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USING NEURAL NETWORK IN RADAR EMITTER'S IDENTIFICATION

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ABSTRACT

A region of the microwave band can contain many radar signals from different emitters. There are few techniques for identification of emitters on the base of measuring the parameters of their received signals. However, these techniques are utilized OFF-line. In modern electronic warfare, the ON-line techniques in the processing and decision are required. It is assumed that the electronic support measurement (ESM) receiving system is used to measure radar parameters. These parameters are : the carrier frequency (F), the pulse width (PW), the antenna scan rate (RPM), the angle of arrival (AOA) and the time of intercept (TOI) for each pulse. Data processing in ESM contains two basic functions: deinterleaving (sorting or classification) and emitter identification. ESM systemn applies some algorithms to classify the radar emitters and the resulting radar parameters F, PW, PRF, RPM are called the emitter descriptor vector. They are used in emitter identification by comparison with an existing library.

This paper suggests a novel technique to identify radar signals using neural network on simulated radar parameters. A fully connected feed forward network (back propagation) is designed and implemented. The designed network consists of three layers. The input layer contains four processing elements that correspond to the four measured radar parameters resulting from the classification process. The hidden layer consists of five processing elements. The output layer consists of ten processing

elements that correspond to the number of emitters in the library. The proposed network is tested by several examples to verify the design concept.

1 INTRODUCTION

In the dense electromagnetic environments encountered in modern warfare, the large number of independent emitters will cause an ESM system to receive a seemingly random pulse stream consisting of interleaved pulse chains. In order to identify individual emitters, their pulse trains must be segregated. Previously, ESM systems have relied on operator interpretation of the receiving system output to achieve this. However, some form of automatic ESM processing is now required to overcome high-received pulse rates and provide a "real time" response [1].

A simplified block diagram of an ESM receiving system is shown in Fig. 1.

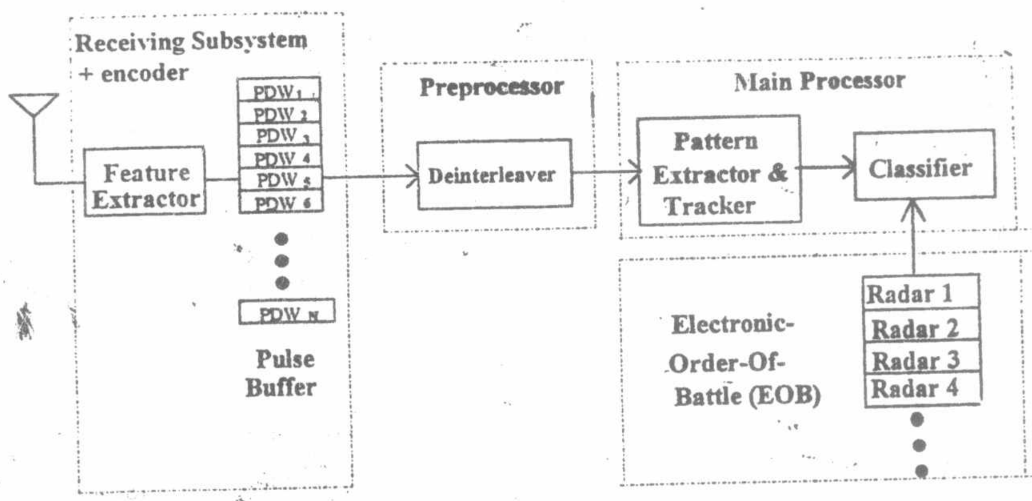

Fig. 1 General block diagram of an ESM receiving system.

The feature extractor represents the RF receiver hardware, the parameters measurement and encoding circuitry. The output of the feature extractor is a pulse descriptor word (PDW), which contains the feature values of the intercepted signal (i.e., frequency, amplitude, pulse width, TOI, and (in some cases) the emitters azimuth and elevation bearings.

The sorting, or deinterleaving function, is the clustering of incoming radar pulses into groups. In principle, each group or cluster should represent a single radar or emitter. The task of isolating a particular signal from a specific emitter is difficult to be accomplished, since the parameter boundaries between different signals may overlap, and the measurement error can cause the measured signal characteristics to become inexact or "fuzzy". A proper choice of the signal parameters that are used for sorting as well as a proper assignment of their relative importance in the decision process can minimize some of the problems caused by inexact, or ambiguous signal characteristics.

The final two blocks of Fig. 1 support the task of classifying and identifying the intercepted signals. The pattern extractor and tracker (PET), uses the sorted information from the deinterleaver to compute any patterns (e.g. PRI pattern) that may be contained in each data cluster (emitter) by using the appropriate data item from the PDWs stored in a cluster. The pattern extractor and tracker represent a long-term memory for the clusters that were formed by the deinterleaver. At last, the classifier relates each data cluster in the (PET) to a particular emitter.

