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A NEW APPROACH BASED ON WAVELET NERO GENETIC NETWORK FOR AUTOMATIC TARGET RECOGNITION WITH X-BAND DOPPLER RADAR

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ABSTRACT

In this study, a Mexican Hat Wavelet scalogram neural genetic network approach is proposed for signal classification. The Wavelet Scalogram network uses a Levenberg-Marquardt multilayer feed-forward neural network-genetic algorithm hybrid structure, and its input layer constitutes the feature extraction part, whereas the hidden layer and output layer constitute the signal classification part. From the physics point of view, it is shown that the time-shifted, frequency-modulated, and scaled Mexican Hat Wavelet scalogram is available for a basic model for the 1-D target Doppler signal of high-resolution radar. Logarithmic Normalization Method (LNM) was proposed for increasing efficiently of feature extraction phase of Wavelet Nero Genetic Network and classification. Two experiment examples show that the Wavelet Nero Genetic Network (WNGN) approach has a higher recognition rate in radar target recognition from Doppler signals as compared with several existing methods.

Keywords: *Signal representation, Mexican Hat Wavelet Scalogram time-frequency representation, neural network, radar target recognition, genetic algorithms.*

1. INTRODUCTION

There are two important problems in signal classification. One is the feature extraction problem from the input signals, and the other is the problem of classification based on the extracted features. The feature extraction is also called the signal representation; its purpose is to extract some salient features from the raw data collected in the data acquisition phase. Such a representation is called a feature vector [1].

Radars use Doppler frequency to extract target radial velocity (range rate), as well as to distinguish between moving and stationary targets or objects such as clutter. The Doppler phenomenon describes the shift in the center frequency of an incident waveform due to the target motion with respect to the source of radiation. Depending on the direction of the target's motion this frequency shift may be positive or negative. A wave from incident on a target has equipages wave fronts separated by λ, the wavelength. A closing target will cause the reflected equipages wave fronts to get closer to each other (smaller wavelength). Alternatively, an opening or receding target (moving away from the radar) will cause the reflected equipages

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wave fronts to expand (larger wavelength) [2-4]. In former automatic target recognition studies, 1-D Doppler signals of HRR were used directly by being feature. Disadvantages of this method are varied according to time and frequency shift of 1-D Doppler signal. Therefore last studies in this subject used 3-D Time-Frequency Representations (TFR) of these 1-D Doppler signals due to motion compensate and very suitable time-frequency localization features of TFR.

Most of the work in high range resolution (HRR) target recognition has been done by or sponsored by the military. The approaches taken by various researchers as summarized by [1] appear to ignore the benefits that can be gained by proper transformations of the input signal. The wavelet transform [2]-[4] is a new tool has been used in image compression, edge detection, image classification, and more recently, in target recognition. In automatic target recognition (ATR) the most important objective is to separate the various target classes [5]. Some researchers have explored the use of wavelets to provide a richer feature space [5]-[9]. However there is little evidence of widespread use of this technique.

In the past, engineers have used transforms such as the fourier transform to transform the signal from a time base to a frequency base [10]. Although this is useful for some applications, target recognition of HRR signals improved only a little under this transform. The reason for this lies in the fact that the fourier transform tells us that a feature occurs somewhere in the signal, but not where. Wavelets bring a new tool to HRR signal classification. The benefits of using wavelets [11], [12] are that the new transforms are local; i.e., the event is connected to the time when it occurs. Researchers who have used wavelets for target recognition (especially HRR) have found that the original feature space can be augmented by the wavelet coefficients and will yield a smaller set of more robust features in the final classifier [7], [11-14].

The automatic target recognition has been influential method by using Doppler signals in recent years. There are realized some automatic target recognition applications by using classical signal processing techniques and target echo signals in literature, but proposed feature extraction and signal classification methods haven't been found in literature for automatic target recognition HRR X-band radar by using 3-D Time-Frequency Representations (TFR) of 1-D Doppler signals. Advantage of proposed method has better feature extraction than in the case of conventional method. Because, Logarithmic Normalization Method (LNM) was used in here. Detail of LNM will be given in Section 5. In addition, Wavelet Nero Genetic Network (WNGN) approach has a higher recognition rate in radar target recognition from Doppler signals as compared with several existing methods.

