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## APPLICATION OF BPN AND LVQ NEURAL NETWORKS FOR RADIOHOLOGRAPHY IMAGE RECOGNITION

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### **Abstract**

*Informative indication is taken from a contour obtained upon filtration of a radioholography image. Recognition is performed by classification of the types of aircrafts. BPN and LVQ neural networks are used by making comparative analysis of the two approaches.*

### **1. Introduction**

One of the important directions of the contemporary radiolocation is the creating of methods for having the whole information that is contained in the radiolocationable signals and noises. Radiolocationable recognition is a part of this direction. It includes definition of the radiolocationable characteristics of different objects, a choice of informative indication and decisive rules for recognition [1]. There are many ground, overwater, air and other targets called 'lying' targets, which vary greatly by their parameters and characters. This poses serious challenges and calls for upgrading and following development of the theory and practice of radiolocationable recognition.

Using radiology approaches to synthesize radiolocationable images provides the opportunity to estimate the shape and the size of the radiolocationable target, as well as the typical indication of the object, on which radiolocationable recognition can be performed [6].

The interest of the specialists working in the sphere called 'intelligent' modeling to the application of shapes of artificial intelligence (AI) in recognition systems has suddenly grown up lately. The great variety of types of neural networks, as well as of radiolocationable recognition systems requires profound analysis and experimental work which purpose is achieved best when the shapes of AI are selected. [2 ]

## 2. Choice of informative indication

### 2.1. Methods for obtaining a contour

The contour of the object is reputed to be the most informative in object recognition. Methods for having a contour are separated in two groups:

- gradient methods -- based on the mark of the first or the second derivative;

- methods, based on a functional approximation and on the analysis of the spectrum of the ingoing image in the sphere of the spatial frequency.

Spatial element with  $x$  and  $y$  of the function  $f(x,y)$  is done in gradient methods for separation of edge and limits. The module of the gradient value is defined for this function, which forms gradient image  $J(x, y)$ :

$$(1) \quad J(x, y) = \|\nabla f(x, y)\| = \sqrt{J_x^2 + J_y^2} = \sqrt{\left(\frac{\partial f(x, y)}{\partial x}\right)^2 + \left(\frac{\partial f(x, y)}{\partial y}\right)^2}$$

From gradient image we pass to its double presentation to the following formula:

$$(2) \quad b(x, y) = \begin{cases} 1, & \text{ако } J(x, y) \geq \mathcal{G} \\ 0, & \text{ако } J(x, y) < \mathcal{G} \end{cases}$$

where  $\mathcal{G}$  is a threshold.

Usually, the value of the threshold is defined by analyzing the histogram of the gradient presentation:

$$(3) \quad J(x, y), \quad x = 1, 2, \dots, N, \quad y = 1, 2, \dots, M$$

The image is stored in the memory of the computer by its discrete (figure) presentation:

$$g(i, j), \quad i \in 1, 2, \dots, N, \quad j \in 1, 2, \dots, M. (4)$$

The marks of the derivative for the function  $g(i, j)$  are accomplished by finite differences, performing in determinate scheme (single, double), called differential (gradient) operators.

Such gradient methods are Roberts, Sobel, Canny, LoG, Prewitt and zero-crosses.[2]

Another group includes:

- method, based on functional approximation;
- method, based on the analysis of the spectrum of the incoming image in the sphere of the spatial frequency.

The methods of this group require a lot of calculations, which makes difficult their use.

Methods in MATLAB7.0 are used for receiving the contour of the image[3]. The method for the contour's assignment is chosen on the basis of experiments with tentative objects.

A selection of  $n = 30$  images is chosen to choose a method for obtaining the contour. The selection contains images of aircrafts which are accepted as models.

A contour of the object (aircraft) and the number of the points lying on it in each method is defined for each image of the selection. The results from the experiment are shown on Table 1. From the received results we can see that when Roberts's method is used, the greatest number of points of the contour is given, therefore it is the most informative. Another priority of this method is that the contour thins out but it does not end. That is why Roberts's method is chosen to obtain the contour of the image.

Obtaining the contour and taking the coordinates of its points down is done accordingly by MATLAB7.0, the functions *edge* and *find* [3].

## **2.2. Finding indication from a contour**

### **2.2.1. General characteristic of the indications of the objects and vector formation from indications.**

Composing of a basis of information related with the characteristics of the investigated objects is necessary to make concrete classification of flying objects in the described groups.

These are morphology characteristics describing the shape and the special geometric features of the investigated objects or their silhouette projections[2].

The contour curvature of the object silhouette, its area,

circumference, fuselage axis, width of the aircraft's wings, symmetry of the contour and others treat to this group.

