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ENHANCED ARTIFICIAL NEURAL NETWORK ALGORITHMS FOR FAST RADAR THREATS IDENTIFICATION

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ABSTRACT

In this paper, an enhanced algorithm for radar threat identification and based on the artificial neural network (ANN) is proposed. Four radar parameters are used as the inputs for the suggested ANNs. These parameters are: 1) the radio frequency, 2) the pulse repetition frequency, 3) the pulse width, and 4) the scan rate. A lot of work has been done to select the suitable structure of the ANNs. The chosen ANNs achieve minimum sum square errors and short time training. Also, they provide the highest success rate over all the examined networks. It is found that, one can choose a single hidden layer ANN structure with 12 nodes in the hidden layer or a double hidden layer with six nodes in each hidden layer. These ANN provide 100% success rate. Due to the simplicity of the ANNs structure, it can be used for on-line analysis. To use the developed ANN algorithms for radar threat identification in the on-line analysis, the main requirement is to finish the training phase beforehand.

KEYWORDS

Radar Identifications, Neural Networks,

Egyptian Armed Forces

I. Introduction

Radar is a key sensor in most modern weapon systems. Its ability to function in all weather environments at long ranges is unmatched by any other available sensor. Thus, it is used extensively in control and guidance of weapon systems. Hence, it is a prime target for electronic warfare. There are many classifications for radar types [1] from different points of view. First, according to the radar location (Land-based, Naval, Airborne, and Space-based radars). Second, according to the radar application (Surveillance, Target acquisition, Weapon control, Aircraft control, Missile guidance, Navigation and Mapping radars). Third, according to the design principles (2-D search, 3-D search, Moving target indicator, Pulse Doppler and Special purpose radars).

Knowing the correct type of the intercepted radar signal is important in Electronic Intelligence (ELINT) applications for two reasons. First, helps to determine the threats and the priority. Second, determines the suitable counter actions against these threats. In this paper some enhanced artificial neural network (ANN) algorithms are used for solving the problem of radar threats identification. In the ANNs approach, all the extracted radar parameters are considered simultaneously. So, the time order of applying the extracted parameters does not affect on the probability of correct decision about the radar type. For that reason, it is suggested that the use of the ANN approach in radar identification process may have better performance than the decision theoretic approach (threat libirary). The ANNs are successful in many practical applications including control [4], signal processing [5], pattern recognition [6], modeling [7], manufacturing processes [8] and modulation recognition process [9]. In the next section we introduce the suggested structure of the ANN for the radar types identification process. In Sec. III, the choice of ANN architectures and the method of speed up the computations are introduced. A summary of the results of the behavior of ANN in radar identification problemis introduced in Sec.IV . Finally, the paper is concluded in Sec. V.

II. Suggested Structure for ANN Based Radar Types Classification

The developed algorithm based on the ANN approach is composed of three main blocks. These are: A) the pre-processing in which the required radar parameters are extracted from every realization as well as the data sets used in training and test phases of the ANNs are determined, B) training and learning phase to adjust the identifier structure, and C) test phase to decide about the type of the intercepted signal.

A) The Pre-processing

In this work, the identification of radar types depends on comparison of the intercepted radar parameters with the parameters of well-known radars. These parameters include, carrier frequency, pulse repetition frequency, pulse width, and antenna scan rate. It is worth noting that the extraction of the suitable radar parameters should be finished in a pre-processing stage. Assuming that there are Ms data sets available about each of the radar of interest. Some of the available Ms data sets are used in the training phase to adjust the ANN structure, while the others are used in the test phase to measure the performance and to decide about the intercepted radar type. In the proposed ANN algorithm, from each simulated radar type (500 realizations) the first 100 realizations are used in the training phase. Meanwhile, in the test phase, all the simulated realizations are used to measure the performance.