In this developed method, 3-D Mexican Hat Wavelet Scalogram Time-Frequency Representations (TFR) of these 1-D Doppler signals was used due to motion compensate and very suitable time-frequency localization features of Wavelets. Wavelets bring a new tool to HRR signal classification. The benefits of using wavelets [15] are that the new transforms are local; i.e., the event is connected to the time when it occurs. Researchers who have used wavelets for target recognition (especially for HRR) have found that the original feature space can be augmented by the wavelet coefficients and will yield a smaller set of more robust features in the final classifier [7], [13], [14].

The rest of this paper is organized as follows. The Mexican Hat Wavelet scalogram is described in Section II. Wavelet Nero Genetic Network is proposed for signal classification in Section III. The developed method is presented in Section IV. The classification is explained to evaluate the effectiveness of the Wavelet Nero Genetic in radar target recognition using real target Doppler signals by comparison with other methods in Section V . The realized weight optimization and classification application by Wavelet Nero Genetic Network Classifier is given in Section VI.

2. WAVELET ANALYSIS

Wavelet analysis has been applied to many geophysical time series over the past ten years by various authors. In its particulars, it remains open to interpretation and debate [5]. The wavelet transform is a useful alternative to the fast Fourier transform (FFT) for spectral analysis. For non-periodic, non-stationary time series, the FFT transform can give spurious results. A wavelet transform, in the most general sense, is the convolution of a given waveform with a function. The waveform (or wavelet) is restricted in that it must integrate to zero over the interval from negative infinity to infinity, as well as over an interval on the order of or shorter than the length of the function being transformed [6]. The convolution is performed for a set of scaled versions of the wavelet. A strong output is given where the shape of the chosen wavelet closely matches the shape of the time series. For wavelets that are essentially periodic over their nonzero interval, this response is related to the frequency content of the time series [7-8].

An example of such a periodic wavelet is the Mexican hat wavelet. It is the negative of the second derivative of a unit area Gaussian given by:

$$g(t')=\left(\frac{1}{2\pi}\right)^{1/2}(1-t'^2)e^{-t'^2/2} \tag{1}$$

The wavelet transform W(t, a_n), is taken at some chosen scale, a_n, by the convolution:

$$W(t,a_n)=\left(\frac{1}{a_n}\right)^{1/2}\int_{-\infty}^{\infty} g\left(\frac{t'-t}{a_n}\right)f(t')dt' \tag{2}$$

where $f(t')$ is 1-D signal.

The Mexican hat wavelet is relatively wide in the spectral domain, meaning that at a given scale the Mexican hat responds to a range of frequencies in the time series. The magnitude of the Continuous Wavelet Transform is called the scalogram. We can make 2 dimensional plots of the scalogram with time on the horizontal axis, scale on the vertical axis, and amplitude given by a gray-scale colour.

The Mexican Hat wavelet and its Fourier Transform are:

$$W(t)=(1-t^2)e^{-t^2/2} \tag{3}$$

$$W(f)=\sqrt{2\pi}(2\pi f)^2 e^{-(2\pi f)^2/2} \tag{4}$$

The scalogram is squared modulus of wavelet transform:

$$S=|W|^2 \tag{5}$$

For above reason, the Mexican hat wavelet scalograms are interesting features in signal classification. A natural question to ask is how to extract the features with more meaningful information from the 3-D space to classify signals efficiently. Unless a sophisticated signal-processing scheme is used to extract some sort of useful information from this huge space, the resulting classification procedure may be too slow for real-time applications. In this context, the artificial neural networks are a very useful signal processing because of their learning and generalizing ability, together with the substantial data-handling capacity by parallel processing. These remarkable properties of neural networks have made them very attractive for numerous engineering applications such as pattern recognition, speech processing, and so on [16]. The genetic algorithm is an optimization technique. The genetic algorithm constituted a hybrid feature extraction and classification algorithm with Levenberg-Marquart neural network in where.

2.1. Time - Frequency Moments of the Mexican Hat Wavelet Transform

When using two-dimensional signal representation it arises the dimensionality problem. For an N-point time series, when the frequency axis of the time-frequency distribution has M points, the signal representation has M x N points. To describe the signal with as few variables as possible, the use of geometric moments is proposed [17]. By using the moments, the reduction of dimensionality is achieved without loosing the classification accuracy.