The properties of the objects related with the shape of the typical representative plane for the different groups, the location of the wings in relation to the fuselage axis and others can be estimated based on the analysis of the morphology characteristics. The analyses of the investigated objects are based mostly on the morphology characteristics of the objects silhouette images in many investigations connected with the creating of automation methods and instruments for aircrafts recognition[5]. In general, the morphological properties of the silhouette images have great potential. However, the results of the published investigations show that their potential of aircrafts in 2D-images is not used enough. This refers mostly to the approaches that ensure invariant for the scale, rotation and translation of the object in the frame. Another recognition approach must be searched according to this base.

The following vector from indications has been formed to recognize separate types of aircrafts (specific 'Stealth', military, vehicular) in a contour synthesized after a cultivation of radioholographic image:[6]

1. an attitude  $A$  of the width to the length of the object where the width is the distance between the most distant points of the wings and the length is the distance between the most distant points of the fuselage axis;

2. an incidence  $\alpha$  of the right which connects the mass centre and the most distant point of one wing in relation to the fuselage axis.

3. the position of the mass centre in relation to the geometric environment of the fuselage axis. The difference 'geometric environment-mass centre' -  $L_r$  is calculated.

4. width of the aircraft's wing -  $L_k$ .

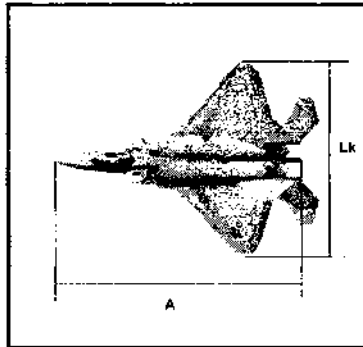
The indications for 'F22' are shown in Fig.1.

In this way the introduced indications are invariant in respect of the scaling and translation of the object in the frame.

The typical values calculated for the relevant indications of the separate types of aircrafts are shown on Table 2.

Table 1. Number of points from the contour of the image, obtained in the different methods.

Number of the image	Method of Robert's	Method of Sobel's	Method of Prewitt's	Method of Canny's	Method of zero-crossing's	Method of LoG's
1	669	480	508	478	480	480
2	599	436	446	438	437	437
3	625	464	480	458	458	458
4	604	449	469	451	450	450
5	648	467	491	461	463	463
6	650	466	516	466	470	470
7	622	460	478	462	463	463
8	608	432	445	434	435	435
9	638	483	510	478	480	480
10	616	449	502	449	449	449
11	578	430	448	431	429	429
12	682	489	521	486	490	490
13	618	459	497	456	459	459
14	672	492	533	492	493	493
15	603	443	477	440	443	443
16	671	497	540	495	499	499
17	615	469	512	466	469	469
18	608	452	473	447	448	448
19	603	438	464	436	440	440
20	620	429	456	429	435	435
21	577	416	433	414	413	413
22	554	412	416	414	414	414
23	554	408	414	409	408	408
24	604	449	485	448	450	450
25	659	479	499	478	478	478
26	589	436	455	437	436	436
27	629	459	497	458	460	460
28	608	450	482	448	447	447
29	588	431	467	432	432	432
30	663	503	520	497	495	495



*Fig.1. A diagram of aircraft F22 and its geometric size*

The following classification and the relevant recognition of the aircrafts can be made by Table 2 according to the enunciated indications and received costs for the concrete type of aircraft.

1. The aircrafts can be classified in three groups according to the indication attitude: Specific, Military and Vehicular.

2. The second group of aircrafts can be separated according to the indication position of the mass centre in relation to the geometric environment of the fuselage axis on Bombers, Destroyers and UAV.

The following classification and relevant recognition of the aircrafts can be made by table 2 according to the enunciated indications and received costs for the concrete type of aircraft:

Because of the fact that UAV have a typical cost of the attitude A that is notable from the cost for the other types of aircrafts, this group could be separated and classified correctly in attitude.

3. The vehicular aircrafts could be recognized by the indication A as a type *An* or as a type *Boeing*. The number of the aircraft's engines can be defined by the indication width of the wings because those with more engines 4, 6 have greater width of the wings.

For their obtaining the program environment MATLAB7.0 is used [3]. The program for assignment and calculating the relevant indications conditions the received images in the following way:

- the obtained image passes through a cultivation that separates the contour of the object.
- calculates the coordinates of the mass centre.
- the coordinates of the last points of the wings and the fuselage axis (conditionally represented as head and tail) are extracted.
- calculates the costs of the indications.

