GROUND RADAR TARGET CLASSIFICATION USING SINGULAR VALUE DECOMPOSITION AND MULTILAYER PERCEPTRON

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Abstract

The paper deals with classification of ground radar targets. A received radar signal backscattered from a ground radar target was digitized and in the form of radar signal matrix utilized for a feature extraction based on Singular Value Decomposition. Furthermore, singular values of a backscattered radar signal matrix, as a target feature, were utilized for Radar Target Classification by multilayer perceptron. In learning phase of a multilayer perceptron we used the learning target set and in the testing phase the testing target set was used. The learning and testing target sets were created on the basis of real ground radar targets.

Keywords

Ground radar target classification, ground radar target, radar signal, Singular Value Decomposition, SVD, multilayer perceptron

1. Introduction

In this paper we are interested in classification of ground radar targets. Backscattered electromagnetic energy represented by received radar signal is detected, sampled and stored as a radar signal matrix, **X**. This signal matrix, **X**, is utilized for the classification. A classification system based on the use of a multilayer perceptron is developed as a classifier with learning.

In the learning phase, a multilayer perceptron uses a learning set consisting of real ground radar targets. A real ground radar target is observed in a “basic” position, i.e., each ground radar target of a learning set is represented by the only observation angle profile. The goal of this approach is a minimization of the learning set.

In the testing phase, the classification of a real ground radar target is performed on the basis of a multilayer perceptron. The real ground radar targets are detected in real situations, i.e., they are detected at different distance, angle, etc. It results in fact that a backscattered radar signal, being classified, represents a geometric projection of an etalon ground radar target of the learning set. This geometric projection can be concerned as a translation, rotation and dilatation of real ground radar targets of the learning set. Goal of this paper is an invariant classification of a geometrically transformed real ground targets by minimum learning set, which is created by only ground radar target etalon for each class of classified ground radar targets.

Circumstances defined above enable minimization of computational complexity of a classification process, i.e. a minimization of learning and testing time, and minimization of memory capacity for both learning and testing sets.

An analysis of applications of a multilayer perceptron in a pattern classification resulted in the fact that multilayer perceptron is a little robust due to geometric transformations of patterns [10], [11]. Since geometric transformations are assumed in classification of ground radar targets, the multilayer perceptron alone is not suitable to solve this problem. However, there are two ways how to solve the invariant classification of geometrically transformed ground radar targets. The first of them is the utilization of a different model of neural network, which is suitable for an invariant pattern classification. The second one is a generation of invariant features for pattern classification. However, a limitation of a problem solution is simplicity of a neural network model and its learning algorithm [2], [16], [17].

An analysis of chosen models of a neural network with relatively simple structure does not show better results in the field of invariant pattern classification if compared to a multilayer perceptron. Therefore the second approach was used for pattern classification (Ground Radar Target Classification). The approach is based on invariant feature generation. We used Singular Value Decomposition (SVD) [1], [7], [8], [9].

The chosen approach consists of two steps. The first step is a generation of invariant features for Ground Radar Target Classification by decomposition of signal matrices into singular values. The second step is a pattern classification by multilayer perceptron. As presented later, this approach enables classification of ground targets by radar.

In the part 2, we define the matrix of a backscattered radar signal, **X**, describe a generation of invariant features by SVD matrix decomposition and classification of ground radar targets by means of singular values and multilayer perceptron.

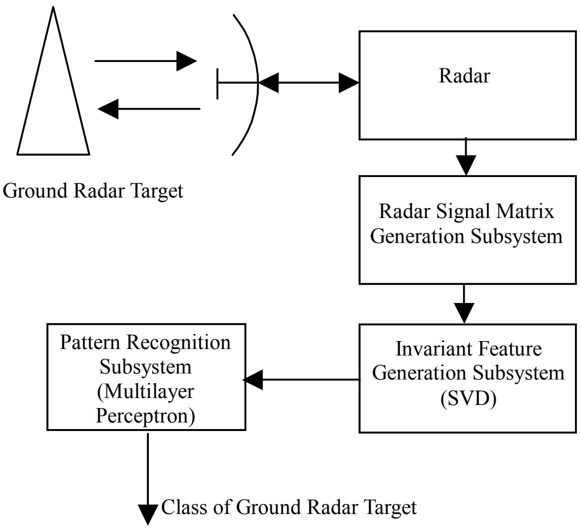

Fig. 1 Structure of invariant classification of ground radar targets

2. System for ground radar target classification

The system for classification of ground targets by radar corresponds with the structure of the classification process (Fig. 1). It consists of 3 following subsystems: a radar signal matrix generation subsystem, invariant feature generation subsystem, and pattern classification subsystem.