The time and frequency moments are calculated from the Mexican Hat Wavelet transform of the signal.

$$m_t=\int_{-\infty}^{+\infty} w^p W_x(t,w)dw \tag{6}$$

$$m_f=\int_{-\infty}^{+\infty} t^p W_x(t,w)dt \tag{7}$$

The adequate classification requires a relatively small set of moments [16]. For the purpose of fault signal classification we used first and second order moments.

3. WAVELET NERO GENETIC NETWORK CLASSIFICATION

A genetic algorithm was proposed to determine forty-two optimal input weights of Wavelet neural network. Therefore, Wavelet Nero Genetic Network hybrid algorithm was used in there. Structure of the WNGN hybrid algorithm is shown in Fig. 1.The typical Levenberg-Marquardt (LM) neural network was used in this structure. Inputs of this LM neural network are the underlying signals $\{x_i\ ,\ i=1,.....,N\}$ with $x_i=[x_i(1),.......,x_i(L)]^T$, and outputs are $\{y_m, m=1,...,M\}$. The goal of the WNGN is to classify N signals under consideration into P classes of signals using maximum interclass separability.

3.1. Construction of the Wavelet Nero Genetic Network

Construction of the Wavelet Nero Genetic Network hybrid algorithm is given in Figure 1. Structure of used Levenberg-Marquardt neural network – Genetic algorithm hybrid classifier is given in Figure 2.

Here, the structure of the genetic algorithm is used for determining forty-two optimum initial input weight values of Levenberg-Marquardt neural network classifier.

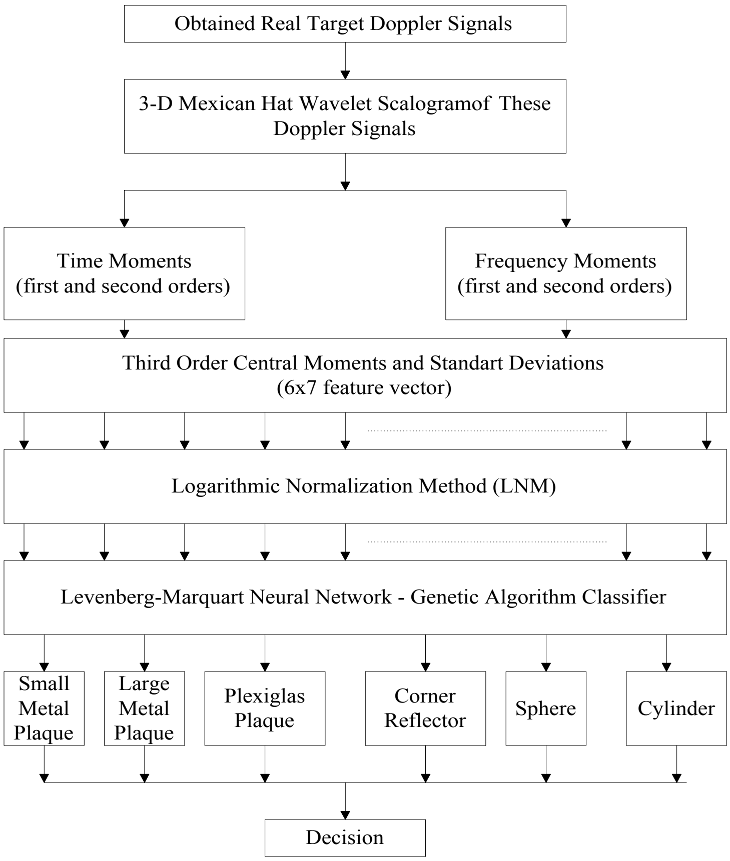

Fig. 1. Block Diagram of the Wavelet Nero Genetic Network

3.2. Algorithm of the Wavelet Nero Genetic Network Classifier

Firstly, twenty random individuals which are formed from total two-hundreds-fifty-two bite was chosen as initial population. Each individual has forty-two initial input weights. Each string at individual explains a weight. Namely, an individual has forty-two strings.