### 2.2.2. Estimation of the information of the enunciated indications

Interval marks are used for estimation of the information of the introduced indications [1]. A confidential interval is made for the middle cost and Student's distribution is applied:

$$(5) \quad T = \frac{\bar{X} - E[X]}{s} \sqrt{n}$$

where  $\bar{X}$  and  $s$  are the marks of the middle cost and the middlesquare diversion of the costs of the relevant indication accordingly;

$n$  - volume of the extract data;

$E[X]$  - middle cost of the indication .

The confidential interval usually has symmetrical frontiers according to the point mark. The cost of these frontiers depends on the stages of familiarity  $k = n - 1$  and the wished confidential probability  $\gamma$ . The confidential interval for the middle cost is in the equation:

$$(6) \quad I_{\gamma,k}^{E[X]} = \left( \bar{X} - t_{\gamma,k} \frac{s}{\sqrt{n}}; \bar{X} + t_{\gamma,k} \frac{s}{\sqrt{n}} \right)$$

where  $t_{\gamma,k}$  is Student's criterion.

The conterminous relative mistake  $\Delta_{\gamma,k}$  that is allowed in an exchange of the middle cost and its mark is calculated:

$$(7) \quad \Delta_{\gamma,k} \approx t_{\gamma,k} \frac{s}{\sqrt{n} \bar{X}} \cdot 100, \%$$

The confidential intervals of the indications, estimated at (6) for particular types of aircraft are presented on Table 3, 4, 5 accordingly.

Table 2. Values of the indications for the particular types of aircraft														
Type of aircraft	Xw 1	Yw 1	Xw 2	Yw 2	Xn ax	Yn ax	Xopt	Yopt	Xc	Yc	A= w/le.	Alfa	N= Xc- Xmd	
*****														
F22	328	92	328	365	73	232	411	237	274	239	0.807	66.83	-32	
F117	72	125	250	128	161	351	161	116	161	203	0.755	41.25	-30.5	
Military aircraft Exterminators														
Mirag 2000 EU	363	275	363	109	191	123	191	409	191	304	0.58	54.94	-38	
Su - 34 RU	275	145	275	393	8	270	387	270	237	270	0.654	72	-39.5	
Jaguar EU	258	213	258	32	17	123	337	123	224	123	0.566	20.71	-47	
F16 USA	328	73	328	276	119	176	418	176	307	176	0.679	78	-38.5	
Bomber														
Tu 160 RU	339	102	339	242	104	174	392	174	272	174	0.486	45.447	-24	
Buccane- er EU	236	41	236	199	86	121	330	121	217	121	0.647	76.35	-9	
Reconnaissance														
UAV											1.4706	90	-	
											1,559	90	-	
											1,63	90	-	
											1,71	90	-	
											1.9238	90	-	
Type of aircraft	Xw 1	Yw 1	Xw 2	Yw 2	Xn ax	Yn ax	Xopt	Yopt	Xc	Yc	Le.	W	N= Xc- Xmd	
Transports Boeing - USA														
B 7474 engines											70.66	84.44	0.912	-
B• 7572 engines											47.3	45	0.9514	-
B• 7672 engines											48.5	47.6	0.9814	-
An - RU														
An - 722 engines											28.07	31.89	1.1361	-
An - 224 engines											57.90	64.40	1.1123	-
An - 1244 engines											69.1	73.30	1.0608	-
An - 2256 engines											84.00	88.40	1.0524	-



Table 3. Confidential intervals and border relative error for indication A

Type of aircraft	Down border	Upper border	*, % **
Stealth	0.7575	0.8077	
Military			
Exterminators	0.56	0.6789	
Bombers	0.486	0.647	
UAV	1.4706	1.9238	
Transports			
Boeing	0.912	0.9814	

\*=  $\Delta_{1,x}$ ; \*\*=  $\gamma=0,95$

Table 4. Confidential intervals and border relative error for indication  $\alpha$ .

Type of aircraft	Down border	Upper border	*, % **	*, % ***
Other types of military aircraft	78,9316	85,9434	4,2529	7,8103
UAV aircrafts	90			

\*=  $\Delta_{\gamma\kappa}$ ; \*\*=  $\gamma=0,95$ ; \*\*\*=  $\gamma=0,99$

Table 5. Confidential intervals and border relative error for indication  $L_r$

Type of aircraft	Down border	Upper border	*, % **	*, % ***
Exterminators	34.915	46.585		
Bombers	9	24		

\* =  $\Delta_{\gamma\kappa}$ ; \*\* =  $\gamma=0,95$ ; \*\*\* =  $\gamma=0,99$

Table 6. Confidential intervals and border relative error for indication  $L_k$

	Boeing	
	2 engines	4 engines
Lk	<56.02	>56.02

Table 7. Confidential intervals and border relative error for indication  $L_k$

	An		
	2 engines	4 engines	6 engines
Lk	<48.145	80.85 < Lk < 48.145	>80.85

They are obtained using the program environment MATLAB 7.0 [3].