Some suggested methods for measuring the specified radar parameters are presented in this paper. The radio frequency of a signal can be estimated in the frequency domain, using either the periodogram or the frequency-centred method. In the periodogram method, the carrier is estimated as the location of the largest peak of the average spectrum. As the spectrum of radar signals have a carrier component, this method may be good for carrier frequency estimation but it requires long signal duration (average). Also, the carrier frequency can be estimated using the frequency-centred method [9] as

$$f_c = \frac{\sum_{i=1}^{N} i\left|Z(i)\right|}{\sum_{i=1}^{N} \left|Z(i)\right|} \tag{1}$$

where $\{Z(i)\}$ is the squared spectrum sequence of the analytic signal associated with a real signal. Also, the carrier frequency can be estimated in the time-domain using the zero-crossings of the RF signal. So, the carrier frequency can be estimated [9] as follows

$$f_c \quad \frac{Mx \ - 1}{\sum_{i=1}^{N} y(i)} \tag{2}$$

where Mx is the number of zero-crossings in the received radar pulse and $\{y(i)\}$ is the zeros-crossing difference sequence.

There are many practical techniques for pulse repetition interval and pulse width estimation [10]. It is well known that the radar signals have (Sin (x) / x)2 spectrum shape with main lobe width equals to twice the reciprocal of the pulse width and the spectral lines separation equals the PRF. Thus, by observing the averaged spectrum one can estimate the

PRF and PW of a radar signal. Furthermore, [10] presents three methods for symbol transition sequence extraction and they can be used for automatic pulse width and pulse repetition interval measurement. These are: 1) the zero-crossing, 2) the derivative and 3) the Wavelet transform methods. After determining the pulses transitions sequences by one of these three methods, the differences between successive transitions are calculated. For fixed radar parameters, the results will be one of two values. The smallest one is corresponding to the pulse width and the largest one is corresponding to the pulse repetition interval.

Ten radar types are selected from [11] to check the ability of using the developed ANN algorithm in radar types identification problem. The parameters of the radar types under consideration are listed as a sample library in Table 1. It is clear that, some of the parameters have fixed values (single or a list of values) such as the pulse repetition frequency, the pulse width, and the scan rate. On the other hand, the radio frequency takes a range of values. The specified parameters for the selected radars are generated with some tolerance (10%) to increase the degree of realism.

Table 1: List of Radar Parameters of Interest.

Types	Radio Frequency (MHz)	Pulse Repetition Frequency (Hz)	Pulse Width (μ sec.)	Scan Rate (RPM)
Radar 1	1250 – 1350	774	13, 26, 39	6, 12, 15
Radar 2	1250 – 1350	667, 800	2.9, 3.5	20, 22
Radar 3	2700 – 2900	300, 405	2	7.5
Radar 4	2900 – 3100	250	6.5	6
Radar 5	3100 – 3400	2793, 5050	10.75	12,20
Radar 6	9275 – 9475	200, 4500	0.8, 1.5	24
Radar 7	10000 – 10250	8600	6.25	1, 2
Radar 8	9000 – 13500	1900, 205 0	0.5, 1.75	16, 44
Radar 9	1250 – 1350	244	6	3.3, 5, 6.6, 10
Radar 10	9320 – 9430	200, 300, 800	0.38, 1, 2.5	4.5, 8, 12

B) Training Phase

The objective of training a network is to find the optimum weights and biases to minimize the error between the network output and the correct response. There are many types of learning methods to achieve the minimum error [12]. These are error-correction learning (back propagation), Hebbian learning, competitive learning, and Boltzman learning. A popular criterion is the minimum mean squared error between the network output and the correct response. Also, there are many learning paradigms such as supervised, unsupervised, and self-organized learning [2]. In supervised learning, the training data must be provided in terms of input/output pairs denoted as [X, T] = { [x1, t1], [x2, t2], ... , [xL, tL] }, where xi is a (Ix1) vector and I is the number of nodes in the input layer, ti is a (Ox1) vector, O is the number of nodes in the output layer, and L is the number of training pairs. Both the back propagation and the supervised learning paradigm are used in all the developed ANN algorithms introduced in this paper. The chosen ANNs are adaptively trained using momentum back propagation learning. In this paper, all the networks used are adaptively trained to reduce the sum squared error, SSE, defined in terms of the difference between the calculated output and the actual target. The training SSE for the two network types is defined as follows