The classification of ground targets by radar consists of the following processes:

- Backscattered radar signal is sampled, digitized, and stored into the radar signal matrix, **X**. Because Ground Radar Target Classification is performed by multilayer perceptron, in order to generate the radar signal matrix, **X**, we used the learning and testing sets of ground radar targets.
- The matrix, **X**, is used for an invariant feature generation by singular values in the invariant feature generation subsystem.
- Singular values of a backscattered radar signal matrix are used as patterns for the invariant Ground Radar Target Classification by multilayer perceptron in the pattern classification subsystem.

2.1 Radar signal matrix generation

The aim of the radar signal matrix generation subsystem is to sample and store a backscattered radar signal into the radar signal matrix, **X**. Firstly a backscattered radar signal is sampled and stored into the signal memory. Then it is transformed into the radar signal matrix, **X,** for utilization in a feature generation subsystem.

Matrix of backscattered radar signal is defined as follows

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & & x_{1N} \\ x_{21} & x_{22} & \cdots & & x_{2N} \\ & & \ddots & & \\ \vdots & \vdots & & x_{kn} & \vdots \\ & & & \ddots & \\ x_{K1} & x_{K2} & \cdots & & x_{KN} \end{bmatrix} \tag{1}$$

where K is the number of repetition periods during which the backscattered radar signal is transformed into the signal matrix **X**; N is the number of samples of a backscattered radar signal in 1 period; x_{kn} is signal sample; $k = 1, 2, \dots K$, and $n = 1, 2, \dots N$.

2.2 Invariant feature generation

The decomposition of the signal matrix, $\mathbf{X}$, into singular values is defined as follows [3], [4], [5]

$$\mathbf{X} = \mathbf{U}\,\mathbf{S}\,\mathbf{V}^{\mathrm{T}} \tag{2}$$

where **U** is a matrix of orthonormal row–oriented eigen-vectors of ($\mathbf{X}\mathbf{X}^{\mathrm{T}}$); **V** is a matrix of orthonormal column–oriented eigen-vectors of ($\mathbf{X}^{\mathrm{T}}\mathbf{X}$); **S** is a diagonal matrix of singular values of the signal matrix **X**; and $^{\mathrm{T}}$ is a transpose matrix operator.

The singular values $s_{k,n}$ are defined by the characteristic equation in the form of

$$\left|\mathbf{X}^{\mathrm{T}}\mathbf{X} - \lambda\,\mathbf{I}\right| = 0 \tag{3}$$

Solutions of (3) are eigen-values λ_k. Singular values $s_{k,n}$ can be computed as follows

$$s_{k,n} = \sqrt{\lambda_k} = s_k \quad \text{for } k = n \tag{4}$$

Then we define the matrix of singular values by following

$$\mathbf{S} = \operatorname{diag}\left[s_1, s_2, \dots, s_{\mathrm{N}}\right] \tag{5}$$

It is characteristic that

$$s_k \geq 0,\ k = n, \quad \text{and} \quad s_k = 0,\ k \neq n \tag{6}$$

Let the matrices **U** and **V** be expressed in the forms using column vectors as follows

$$\mathbf{U} = [\ \mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_N\ ] \tag{7}$$

$$\mathbf{V} = [\ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N\ ] \tag{8}$$

then the signal matrix **X** can be expressed by sub-matrices $\mathbf{X}_k$ and decomposition of **X** into singular values, by (2), is

$$\mathbf{X} = \sum_{k=1}^{N} \mathbf{u}_k\, s_k\, \mathbf{v}_k^{\mathrm{T}} = \sum_{k=1}^{N} \mathbf{X}_k \qquad \text{for} \quad k = n\,. \tag{9}$$

Expression $\mathbf{X}_k = \mathbf{u}_k\, s_k\, \mathbf{v}_k^{\mathrm{T}}$ is an outer product of a decomposition of the radar signal matrix **X** into singular values and expresses the elementary matrix $\mathbf{X}_k$ of a received radar signal. The elementary sub-matrix $\mathbf{X}_k$ is projection of the radar signal matrix **X** into sub-space in the direction of eigen-vector $\mathbf{u}_k$ in N-dimensional orthogonal space of eigen-vectors $\mathbf{U}^N$. The singular value s_k represents the oriented energy of sub-matrix $\mathbf{X}_k$ [14], [15].