**3. Using neural networks for objects recognition by classification.**  
Comparative analysis of two types of neural networks - BPN and LVQ is made.

**3.1. Presenting of the entrance data for the neural networks**

The application of the neural networks requires special preparation of the data, at which it will accomplish aircrafts recognition.[4] These indications are defined in p. 2.2.1. When working with real numbers, the error teaching of the neural network is relatively big. That is why, the entrance data are coded with 0 and 1.

The entrance data are coded as follow:

Indication attitude A: This indication is changed in 5 intervals, characteristic for three classes of aircraft – Stealth, Military and Transport, presented in p.2.2.2. The coding of the entrance is the following:

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1,

To the first column corresponds first class (Stealth);

To the second and third – second class (Military);

To the third and fourth – third class (Transports).

The coding of the wished exit (target) is the following

1	0	0	0	0
0	1	1	0	0
0	0	0	1	1,

where to first class corresponds coding 0 0 1;

to second class - coding 0 1 0;

to third class - coding 1 0 0;

➤ Indications  $N$

The coding depends on the intervals:

Exterminators – 34,915 - 46,585 - [0 0]

Bombers – 9 – 24 - [1 1]

Respectively, there are two classes at the end of the neural network

[1 0

0 1].

➤ Width of the wings  $L_k$ .

If the attitude is in the following borders:

- from 0.8701 – 1.0059 – coding is 1;

- from 1.035 – 1.1458 coding is 0.

Respectively the neural network has two exits:

- 0 0 – Boeing;

- 1 1 – An.

### 3.2. BPN neural network

#### 3.2.1. Creating a neural network

Diffusive neural network with converse spreading of the error (BPN) can be created in two ways – by program code or by using dialogue windows.

➤ Creating of the network by dialogue windows.

It is using *Neural Networks Toolbox* of the program package

*Matlab 7.0*.

➤ Creating by program code:

The function, which creates diffusive neural network with converse spreading of the error is *newff*. The first step in creating a “*feedforward*” network is initializing the network object. The function *newff* creates “*feedforward*” network by the code, written as follows:

```
net=newff([],[],{'');
```

Therefore, the code for the data from the table has the following aspect:

```
net=newff([0 1; 0 1; 0 1],[3,8,3],{'tansig', 'tansig'});
```

This command creates network object, and initializes the weights and the diversions of the network. Thus the network is prepared for training. Before starting training of “*feedforward*” network, the weights and the diversions have to be initialized, which is done by the function *newff*.

### 3.2.2. Algorithm for training of the network

The presented algorithm uses the gradient method, which decreases the weights. [7] The gradient method is called backpropagation, which is a training algorithm, in which the weights are moved in the direction of the negative gradient. There are many varieties of the backpropagation algorithm: the most simple implementation of backpropagation is the renovation of the networks weights and diversions in the direction in which the function decreases – negative gradient.

A training multitude of last-number vector couples is used, presenting input image and wanted image. The input image is presented on the entrance layer of HM. The information is spread on the initial layer of the network and then concrete image appears.

The difference between this image and the wanted image represents the operation error of HM. The value of the error can be estimated like middlesquare. If the value of the error is lower than a given threshold, then a next couple is chosen. Otherwise, the vector of the error in the initial layer is used for estimation of the initial errors of the neural from the nearest layer. These errors spread to the previous layer and so on. The errors from each layer are used for correction of the weights of the connections to this layer. The procedure is repeated for all couples from the trained multitude of (input-wanted image).

One round of all couples from the trained multitude is called cycle or epoch. In other words, the meaning of every epoch is the presentation of each couple input-wanted image from the trained multitude only once. The process is repeated for as much epochs, as required that the costs of the error become less or equal to a given threshold (the operation accuracy of the neural network).

### 3.2.3. Simulation of the neural network.

The function **sim** imitates network. **Sim** takes network input  $p$  and network object  $net$ , and returns network output  $a$ . Below is presented the general appearance of the function **sim**:

```
p={ [   ] };  
y=sim(net,p).
```

### 3.3. LVQ

#### 3.3.1. Creating the neural network.

LVQ neural network analogy of BPN network can be created in two ways – by program code or by using dialogue windows.

