process.
iv. There is just one source of underwater sound or sources are sufficiently spaced from each other so that the interference from another source is negligible.
v. The vessel under the test is arranged to run at constant speed and course so as to pass the measurement hydrophone at a known distance.

In addition to these assumptions, there are some conditions on the data used for our purpose. These conditions will be dealt with in Section 4.

3 Algorithm description

3.1 Preprocessing

The first problem that must be handled for the process of marine vessel recognition is signal preprocessing. This section describes the process of existence data preprocessing to extract features and eventually classify data. After acquisition by an analog/digital converter, a well-suited preprocessing can emphasize relevant signal characteristics, optimize the classifier performance, and reduce information redundancy. Since the original sample rate is significantly higher than the signal bandwidth, the sampling rate should be reduced to 2 560 Hz and the signal size set down to 256 points. According to Fig. 1, tonal range of machinery inside the ship is dominated below 1 300 Hz (Urick, 2008), so signal is decimated to reduce the sampling frequency to 2560 Hz. Moreover, each sample is normalized to process unit energy by dividing the square root of its energy (Yang *et al*., 2002) for compensating the distance variation.

The received signal is noisy and this noise is often considered white or Gaussian noise. Signal distribution, which distributes the signal into short time intervals, is one of the noise reduction approaches. Each part of the interval is named as one block with a definite length. During the choice of the time intervals between two consecutive values of digitalized signal, having known sampling period (the inverse of sampling frequency), and care must be taken to guarantee that information is not lost. Therefore, the Nyquist criterion, i.e. the minimum sampling frequency must be greater than twice of the highest frequency component in the original (analogue) signal, and must be satisfied (Oppenheim and Schafer, 1989). Next, a consecutive block of 256 points, without overlapping, is multiplied by a Hanning window. It has equal length and transformed to the frequency domain by short-time Fourier transforms.

The sidelobe effect, caused by the use of a limited time window and the picket-fence effect, caused by the sampling, in the frequency domain are both compensated by the application of a Hanning window (Oppenheim and Schafer, 1989).

$$h(n)=0.5(1-\cos(2n\pi/N)) \tag{1}$$

where N is considered to be the number of samples (data point) and $0\le n\le N$. The value 1 is returned when a one-point window is specified. Now, correlation function of digitized time function can be obtained as follows

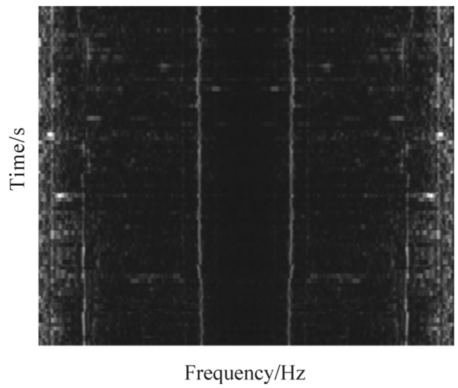
$$r_{xx}(m)=\begin{cases}\sum\limits_{n=0}^{N-m-1} x_{n+m}x_n^*, & m>0\\ r_{xx}^*(-m), & m<0\end{cases} \tag{2}$$

$$c(m)=r_{xx}(m-N) \tag{3}$$

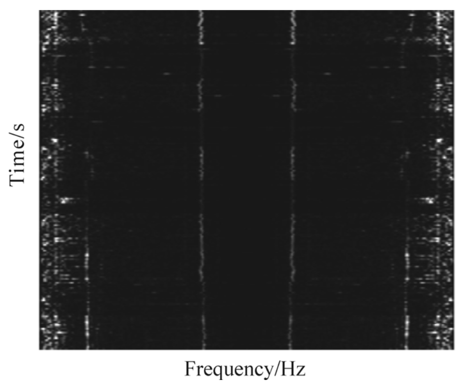
where x is the digitized time function, $c(m)$, $m=1,2,\cdots,2N-1$ is the correlated signal with length N=511, and * denotes the complex conjugate. The operation called correlation is closely related to convolution. In correlation, the value of an output pixel is also computed as a weighted sum of neighboring pixel. The difference is that the matrix of weights, in this case called the correlation kernel, is not rotated during the computation. The advantages of (2) and (3) before Fourier transform of digitized incoming signal are shown in Fig. 3, which displays the noise spectrogram of one of the classes. As displayed in Fig. 3 the outcome spectra has higher resolution and lower noise. By definition, the Fourier transform of $c(m)$ is given by (Orfanidis, 1996)

