

An Intelligent Algorithm for the Process Section of Radar Surveillance Systems

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Received: 03/Nov/2014

Revised: 14/Nov/2015

Accepted: 21/Dec/2015

Abstract

In this paper, an intelligent algorithm for clustering, intra-pulse modulation detection and separation and identification of overlapping radar pulse train is presented. In most cases, based only on primary features of incoming radar signals, the modern electronic intelligence system cannot recognize the different devices of the same type or class. A very important role is played by Measurement and Signature Intelligence. A radar intercept receiver passively collects incoming pulse samples from a number of unknown emitters. The information such as Pulse Repetition Interval (PRI), Angle of Arrival (AoA), Pulse Width (PW), Radio Frequencies (RF), and Doppler shifts are not usable. In the proposed algorithm, for clustering of overlapping pulses received from self-organization neural network SOFM (due to its high accuracy in comparison with other neural networks, such as CLNN and neural networks (Fuzzy ART), and for detecting intra-pulse modulation type, matrix method, and for identifying the radar type, RBF neural network have been used. The simulation results of the proposed algorithm shows that in the presence 5% noise and 5% missing pulse, the accuracy of the clustering part of the proposed algorithm is equivalent to 91/8%, intra-pulse modulation recognition accuracy is 98%, the detection accuracy is 2/99%, and the total output of the algorithm precision is 89/244%, respectively.

Keywords: Pulse Train; Matrix Multiplication Method; Radar Identification; Neural Networks.

1. Introduction

The main parts of the electronic equipment of military forces are radars, thus, identifying them is of particular importance. Figure 1 shows the general division of electronic warfare recently termed as electronic defense [1]. Most of the systems that are used to detect enemy electronic equipment systems are ELINT and ESM. The responsibility of ELINT system is strategically accurate identification of active radars in the region and the responsibility of ESM systems is immediate identification of radars deployed in the threatening equipment so that the type of threats can be revealed by them. In general, the task of ELINT and ESM systems are similar and they are only different in their duration of performance time. With successful and sustained improvements in the technology of constructing effective radars and the immense complexity of the regional combat, the effectiveness of disturbance systems and electronic deception is highly dependent on the performance of radar detection system. Thus, the performance of electronic attack sections (EA) and the electronic protection (EP) in the radar field (Figure 1) directly depend on performance of radar detection systems. Radar detection systems include sections such as antennas, receivers, processors and displayer. In these systems, processor has the task of clustering, separating and identifying radars. [2]

Figure 2 shows block diagram of the processing unit of ELINT and ESM systems. As it can be seen in Figure,

first, the pulse details of word (PDW) is extracting for all of overlapping pulses received in the given time frame and then according to the extracted PDWs, clustering operation is performing on the pulses. Due to the possibility of existing of different pulse trains in clusters, the processor operates separation clusters and eventually detects the pulses on each cluster. Gained information from the identification of pulse trains and pulse PDWs is the basis for comparison with existing data in the radar database that will identify the types of threat. [3]

In the proposed algorithm, for clustering and separation of overlapping pulse strings received from the region radars, neural networks with the feature of self-organization for detection of PRI type and calculating PRI average, by using the methods of matrix multiplication for identification of the radar type, neural networks with radial basis function are used. In section 2 self-organizing neural networks and radial basis function and in section 3, the proposed algorithm will be presented. Sections 4 and 5 respectively evaluate the proposed algorithm and presents the conclusion.

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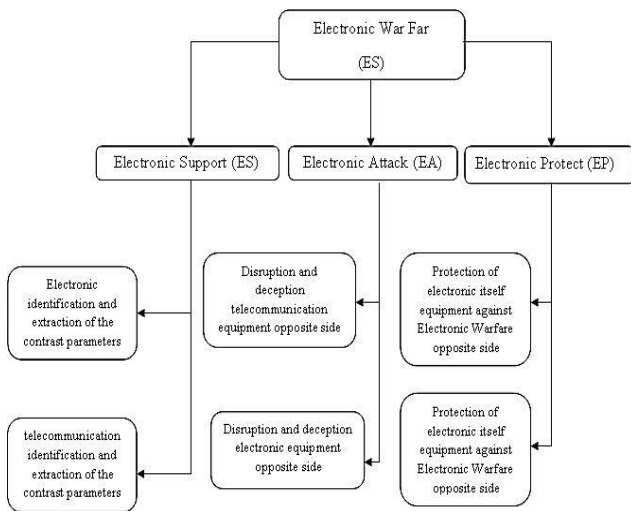


