International Journal of Research in Engineering, Science and Management
Volume-3, Issue-6, June-2020
www.ijresm.com | ISSN (Online): 2581-5792

Automatic Target Recognition in RADAR at Terahertz Frequencies Using RNN and ANFIS

Ramanaboina Kalyani[1*], Dhanika Srinivas[2]
[1,2]*Assistant Professor, Department of Electronics and Communications Engineering, Vignan Institute of Technology and Science, Deshmukhi, India*
*Corresponding author: kalyani.471@gmail.com

***Abstract*: Automatic target recognition (ATR) in RADAR with very high frequency signal (Terahertz range) is increasingly becoming important primarily for modern defense strategy. Signal processing plays a vital role for extracting the appropriate information (features) to train a soft computing tool such as Neural Network and Fuzzy. The recognition rate of such tools is heavily dependent on the extracted feature. In this paper, an efficient method of target recognition at terahertz frequencies using recurrent neural network (RNN) and adaptive Neuro-Fuzzy interference system (ANFIS) is presented. The ATR algorithm is supported by some efficient signal processing techniques to extract the features of the target. The method adopted for feature extraction in this work is wavelet decomposition. A comparison between RNN and ANFIS for target recognition was made and it is reported here that the ANFIS provides better recognition rate than RNN for target recognition in terahertz frequency.**

***Keywords*: Terahertz, Wavelet transform, RNN, ANFIS, Recognition.**

1. Introduction

The ability to detect and recognize a concealed object quickly and correctly from return signal of radar operated in THz band alone under all weather conditions, is of great importance to automatic target recognition (ATR) systems. ATR is an algorithm that locates or detects potential targets and identifies their type. The performance of an ATR system is quantified with appropriate application of soft computing tools as classifiers. As viewed from the time domain, the target waveform can also be regarded as a time sequence such that it can be classified using Recurrent Neural network, more commonly referred to as RNN (feedback NN) which is suitable for time sequence processing. Another approach is hybrid classifier consisting of Fuzzy logic along with neural network, i.e., adaptive neuro-fuzzy interference system (ANFIS). Depending on the ATR application, the problem may be one of a signal from noise or it may be one of separating a target from its surrounding clutter. Such problem can be overcome by using THz frequency signal which can easily penetrate through most of the elements and a very high- frequency compact radar range has been developed to measure scale models of tactical targets. This compact range has demonstrated very good signal-to-noise and is useful in measuring low observable targets [1].

This work describes an ATR system for use in security and surveillance. In this regard, the first aspect is the processing of THz signal and simulation of RADAR system. High frequency radar generates data sets that have significantly different properties from other data sets used in automatic target recognition (ATR). Data are collected from targets by illuminating them with radar waves, and then sensing the reflected waves with an antenna. In this context, to obtain a sound design for the target recognition, two different soft computing tools i.e. RNN and Neuro-Fuzzy were adopted. The reason behind to use of Neuro-Fuzzy system is the Mamdani model and the Takagi-Sugeno-Kang (TSK) model are universal approximators with the ability to interpret IF-THEN rules [2-6]. The emphasis is also given to extract different features from the Radar Target Signal, so that efficient training of soft-computing tools can be obtained. Wavelet transforms [7] were used for extracting the features. In literature, some researchers have explored the use of wavelets to provide a richer feature space [8], [9]. Famili [10] claimed that preprocessing the data allows easier subsequent feature extraction and increased resolution [11].

2. Methodology

In order to recognize an unknown target involving a radar system in a simulated environment, it is important to first generate the pulse that needs to be transmitted. The generated pulse is detected after it gets reflected from the target. The received echo pulse is analyzed to identify the target. In order to achieve this goal the following steps were followed in this work:

- A LFM (chirp) signal for high frequency RADAR was generated and its signal processing was carried out.
- A high frequency RADAR set up was simulated.
- The complete prototype was developed by creating a target environment.
- Signal processing of the return signal was carried out using Wavelet Packet Transform.
- ATR algorithm for analysis of the return signal was designed.
- The detailed environment was simulated and further interfacing of all the component for final design was

carried out.

- Performance enhancement was attempted.