$$C(\omega)=\sum_{m=0}^{N}c(m)\mathrm{e}^{-\mathrm{j}\omega m} \tag{4}$$

where ω is normalized angular frequency given in radians per sample and related to more traditional notion of frequency, f in Hz by $f=(\omega\cdot f_s)/2\pi$ where f_s is the sampling frequency (in sample per second). Fourier transform is employed to analyze and detect the sound signals in many approaches. Although this transform is proven extremely useful and well established, it has principal difficulties to analyze short-time transient sound behaviors. Assorted short-time Fourier transforms, using a variety of windows with different relative advantages, have been developed to address this problem.



(a) Without correlation function



(b) With correlation function

Fig. 3 One sample spectrogram

3.2 Forming the matrix of binary image

In this section, $\boldsymbol{H}$ matrix is formed. Whole of our analysis get involved with this matrix to accomplish our objective. Feature vectors are achieved by this matrix. In other words, the binary matrix— $\boldsymbol{H}$ matrix is formed and altered to a binary image. The individual features are obtained from the pixel characteristics of this binary image. The innovative method of forming this matrix is as follows:

$$S_{i+1} = (\boldsymbol{c}_{i+1}^{\mathrm{T}} \cdot \boldsymbol{h}) + S_i \tag{5}$$

where $S_0 = 0, i = 0,1,2,\cdots,$ $k = N/256$, $\boldsymbol{h}$ is a vector with Gaussian distribution, $\boldsymbol{c}_{i+1}$ is Fourier transform of any part of distributed incoming signal (T denotes the trasnposition). An important comment to draw from (5) is that convolution operation is utilized to gain preferable image quality. Let

$$G_{i,j} = S_i(j) \tag{6}$$

and

$$G_{n_{i,j}} = \frac{G_{i,j}}{\max\{G_{i,j}\}} \tag{7}$$

where i is the row number and j is the column number of $G_{i,j}$. Then (7) is transformed into the $\boldsymbol{H}$ matrix, a binary matrix which is given by

$$\boldsymbol{H} = \begin{cases} 1, & G_{n_{i,j}} \geq M \\ 0, & G_{n_{i,j}} < M \end{cases} \tag{8}$$

with

$$M = \frac{\sum_{i=1}^{r}\sum_{j=1}^{c} G_{n_{i,j}}}{n_r \times n_c} \tag{9}$$

where n_r is the total row number, and n_c is the total column number of this matrix. Fig. 4 displays $\boldsymbol{H}$ binary image matrix of one of the ship classes. In Fig. 4, just half of the $\boldsymbol{H}$ matrix is shown because of symmetry existent.