Fig. 1. The position of radar detection systems in electronic warfare

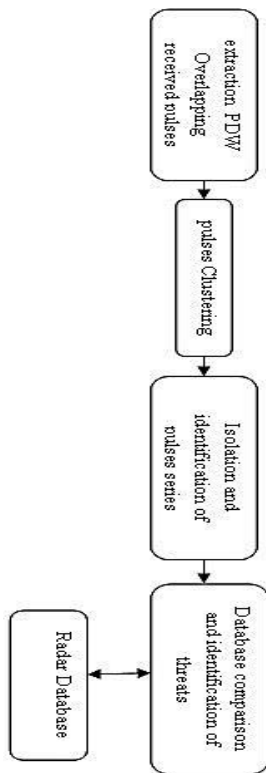


Fig. 2. General block diagram of the processing unit in radar detection systems

2. Self-organizing Neural Networks and Radial Basis Function

One of the most commonly used artificial neural networks is self-organizing neural networks (SONN). Till now several neural networks with self-organizing feature has been reported that three of the most commonly used of them, are CLNN, SOFM and Fuzzy ART networks[4]. CLNN neural networks have a two-layer and leading structure, the first layer is the feature domain encoder and the second layer is competitive layer that its neurons such

generalized themselves to they can recognize the input vectors provided.

Each neuron of the second layer is connected with all neurons of the first layer by weight vectors. Each neuron in the competitive layer through a competitive process by stimulating local connections, stimulates itself and perhaps some neighboring neurons and reduces the activity of the farther neurons by inhibiting connections. In this network, after enough training, each output neuron represents a cluster and its weights represent the center of the cluster. [4,5]

SOFM neural networks are like CLNN, the only difference is that bias is not used in it. In this network, in addition to classifying input vectors, the neighboring neurons recognize adjacent parts of the input space [5]. Fuzzy-neural networks, which have been developed in recent years, use fuzzy logic gates. Fuzzy ART network is a kind of network that combines the theory of fuzzy calculation with the ART1 neural network and accepts binary and analog inputs [6]. Artificial neural networks with radial basis function (RBF) are two-layer networks with radial basis activation functions and have been proposed for various applications in signal processing [4].

Radial basis function is a multidimensional function that its output, depends on the distance of between the input vector and the center vector. In RBF networks nonlinear basis functions can take many forms like as Gaussian and polygons, etc. In practical applications, is using mostly the Gaussian function, which is known as the Gaussian RBF neural networks [7]. Two different types of RBF networks are regression networks and probabilistic networks. Regression networks are mostly used in estimating functions and probabilistic networks in classification problems.

In the probabilistic neural network, when the input vector is applied to the network, the first layer calculate the distance between input vector and the training input and thus provides a vector that its elements determines the distance between the input and training input. The second layer using the first layer output generates vector of probabilities as output of the network. Finally, the competitive transfer function in the second layer selects the maximum probabilities from vector probabilities, and produces 1for that output and 0for the rest of probabilities.

3. The Proposed Algorithm

Figure 3 shows block diagram of the proposed algorithm. In the proposed algorithm, after reception of PDW from detector and pulse analyzer, the normalization operating is performing on the input data to prepare the data to applying for clustering section. After clustering the input pulses into several clusters, types of PRI modulation in each cluster is extracted using matrix multiplication. Then according to the three parameters of pulse width, carrier frequency, and PRI, the radar types detected using PNN neural network. If the recognized

specifications does not matched with existing radars in radar data archive, as a new radar will be added to the radar data archive.

In following, details of the proposed algorithms, including algorithms of clustering section of received strings of overlapping pulses, algorithms of PRI type detection, and separation and identification of radars are presented.

3.1 Algorithms of Clustering Section of Received Strings of Overlapping Pulses:

In this section, an intelligent algorithm is designed for clustering of received pulse trains overlapping, based on self-organizing neural network. Figure 4 shows the flowchart of this part of the algorithm where in the first, three parameters of AOA, RF, and PW from PDW are selected then in the section of pre-processing and normalization, a row or column of symmetric matrix D is calculated as follows, then its elements are normalized between 1 and 0.