The identity of a particular signal is usually inferred by correlating the observed characteristics those stored in the electronic order of battle (EOB) or the library. It is a list that contains the identity and signal characteristics of all known radars or those likely to be encountered. The observed information is often inexact or ambiguous, and since the contents of the electronic order of battle are limited, the inference process inherently contains some degree of uncertainty [2].

Generally, the ESM receiver system has two basic functions; radar parameters measurements and data processing. In most cases the radar parameters to be measured are: angle of arrival (AOA), carrier frequency (F), pulse repetition frequency (PRF), pulse amplitude (PA), and antenna scan rate (RPM).

The ESM data processing has two phases:

-Detinterleaving (sorting) and,

-Identification.

The basic concept discussed her is the problem of identification of radar emitters present in the environment. There are few techniques such as metric techniques [3] that are used for identifying radar emitters. However, these techniques are utilized OFF-line. In modern electronic warfare, the techniques for automatic processing and decision are required to be ON- line.

In this paper, the artificial neural network (ANN) is suggested as a novel technique for identifying radar emitters. The parameters of their received signals are measured. ANNs are successful in many areas such as speech recognition, pattern recognition, signal analysis, classification, noise filtering, identification, ... etc. In the present case, ten types of radar emitters are considered. The key features (parameters) used for identifying radar types are F, PRF, PW and RPM.

2. ANN ARCHITECTURE

A fully connected feedforward back-propagation ANN is designed and implemented. The back-propagation technique is applicable to a wide range of problems and it is the best for classification and identification. It contains the basic elements that are contained in the complicated network types [4].

Recent researches into back-propagation ANN show that almost any function can be synthesized using a back-propagation network with a sufficiently complex single hidden layer. Sometimes, an ANN with two hidden layers and fewer total-processing elements (PES) can do the same task. Using less PES has the advantages of requiring less memory and providing faster convergence. The number of PES in the hidden layer is an important factor to be decided. The more complex the relationship between input data and the desired output, the more PES are required. Also the type of transfer function for PES affects the behavior of the ANN.

A lot of experimental work has been done to choose the optimum network structure. Table (1) shows the success rate of the fully connected back-propagation ANN for different number of PES in the hidden layer with both the sigmoid and tanh transfer functions. Referring to these results, it is found that a fully connected back-propagation ANN using single hidden layer with five PES achieves great success, the considered transfer function is assumed to be tanh. Figure (2) shows the architecture of the chosen network. The input layer contains four PES, each of them is connected to one of the measured radar parameters. The output layer contains ten PES each of them is pointing to one of the radar types.

Table 1. Success rate for back-propagation ANN with single hidden layer for different transfer functions

Number of nodes in hidden layer	Transfer Function	Success Rate
5	Sigmoid	90 %
10		93 %
40		93 %
100		100 %
3	tanh	95 %
4		100 %
5		100 %