A. Generation and Processing of LFM signal for High Frequency RADAR

LFM chirp signal defined in equation (1), the spectrum of which has a good approximation with the rectangular pulse was generated with time bandwidth product of 500, where swept bandwidth β=5THz and pulse length τ=100ps. The ps rectangular pulse has a number of side-lobes which will affect the target recognition creating some kind of harmonics; hence, the SNR will be affected. Different windowing techniques were used to suppress the side lobes, details of which are reported in [12].

$$x\,t = e^{j\frac{\pi\beta}{\tau}t^2} \quad ; \frac{-\tau}{2} \le t \le \frac{+\tau}{2} \tag{1}$$

B. High frequency RADAR setup

Transmitter and the receiver are the major component of the RADAR setup. The most critical parameter of a transmitter is the peak transmits power. The required peak power is related to many factors including the maximum unambiguous range, the required SNR at receiver, and the pulse width of the waveform. Among these factors, the required SNR at the receiver is determined by the design goal of Probability of detection (Pd) and Probability of false alarm (PFA), as well as the detection scheme implemented at the receiver [13]. To make the radar system more feasible, pulse integration technique was used to reduce the required SNR. Further reduction of SNR can be achieved by integrating more pulses, but the number of pulses available for integration is normally limited due to the motion of the target or the heterogeneity of the environment. Once obtain the required SNR at receiver, the peak power at the transmitter was calculated using the radar equation.

The function of the receiver is to take the weak echoes from the antenna system, amplify them sufficiently, detect the pulse envelope, amplify the pulses, and feed them to the indicator. It was assumed that the only noise present at the receiver is the thermal noise, so there is no clutter involved in this simulation. The power of the thermal noise is related to the receiver bandwidth. The receiver's noise bandwidth is set to be the same as the bandwidth of the waveform.

In a monostatic radar system, the radiator and the collector share the same antenna, so the antenna was first defined. To simplify the design, a short dipole antenna was chosen for the polarized target as because the polarization of this antenna is linear. For the stationary target, an isotropic antenna [14] was used. The antenna needs to be able to work at the operating frequency of the system (5THz), and hence the antenna's frequency range was set to 5-15 THz.

C. RADAR target environment

A number of different factors determine how much electromagnetic energy returns from the target to the source such as:

- Material of which the target is made;
- Absolute size of the target
- Relative size of the target (in relation to the wavelength of the illuminating radar);
- The incident angle (angle at which the radar beam hits a particular portion of target which depends upon shape of target and its orientation to the radar source);
- Reflected angle (angle at which the reflected beam leaves the part of the target hit, it depends upon incident angle);
- The polarization of transmitted and the received radiation in respect to the orientation of the target.

5 targets of different characteristics were considered, with properties as given in the table 1. The reflected signal is given by:

$$y = \sqrt{G}X \tag{2}$$

where `X' is the incoming signal vector and `G' is the target gain factor, (a dimensionless quantity). Each element of the signal incident on the target is scaled by the gain factor. For polarized waves, the single scalar signal, X, is replaced by a vector signal (EH, EV) with horizontal and vertical components. A scattering matrix, S, replaces the scalar cross section, σ. Through the scattering matrix, the incident horizontal and vertical polarized signals are converted into the reflected horizontal and vertical polarized signals:

$$\begin{bmatrix} E_H \\ E_V \end{bmatrix} = \sqrt{\frac{4\pi}{\lambda^2}} \begin{bmatrix} S_{HH} & S_{VH} \\ S_{HV} & S_{VV} \end{bmatrix} \begin{bmatrix} E_H \\ E_V \end{bmatrix} = \sqrt{\frac{4\pi}{\lambda^2}}\, S \begin{bmatrix} E_H \\ E_V \end{bmatrix} \tag{3}$$

Table 1
Different radar target

Target	Mode	Radar Cross Section	Position in Axis [x:y:z]
Target1	monosatic	1	[700:500:0]
Target2	monosatic	10	[100:300:0]
Target3	monosatic	.001	[380:800:700]
Target4	monosatic	.06	[450:900:600]
Target5	monosatic	100	[50:400:0]

D. Feature extraction using Wavelet transform

There are two important problems in signal classification for radar target recognition. One of them 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 appropriate features from the raw data collected in the data acquisition phase. Such a representation is called a feature vector. In literature, some researchers have explored the use of wavelets to provide a richer feature space [8]. Nevertheless, there is little evidence of widespread use of this technique.