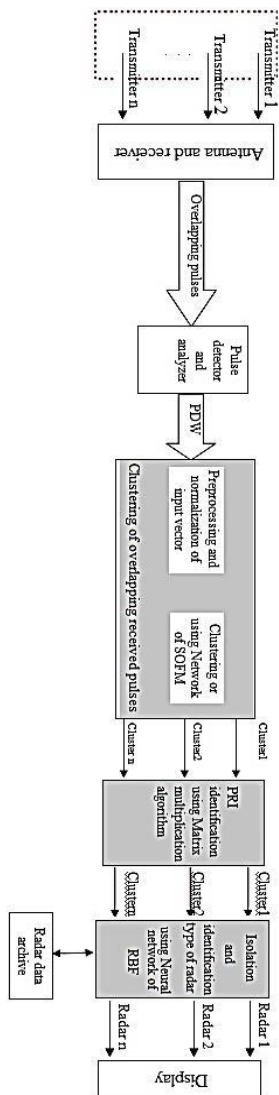


Fig. 3. Overall block diagram of the proposed algorithm

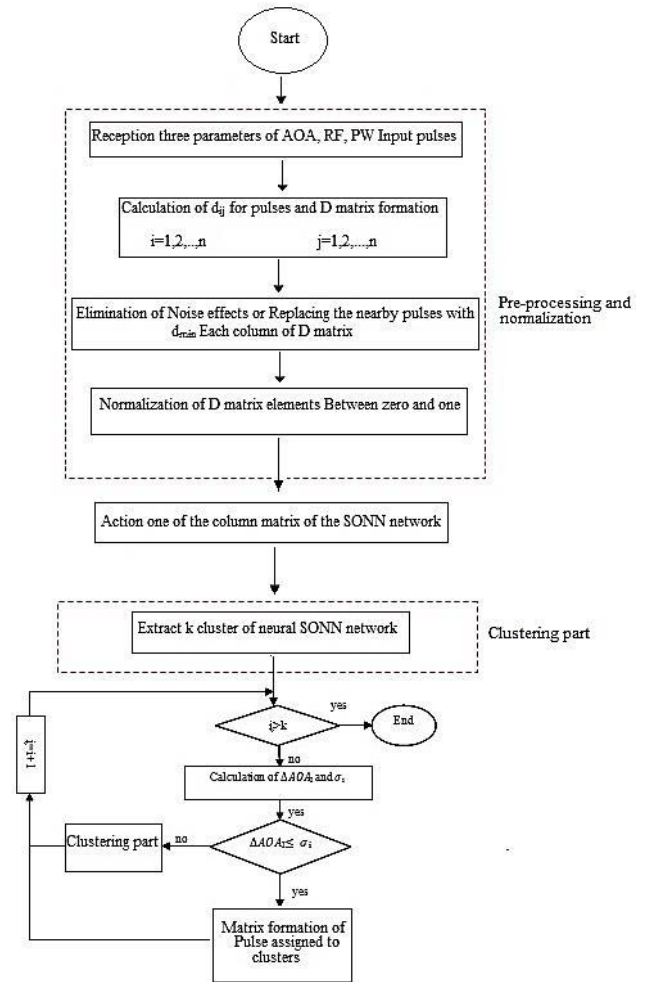


Fig. 4. Flowchart of the clustering of the proposed algorithm.

$$D = \begin{bmatrix} 0 & d_{12} & \dots & d_{1n} \\ d_{21} & 0 & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & 0 \end{bmatrix} \quad (1)$$

$$d_{ij} = \sqrt{\frac{(AOA_i - AOA_j)^2}{\sigma_{aoa}^2} + \frac{(PW_i - PW_j)^2}{\sigma_{pw}^2} + \frac{(RF_i - RF_j)^2}{\sigma_{rf}^2}} \quad (2)$$

The values of one of the rows or columns of the matrix D are applied to SONN neural network and with training the network, clustering pulses are performing. For each cluster, difference of the entry pulses angle are compared with the value (the value is selecting with respect to the accuracy requires to measure the entry angle radars in operation area, at this point the value has been set at 2.5° with respect to the accuracy of the existing systems), if the difference of entry angle of pulses was less than 2.5°, for that cluster matrix M calculates as equation (3), and if it is more than 2.5°, that cluster is archiving. Then for each cluster of the archive, the algorithm is executed and the process will be continued until the number of clusters in the archive is zero.

$$M = \begin{matrix} & c_1 & c_2 & c_3 & \dots & c_k \\ p_1 & \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \end{bmatrix} \\ p_2 & \begin{bmatrix} 0 & 0 & 1 & \dots & 0 \end{bmatrix} \\ p_3 & \begin{bmatrix} 0 & 0 & 0 & \dots & 1 \end{bmatrix} \\ p_4 & \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \end{bmatrix} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ p_m & \begin{bmatrix} 0 & 0 & 1 & \dots & 0 \end{bmatrix} \end{matrix} \quad (3)$$

3.2 PRI Type Recognition Section of the Proposed Algorithm

After the clustering process, the obtained clusters enter the intra-pulse modulation detection section and calculation section of PRI average. In this section, matrix multiplication technique is using the following way that its aim to detecting of techniques of fixed PRI, PRI stager, PRI Jitter and calculating mean of PRI clusters.

