Combining Principal Component Analysis Methods and Self-Organized and Vector Learning Neural Networks for Radar Data

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ABSTRACT:
The primary task of systems with real-time signal processing is to identify radars in the operating environment and to classify them based on prior system learning and to perform high-speed, real-time operations, especially where the received signal is an immediate threat such as missiles and requires war systems. Electronics should respond as soon as possible as an alarm. The purpose of this study is to use the results of this research to classify the information extracted by radar interception systems, which is achieved after the input signal selection stage and the correct selection of classification algorithms, and the other is accelerated by the learning vector quantization method. In this paper, we have presented a numerical method called a learning vector quantization, a method for data retrieval. In this method, the neural network algorithms are first organized to generate the required coding, and in the next step the digital vector learning algorithms will be created to retrieve the data. In this article, we will also consider each database benchmark. The implications of the usual implementation of universal command and control practices and their use of conventional restraint methods are a clear indication.

KEYWORDS: LVQ, SOM, PCA, Radar.

1. INTRODUCTION

In today's world, information has emerged as one of the most important production factors.[1] Since the end of World War II there have been many advances in the areas of science, genetic algorithms[2], hardware[3], software[4], phase lock loops[5], distributed production resources[6], Neural networks [7], cryptography and watermarking[8].

As a result, efforts to extract information from the data have attracted the attention of many involved in the information industry [9]. Advances in information science and technology provide new techniques and tools to overcome the continued growth and diversity of databases [10]. These advances have come in both hardware and software [11]. Data mining is one of the recent advances in data management technologies. Data mining is a set of techniques that allow a person to move beyond ordinary data processing and help extract information that is hidden or hidden in the data [12]. Electronic back-up systems are passive systems that measure the radiation emitted by many systems, measure and measure the characteristics of each received pulse, and then measure pulses belonging to a similar emitter to determine and extract the detected radar parameters and properties[13]. The purpose is to search, intercept, locate and analyze radar signals in military surveillance and surveillance [14]. In an electronic warfare environment, the pulses of the active radar pulses are merged and received by the radar interceptors [15]. These pulse strings have different properties that make them distinct. These features will vary depending on the type of radar and threats [16]. The characteristics of each radar are determined by several main parameters, including direction, pulse reception time, frequency, pulse width and pulse amplitude [17]. By collecting a large number of these records and characteristic components, a reference and efficient dataset can be formed. It is used to identify, predict, classify and label radars [18].

2. ISSUES AND PROBLEMS RELATED TO THE SUBJECT

Currently, the process of radar pulse separation usually involves one or more parameters related to a pulse such as Figure1. For example, in the single-parameter states, the pulse-time parameter is used to separate the pulses in the receiver and to assign it to the specified radar.

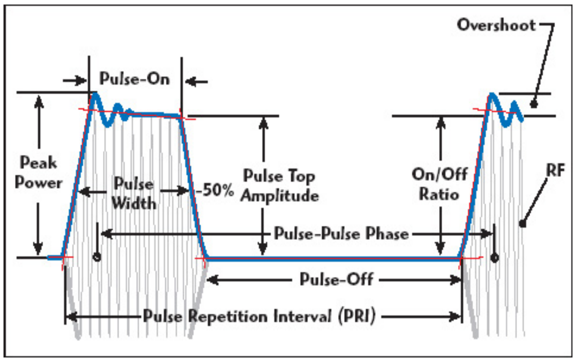

Fig. 1. Display of a Radar Pulse.

In the second case, other parameters are also used. Therefore, according to the above mentioned methods of pulse separation are divided into mono-parametric and multi-parametric methods.

But in radar sorting operations we have to compare and evaluate several parameters of that detected pulse, as opposed to the single-parametric high-speed method, or the second or multiparametric method, which increases the complexity of the work, in which case the accuracy of the system will be overshadowed. In addition, as the number of pulses increases, the process of evaluating and detecting the radar is complicated by several parameters.