The idea is to decompose the signal into a number of subspaces using the wavelet functions (Symmlet, Daubechies, etc). Such decomposition is usually achieved by translating (pushing to the right or to the left) and scaling (amplifying or attenuating) the selected wavelet function and projecting the signal on the subspace represented by the specific scaling and translation. For wavelet packet decomposition of the Radar Return Echo (RRE) waveforms, the tree structure was used as a binary tree at depth m=1. Wavelet packet decomposition was applied to the RRE signal using the Daubechies-4 wavelet packet with the Shannon entropy defined as:

The norm entropy, of the waveforms was then calculated at the terminal node signals obtained from wavelet packet decomposition, defined as:

$$E\ S\ = -\ \ S^2 \log S^2 \qquad (4)$$

The norm entropy, of the waveforms was then calculated at the terminal node signals obtained from wavelet packet decomposition, defined as:

$$E\ S = \ \frac{S_i\ P}{N}_{\ i} \qquad (5)$$

where, the wavelet packet entropy `E' is a real number, `S' is the terminal node signal and Si is the waveform of terminal node signals. Same as the entropy, the energy and variance of the coefficients with waveform length was calculated.

E. Automatic Target Recognition

Detection and location of different targets buried in ground or constructional walls depends to a great extent on the knowledge of expected target return response [15]. Recurrent Neural Network (RNN) was used to track the time varying contextual information and subsequently to make discrimination between adjacent targets [16]. The RNN model that has been developed is shown in Figure 1.

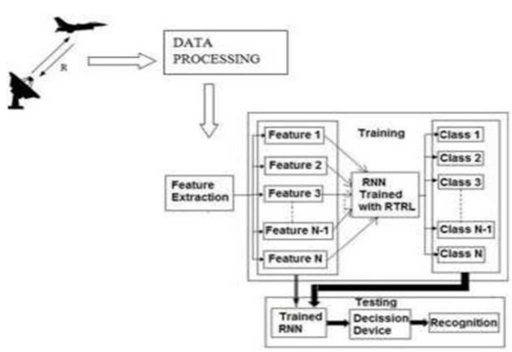

Fig. 1. System model of the RNN based ATR System

The model is constituted by an RNN which performs target recognition using returns received signal. The training data set is prepared by certain efficient signal processing steps as discussed above. Five different targets of different RCS is considered with different position as mentioned in Table 1. The data are arranged in columns to train the RNN and in testing phase some variety of databases are collected by changing the environmental parameters. Before training a feedback network, the weight and biases must be initialized. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed forward networks is mean square errors. The network was trained by using three back propagation algorithms, namely: Levenberg-Marquadt (LM) backpropagation algorithm, Quasi-Newton back propagation algorithm and Scaled Conjugate Gradient (SCG) back propagation algorithm.

The difficulties associated with ANNs include dimensionality and generalization related problems. A better approach incorporated here is a hybrid system consisting of Neural Network and Fuzzy logic. Designing of a soft computing algorithm for ATR in THz frequency band RADAR using Fuzzy-Neuro/Neuro-Fuzzy is a main concern here. Adaptive Neuro fuzzy inference system (ANFIS) is a kind of neural network that is based on Takagi Sugeno fuzzy inference system. Here ANFIS was used for recognition. Two parameters x and y were used as input and output by using segmentation and feature extraction data. Then Membership Function (MF) and type of Membership function and the epoch number to train data and get output were set. The designed ANFIS consist of six layers namely: Input node layer, Degree of membership layer, Rule node layer, Normalization layer, Defuzzification layer and Output layer. To perform parameter adjustments in learning, ANFIS needs partitioning of the input space according to the target classes.

3. Results and Discussion

The analysis carried out is primarily the receiver operating characteristics (ROC) which represent the relationship between Pd, PFA and SNR. Figure 2 shows the ROC for different SNR with and without pulse integration technique.

