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A FEEDFORWARD LINEAR NEURAL NETWORK WITH HEBBA SELFORGANIZATION IN RADAR IMAGE COMPRESSION

ABSTRACT

The article presents the application of the feedforward neural network with Hebba selforganization to radar images compression. Influence of number of neurons and size of segments of a radar image to its compressed form is checked.

INTRODUCTION

The application of radar images in navigation is not a new idea. A common method of using radar image to fix position is finding on a radar image a point of known location and determination the ship position with relation to this point using to this purpose distance and bearing. But situations happen when a navigator is not able, because of different reasons, to find any characteristic point on a radar image, which he could assign a position and then on the basis of it determine his own position. In such cases we can apply comparative navigation methods or algorithms from the artificial intelligence domain like for example neural networks (multilayered perceptron, RBFNN, HRBFNN, GRNN, neurofuzzy network), which using knowledge located into sample radar images are able, on the basis of a registered radar image, fix an approximated ship's position. For the sake of huge amount of information, included in a radar image and difficulties with its processing during satisfactory period of time it is convenient to transform available radar images to a more compact form, preserving the most important features of the original. The article presents one of the methods that could serve to this purpose – a feedforward linear neural network with Hebba selforganization that implements PCA transformation.

There are a lot of image compression methods but there is a problem with estimation of their usefulness in radar images processing and position approximation methods. Presented in [4] and [5] results are based on estimating the compressing Kohonen neural network using position accuracy achieved by the positioning system based on radar images compressed by this neural network. Thus, we have the estimation of the given solution without knowledge about contribution of each part of the system to the final result.

Just, for that reason, it was necessary to find a universal criterion of estimation of the radar image compression algorithms, with reference to the position approximation systems. The most important question was to determine what kind of compression will help and what can be considered as an obstacle in the process of fixing the position by approximation system. It was proved that in case when the learning process of the positioning system will use original compressed radar images – we will have a large set of examples of original radar images taken from the coast area under consideration – then the goal at the compression phase is to save all relations between original radar images in the compressed images domain. This means the situation, when similar radar images will possess representatives in the compressed images domain also similar to each other. Solutions, which would disperse compressed radar images equivalents from positions close to them, would increase the speed of the changeability of the approximating position function in the areas where data are similar to each other but simultaneously are characterized by the considerably different value of the position function. The position function can be presented by the following [3]:

$$f(\mathbf{d}) = \mathbf{p} \tag{1}$$

where: **d** is an compressed radar image and **p** is a latitude and longitude vector.

To ensure appropriate accuracy of positioning system these areas would have to be represented by greater number of learning data extending simultaneously calculation time in the learning or conclusion stage. The evaluation function of radar images is as follows:

$$E = \frac{1}{c}\sum_{i<j}^{n}\left[\left(a_{ij} - a_{ij}^{*}\right)^{2} / a_{ij}\right] \tag{2}$$

$$c = \frac{n(n-1)}{2} \tag{3}$$

where: n – number of test radar images with corresponding features vectors;
i, j – indexes of consecutive radar images and their compressed equivalents;
a_{ij} – normalized Euclidean distance between two radar images;
a^*_{ij} – normalized Euclidean distance between two compressed images.

RADAR IMAGE COMPRESSION

One of the most popular image compression methods is PCA (Principal Component Analysis). It is the statistical method determining linear transformation $\mathbf{y} = \mathbf{Wx}$, that convert a description of a stationary stochastic process in the form of the vector $\mathbf{x} \in R^N$ into the vector $\mathbf{y} \in R^K$ through the matrix $\mathbf{W} \in R^{K \times N}$, where K<<N, in the way that the output domain with reduced dimension preserves all the most important information concerning the process.

During conducted tests the network implemented Sanger rule that enables to determine many of eigenvalues was used. The network is organized in the form of many independent neurons generating following output signals [2]:

$$y_i(l) = \sum_{j=0}^{N} W_{ij}(l) x_j(l) \tag{4}$$

The process of synapses values $\mathbf{W}_i$ determination could be presented as follows:

$$\mathbf{W}_i(l+1) = \mathbf{W}_i(l) + \eta\left(y_i(l)\mathbf{x}'(l) - y_i^2(l)\mathbf{W}_i(l)\right) \tag{5}$$

$$\mathbf{x}'(l) = \mathbf{x}(l) - \sum_{h=1}^{i-1} \mathbf{W}_h(l) y_h(l) \tag{6}$$

During the researches the solution with decreasing value of η was assumed

$$\eta(l) = \frac{\eta(0)}{l^{\gamma}} \tag{7}$$

γ rate was altered in the following range (0,5, 1). The initial value of η was fixed according to the following rule: $\eta(0) = 0.5[\mathbf{X}^T\mathbf{X}]$.