Of course, we can classify based on a single parametric method, but in this case, due to the large number of radars in a region and the ever-expanding advancement of radars in transmitting different behavior patterns in one or more of their parameters at any given moment, the classifications performed will be greatly varied. This causes problems. Despite the problems and problems associated with mono-parametric methods, these methods will be faster at multiparametric environments than in simple and not too complex environments. It will be explained later that the monoparametric method does not fit all radar behavior patterns (Jitter,Stagger).

For example, if we want to classify based only on the frequency parameter, for example, suppose that the system detects multiple radar pulses and extracts their information, there is no interference between them and the frequency behavior pattern of all of them is constant. If this is the case then it may be appropriate to select the method for classification.

However, if the behavior pattern of the received radar pulse frequency is of the type (agile or Diversity) or of the type, then because of the nature of the same behavioral output pattern, it contains several radars, while in fact all of these frequencies belong to one radar. This is also true for the pulse repetition parameter, as explained above, because of the variability of pulse repetition behavior patterns, this also causes a frequency-like problem (some popular types of pulse repetition patterns include: Jitter, Stable, Stagger, Periodical, Dwell&Switch). Therefore, a multi-parameter method is needed to classify radar signals, in which case the radars are classified based on their pulse characteristics and will limit the batches and thus speed up searches and comparisons in future reference. Now that we have come to a simple example, we conclude that in a particular scheme we have to use a multi-parameter classification method, another challenge, or indeed the main challenge of the scheme, is to overlap a parameter's number intervals (assuming the frequency parameter) with a specified radar. The intervals are the same parameter than another specified radar. In other words, for the three reasons given below the number ranges, some important parameters overlap, making the need for data classification in such systems (radar interception systems) even more urgent. These are three reasons:

* Behavior patterns of some radar parameters such as frequency, pulse repetition rate and pulse width.

* Noise in the received signals which causes the parameter values to change.

* Uncertainty in the processor unit of the system that extracts the parameters of the parameters.

The general template for the training algorithms is divided into four stages by example with the classification process:

* Collecting data
* Data preprocessing
* Apply classification algorithms
* Evaluation of applied algorithms

3. COLLECTING DATA

Collecting data

At this stage, the relevant data were collected from the database of various systems and during this phase, 17 radar information was obtained and used by AJA trustees.

4. DATA PREPROCESSING

As the information was reviewed and verified by experts in this field, so we didn't face problems like missed goal, duplicate goal and so on. The only challenge was that because the format of the radars is as in Table 1.

Table 1. Examination of radar parameters in different radars.

Frequency	pulse width	Repeat pulse	radar name
2000-2200	0.1-0.4	2-4	R1
9340-9348	2-6	133-200	R2

That is, the values of frequency segments, pulse width and pulse repetition interval are cited and there is no information on their exact values or data distribution to calculate the mean, standard deviation, and so on.

4.1. Selection and Reduction of Features using Principal Component Analysis

In this section, we review the method of selecting attributes using principal component analysis. One of the most common applications of this method is to reduce the redundancy of a dataset (Pearson et al., 1991, 559 to 572). Naturally, when it comes to reducing redundancy, we need a measure to measure it. The criterion for measuring redundancy in the principal component analysis method is the existence of a correlation between the dataset or the observation vector; therefore, it is based only on the first and second hierarchical moments. Principal component analysis begins with a vector of observations. If the N-dimensional vector X is observable and the goal is to achieve the next M-vector (M <N), whose redundancy has been eliminated by the correlation between its elements, this is done by finding a new device conversion. Convert X to these coordinates with unrelated elements. The first step in the principal component analysis method is to zero the mean of X by relation 1:

$$X \leftarrow X - E\{X\} \quad (1)$$

Then the linear combination of the X elements is formed as relation

$$y_1 = \sum_{k=1}^{N} w_{k,1} x_k = w_1^T X \quad (2)$$

In this respect, y_1 is called an integral of X, if its variance is maximal. To solve this problem we need to limit the soft w_1 to avoid the unlimited increase of y_1 according to Relation 3:

$$\|w_1\| = \sum_{k=1}^{N} \left|w_{k,1}\right|^2 = 1 \quad (3)$$

With the condition of relation 3, the cost function is formed as relation 4:

$$J_1(w\varepsilon\hat{X}_1) \equiv E\{y_1^2\} = w_1^T E\{XX^T\} w_1 = w_1^T C_X w_1 \quad (4)$$