Then, Levenberg-Marquardt neural network was trained by giving each of twenty individuals to input of the Levenberg-Marquardt neural network classifier. After this training, obtained Mean Square Error (MSE) was compared with target error for fitness function and if MSE is smaller than target error, this individual is stored in the memory. If MSE is bigger than target error, this individual is eliminated and another random individual formed instead of eliminated individual. Thus, Levenberg-Marquardt neural network classifier was trained one each for twenty individuals. Then, this obtained twenty individuals were cross over at twenty per cent and was applied to mutation at five per cent.

Initial population was composed with obtained new twenty individuals.

This process is repeated for next generation. We studied for finding optimal initial weights of the Levenberg-Marquardt neural network.

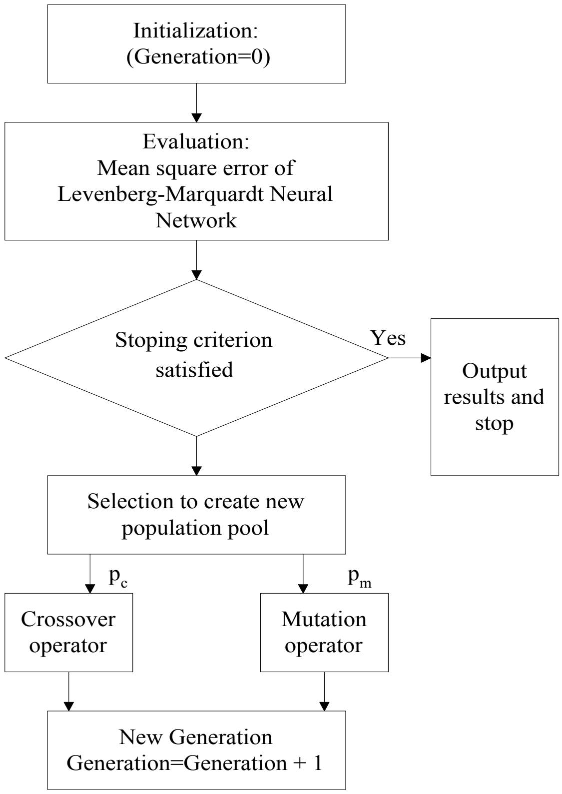

Fig. 2. Structure of the Levenberg- Marquardt neural network – Genetic algorithm hybrid classifier

4. EXPERIMENTAL STUDY

In this study, pulsed radar Doppler signals were used as real input space. An efficient feature extraction method was developed for six target objects to separate one from the others. Experimental application was realized on having educational purpose and multi function 9620/21 Model Lab-Volt radar experiment set. Pulse echo signals were received to computer media by using data accusation card has 1 Khz sample frequency.

The pulsed radar system parameters were adjusted as bellow:

- Pulse width: 1 ns
- RF oscillator: 9.4 Ghz
- Pulse Repeat Frequency (PRF): 216 Hz

Used pattern recognition mechanism and calculate scheme which are given in Figure 1. We can see that the feature extraction is the most important part of pattern recognition system , and directly impresses accomplished of classifier.

4.1. Feature Extraction

The feature extraction is the most important part of pattern recognition and correct pattern classification key. The purposes of the feature extraction from signals both raise the accomplishment of classifier and reduce the classification time. The other advantages are reduce the processed data to minimum level, and prove safe of recognition system. Therefore extracted features aren’t impressed from uncontrolled parameters in system, the extracted features should be determined. Thus, the features may be generalized and security of systems may be raised [18]. Features extraction of unstable signals is commonly interested in composition of the time-frequency region [8], [9]. Thus, definitely data, which includes both transient alteration and frequency alteration, can be extracted from radar Doppler signals. In preceding studies, the stochastic modeling methods, namely, AR(p) and ARMA(p,q) have been applied [17], [18] for the classification of radar returns. They are historically well known for resolving the spectral peaks of a short data record, but this only cannot be the basis for classification. The amount of clutter spectral spread is a good indication of the source of clutter.

An alternative technique based on Scalogram, is proposed for the classification of the radar returns. It is a powerful tool for analyzing time-varying spectra of clutter like signals and has been widely in use for the detection of targets [19].