#### 3.3.2. Creating LVQ by program code

The LVQ network could be created by the *newlvq* function.

```
net= newlvq (PR,S1,PC,LR,LF)
```

where:

- PR is a  $R \times 2$  matrix of minimal and maximal values for R input elements.

- $S^1$  is the number of the first layer of hidden neurons.

- PC is a  $S^2$  element vector with the percentage for the typical class

- LR is the precision of education (by understanding 0.01).

- LF is the educating function (by understanding *learnlv1*).

After calling the *newlvq*, a net with 10 neurons in the first and 15 neurons in the second layer will be created with its arguments, The first layer of weights are initiated in the center of the input range with a *midpoint* function.

The prime values of the first layer of the weight matrix are checked with:

```
net.IW{1,1}
```

```
ans =
```

```
.....
```

The weights of the second layer are checked with:

```
net.LW{2,1}
```

```
ans =
```

```
.....
```

In this way, the competitive neuron and the neurons in the line layer it is connected to can be determined.

All other weights between the competitive and the line neurons are equal to 0.

#### 3.3.3. Algorithm of education.

The educating function for the *LVQ* net is *learnlv*, and it is used by understanding. The education in the competitive layer is based on a pair of input and target neurons.

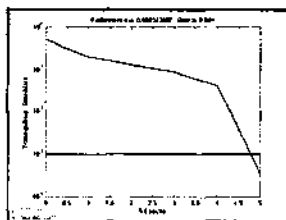
The simulation of the *LVQ* neuron network is done in a way similar to

the simulation of the *BPN* neuron network, and this procedure is described in point 3.2.3.

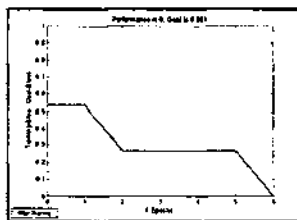
**3.4. Comparison of *BPN* and *LVQ* neuron networks according to the number of the training epochs.**

200, 500 and 1000 epochs have been offered. A comparative analysis of the training errors of the two networks with reference data has been made.

200 epochs.



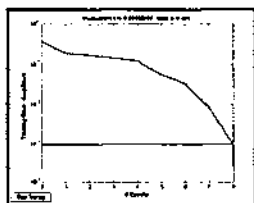
a)



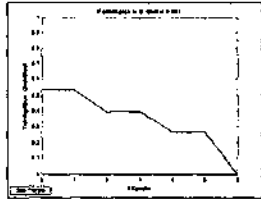
b)

Fig.2. Training of the neuron nets for 200 epochs –  
a) *BPN* neuron network, b) *LVQ* neuron network.

500 epochs.



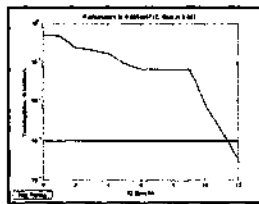
a)



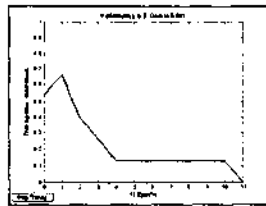
b)

Fig.3. Training of the neuron networks for 500 epochs –  
a) BPN neuron network, b) LVQ neuron network.

1000 epochs.



a)



b)

Fig.4. Training of the neuron networks for 1000 epochs –  
a) BPN neuron network, b) LVQ neuron network.



The desired level of mean square level of erroneous answers is 0.001. The average values of the reached level for both networks is presented on Table 8. The number of the epochs needed for reaching the level is shown, too.

*Table 8. Values of the average level of errors and number of epochs for training BPN and LVQ neuron nets.*

Number of epochs	BPN		LVQ	
	Average level of errors	Number of epochs needed for reaching the level	Average level of errors	Number of epochs needed for reaching the level
200	0.000343	5	0	6
500	0.000964	8	0	6
1000	0.0003357	12	0	12

**Conclusion:** We see from the results, that the LVQ neuron network reaches the wanted level of precision 0.001 unlike the BPN neuron net. The LVQ network gets trained for 12 epochs when 1000 are given, while if a smaller number of epochs is given (200, 500) it gets trained faster. Therefore, when experimenting with real objects it is better to use an LVQ neuron network with 500 epochs of training.

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## ПРИЛОЖЕНИЕ НА BPN И LVQ НЕВРОННИ МРЕЖИ ПРИ РАЗПОЗНАВАНЕ НА РАДИОХОЛОГРАФСКО ИЗОБРАЖЕНИЕ

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### Резюме

От контур получен след филтрация на радиохолографско изображение са снети информативни признаци. Извършено е разпознаване чрез класификация на типове самолети. Използвани са BPN и LVQ невронни мрежи като е направен сравнителен анализ на двата подхода.