In relation 4, C_X is the covariance matrix N × N of the vector X. The goal is to maximize the criterion J_1 (w_1) according to the relation condition 3. Based on the principles of linear algebra we can prove that the answer to this optimization problem is in the form of a relation of 4:

$$w_1 = e_1 \quad (5)$$

In relation 5, e_1 is the eigenvector corresponding to the largest eigenvalue of the matrix C_X, and w_1 is thus found to be the first axis of the coordinate system. Find the other axes of this coordinate system as follows; then a criterion similar to relation 4 is defined as relation 6:

$$J_1(w_1) \equiv E\{y_\mathrm{i}^2\} = E\left\{\left[\sum_{k=2}^{N} w_{k,i} x_k\right]^2\right\} = w_\mathrm{i}^T C_X w_\mathrm{i} \ \ , \ \mathrm{i} = 1,2, \dots, \mathrm{N} \quad (6)$$

In this case, each of the principal components with the pre-extracted components is assumed to be unrelated by the relation 7:

$$E\{y_m y_k\} = 0, 0 < k < m \quad (7)$$

As a result, the main components in question are obtained by X-ray sequencing on special matrices of the C_X matrix. In other words, the axes of the new coordinates are equal to the C_X special vectors, respectively. In relation 8 the e_i are the eigenvectors corresponding to the eigenvalues of C_X, respectively:

$$w_i = e_i \, , i = 1,2, \dots, N \quad (8)$$

$$d_1 \geq d_2 \geq \cdots \geq d_N \quad (9)$$

Now if the w_i obtained from relation 8 are placed in relation 6, one of the important features of the principal component analysis method is obtained:

$$E\{y_m^2\} = E\{e_m^T XX e_m\} = e_m^T C_X e_m = d_m \quad (10)$$

According to the relation of the 10 variances of the X-ray vector on the first new axis of the coordinates of the principal component analysis, the highest value is observed for the other axes, respectively. The significance of the problem is that for many natural signals, the eigenvalues of the covariance matrix tend to zero rapidly. Therefore, most of the X vector energy can be neglected in a finite number of coefficients of the sum of the principal components and other coefficients. This feature of principal component analysis has led to its use in compression discussions.

Classification algorithms used for learning and self-organizing vector digital neural networks

Neural networks can be called, neglected, electronic models of the neural structure of the human brain. The mechanism of learning and training of the brain is mainly based on experience; electronic models of neural networks are based on this model. The way such models deal with problems differs from the computational methods typically adopted by computer systems. The neural networks consist of a series of layers consisting of simple components called neurons that work in parallel.

One of the applications is the data locking mechanism. Of the three types used for a fasting machine, the digital vector is the learning vector. In fact, the learning vector quantization created the idea of a self-organized neural network for a closed brain. My neural network is organized based on a competition that has the capabilities of data folders. In this case, neurons are the fastest-growing types of data available. This is the weight of communication. In this method, the basic neurons are topology and, depending on the type, have different ontologies. Self-organizing neural networks can separate the data structure that you do not have. In the neural network itself, the conceptual framework of learning is unobserved. You have two neurons in your neural network: three inputs and three competitors.

Includes neurons whose inputs compete fully with the neurons that make up the full connectivity.

In (1), we have a two-dimensional puzzle in which the data are expressed by two z1 and z2 numbers. The learning vector quantization algorithm group is 4, which is 3 times the number of circles (for circles, diagonals, and angles).