In this study for feature extraction, firstly real Doppler signals of each of the different targets were received from Lab-Volt Radar education set. Secondly, Mexican Hat Wavelet Scalogram (MHWS) which was given at Equations 1-5 was applied to obtained target Doppler signals. Thus, 3-D dimension images of the target Doppler signals were obtained. Afterwards, first and second orders time and frequency moments of these 3-D images were obtained by using equations (6-7). Standard Deviation (STD) and Second Order Central Moments (CM) for each of these first and second orders time and frequency moments were calculated, but this calculated STD and CM may be very big and very small values. This situation may bring about false classifier results, very big and very small values are divergence, because feature vector was distributed to large space. In this study, Logarithmic Normalization Method was proposed to prevent this divergence problem. The Equation 10 gives formulation of LNM.

Here, φ = standard deviations and second order central moments each of first and second orders time and frequency moments of these 3-D images.

$$f(x) = \left|\log_2(\varphi)\right| \tag{10}$$

Thirdly, Gauss white noise which was given at Equation 11 was applied to obtained standard deviations and second order central moments for testing classification performance of WNGN. SNR ratios of This Gauss white noises were changed as 1, 2, 3, 4 respectively [19], [20].

In conventional method, these obtained standard deviations and second order central moments are used directly as feature vector, but the conventional method has a few disadvantages. These disadvantages are:

1. The obtained feature values may be negative or positive values. This situation isn't wanted for feature vector space. Mostly, we desire all values of the feature vector are positive because of easy and correct classification results.
2. The obtained feature values may be very small or very big. It isn't wanted for feature vector space as well. The more large scale training data, the more difficult classify of this data.

In this study, the proposed method was preferred more than conventional method because of these disadvantages.

Obtained STDs, CMs with conventional method and proposed method were given on Table-1 and Table 2 respectively. For conventional method, maximum feature value was calculated 43623000 and a minimum feature value was calculated 5.3740. For proposed method, maximum feature value was calculated 25.3786 and minimum feature value was calculated 2.4260.

$$c = \sqrt{\frac{\sigma_s^2}{\sigma_w^2 10^{SNR/10}}} \tag{11}$$

Here, σ_s^2 is signal variance, σ_w^2 is noise variance, SNR is signal / noise ratio, c is noise scale constant [21].

The Mexican Hat Wavelet Scalogram of pulsed radar doppler signal of small metal plaque target is shown in Figure 3.

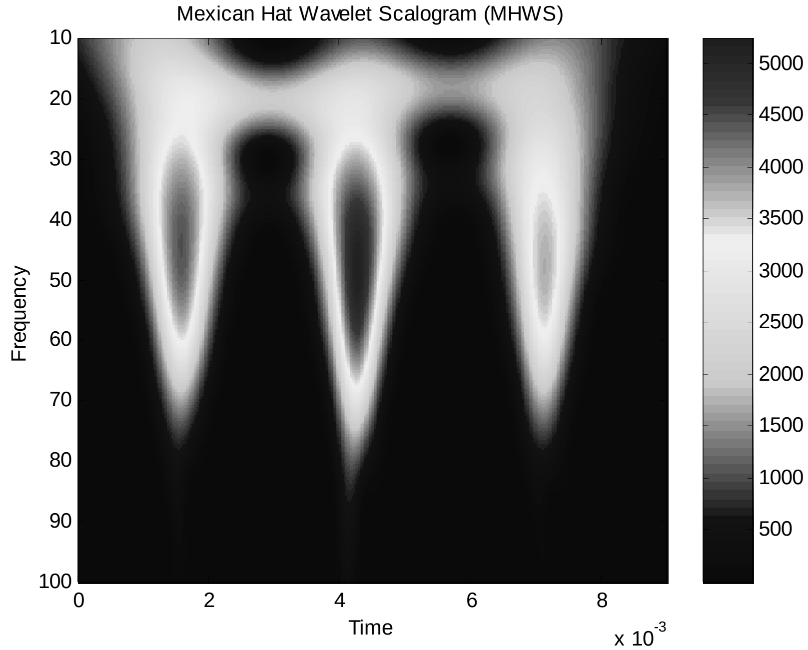

Fig. 3. To be obtained Mexican Hat Wavelet Scalogram of small metal plaque target pulsed radar Doppler signal.