1- In the network with single hidden layer, the SSE is defined by

$$SSE = \sum_{i=1}^{O} \sum_{j=1}^{L} E \ (i, j), \qquad (3)$$

where,

$$E = (T - A2\ )2 \qquad (4)$$

T is the actual target and A2 is the calculated target and is given by

$$A2 = W2 \ Log\_sigmoid \ \{W1 \ Pin + B1\} + B2 \qquad (5)$$

W1 and B1 are the weights and biases of the hidden layer containing S nodes, W2 and B2 are the weights and biases of the output layer, and Pin is the input data vector. The activation functions associated with the hidden layer is the Log_sigmoid function [9] and that associated with the output layer is the Linear function [9]. Let the number of realizations used for training be L. The dimensions of all the matrices and vectors used can be expressed as follows: Pin, W1, B1, b1, A1, W2, B2, b2, and A2, are respectively (IxL), (SxI), (SxL), (Sx1), (SxL), (OxS), (OxL), (Ox1), and (OxL) matrices and B1 is given by [b1, ..., b1], and B2 is given by [b2, ..., b2].

2- For the double hidden layer, the SSE is as given by (3) but (4) is re-expressed by

$$E = (\ T - A3\ )2 \qquad (6)$$

Where, A3 is the calculated target and it is given by

$$A3 = Log\_sig\{W3[Linear\{W2[Log\_sig\{W1Pin+B1\ \} +B2]\}]+B3\} \qquad (7)$$

W1 and B1 are the weights and biases of the first hidden layer containing S1 nodes, W2 and B2 are the weights and biases of the second hidden layer containing S2 nodes, W3 and B3 are the weights and biases of the output layer, and Pin is the input data vector. The activation functions associated with the first hidden layers and the output layer are the Log_sigmoid function [9] and that associated with the second hidden layer is the Linear function [9]. Let the number of realizations used for training be L. The dimensions of all the matrices and vectors used can be expressed as follows: Pin, W1, B1, b1, A1, W2, B2, b2, A2, W3, B3, b3, and A3 are respectively (IxL), (S1xI\), (S1xL), (S1x1), (S1xL), (S2xS1), (S2xL), (S2x1), (S2xL), (OxS2), (OxL), (Ox1), and (OxL) matrices and B1 is given by [b1, ..., b1], B2 is given by [b2, ..., b2]. and B3 is given by [b3, ..., b3]. The outputs of the training phase are the weights and biases of the trained network that will be used in the test phase. The training phase procedure of the networks with single and two hidden layers are depicted in Fig. 1.

C) Test phase

In the ANN test phase, the only data needed from the trained networks are their weights and biases. The radar parameters of the set of realizations to be used in the test phase are introduced to the trained network. Generally, the test phase comprises the following steps:

- The actual target matrix, T, is defined for radar types as an identity matrix.
- For every realization of the test group, the corresponding output vector, A2 or A3, based on the number of hidden layers used, is computed.
- The element corresponding to the maximum value in the output vector is set to 1 and the other elements are set to 0.
- The modified output vector should correspond to one of the columns of the matrix T and this correspondence is taken as the deduced radar type.
- Repeat the whole procedure for each realization in the test group.

