CLASSIFICATION OF TEXTURE IMAGES WITH THE USAGE OF ARTIFICIAL NEURAL NETS AND HIGHER-ORDER STATISTICS

A.M. Akhmetshin, D.A. Mikhalev

Dniepropetrovsk state university

Abstract

The object of the research is photos of metal-graphic microstructures.

The aim of the work is the choice of algorithmic and elaboration of software for effective classification of texture images with the help of neural nets, and also classification the process of exactness rise researches of questions and diminution of general processing time of texture images.

The method of the research is comparative analysis of two classifiers, the first one is built on Hamming neural net, the second one is built on Kohonen neural net.

Results of the researches were employ for classification of the photos of metal-graphic microstructures, which were obtain through digital photoscanner.

1. Introduction

The concept of the texture is more often used in different areas of a science and engineering, such as hylology and research of mining and metallurgical processes, the control of the quality of industrial production, image processing of the metal-structures. It follows from the fact, that the surfaces of a great number of real objects in these fields are textures and under condition of their homogeneity, they can be described with the help of a comparatively little number of parameters. By virtue of this, fact, the solution to this problems of the texture classification is actual, in particular, in geology and geodesy, in a snap analysis of micro- and of macrostructures in metallurgy.

The general scheme of texture classification is shown in the fig. 1.

As well as in the system of pattern recognition, two main tasks can be determined here: the first one is feature extraction and the second one is classification of textures to the evaluated features.

Two different approach to extraction of texture features is considered in the work. The first one is connected with higher-order statistics and is based on calculation of third-order cumulant. The second one is based on the statistics of the second order and consists in calculation 10 texture features from spatial gray-level dependence (SGLD) matrices.

Structurally the classifier is represented by two principally different schemes of artificial neural net. The first classifier, which is used during calculation of third-order cumulant, consists in application of Hamming neural net, the second one, which is used during calculation of statistics of second order consists in application Kohonen's self-organizing maps.

There are 5 test images of microstructures, each of which represents the separate class. The size of each image for a simplicity of a illustration is selected 128×128. All these images are shown on fig. 2.

One of the main problems during the classification of textures consists in uncertainty of texture images orientation. In this connection each texture, presented on the fig. 2, in addition can be rotated on 90^0, 180^0 and 270^0. Thus, 20 images from 5 classes are presented.

It is required to interprete the input image correctly and refer it to one of 5 classes.

2. Feature extraction

2.1. Higher-order statistics

For the selection of informative features of textures the apparatus of higher-order statistics can be used, and as features the estimation of 3-rd order cumulants can be used [6].

Cumulant is one of the numerical characteristics of random variables, it is closed to concept of the moment of the high order. In practice, for the finite sampling of data $\{x(n)\}_{n=0}^{N-1}$ the cumulantes are calculated according the following formulas:

second-order cumulant:

$$\hat{C}_{xy}(k)=\frac{1}{N_3}\sum_{n=N_1}^{N_2} x^*(n)y(n+k), \qquad (2.1)$$

third-order cumulant:

$$\hat{C}_{xyz}(k,l)=\frac{1}{N_3}\sum_{n=N_1}^{N_2} x^*(n)y(n+k)z(n+l), \qquad (2.2)$$

where $N_1, N_2 \in [0, N]$. N_3 are usually set equal to N and calculated their estimations are asymptotically unbiased.

The algorithm for application of the higher-order statistics apparatus (algorithm 1) for obtaining the matrix of informative features of textural images consists of the following steps [8]:

1. Texture image I(x, y) is transformed in one-dimensional array y(k) by joining of successive rows in a sequence.

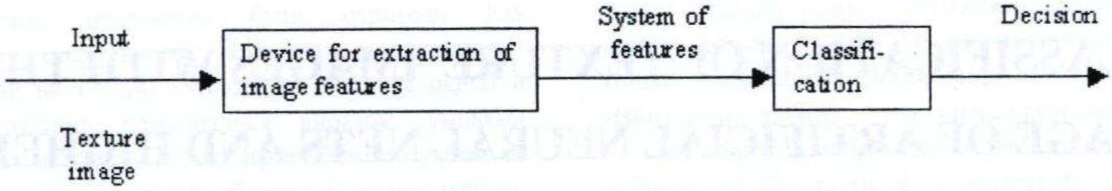

Fig. 1. The generalized scheme of texture classification and recognition.