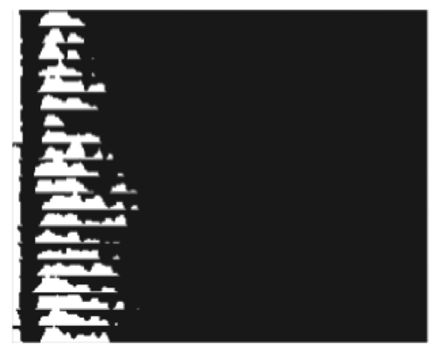


Fig. 4 *H* matrix of one of the ship classes

3.3 Extraction of features

In this step, for features extraction, first of all the value of spectra in frequency interval of $\boldsymbol{H}$ matrix is put into a zero matrix with the same dimensions as $\boldsymbol{H}$ matrix. This zero matrix is named as $\boldsymbol{Q}$ matrix. Then, consider bin intervals as shown in Table 1. After determination of the mentioned intervals, the number of pixels with the value of one in these intervals and the number of total pixels with the value of one in $\boldsymbol{Q}$ matrix are determined. Next, the values calculated from determination intervals are divided into the number of total pixels with the value of one and then put into a vector. Finally, this vector, which has 11 elements, is normalized. One sample of bin intervals selection is shown in Fig. 5.

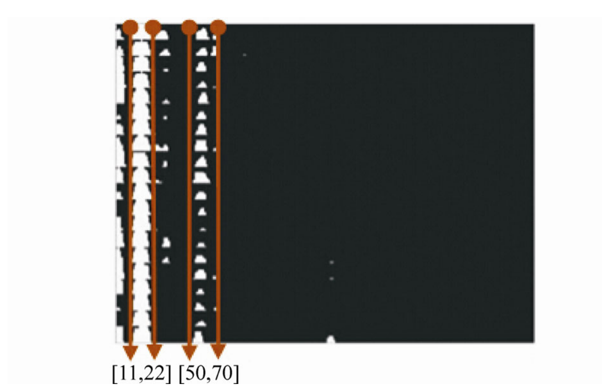


Fig. 5 One sample of bin intervals selection

Table 1 Considered bin intervals

Bin numbers	Bin intervals
Bin (1)	[1, 5]
Bin (2)	[2, 30]
Bin (3)	[2, 45]
Bin (4)	[11, 22]
Bin (5)	[14, 34]
Bin (6)	[18, 60]
Bin (7)	[30, 56]
Bin (8)	[50, 70]
Bin (9)	[70, 100]
Bin (10)	[96, 178]
Bin (11)	[193, 208]

3.4 Neural network classification

Various neural network classifiers using feed forward networks have been proposed in the field of pattern recognition and signal processing. In this paper, a neural network is designed to perform the classification of related sound from ships. The discriminating features are employed to train a neural classifier based on a feed forward neural network. The architecture of neural network is shown in Fig. 6. This network is a three-layer network with 11 input nodes, 7 nodes in the hidden layer and 5 output nodes. The 7 nodes in the hidden layer are found, by a discriminating analysis, to be sufficient for the proposed classification task. Each output node was assigned to one specific class. The network was trained using the back propagation learning algorithm with the learning rate being varied adaptively as a function of the output error. All neurons had hyperbolic tangent function as their activation function.

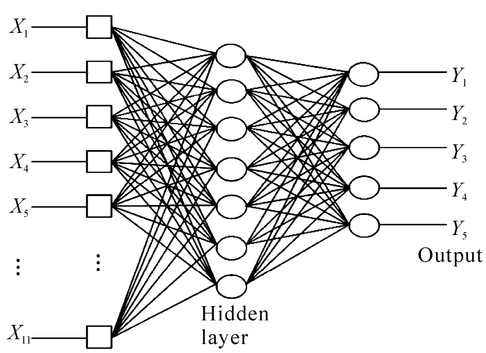


Fig. 6 Architecture of the neural network

The classification efficiency was obtained as the percentage of the spectra of all classes that were correctly classified. As the algorithm's name implies, the errors propagate backwards from the output nodes to the input nodes. Technically speaking, backpropagation calculates the gradient of the error of the network regarding the network's modifiable weights. Backpropagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). The explanation for the ANN would take the following form:

Backpropagation learning algorithm for a 3-layer network (only one hidden layer)

initialize network weights
do
for each training example ex
prediction=neural-net-output(network, ex)
actual=teacher-output (ex)
compute error (prediction-actual) at the output units
compute Δw_h for all weights from hidden layer to output layer
compute Δwi for all weights from input layer to hidden layer
update network weights
until all examples classified correctly or another stopping criterion satisfied
return the network

where, Δw_h is the delta rule for all weights from hidden layer to output layer and Δw_i is the delta rule for all weights from input layer to hidden layer.