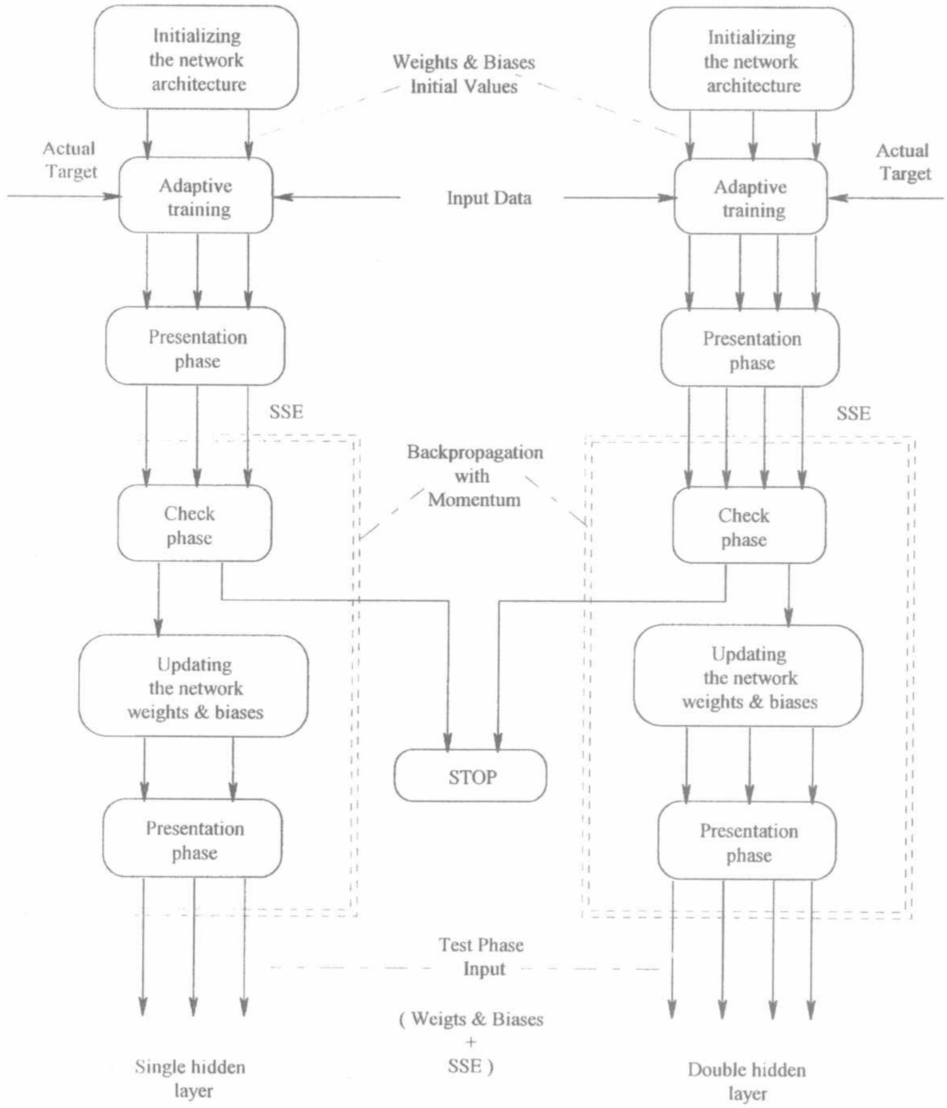

Figure 1. Training phase procedure of the ANN algorithms

III. Choice of ANN Architecture and Speed up the Computations

The artificial neural network based radar types identification process involves trying different architectures, learning techniques and training parameters in order to achieve an acceptable success rate. The selection of the network parameters is based on choosing the structure that gives minimum sum-squared errors SSE in the training phase, and maximum probability of correct decisions in the test phase. Two network types, based on the number of hidden layers, are considered for radar types identification. These are: 1) single hidden layer network, and 2) two hidden layers network. A lot of work has been done to choose the optimum network structure. All the tested networks contain a 4-node input layer, a 10-node output layer, and they are differ in the number of hidden layers and the number of nodes in each hidden layer. It is found that all the tested networks required a long training time, as the radar parameter values have different ranges for different radar types. For example; the value of the radio frequency for type 1 is of order 109 Hz and of order 1010 Hz for type 7. So, normalization of the datasets is used to speed up the training and learning phase. Normalizing the datasets reduces the range of their values to be [0 - 1], and this leads to avoiding the problem of long training time. However, the normalization should be applied in the test phase as well as in the training phase.