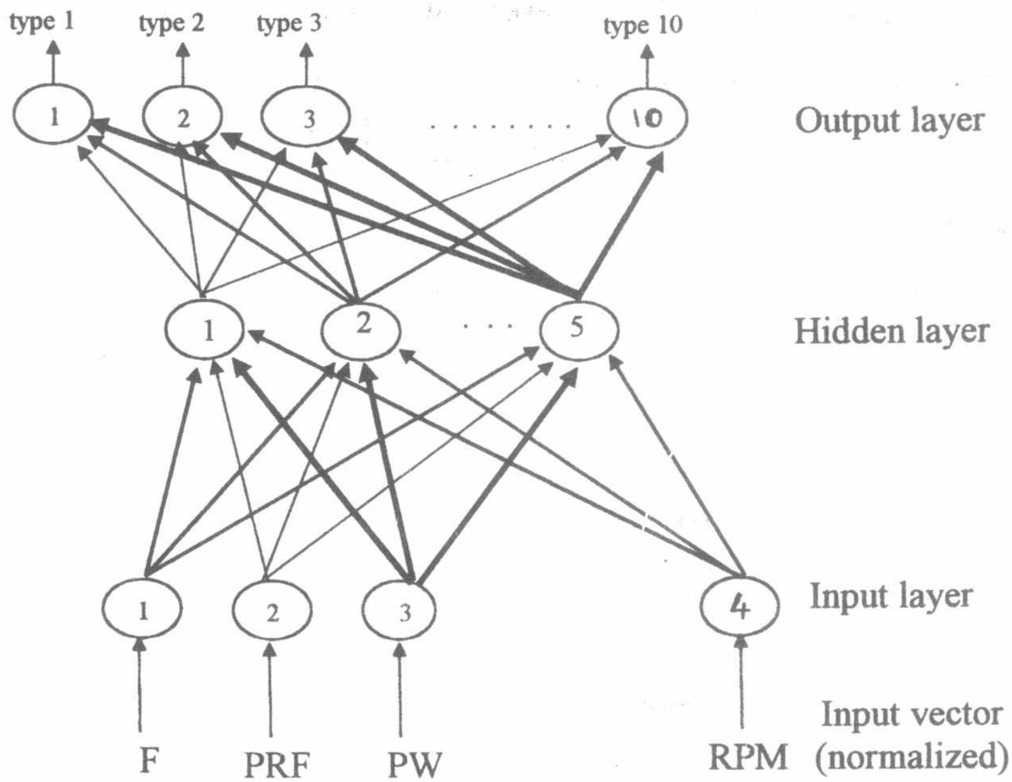

Fig. 2 ANN architecture (4-PES input layer, 5-PES hidden layer, 10-PES output layer)

3. DATA REPRESENTATION

Data generated for training and for testing is based on the value of the parameters of the considered radar, which are listed in table 2. Some of the parameters (PRF, PW, RPM) have one or more fixed values, while the others (as F) are given to be within a range. The measured accuracy of the fixed value parameters are assumed to be

$\Delta_{PW} = \pm 10\ \%$

$\Delta_{PRF} = \pm 2\ \%$, and

$\Delta_{RPM} = \pm 5\ \%$

For each of the fixed value parameters, ten different values are randomly selected within the corresponding limits of accuracy and for frequency (F), ten values are selected within the given range.

A computer program is designed and implemented using c^{++} language to create the simulated frames that represent input data. This data covers all the possible combinations of the selected values for input parameters.

The emitters identification back-propagation network has been divided into a training (learn) set and a test set. The training set for ANN (particularly back-propagation) should contain only "good" data (no doubtful data or data records with missing field) and also must be divided between the various outcomes.

Table 2 The parameters of the ten considered radars

	F (MHz)	PRF(Hz)	PW(μs)	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	2000 - 4500	0.8 - 1.5	24
Radar 7	10000→10250	8600	6.25	1 - 2
Radar 8	9000→9600	1900 - 2050	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

3. TRAINING THE ANN

The network training is achieved on 9000 frames for each type of interest. The objective of training the network is to find the optimum weights to minimize the error between the desired response and the network actual output using back-propagation technique. The training data frames must be provided in terms of input/output pairs; i.e. for each data row, the corresponding desired target is defined. The network produces an actual response that can be compared with the desired one, the error between them is used to adjust the weights in the network so that the next time network output will be a bit closer to the desired response. The choice of the best ANN structure is based on choosing the network that achieves highest success rate.

4. TEST PHASE STEPS

The test phase comprises the following steps :-

1.The key features of the set of realization to be used in the test phase are introduced to the trained network.

2.For every frame of the test-input data, the corresponding output vector is obtained.

3.This vector is modified such that the output element corresponding to the maximum value is set to "1" while the other elements are set to "0".

4.For the good-trained network, the modified output vector should corresponding to the actual target type. Obtained results are collected in the target matrix (T). It is a 10x10 matrix, its rows corresponding to the actual radar types arranged in ascending order introduced in the test frames and its columns are corresponding to the resulting output vectors obtained when applying the test frames.

5. PERFORMANCE EVALUATION

The performance of the network under consideration is tested by 1000 frames for each radar type. Table (3) show the success rate for fully connected back-propagation ANN using tanh transfer function if the hidden layer has 3-PES, it achieve 100% success rate for 9 types and 33 % for one type only. The wrong decision for radar type number 6 is due to the overlapping between the input data of

Table. 3. Success rate of 3 PES hidden layer.

Test output vectors

	1	2	3	4	5	6	7	8	9	10
1	100%									
2		100%								
3			100%							
4				100%						
5					100%					
6						33%		66%		
7							100%			
8								100%		
9									100%	
10										100%

Table (4) Success rate of 5 PES hidden layer.

Test output vectors

Radar types	1	2	3	4	5	6	7	8	9	10
1	100%									
2		100%								
3			100%							
4				100%						
5					100%					
6						100%				
7							100%			
8								100%		
9									100%	
10										100%

radar type numbers 6 and 8 as shown in table (2). While in case of 5-PES hidden layer, network achieves 100 % success rate for each type as shown in table (4).

CONCLUSION

The proposed ANN is feed forward back-propagation fulfills the task of radar emitter type identification; one out of ten given emitters. The network contains three layers; the input layer with 4 PEs, the output layer with 10 PEs and the hidden layer with 5 PEs. The bipolar tanh transfer function is considered. After learning, testing shows that this architecture has great success in fulfilling the required task.

In this application, the output form, one out of ten, simplifies the problem because the greatest output is considered to take the value "1" and all the others take the value "0". This ON-line technique can be extended for greater number of radars.

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