Table 1. Obtained STDs and CMs with the conventional method.

	Obtained standard deviations and second order central moments with the conventional method						
Target Type	**2nd CM of 1th FM**	**STD of 1th FM**	**STD of 2nd FM**	**2nd CM of 1th TM**	**2nd CM of 1th TM**	**STD of 1th TM**	**STD of 2nd TM**
Small Metal Plaque	28.8220	5.3740	2060.7	1595.5	56.4343	133550	365.0626
Large Metal Plaque	396.5888	19.9346	134200	490.5648	31.2915	21071	205.0739
Plexiglas Plaque	1512	38.9216	23217	23434	108.1358	467240	682.8856
Corner Reflector	242.9137	15.6014	6574300	8494.4	92.0726	4682700	3057.2
Sphere	4253.1	65.0015	60616	232.0191	15.2169	43623000	6597.9
Cylinder	110.5381	10.5239	998010	44361	420.8318	2156700	1467.1

Table 2. Obtained STDs and CMs with the proposed method.

	Obtained standard deviations and second order central moments with the proposed method						
Target Type	**2nd CM of 1th FM**	**STD of 1th FM**	**STD of 2nd FM**	**2nd CM of 1th TM**	**2nd CM of 1th TM**	**STD of 1th TM**	**STD of 2nd TM**
Small Metal Plaque	4.8491	2.4260	11.0089	10.6398	5.8185	17.0270	8.5120
Large Metal Plaque	8.6315	4.3172	17.0340	8.9383	4.9677	14.3630	7.6800
Plexiglas Plaque	10.5622	5.2825	14.5029	14.5163	6.7567	18.8338	9.4155
Corner Reflector	7.9243	3.9636	22.6484	13.0523	6.5247	22.1589	11.5780
Sphere	12.0543	6.0224	15.8874	7.8581	3.9276	25.3786	12.6878
Cylinder	6.7884	3.3956	19.9287	15.4370	8.7171	21.0404	10.5188

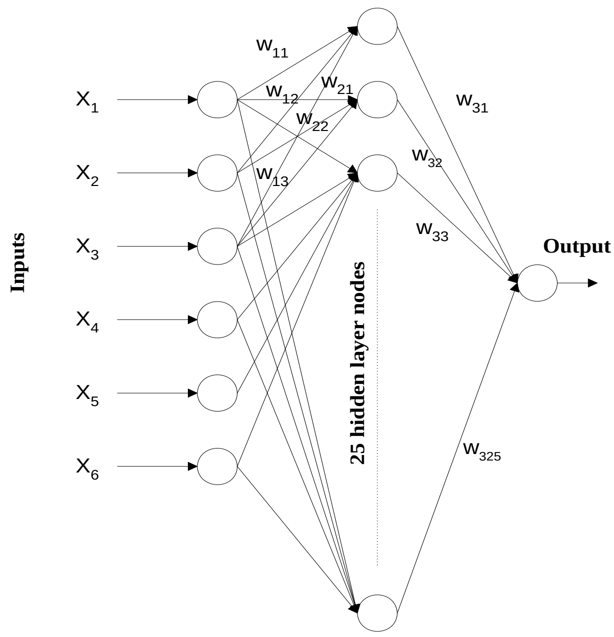

Fig. 4. Used Levenberg-Marquardt (LM) Neural Network Structure.

4.2. The Classification

In this study, input space of the pattern recognition obtained by using feature extraction method which was given in Section 4.1. Then, Wavelet Nero Genetic Network (WNGN) classifier algorithm was used for radar targets classification. In this application, the Levenberg-Marquardt neural network was embedded into WNGN. The purpose of used genetic algorithm in this classifier is optimization of the input weights of the Levenberg- Marquardt neural network

Parameters of Used Levenberg-Marquardt (LM) Neural Network Classifier

The used Levenberg-Marquardt (LM) neural network structure has three layer. Other features of used Levenberg-Marquart neural network structure are given below:

- Input size=6x7

- Training goal=0.0000000001
- Learning rate=0.9
- Output size=6
- Node number of input layer=6
- Node number of hidden layer=25
- Node number of output layer=1