In the training phase, the dataset corresponding to each parameter are normalized with respect to the maximum value over all the segments used in the training phase. In the test phase, two cases are considered: 1) all the segments, that used in the test phase, are available at the beginning (off-line analysis), and 2) not all the segments are available at the beginning, only one segment is available at a time, (on-line analysis). Thus, three suggested ways for the normalization in the test phase are considered. First, the maximum value is taken over all the test data (off-line analysis only). Second, the maximum value of the training data is considered as the maximum for the test data. Third, the maximum value of the test data is consider as the maximum value of the training data then updating this maximum value by comparing the value of the extracted parameter for every segment with the previous maximum value considered. Note that, in the third method the initial maximum value is taken as the maximum value over the datasets used for training phase.

For the single hidden layer ANN, the numbers in Table 2 are based on the 100 realizations for each of the 10 radar types. It is observed that the 8, 10, 11, 12, 14, 15, 18, 20, and 25 nodes in the hidden layer of ANNs achieve 100% success rate while the other tested networks (4, 5, 6, and 7 nodes in the hidden layer) do not. Dependence of the SSE on the number of epochs for different number of nodes in the hidden layer is displayed in Fig. 2. It is clear that a 12-node hidden layer for radar types identification is better than choosing any of the other tested networks with respect to the SSE. So, a network with 4-node input layer, a 12-node hidden layer and a 10-node output layer is considered further to evaluate the performance of the single hidden layer ANN algorithm.

For the double hidden layer ANNs, the numbers in Table 3 are based on the 100 realizations for each of the 10 radar types. It is clear that the networks with (4, 4), (5, 5) (6, 6), (7, 7), (8, 8), (9, 9), and (10, 10) in the hidden layers achieve 100 % success rate while, the other tested network (3, 3) does not. Dependence of the SSE on the number of epochs for different number of nodes in the hidden layers is displayed in Fig. 3. It is clear choosing the (6-6) ANN for radar types identification is better than the other ANNs with respect to the SSE and as it requires less training time. So, a network with 4-node input layer, a (6-6) nodes in the hidden layers and a 10-node output layer is considered further to evaluate the performance of the double hidden layer ANN algorithm.

Table 2: Overall performance for the single hidden layer trained ANNs

Number of Nodes in hidden layer	Number of Epochs	Minimum SSE	Overall probability of correct decision %
4	10000	402.01	63.6
5	10000	327.88	80
6	10000	249.8	80
7	10000	171.37	90
8	10000	109.21	100
10	10000	34.08	100
11	10000	25.21	100
12	10000	22.84	100
13	10000	30.16	100
14	10000	28.12	100
15	10000	23.48	100
18	10000	25.51	100
20	10000	30.76	100
25	10000	24.9	100

Table 3: Overall performance of the double hidden layer trained ANNs

Number of Nodes in hidden layers	Number of Epochs	Minimum SSE	Overall probability of correct decision %
3, 3	10000	103.13	99.75
4,4	10000	5.5×10^{-21}	100
5,5	4503	9.33×10^{-21}	100
6,6	1716	9.43×10^{-21}	100
7,7	2241	9.67×10^{-21}	100
8,8	2618	9.98×10^{-21}	100
9,9	3070	9.81×10^{-21}	100
10,10	2290	9.33×10^{-21}	100