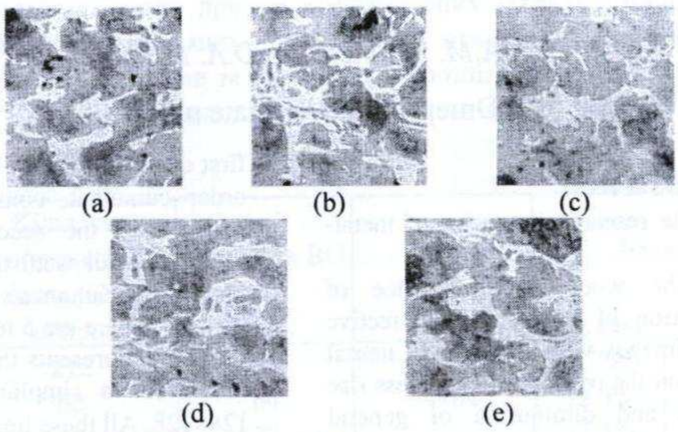

Fig. 2 Textures of different classes

2. The dimension of matrix of estimated cumulants is 2*n+1.
3. Time-series y(k) is segmented into records of m samples each, with no overlap; the biased estimates of the third-order cumulants are obtained from each segment on the formula (2) and then averaged.
4. As result the matrix C(x, y) is calculated where (i, j) element of matrix is the estimate of C_{3y}(i-n-1, j-n-1) for i, j = 1, ..., 2*n+1.

2.2. Spatial gray-level dependence (SGLD) matrices

The essence of one of most widely used methods of description of texture consists in calculation of texture features from spatial gray-level dependence (SGLD) matrices.

The *(i, j)*th element of the SGLD matrix is the joint probability that gray levels *i* and *j* occur in direction at a distance of θ pixels apart in an image. Ten texture features, including correlation, entropy, angular second moment, mean, difference entropy, contrast, inverse difference moment, deviation, different angular second moment, different mean were used. The definition of the texture measures are given in the literature [1, 2, 4].

These measures were extracted from each SGLD matrix at pair distance d = 5 and four directions (0°, 90°, 180°, and 270°). These features contain information about image characteristics such as homogenity, contrst, and the complexity of the image.

3. Classification

3.1. Hamming neural network

Among the different configurations of artificial neural networks there are the ones, in which classification according the principle of training, strictly speaking, doesn't approach either training with the teacher, or training without the teacher [4]. In such networks the weight coefficients of synapses set up only once before the beginning of work of the network on the basis of the information about processed data, and all training of the network is amounted to this calculation. The Hamming network falls into the class of networks with similar logic of work which is usually used for organization of associative memory. This network is used in case of the binary input images.

Neural net solution of this task can be obtained on the basis of the Hamming architecture. The network has one layer of identical neurons, number of which is equal to quantity of classes. Each neuron is coupled to each the input, which number is equal to the dimension of considered library of images.

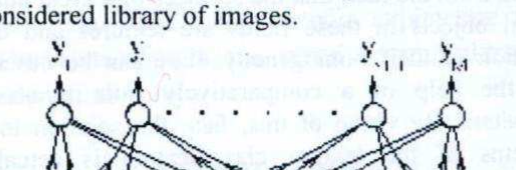

Fig. 3. Hamming neural network

The network choose the sample with minimum of Hamming distance to unknown input signal, therefore as a result one output of the networks appropriating to this sample will be activated.