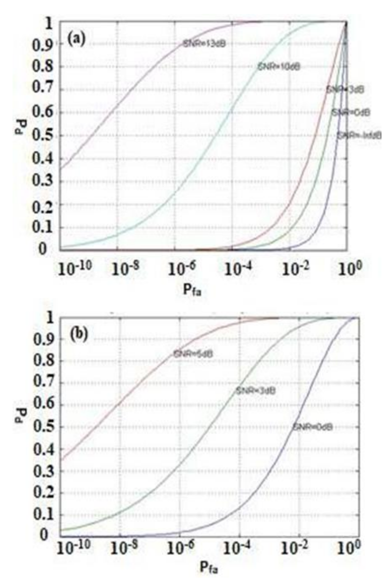

Fig. 2. (a) ROC curve without numerical pulse integration and (b) ROC curve with numerical pulse integration

The radar signal is then transmitted to the direction of the simulated targets using a radiator, and then, the reflected echoes are collected using the collector. The spectral analysis of the reflected signal was carried out, and from Figures. 3(a) and 3(b), it is shown that most of the energy of the LFM return echo is compressed into a narrower spike, which determines the target detection. The energy spectral density (spectral analysis of the signal) is the important factor, difference in which gives the information related to the desired target.

From this part a big matrix of complex data containing the different characteristics of all targets are received. Hence now it is important to extract out the more convenient features of different targets.

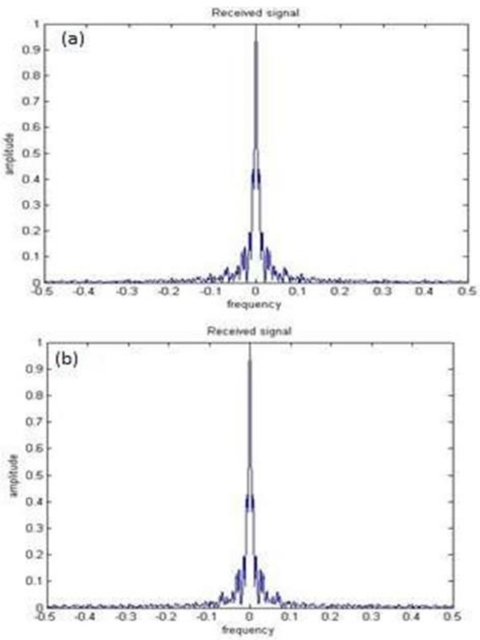

Fig. 3. (a) Spectrum of the reflected signal from Target 1 and (b) Spectrum of the reflected signal from Target 2

Each return echo from target contains a matrix of 200X20 for twenty numbers of pulses. After extracting feature using wavelet packet transform up to one level, it contains one (20 = 1) feature in level 0 and two (21 = 2) features in level 1. So all together the matrix contains 6X3 for a single pulse. Since one target contain twenty pulses and due to feature extraction we get 6X3 matrix for one pulse, so all total 20 pulses contain a matrix of 6X60. Analyzing the feature vector, it is seen that the first columns of all the pulses of one target is almost similar as well as the second and third columns also. So separating the first columns of one target in to a different vector i.e. `X' and second and third columns in to another vector i.e. `Y' and `Z' respectively and mean of each three vectors were calculated separately. This same process is applied to the other targets and at the end it was found that each target contains a data of 6X3. In the next process this data is used to train a neuro-fuzzy system.

Recurrent networks are the state of the art in nonlinear time series prediction, system identification, and temporal pattern classification. As the output of the network at time ‘t’ is used along with a new input to compute the output of the network at time t + 1, the response of the network is dynamic [16]. At each time step, new inputs are fed to the network. The previous contents of the hidden layer are passed into the context layer. These then feed back into the hidden layer in the next time step [17, 18]. The training algorithm used is TLRN (back propagation through time), which is more advanced than standard back propagation algorithm [19-23].

The design parameter for RNN is shown in Table 2. Figure 4(a) shows the structure of the network which shows the connection between three layers and number of neurons in each layer.