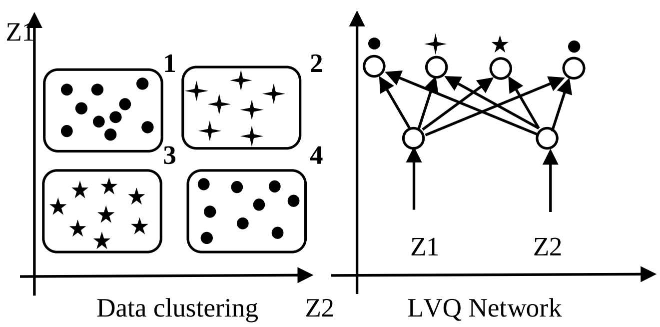

Fig. 2. The output of the learning vector quantization algorithm for the data classification problem algorithm.

4.2. Discussion and Research Findings

As mentioned above, the learning vector quantization algorithms are self-organized neural networks for data retrieval. In fact, the learning vector maker considers the learning method with the observer 2 as theoretically based on the data. In other words, the learning vector quantization algorithms are simplified with the supervisor fixing and improving the boundaries of the neural networks based on the neural network.

Fig. 3. Data classification is organized by neural network and digitized by the learning vector

Creates a cache with the name of its neural network to get the code-books. Here, at the beginning of the weight diagram, the simple value is given) In addition to the simple value method, the methods of locating the data can be simplified (the value should be the same). It is made up of topology, based on the number of neurons and the closest to the wells.

For example, consider effects 2, neuron 4, and neuron 3 and 5 (its neurons 1 and later). Then, in three self-organizing neural networks, the neuron approach to it is called the input data that is simply selected. The basement near the base is ideal. After some close neuron, we show the value of the basal neuron at the α rate, based on the topology (assumed to be linear).

If the rate is less than 0.01, the learning process and time alone have come to an end. That should have been the boundary that would have been worse if the rates had been lowered. After this step, on the basis of axioms such as the effect, each neuron is selected. In other words, check it out. Three neurons that represent the object and, from among them, consider each prober as the representation of that neuron. For example, if a neuron shows a 3-digit circle, 4-digit perpendicular, and 20-square-digit, it looks like a square neuron.

After this step, enter the neuron based on the base marker (S), for the input vectors that are entered in the desired way (simple). Struck with some data, increased weight and in all other cases (including reward and three):

$$E\{y_m^2\} = E\{e_m^T X X e_m\} = e_m^T C_X e_m = d_m \quad (11)$$

4.3. Presented Method Evaluation

In this section, we will examine the usual method of substitution. The standard global command and control prayers are designed for this purpose.

Table 2. The learning vector quantization algorithm, with regard to the number of neurons for Wine Prayer.

The number of neurons	3	4	5	6	7
The accuracy of the algorithm	97.2	97.2	97.2	98.2	99.4
Number of loop repeats	7	5	6	6	6

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The converter, which is observable for 7 neurons, seems to be a very useful method for axial prayers. For the purpose of the conventional method, Table (3) effectively compares this method with the other method. The view presented in Table (3) is presented in the suggested method.

Table 4. Comparison of the performance of the proposed method with some other common methods.

Data set	C4.5	RIPPER	CBA	CMAR	CPAR	Modiffied KNN	Presented method
IRIS	95.3	94	94.7	94	94.7	94.67	98
WINE	92.7	91.6	95	95	95.5	94.67	99.4
GLASS	67.7	69.1	73.9	70.1	74.4	74.63	74.3

In this paper, a restraint method is introduced on the learning vector quantization principles, which are initially organized only in the neural networks of the neural network.

The learning vector quantization algorithm then organizes its neural network algorithm and delimits the boundaries of the brain separator types. The results show that this algorithm is very efficient and, in contrast to other commonly used restraint methods, it is advisable for the project to continue in the list.

• Use other intelligent structures such as ANFIS to improve performance

• Add a class as unknown radars

• Combination of several different classifiers to increase accuracy of detection.

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