This method involves the following steps:

- For N pulse, harmonic matrix of cluster is formed as follows:

$$HM = \begin{bmatrix} 0 & 1 & 2 & 3 & \dots & N-1 \\ 1 & 0 & 1 & 2 & \dots & N-2 \\ 2 & 1 & 0 & 1 & \dots & N-3 \\ 3 & 2 & 1 & 0 & \dots & N-4 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ N-1 & N-2 & N-3 & N-4 & \dots & 0 \end{bmatrix} \quad (4)$$

- Matrix of the difference in arrival times of pulses is calculated which is a symmetric matrix.

$$\Delta TOA(I,j) = |TOA_j - TOA_i|, 1 \leq I,j \leq N \quad (5)$$

$$\Delta TOA = \begin{bmatrix} 0 & d_{12} & d_{13} & d_{14} & \dots & d_{1N} \\ d_{21} & 0 & d_{23} & d_{24} & \dots & d_{2N} \\ d_{31} & d_{32} & 0 & d_{34} & \dots & d_{3N} \\ d_{41} & d_{42} & d_{43} & 0 & \dots & d_{4N} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & d_{N3} & d_{N4} & \dots & 0 \end{bmatrix} \quad (6)$$

- By multiplying matrix of difference in arrival times of pulses and the inverse matrix of HM, the detection matrix of pulse train identifying (PTI) is obtaining.

$$PTI = \Delta TOA \times HM^{-1} \quad (7)$$

To reduce the computational complexity, we can only compute the main diagonal elements instead of calculating PTI matrix with the following equation:

$$V_{PTI}(i) = \sum_{j=1}^N (\Delta TOA_{ij} \times HM_{ji}^{-1}), i = 1, 2, \dots, N \quad (8)$$

- With reviewing of VPTI vector elements, the used technique in PRI is specifying.

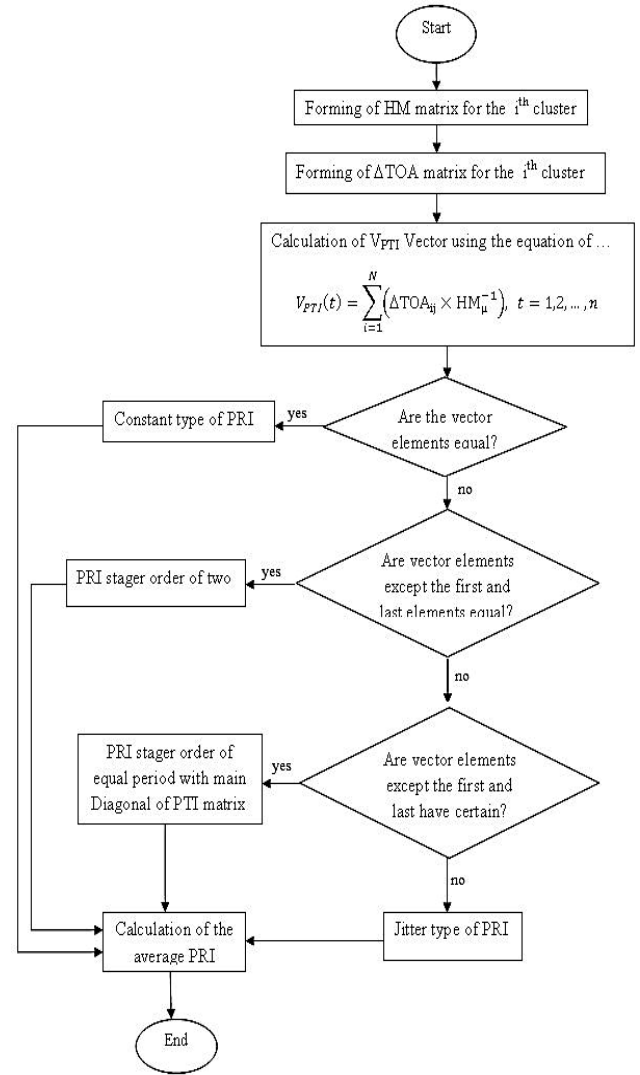


Fig. 5. Flowchart of PRI detection section of the proposed algorithm

3.3 Separation and Identification Section of the Proposed Algorithm:

The first step to identifying the type of radar by PNN neural network, formation of the pulse descriptor word vector (VPDW). To form vector VPDW from three inherent parameters of the radar such as RF, PRI and PW are used [10]. VPDW vector is formed for Ith cluster with N received pulses as follows.