It is reached by introduction of additional feedbacks between neurons arranged by a principle "lateral braking". Such mechanism is called "Winner Take All" (WTA) [4, 7].

3.2. Self-organizing maps

Self-organizing map (SOM) is neural net with straight ties, in which the teaching algorithm without teacher is used. By means of process, which named is self-organize, from outgoing elements SOM will make the topologic conception of initial data.

Algorithm SOM is based on competitive teaching without teacher. It provides reflection, preserving the topology, from space of big dimension on elements of map. Elements of the map, or neurons, usually make a two-dimensional grid. Thus this reflection is the reflection from space of big dimension on flatness. Property of topology preservation of signifies, that SOM distributes the similar vectors of input data on neurons: points, which is near to each other in space of inputs, on near situated elements of map in SOM.

Kohonen's net consist of r neurons, according to number of classes: to each class corresponds its neuron, and inside out. Input vector X is given on net input, and on input of each neuron. Its dimension n depends on task. Each neuron calculates function f from input vector I, and as answer of net the number of that neuron is given out (this vector get in class with this number), significance of function f in which receive maximum (or minimum, as more convenient). So the principle "winner take all" (WTA) is used.

4. Realization

4.1. Classifier, built on the base of the third-order cumulant

At the first stage of the calculation of texture of informative features the algorithm 1 was used. The size of segments, into which initial array is divided, is selected equal to m = 128. The size of the matrix of 3-rd order cumulant C is equated 2*n+1 = 129, i.e. n = 64. The example of such matrix for the class, presented on fig. 2.a, is shown on fig. 4.

As it has been already pointed, that the input signals for Hamming network are binary. Therefore during the transition to the stage of the classification of initial images it is necessary to make them binary. The threshold for binarization was set equal to 0. Thus, if $C(i, j) \geq 0$, then that $B(i, j) = 1$, if $C(i, j) < 0$ then $B(i, j) = 0$, where $i, j = 1, \ldots, 2*n+1$, B is binary matrix of informative features of texture.

The example of the matrix B for the class, presented in the fig. 2.a, is shown in the fig. 5.

The fig. 5 demonstrates, that binary feature matrixes for different orientations of textures differ considerably. It is connected, first of all, to the following: for obtaining of the rating matrix of cumulants the initial input was transformed in to the one-dimensional array, and as the image rotates the origin displaces it causes the change of.

It was empirically proved, that the best vector-samples for the Hamming network would be 3-d order cumulants averaged on all four rotations.

Thus, algorithm of the work of the system of texture images recognition (algorithm 2) consists of following steps:

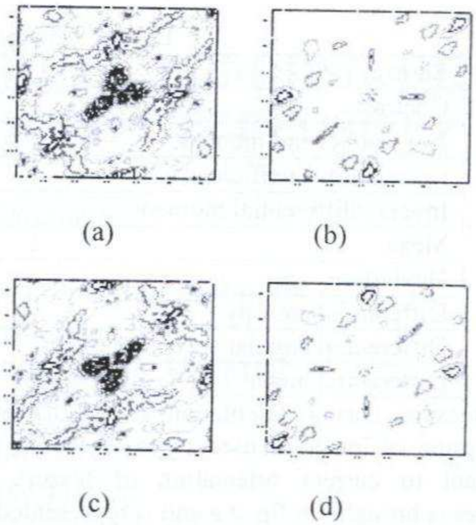

Fig. 4. Third-order cumulants for the textures of the class presented on fig. 2.a in level lines images:
(a) orientation 0^0; (b) orientation 90^0;
(c) orientation 180^0; (d) orientation 270^0;