Table 2
Design specifications of RNN

No. of neurons in input Layer	6
No of neurons in Hidden Layer	20
No. of neurons in output Layer	6
No of epochs	2000
Transfer Function Used	tansig
Adaption Learning Function	gradient descent back propagation
Performance Function	MSE
Network Type	Elman Back propagation
Goal	0.001

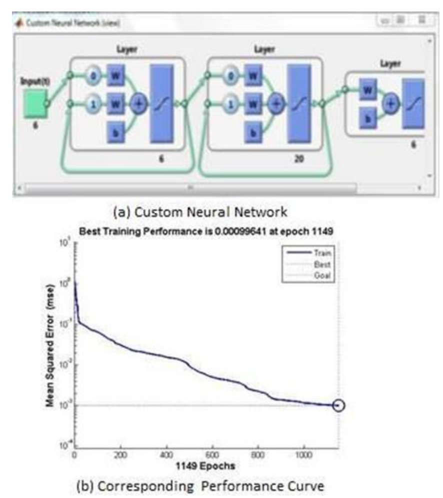

Fig. 4. Custom RNN and its Performance Curve

The input to the neural network consists of the feature vectors that are extracted from the received echo of each target. The wavelet packet transform decompose radar return signal in to a 6X60 matrix. The radar return signal of five targets consists of 200X100 matrix, which gets reduced to 6X300 after feature extraction. This 6X300 is the input of the neural network. A neural network target is given against the input vector which has same number of columns with that of the input. The neural network is now trained by applying gradient descent algorithm. The MSE curve shows the performance of the training in Figure 4(b). The maximum error goal is set to 0.001 so that it can give almost 100% accuracy of recognition. The training stops when set minimum goal is reached. The trained network is at first tested with same data and later tested with data that are collected in different environment but having the target parameters as it was before. We can conclude from the Table 3 that this system shows recognition with average 80% accuracy.

Table 3
Testing table for RNN

Title	Target				
	1	2	3	4	5
Total no. of samples	20	20	20	20	20
Correct Recognition	17	16	16	16	15
Incorrect Recognition	3	4	4	4	5
Recognition Rate	85%	80%	80%	80%	75%

To perform parameter adjustments in learning, ANFIS needs partitioning of the input space according to the target classes. The design specification of the ANFIS system is shown in Table 4.

Table 4
Design Specification of ANFIS

No. of FIS	5
No. of Class in each FIS	3
No. of Membership Function in each Class	3
No. of Output against one FIS	1
Type of Membership Function	Gaussian
No. of Epoch	200
Error Tolerance	0.001

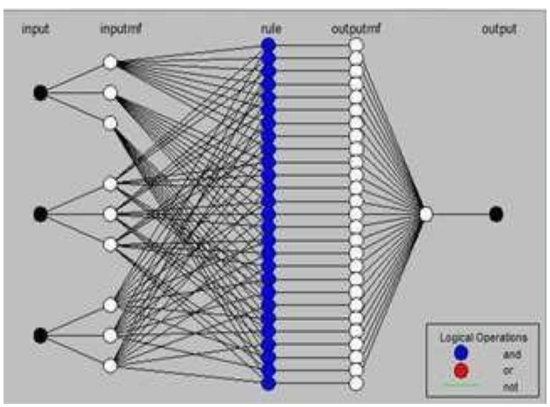

Fig. 5. FIS structure

The whole dataset for one target is (6X3). Now a target for ANFIS is given against this data and a FIS is made by following the above specification. The generated FIS is now trained with the given input. When the training reached the minimum goal mentioned, the process stops. Now the FIS is tested with the trained data and if training is good then the FIS output and train output is overlapped. This FIS is then exported to a file so that it can be used for testing. Likewise, all total five FIS is made for five different targets. Figure 5 shows the FIS structure of one target, and it is seen that for one target it takes the total no of input as 3 as because after combining the first columns together and so on with second and third columns, hence a single target will consist of (6X3) matrix. For each input it takes three membership functions and according to the data the membership function is fitted. After completing the process of making FIS this is now evaluated to understand whether it recognize the trained data or not. The FIS is trained with the separated mean of columns that contain size of (6X300) matrix but in case of testing, the FIS was tested with each pulse without calculating the mean and it is found that almost 100% recognition is achieved. After testing it for twenty pulses, it is tested with other data that are collected with same target but a little change in environmental parameter. This process is continued for all the targets and the recognition accuracy is given in the following Table 5.