$$V_{PDW}(i) = [PDW_1(i) \quad PDW_2(i) \quad \dots \quad PDW_N(i)] \quad (9)$$

In which PDW for jth pulse of ith cluster is defined as in the equation (10):

$$PDW_j(i) = \begin{bmatrix} RF_j(i) \\ PW_j(i) \\ PRI_j(i) \end{bmatrix} \quad (10)$$

Thus for m cluster, the pulse descriptor word vector is as follows:

$$V_{PDW} = [V_{PDW}(1) \quad V_{PDW}(2) \quad \dots \quad V_{PDW}(m)] \quad (11)$$

Then mean of VPDW vector for m clusters are calculated as follows:

$$\bar{V}_{PDM} = \begin{matrix} \overline{RF1} & \overline{RF2} \dots & \overline{RFm} \\ \overline{PW1} & \overline{PW2} \dots & \overline{PWm} \\ \overline{PRI1} & \overline{PRI2} \dots & \overline{PRI m} \end{matrix} \quad (12)$$

To learn the above-mentioned neural network, first, the matrix of \bar{V}_{PDW} of all the radars in radar data archive is calculating and training to the network. Also for the input clusters \bar{V}_{PDW} matrices are calculated and applied to the network for detection. The network detects the type of radar corresponding to each cluster by comparing \bar{V}_{PDW} matrix of the input clusters with what has been trained. Figure 6 shows the flowchart of this section of the proposed algorithm.

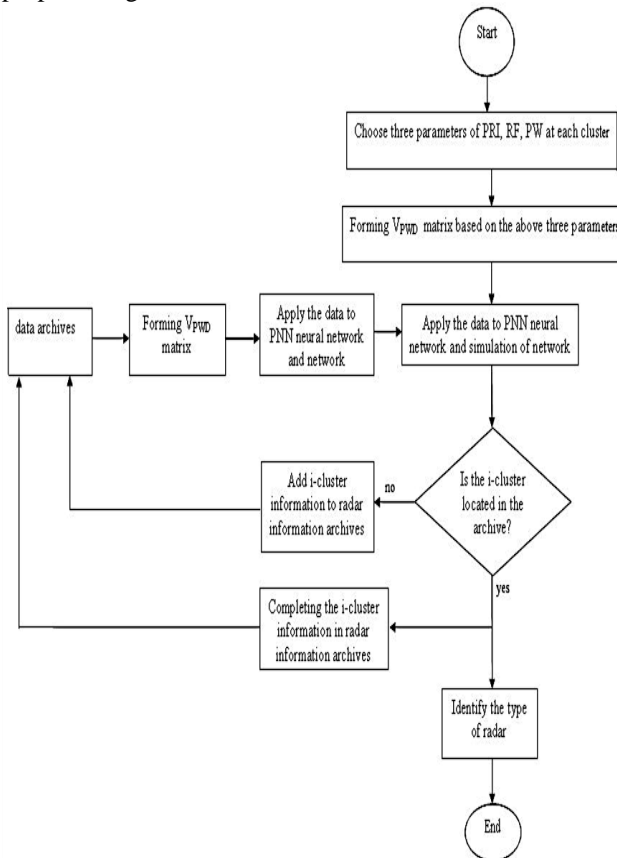


Fig. 6. Flowchart of identification section of the proposed algorithm

4. Reasons for Selecting Neural Network and Evaluating of the Proposed Algorithm

A. Selection of SOFM Neural Network and Evaluation of Clustering Section

Among the most commonly used self-organized neural networks (CLNN, SOFM and Fuzzy ART), must be selected the most suitable for clustering section of proposed algorithm. For this purpose, first, the networks are simulated using MATLAB software and then the produced data for the three parameters AOA, RF and PW

from five radars, as specified in Table 1 are applied to them. These three networks have been proposed for clustering section and were compared in the terms of accuracy of clustering (error) and convergence time.