EXPERIMENTAL RESULTS

The researches were conducted in order to examine influence of the size of radar images segments to the compressed form of these images. Every image used during tests, the size of 100x100 pixels, was subjected to the process of segmentation (segments of the same size) and subsequently for a chosen size of the segment, the number of eigenvectors was determined. Amount of eigenvectors was fixed in the way that regardless of the segment size the size of the compressed image should be the same – 200 units of information. The following size of segments and numbers of eigenvectors combinations were checked – (5x10 pixels, 1 eigenvector per segment), (10x10, 2), (10x20, 4), (20x25, 10), (20x50, 20), (50x100, 100), (100x100, 200).

During the experiments, 31 original black and white radar images coming from the Gdansk Bay area were used (a distance between consecutive registrations of radar images is about 600 m) and 93 derivatives of these images. Each original image had additionally 3 converted from it equivalents which sums to 4 image series – each consisting of 31 images from different positions (primary series no. 1 with the originals and series no. 2, 3 and 4 with the copies). Images with the same indexes in each of the series corresponded to the same ship position (position registered using GPS). Additional radar images were constructed by the rotation of original images at an angle from the range of <–3°, +3°> and then after the rotation, deformations to original images were introduced. The rotation was used in order to take a gyro compass error into consideration. A gyro compass is envisaged to use in the positioning system to determine a direction – to arrange radar images according to the N – S direction. The magnitude of introduced deformations was different for each of consecutive images series. The smallest differences occurred between series no. 1 and no. 2, next between series no. 1 and no. 3 and the biggest disparity was between images series no.1 and no. 4.

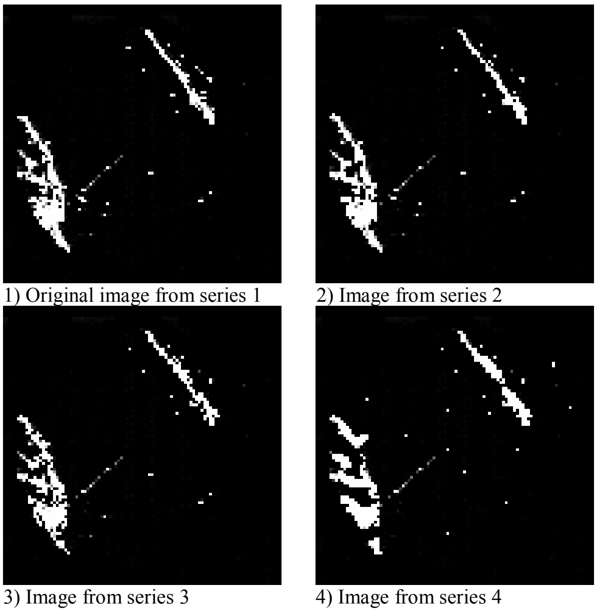

Fig. 1. Hypothetical radar images used during researches

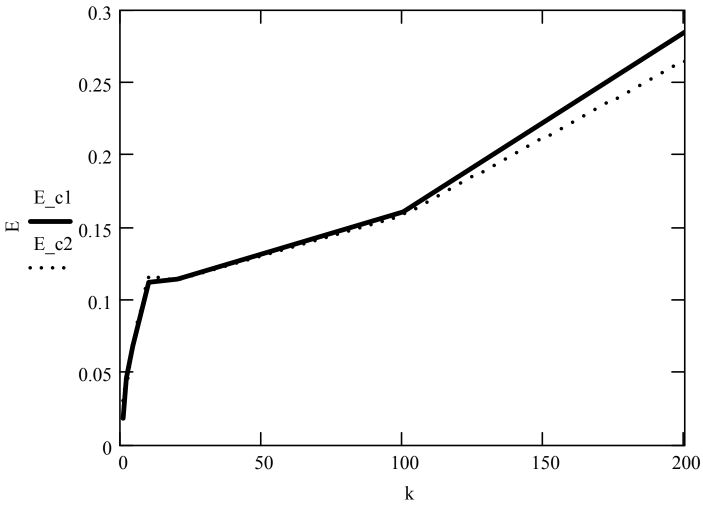

Fig. 2. The evaluation of radar images compression (E_c1 – compression with the application of the images from series no. 1, E_c2 – compression with the application of the images from series no. 2). k is the number of eigenvalues

CONCLUSION

The coastal positioning system working on the basis of radar images usually requires preprocessing of these images to the more complex form that should however preserve the most important features of the original. There are a lot of methods that could serve to this purpose and one of them is PCA and its adaptive implementation – linear feedforward neural network with Hebba selforganisation. This method was checked in the context of its application to features extraction from radar images presenting input data to the coastal positioning system. The evaluation criterion was the error function (1) that determines the degree of preserving relations occurring in the radar images domain after the compression. The most interesting from the constructed positioning system point of view is appropriate determining the size of a single segment of a radar image as well as the number of eigenvectors per segment. Matching these parameters is crucial for the compression system performance. The fig. 1 shows that the application of the smallest segments and only first eigenvector per segment is the solution that the most faithfully preserves all similarities occurring between radar images. Gradual increase of the size of each segment and the number of eigenvectors corresponding to a single segment causes that results accomplished by the compression subsystem are worse and worse.

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