4 Experimental results

The above algorithm is applied for spread estimation to a bank of real acoustic radiated noises of marine vessels. The data bank and discriminating features utilized for these data are explained prior to anything.

4.1 Data bank explanation

The suggested algorithm has been used for classification of five different classes of ships including boat, medium ships with weight of 1 248, 2 592, and 3 660 t in three classes, heavy ship with weight of 35 573 t. The number of data files, training files, and test files are 20, 14 and 6, respectively. Firstly, the runs are separated into two groups to be used in the training and testing phase of the classifier. Each signal template contains 256 data points, i.e., samples. The sampling rate is 2 560 Hz. For this sampling rate, 256 data points are enough to capture the essential characteristics of all the transient types. The training and testing sets include examples from 3 different SNR groups (without noise, 5, and 10 dB). The first group is the reference, i.e., without noise, group. The other groups are created by adding more ambient ocean noise to this reference group. It is proven by repeated training and testing experiments that the recognition rate of all training samples is 100%; and the recognition rate of test samples is shown in Tables 2–4. The SNR is computed as the ratio of the peak signal power to the background-noise power expressed in decibels. Thus, some noisy exemplars are also included in our experiments to test the performance of the classifier with low SNR signals. Discriminating feature in this algorithm is percentage of pixels with value of one which is just 11 features. This discriminating feature is selected and suggested by the authors.

4.2 The performance evaluation of the proposed method and the fractal-based method

The performance of the proposed method and the fractal-based method in radiated noise classification is compared in this section. The data bank introduced in subsection 3.1 is used for this comparison.

Table 2 Percent of correct recognition accuracy of the proposed and fractal based method without any added noise %

Method	Target Class					Overall
	1st Class	2nd Class	3nd Class	4th Class	5th Class	
Fractal based method	83.33	100	100	100	83.33	93.33
Proposed method	100	100	100	100	100	100

Table 3 Percent of correct recognition accuracy of the proposed and fractal based method with SNR=5 dB %

Method	Target Class					Overall
	1st Class	2nd Class	3nd Class	4th Class	5th Class	
Fractal based method	56.5	0	80.83	97.33	0	46.93
Proposed method	70.67	99.67	100	100	100	94.07

Table 4 Percent of correct recognition accuracy of the proposed and fractal based method with SNR=10 dB %

Method	Target Class					Overall
	1st Class	2nd Class	3nd Class	4th Class	5th Class	
Fractal based method	58.33	0	97.83	100	0	51.23
Proposed method	76	99.67	100	100	100	95.13

In each performance comparison, some data files from each class are used for training the neural networks and the rest of them are used for performance evaluation. Performance evaluation of the proposed algorithm and fractal based algorithm in noisy condition with SNR=5 dB, SNR=10 dB, and without noise condition are shown in Tables 2–4. The comparative results, presented in Tables 2–4, indicate better recognition ability and more robust performance of the proposed method than the fractal-based method.

5 Conclusions

In this paper, a method that is able to recognize and classify the radiated noise of marine vessels is proposed. In addition, a new approach based on short-time Fourier transform is given to form a binary image to extract effective features. This binary image is made from frequency spectrum of signal segmentations. Extracted features are given to the input of neural network. Next, the kind of vessel will be determined. Experimental results demonstrated the ability of the proposed method. The correct recognition accuracy in these five classes is 94.07% with 5 dB S/N ratio, 95.13% with 10 dB S/N ratio, and 100% without any added noise. At the end, performance evaluation of suggested method shows that the proposed method has better performance in comparison to fractal based method. This algorithm has two considerable advantages, most noise immunity and high performance recognition with just 11 features.

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