Table 1. Five radars with different capabilities

rada r	AOA (deg)	RF (MHz)	PW (μs)	PRI (μs)	PA (dB)	PRI Type	RF Type
1	32	2780	3.1	2300	10	Stable	Stable
2	38	2887	2.7	2600 2800 2900	28	3 Order stagger	Stable
3	45	2670	1.3	3000	14	Jitter	Stable
4	35	2500	0.8	2700	45	Stable	Jump
5	48	2712	0.23	3100	37	Stable	Agile

Figure 7 shows the errors of the three networks for the various iterations of training. As can be seen, the networks have converged after 300 iterations. For 300 times iterations of the training, the network's error and the time required to training the network that is convergence time which represents the computational complexity, are given in Table 2 (the calculations are done by Pentium 4 computer with 2 GB of RAM).

As can be seen, the error of SOFM neural network is less, thus this network was chosen for clustering section of the proposed algorithm. According to Table 2, the clustering section of the proposed algorithm with choice of SOFM neural network and 500 times iteration training has an accuracy of about 91.8% (8.2% error).

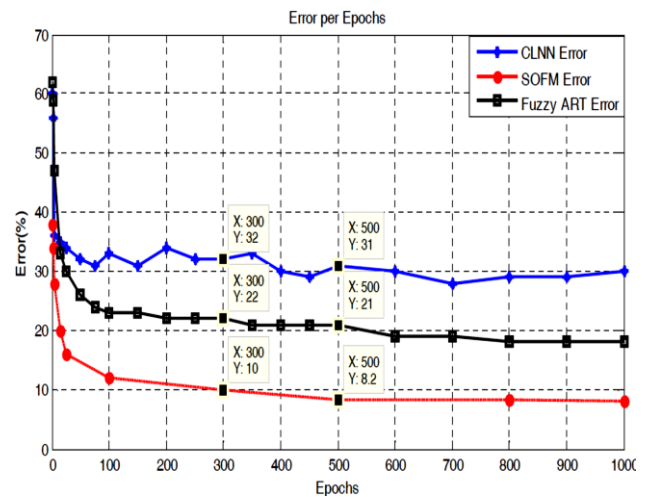


Fig. 7. Comparison of errors of CLNN, SOFM and Fuzzy ART neural network

Table 2. Output error and training time of self-organizing networks in the clustering section of the proposed algorithm.

The time required for training Repeat 500 times (s)	Error after 50 0times of training	The time required for training Repeat 300 times(s)	Errorafter 300 times of training	Kind of self-organizing networks
78	8.2%	45	10%	SOFM
25	21%	15	22%	Fuzzy ART
11	31%	6	32%	CLNN

B. Assessment of Recognition Section of Inter-pulse Modulation Type

For the evaluation of this part of data's produced, Table 1 was used. For data that generated from the angle of arrival and pulse width, the changes were added as Gaussian noise with a variance of 5%. For data relating to the frequency based on the technique, frequency change of variances is different. The variance of changes in fixed frequency radars is set as 5%, in radars with capability of frequency jumping is set as 10%, and in radars with capability of frequency agility changes is set as 30%. For generated data from the PRI parameter, the variance of changes in radars with fixed PRI technique was set at 5%, in Astgger PRI technique is set as 10%, and in jitter PRI technique is set as 30%, and the generated data was applied to the algorithm matrix multiplication considering 5% of missing pulses. By running the algorithm for 1000 times and calculating the average of errors, the accuracy of the algorithm was 98% obtained.

In this section, instead of calculating the pulse train identifying matrix, only calculation of the main diagonal elements is proposed (pulse train identifying vector: VPTI) in equation 8. To compare calculation time of the two equation, pulse train with PRI = 10 and N = 8, with 5% of missing pulses, and 5% error and PTI matrix and VPTI vector was calculated as follows.

$$PTI = \begin{bmatrix} 10.0470 & 0.0658 & 0.0280 & 0.0494 & 0.0124 & 0.0167 & 0.0304 & 0.0014 \\ 0.0131 & 9.9942 & 0.0280 & 0.0494 & 0.0124 & 0.0167 & 0.0304 & 0.0014 \\ 0.0131 & 0.0658 & 9.9564 & 0.0494 & 0.0124 & 0.0167 & 0.0304 & 0.0014 \\ 0.0131 & 0.0658 & 0.0280 & 10.0337 & 0.0124 & 0.0167 & 0.0304 & 0.0014 \\ 0.0131 & 0.0658 & 0.0280 & 0.0494 & 10.0708 & 0.0167 & 0.0304 & 0.0014 \\ 0.0131 & 0.0658 & 0.0280 & 0.0494 & 0.0124 & 10.0752 & 0.0304 & 0.0014 \\ 0.0131 & 0.0658 & 0.0280 & 0.0494 & 0.0124 & 0.0167 & 10.0615 & 0.0014 \\ 0.0131 & 0.0658 & 0.0280 & 0.0494 & 0.0124 & 0.0167 & 0.0304 & 10.0325 \end{bmatrix}$$