The used Levenberg-Marquardt (LM) Neural Network Structure is given in Figure 4.
Input weights matrix of Levenberg-Marquardt (LM) Neural Network is given as below (Equation 12):

$$w = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} & w_{16} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} & w_{26} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} & w_{36} \\ w_{41} & w_{42} & w_{43} & w_{44} & w_{45} & w_{46} \\ w_{51} & w_{52} & w_{53} & w_{54} & w_{55} & w_{56} \\ w_{61} & w_{62} & w_{63} & w_{64} & w_{65} & w_{66} \\ w_{71} & w_{72} & w_{73} & w_{74} & w_{75} & w_{76} \end{bmatrix} \quad (12)$$

In this study, input space of the pattern recognition was obtained by using feature extraction method which was given in Section 4. Then, Wavelet Nero Genetic Network (WNGN) classifier algorithm was used for radar targets classification. In this application, the Levenberg-Marquardt neural network was embedded into WNGN. The purpose of used genetic algorithm in this classifier is optimization of the input weights of the Levenberg- Marquardt neural network. If initial input weights of neural network is optimized, training time of neural network will shorter than used random initial input weights of neural network. Therefore, we used both Levenberg-Marquardt neural network and genetic algorithm for short time training and more efficient classifying results.

Then, for testing accomplishment of WNGN classifier, Gauss white noise which was given at Equation 11 was applied to this obtained features vector of 3-D time-frequency distribution images. SNR ratios of this Gauss white noises were changed 1, 2, 3, 4 respectively [21-24]. Obtained 6x28 data feature vector which was stated in Section 5.1 was given inputs of LM classifier as input sets. Outputs of this LM classifier formed from a decision space = {small metal plaque, large metal plaque, Plexiglas plaque, corner reflector, sphere, cylinder} that represents six number different real radar targets. Using 6x28 numbers noisy test data for each of six number targets tested this LM classifier. Obtained optimal initial input weights of Levenberg – Marquardt neural network by using WNGN algorithm and generation numbers - training iteration numbers of WNGN algorithm are given on Table 3 and Table 4. The variation space of weights was selected [-1,1] with 0.25 sensitivity. While the generation number of WNGN increases, the iteration number of WNGN decreases and training Mean Square Error (MSE) of Levenberg-Marquardt neural network. The obtained classification performance results of the LM classifier by using most optimal initial input weights that are given on Table 4. Classification performance of Levenberg-Marquardt neural network classifier by using 6x28 test data are given on Table 5 and Table 6

5. CONCLUSION

In this study, proposed feature extraction method in Section 4 was applied to real pulsed radar 1-D Doppler signals. Using WNGN classifier composed A hundred percent determination functions. In addition to, there are clear differences among the determination functions that are seen from Table 5 and Table 6. These indicators show that extracted feature from natural inputs is strong and effective. According to classification performance, the proposed method by using WNGN classifier and LNM is more superior than conventional method as seen on Table 5 and Table 6.

Novelty in our study, it was used 3-D time-frequency distribution images of 1-D Doppler signals and calculated time moments and frequency moments of these 3-D T-F distribution images. Using the proposed WNGN algorithm optimized initial input weights of Levenberg–Marquardt neural network. LNM was added to proposed method in reference 9.

The determination functions of system at decision space are very clear. The features which were selected for feature vector very good summarize [25-28]. In addition to, WNGN is selected as classifier. Because this classifier add learning and decision extraction feature from learned to system. WNGN is a supervised classifier. The other advantage of the proposed WNGN method is using both Levenberg-

Marquardt neural network and genetic algorithm for short time training and more efficient classifying results. If initial input weights of neural network are selected appropriate, the training time will decrease and obtain more efficient classifying results than conventional Levenberg-Marquardt neural network classifier. Because initial input weights is selected random. This situation brings about more long training time. The training and testing times are wanted short at the real time applications. While the generation number of WNGN increases, the training time and iteration number of WNGN and training Mean Square Error (MSE) of Levenberg-Marquardt neural network. Mean square error decreases. This situation is seen on Table 3 and Table 4. Initial input weights on Table 3 were obtained 2-generation number and 351 training iteration numbers with 10^{-7} mean square error. Initial input weights on Table 4 were obtained 24-generation number and 19 training iteration numbers with 10^{-10} mean square error. The obtained classification performance results of the LM classifier by using most optimal initial input weights, which are given Table 4.