The singular values s_k are real positive numbers. If the singular values are ordered into monotonously decreasing set as follows

$$s_1 \geq s_2 \geq \ldots \geq s_M > s_{M+1} \approx s_{M+2} \approx \ldots \approx s_N \approx 0 \quad (10)$$

then the following approximated relation holds true

$$\mathbf{X} = \sum_{k=1}^{N} \mathbf{u}_k\, s_k\, \mathbf{v}_k^{\mathrm{T}} \approx \sum_{k=1}^{M} \mathbf{X}_k = \mathbf{X}_M \quad (11)$$

Eqn. (10) expresses the approximated representation of the signal matrix **X** by SVD (2). The error of an approximation of the signal matrix **X** expressed by Euclidean metric is

$$\left\| \mathbf{X} - \mathbf{X}_M \right\|^2 = \sum_{k=M+1}^{N} s_k^2 \quad (12)$$

(small compared to other linear orthogonal transforms).

The signal matrix **X** is expressed by a vector of singular values **S** and matrices of eigen-vectors **U** and **V**. Eigenvectors **U**, **V** and a matrix of singular values **S** contain all the information about the signal matrix, **X**. But substantial information about a signal matrix, **X,** is stored in the matrix of singular values, **S**. Therefore there is an idea of utilization of singular values as features for pattern classification. Results of an analysis of the singular values are due to the fact mentioned above [7], [8], [9], [14], [15].

Singular values of the signal matrix **X** were used as a features for the invariant Ground Radar Target Classification by multilayer perceptron.

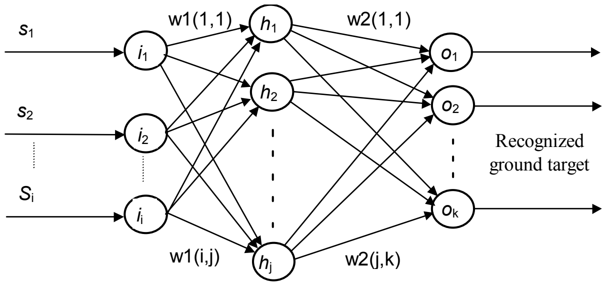

Fig. 2 Structure of the pattern classification subsystem based on multilayer perceptron

2.3 Pattern classification

The structure of a multilayer perceptron, which was used for Ground Radar Target Classification, consists of input (i), hidden (h), and output layers (o) (Fig. 2). The number of neurons in the input layer is due to the number of singular values needed for classification of ground radar targets. The number of neurons in the hidden layer was determined experimentally due to results of Ground Radar Target Classification. The number of neurons in an output layer is determined by number of recognized classes of ground radar targets. The back-propagation algorithm was used for learning of the multilayer perceptron [12,13].

3. Ground radar target classification

In order to classify ground radar targets we used a real radar signal received by non-coherent battlefield radar. The radar parameters are as follows:

- Pulse width 400 ns
- Pulse repetition frequency 4 kHz
- Frequency band J
- Signal-to-noise ratio (SNR) 16 dB.

In order to digitize a received radar signal we used 10–bit digitizer, PCI–9810. The sampling period of the digitizer was T_{SAMPLE} = 50 ns, i.e. we got a sampled profile of a ground radar target consisted of several tens of samples.

We used learning and testing sets for classification of ground radar targets. Both the learning set and testing set consisted of the 8 following classes of ground radar targets: masts**,** big buildings, small buildings, trees, cars, trucks, chimneys, and bushes.

A digitized radar signal was stored either in the etalon radar signal matrix, **C,** or in testing radar signal matrix, **X**.

S. V.	Class No. 1	Class No. 2	Class No. 3	Class No. 4	Class No. 5	Class No. 6	Class No. 7	Class No. 8
s_1	27.15	38.32	39.87	30.99	28.63	28.74	27.43	27.26
s_2	1.69	1.67	1.81	2.10	2.01	3.00	1.75	1.72
s_3	0.61	1.02	0.77	1.06	1.79	2.22	0.56	0.74

Tab. 1 The singular values of learning set ground radar targets

Each class of the learning set was represented by one real etalon ground radar target. Each class of the testing set consisted of 10 real ground radar targets which corresponded to those of learning set; e.g., class of buildings, class of trees, class of cars, etc.

A profile of each etalon ground radar target was sampled 100-times and a mean value of those 100 profiles was used for a generation of the etalon ground radar target matrix $\mathbf{C}_i$, for I = 1, K, 8, where i stands for the number by which a certain class is assigned. The matrix $\mathbf{C}_i$ represents a learning set.

A ground radar target of a testing set was sampled just ones for the generation of the signal matrix **X**. A singular values of matrices **C** and **X** were computed using equations (2), (3), and (4).

Singular values were ordered into a monotonously decreasing set corresponding to the equation (10). Analysis of singular values shows that for Radar Target Classification it was sufficient to utilize just 3 singular values, s_1 to s_3. The examples are shown in Tab. 1.