$$V_{PTI} = [10.0470 \ 9.9942 \ 9.9564 \ 10.0337 \ 10.0708 \ 10.0752 \ 10.0615 \ 10.0325]$$

As can be seen, the obtained elements for the vector VPTI were the same as the main diagonal elements of the PTI matrix. However, the computation time of VPTI vector is less than the PTI matrix. Figure 8 shows the computation time for VPTI vector and PTI matrix for the different numbers of input pulses (calculated by computer, Pentium 4 with 2 GB of RAM). As seen in this figure, when the number of input pulses is high, computation time of VPTI vector is much less compared to PTI matrix.

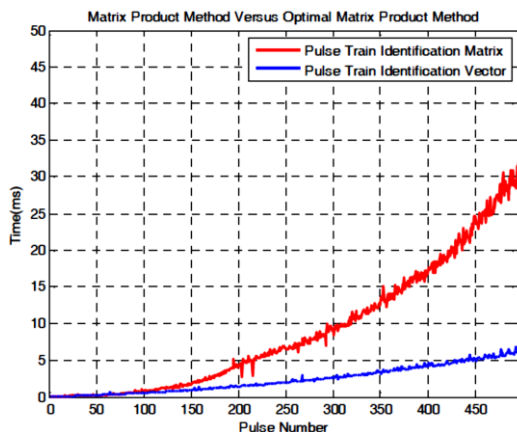


Fig. 8. Comparison of computation time of VPTI vector and PTI matrix

C. Selection of PNN Neural Network and Evaluation Section of Radar Type Identification

PNN neural network, is a type of RBF neural network which has high learning speed compared to perceptron multilayer neural networks and other monitoring networks, and is suitable for real-time processing applications. Also, with increasing of data training, it has better performance than MLP networks [10,11]. According to the mentioned features, PNN neural network was preferred to the MLP neural network for identification part of the proposed algorithm.

For the evaluation of the identification part of the algorithm, production data including RF, PRI and PW parameters of 20 practical radars with specifications as shown in Table 3 were applied to the PNN neural network and the network is training. After training the data's of 20 radars in Table 3, by introducing new input vectors we can recognize specification of related to them. For this purpose, a new input vector was applied to PNN network and the results were evaluating.

Each radar which is closer to the radars in the archives that radar will be announced as chosen, and if the difference is more than a given amount, it is considered as new radar and its specifications are added to the radar data archive.

To demonstrate this, pulse train of three radars (Table 2) was produced and applied to the PNN neural network with an error of 10% and 10% of missing pulses (Table 4). Produced data from three radars are shown in figure 9.

The results of learning (20 radars in Table 3) and applied the pulse train of three radars in Table 4 to the PNN neural network are shown in figure 10. In this figure, the circular points present the classification of 20 radars and star points related to the three radars which applied for detection. As shown in figure 10, the points resulting from the applying the three radars (the star points) are close to the learning points of the radars 3, 12 and 17. thus can be conclude that the three radars are correctly recognized. The results of Monte Carlo simulations with 1000 iterations shown that the proposed method to identifying the separated pulse trains with 5% error and 5% missing pulses, have the accuracy of about 99.2 %.

Table 3. Characteristics of the radars in the archive

Type Radar	PRF(MHz)	PW(μs)	RF(MHz)
Rdar 1	500	2	1000
Rdar 2	300	4	1500
Rdar 3	850	20	2500
Rdar 4	1500	1.2	3000
Rdar 5	800	20	3500
Rdar 6	700	1	3000
Rdar 7	900	100	2800
Rdar 8	2300	36	4000
Rdar 9	500	3.3	5000
Rdar 10	2800	1.2	5150
Rdar 11	500	3	8000
Rdar 12	6000	1.5	9000
Rdar 13	200	0.4	20000
Rdar 14	300	0.02	20000

Type Radar	PRF(MHz)	PW(μ s)	RF(MHz)
Rdar 15	3000	10	18000
Rdar 16	2400	0.14	33000
Rdar 17	675	1.1	16200
Rdar 18	300	0.02	18000
Rdar 19	300	0.02	13000
Rdar 20	400	3	4300

Table 4. Characteristics of 3 radars implemented to evaluate the identification part of the proposed algorithm