In radar pattern recognition studies at the future, systems, which are less, affected by noise and environment may be realized.

Table 3. For generation number = 2 and iteration number = 351, obtained optimal initial input weights of Levenberg – Marquardt neural network by using proposed WNGN algorithm with MSE=10^{-7}.

W_{11}= 0	W_{12}= -0.125	W_{13}= 0	W_{14}= 0.250	W_{15}= 0.125	W_{16}= 0
W_{21}= 0.125	W_{22}= 0.250	W_{23}= 0	W_{24}= -0.125	W_{25}= -0.125	W_{26}= 0.250
W_{31}= 0	W_{32}= 0.50	W_{33}= 0.50	W_{34}= 0.125	W_{35}= 0.125	W_{36}= 0.75
W_{41}= 0.75	W_{42}= -0.125	W_{43}= -0.50	W_{44}= -0.75	W_{45}= 0.50	W_{46}= 0.50
W_{51}= 0.125	W_{52}= 0	W_{53}= -0.50	W_{54}= 0.125	W_{55}= 0.250	W_{56}= -1
W_{61}= -0.125	W_{62}= 0.50	W_{63}= 0.125	W_{64}= 0.75	W_{65}= 0	W_{66}= 0
W71= 0	**W72= 0.50**	**W73= 0.125**	**W74= -0.125**	**W75= 0**	**W76= -0.50**

Table 4. For generation number = 24 and iteration number = 19, obtained optimal initial input weights of Levenberg – Marquardt neural network by using proposed WNGN algorithm with MSE=10^{-10}.

W_{11}= 0.125	W_{12}= 0.250	W_{13}= -1	W_{14}= 0.250	W_{15}= -0.50	W_{16}= 0.50
W_{21}= 0	W_{22}= 0	W_{23}= 0.125	W_{24}= 1	W_{25}= 0.125	W_{26}= -0.50
W_{31}= 0.125	W_{32}= -0.50	W_{33}= 0	W_{34}= -0.125	W_{35}= -0.125	W_{36}= -0.250
W_{41}= 0	W_{42}= 0.125	W_{43}= 0.250	W_{44}= 0.125	W_{45}= 0	W_{46}= -1
W_{51}= 0.250	W_{52}= 0.125	W_{53}= 0.50	W_{54}= 0	W_{55}= 0	W_{56}= -0.50
W_{61}= 0.125	W_{62}= -0.50	W_{63}= 0	W_{64}= 1	W_{65}= -0.75	W_{66}= -0.75
W_{71}= 0.125	W_{72}= 0	W_{73}= -0.125	W_{74}= 0.250	W_{75}= 0.125	W_{76}= 0

Table 5. Achievement of LM Classifier (%) by using conventional method.

Target Object	Small Metal Plaque	Large Metal Plaque	Plexiglas Plaque	Corner Reflector	Sphere	Cylinder
Small Metal Plaque	56.45	7.45	9.60	10.25	7.65	3.15
Large Metal Plaque	10.25	65.25	8.75	7.75	3.45	4.45
Plexiglas Plaque	8.75	8.55	67.55	8.75	4.75	9.65
Corner Reflector	7.65	7.50	5.55	53.25	8.65	7.65
Sphere	4.55	5.75	3.75	10.75	65.75	8.95
Cylinder	12.35	5.50	4.80	9.25	9.75	66.15

Table 6. Achievement of LM Classifier (%) by using proposed (by using LNM and WNGN algorithm) method.

Target Object	Small Metal Plaque	Large Metal Plaque	Plexiglas Plaque	Corner Reflector	Sphere	Cylinder
Small Metal Plaque	85.2	5.75	5.65	2.75	2.25	3.60
Large Metal Plaque	3.55	82.35	3.45	1.5	2.55	3.45
Plexiglas Plaque	2.55	4.8	88	1.75	3.25	2.50
Corner Reflector	2.25	2.4	1.50	90.3	2.75	3.25
Sphere	2	3.05	1	2.15	86.75	3.75
Cylinder	4.25	1.65	0.4	1.55	2.45	83.45

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