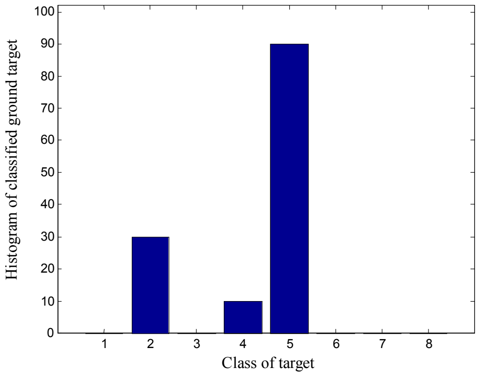

Fig. 3 The histogram (percentage) of correct classification of ground radar target of the class No. 5

Ground Radar Target Classification was performed by multilayer perceptron. Learning of a multilayer perceptron was based on the back–propagation algorithm.

No. of class.	Value of output neuron								Given class	Major. voting
	o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8		
1	0	1	0	0	1	0	0	0	2 and 5	
2	0	0	0	0	1	0	0	0	5	
3	0	0	0	0	1	0	0	0	5	
4	0	1	0	0	1	0	0	0	2 and 5	
5	0	0	0	1	0	0	0	0	4	5
6	0	0	0	0	1	0	0	0	5	
7	0	0	0	0	1	0	0	0	5	
8	0	0	0	0	1	0	0	0	5	
9	0	0	0	0	1	0	0	0	5	
10	0	1	0	0	1	0	0	0	2 and 5	

Tab. 2 Classification of the ground radar target of the class No. 5

The structure of a multilayer perceptron was developed according to a number of singular values, number of recognized classes of ground radar targets, and results of classification. Therefore its input layer consists of 3 neurons, i_1 to i_3, which corresponds to 3 singular values, s_1 to s_3. Output layer consists of 8 neurons, o_1 - o_8, which corresponds to 8 classes of ground radar targets. The number of neurons in hidden layer is 30 (h_1 to h_{30}) and was determined experimentally in accordance with the results of classification.

The process of Ground Radar Target Classification was repeated 10-times. I.e., each ground radar target of the testing set was recognized 10-times and a decision about the class was performed by majority voting (6 from 10). The process, which was repeated 10-times, included sampling of the profile of a target, generation of the signal matrix **X**, SVD for the target feature generation, and classification using a multilayer perceptron.

As an example of Ground Radar Target Classification of the class No. 5 we present Tab. 2. We can see there that the target was classified 3-times into 2 classes (the classification No. 1, No. 4, and No. 10) and one classification was incorrect (the classification No. 5). The target of the class No. 5 was, by majority voting (6 from 10), correctly classified into the class No. 5. The percentage of the classification is shown in Fig. 3.

As mentioned above, Ground Radar Target Classification was performed for 80 ground radar targets of testing set, which were divided into 8 classes (10 targets in each class of the testing set). The percentage of the correct classification during all the experiment is shown in Fig. 4.

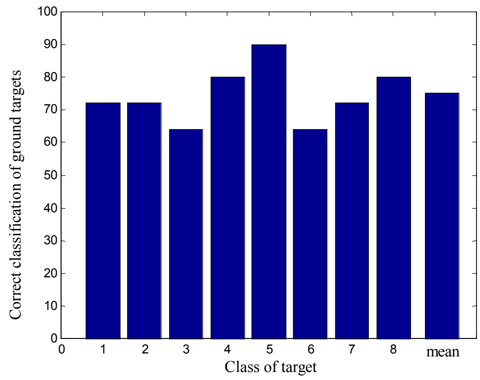

Fig. 4 Percentage of correct classification of ground radar targets

4. Conclusion

Our method of Ground Radar Target Classification, which is based on the use of non-coherent battlefield radar, SVD, and multilayer perceptron brought effective results. The method can be successful when the backscattered signal is over the noise, i.e., the ground radar target signal can be separated from noise by means of the analysis of backscattered radar signal. The efficiency of Ground Radar Target Classification corresponds with SNR. However there is a need of analysis of the relationship between an efficiency of classification and SNR.

The obtained results depicted in Fig. 4 are due to SNR=16 dB. The greatest percentage of a correct classification was obtained in case of the classes of cars and trees, and the smallest one was in case of the classes of small buildings and trucks. In all the experiments the achieved percentage was 65% to 90%. The mean value of the correct classification was 75.2%. That is sufficient enough for such application as the used battlefield radar. This corresponds with results obtained in [2], [6], [16], [17].

As the original results of this paper, we define:

- Usage of SVD and a multilayer perceptron for Ground

Radar Target Classification in case of non-coherent battlefield radar.

- The determination of a signal learning set.
- The experimental results.

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