Number radar in Table 3	RF(MHz)	PW(μ s)	PRF(Hz)	PRF Type
3	2000-3000	20	850	Constant
12	8600-9500	1.5	4800-8100	3 Order staggered
17	16000-16400	1.1	674	Constant

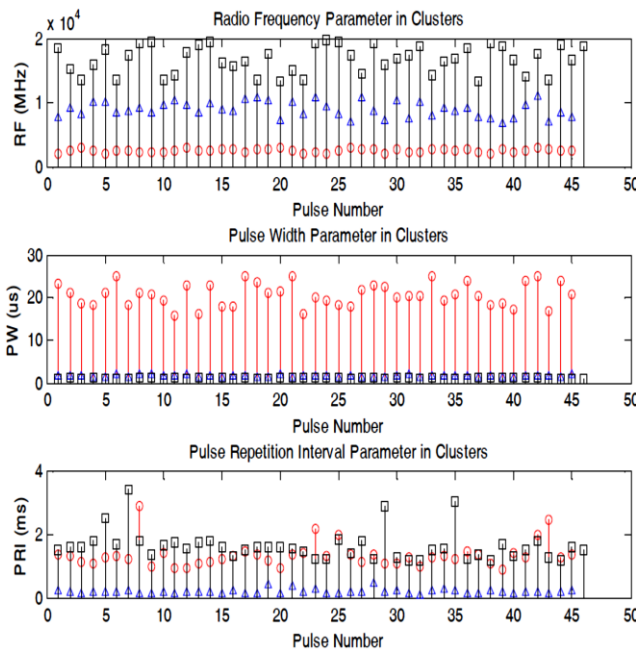


Fig. 9. Data generated from three radars for application to identification part

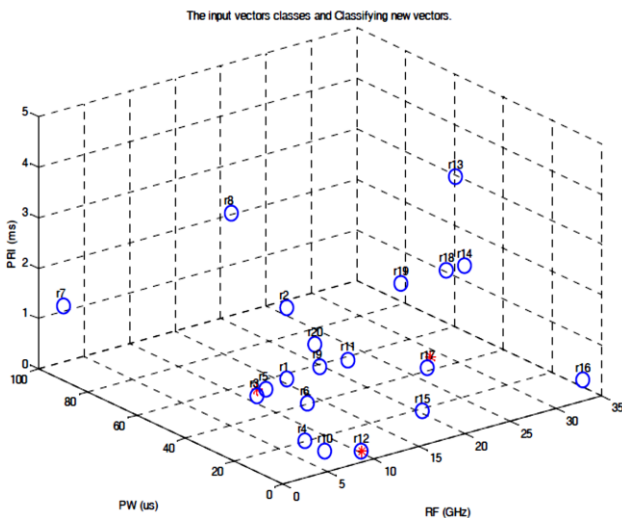


Fig. 10. The output of the RBF network after learning archive radars and detecting new radars

D. The Results of the Evaluation of the Proposed Algorithm

According to the taken evaluation, the obtained accuracy by using statistical methods for different parts of the proposed algorithm are shown in Table 5.

Table 5. Accuracy of the various parts of the proposed algorithm.

Accuracy of equivalent	Part name
91.8%	Clustering part using neural networks
98%	Part of between pulses Modulation recognition using matrix multiplication method
99.2%	Part of Identify radar using neural network

According to the table (5), to identifying radars with stagger and Jitter intra-pulse modulations, capability of the frequency jumping is 89.244 % by applying 5% error and 5% resultant noise, the accuracy of the proposed algorithm.

Table 6 shows the performance time of the proposed algorithm. As can be seen, the total performance time of the algorithm is about 4 milliseconds which it is a good time for operating equipments.

Table 6: Execution time of the proposed algorithm.

Time(ms)	Part name
2	Clustering part using neural networks
1	Part of between pulses Modulation recognition using matrix multiplication method
1	Part of Identify radar using neural network

5. Conclusions

In radar detection systems, the processor must have the least sensitivity toward deliberate changes in the pulse parameters which among TOA parameter have the most contribution. Unlike most methods, the proposed algorithm does not use this parameter in clustering and separating. In the recognition part of the intra-pulse modulation type, because using the matrix multiplication method and the possibility of its implementation using systolic array, processing speed of this section is suitable for real-time systems. In the proposed algorithm, the accuracy of clustering section is 91.8%, the accuracy of recognition part of intra-pulse modulation type for a pulse train with 5% missing pulse and 5% noise is about 98% and the accuracy of identification section for a pulse train with 5% missing pulse and 5% noise is about 99.2%. In general, the resultant accuracy of the proposed algorithm is 89.244 %.

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