Table 5
Testing table for ANFIS

Title	Target				
	1	2	3	4	5
Total no. of samples	20	20	20	20	20
Correct Recognition	18	19	17	16	16
Incorrect Recognition	2	1	3	4	4
The average recognition	90%	95%	85%	80%	80%

The simulation results clearly demonstrate that the adaptive neuro-fuzzy yields improved performance than other networks like ANN as adaptive neuro-fuzzy is a modification of neural network and fuzzy system architecture. The train network is then test for multiple times using same as the training data and gives almost 100% accuracy.

4. Conclusion

Automatic target recognition at terahertz frequency plays a vital role in modern day security system. A comparative study of ATR based on RNN and ANFIS is presented here. With the same data set as a feature vector for both, it was found that the ANFIS performs better than the RNN in case of ATR in terahertz frequency. Twenty sets of samples for each of 5 targets were used to test both RNN and ANFIS system. The average correct recognition rate for RNN was 80% and it was enhanced to 86% while using ANFIS. So it can be concluded that the ANFIS can outperform for target recognition in terahertz frequency with feature sets derived from wavelet decomposition. The atmosphere is the most significant factor in limiting the performance of ATR system in THz frequency band. In real time implements the Terrestrial signals sent at THz frequencies can experience extreme atmospheric absorption, due primarily to water vapor and oxygen. Hence it is best suitable for short distance communications only. The recognition algorithm is designed by considering certain ideal conditions and as such for a variety of environmental conditions giving completely different dataset of same target may not be recognized properly. It is seen that the training process of the neural network take a considerable amount of time. In this regard here the Sugeno model of the Fuzzy Logic has been used in this work. However, handling of data in single fuzzy system exhibit memory related issues which can possibly be minimized by applying different Fuzzy techniques.

References

[1] Quek C., and Zhou R. W. (1996), 'POPFNN-AAR(S): a pseudo outer-product based fuzzy neural network', Neural Networks, Elsevier vol. 9, no. 9, pp. 1569-1581,

[2] Ang K. K., Quek, C., and Pasquier M. (2003), 'POPFNN-CRI(S): pseudo outer product based fuzzy neural network using the compositional rule of inference and singleton fuzzifier', IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 33, no. 6, pp. 838-849.

[3] Antonini M., Barlaud M, Mathieu P., and Daubechies I. (1992), 'Image coding using wavelet transform', IEEE Transactions in Image Processing, vol. 1, pp. 205-220.

[4] Mallat, S. (1991), 'Zero-crossings of a wavelet transform', IEEE Transactions on Information Theory, vol. 37, pp. 1019-1033.

[5] Stirman C., and Nachman A. (1991), 'Applications of wavelets to radar data processing', Defense Technical Information Center, Technical Report, vol. 297.

[6] Famili, A., Wei-Min, S., Weber, R., and Simoudis E (1997), 'Data preprocessing and intelligent data analysis', Intelligent Data Analysis, Elsevier, vol. 1, No. 1-4, pp. 3-23.

[7] Mark J. Rosker and H. Bruce Wallace (2007), 'Imaging Through the Atmosphere at Terahertz Frequencies', IEEE/MTT-S International Microwave Symposium,

[8] Kaustubh Bhattacharyya and Kandarpa Kumar Sarma (2012), 'Automatic Target Recognition (ATR) System using Recurrent Neural Network (RNN) for Pulse Radar', International Journal of Computer Applications, vol. 50.

[9] Goller C. and Kuchler A. (1996), 'Learning task-dependent distributed representations by backpropagation through structure', Proceedings of International Conference on Neural Networks (ICNN'96), IEEE.

[10] Griewank Andreas and Andrea Walther (2008), 'Evaluating Derivatives: Principles and Techniques of Algorithmic Differentiation', Second Edition.