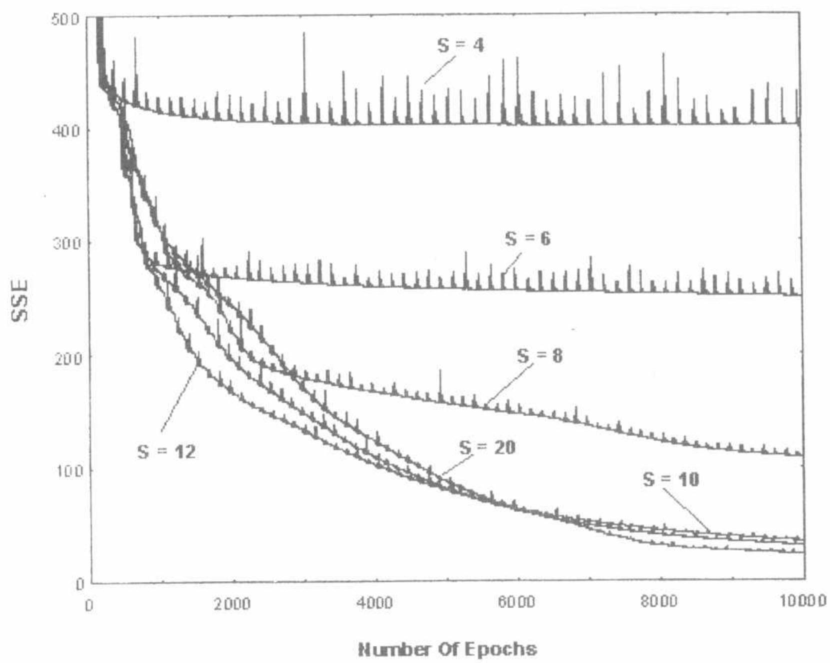

Figure 2: Dependence of SSE on the number of epochs for some of the single hidden layer trained networks

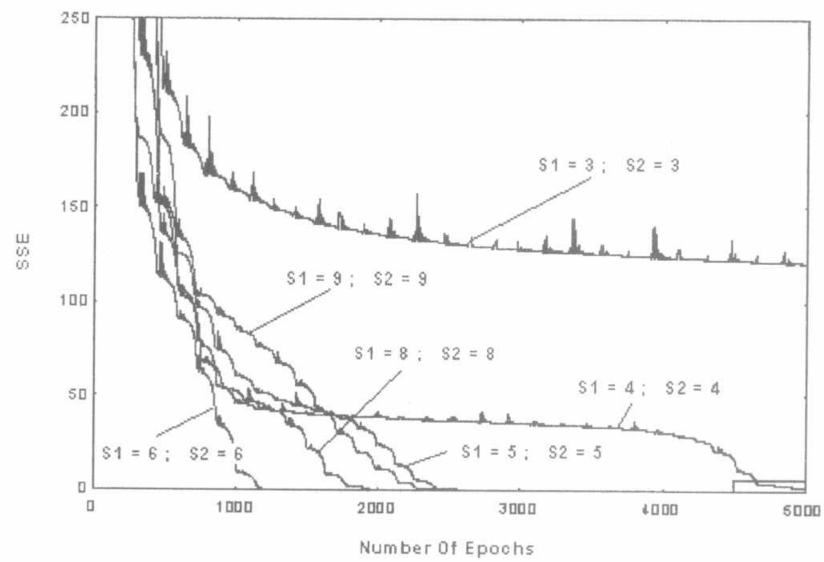

Figure 3: Dependence of SSE on the number of epochs for some of the double hidden layer trained networks

IV- Performance Evaluations

In the developed algorithms, the actual target, T, is (10 x 10) identity matrix. In this matrix, the columns in ascending order correspond to type 1 decision, type 2 decision, …and type N decision. The results of the performance evaluation of the proposed procedure for radar types identification, using the single hidden layers (12-node) ANN present that all radar types have been correctly classified with success rate 100%. The results of the performance evaluation of the proposed procedure for radar types identification, using the double hidden layers (6-6) ANN and derived from 500 realizations present that all types have been correctly classified with success rate 100 %.

V. Conclusions

In the ANN algorithms for radar types identification, a lot of work has been done. Two types of ANN (single and double hidden layer) are considered. It is worth noting that, the training has been done using only 100 realizations for each radar type. Many network structure have been tested to choose the best. In the single hidden layer case it was found that the best network has 12 nodes in the hidden layer. In the double hidden layer case it was found that the best network has 6 nodes in each hidden layer and in both cases, the chosen networks achieves overall success rate 100%.

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