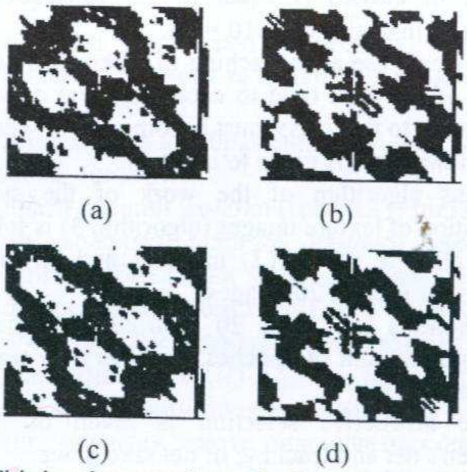

Fig. 5. Third-order cumulants for the textures of the class presented on fig. 2.a in level lines images after binary procedure:
(a) orientation 0^0; (b) orientation 90^0;
(c) orientation 180^0; (d) orientation 270^0;

1. For each of 20 image the cumulants of 3-rd order are calculated.
2. For each of 5 classes averaged 3-rd order cumulants of all four images of the class is calculated, and then it is binaried with threshold 0.
3. All 5 binary matrixes are processing through the Hamming network as vector-samples.
4. On input of the system of recognition unknown test image (one of the described 20 images) is given, and the system should refer this image to the initial class with minimum error of the classification.

4.2. Classifier, built on the base of SGLD features

In elementary phase of practical realization of given classifier is necessary to count the informing features, which in given case are 10 texture features from SGLD matrices.

TABL. 4.1

Texture features from SGLD matrices, shown on fig. 2.a

Entropy	930.2033
Contrast	3.2671e+06
Angular second moment	2.9109e+03
Correlation Coefficient	8.0294e-015
Inverse differential moment	95.8760
Mean	2.4399e+03
Deviation	1.1409e+07
Differential entropy	-1.5082e+04
Differential angular second moment	2.5254e+05
Differential mean	8.9553e+04

Because during calculation of SGLD brightness description of image is used, type of SGLD matrix is invariant to current orientation of texture. Texture features is brought on fig. 2.a and is represented on table 4.1.

For correcting classification the volume of topographic Kohonen's map exemplarily must excel amount of possible classes in twice. In our case the number of classes is equal to 10, consequently, the Kohonen's map size of $2\times10 = 20$.

In ideal case after teaching of Kohonen's net only 1 neuron of net must treat to each class and only neuron, conforming to this class must become active when image of unknown class is given to input.

Thus algorithm of the work of the system of recognition of texture images (algorithm 3) is following:

1. Is calculate the SGLD matrices and on 10 texture features for each of 20 images.
2. Kohonen's net from 20 neurons is initialed and maximum amount of epoches, necessary for teaching of net is set.
3. The instructive selection is given on input of Kohonen's net and teaching of net take place.
4. Unknown testing image is given on input of recognition system (one from 20 described above), this testing images must be refered by the system to one or another initial class with minimum mistake of classification by dint of calculation of statistic features of second order and further usage of Kohonen's net.

5. CONCLUSION

The accuracy classification of both classifiers is equal to 95-100 %. The operating time of the system was 10 minutes for evaluation of one matrix of features and 2-3 seconds for the classification with help of PC: P5-366 MHz/64M. Such a high speed of work of the classifier is reached by the simplicity of the principle of work of the Hamming network. For increase of processing speed of work of the extractor of features (see fig. 1) the size of the matrix of features decreased down to 64×64, however the accuracy of cumulants classification decreased (down to 70 %) as the speed of calculation increases.

Advantages of the method are the high accuracy of the classification and little operating time of the classifier for the class of the PC.

Disadvantages are insufficient speed of work of the system during feature extraction, and also restriction of the number of outputs of the classifier which are equal to number of classes. In this situation, when on input of the system is exited with texture image of metal-structure from the 6-th class, the system will still refer it to one of the initial 5.

Thanks to its work principle, the problem of "6-th class" in Kohonen's classifier will be absent. Besides this device of texture classification, built on base of Kohonen's net, works quicker than Hamming's classifier. First of all this reaches at the expense increase of speed of work feature's extractor. In addition to that invariance of SGLD matrix to orientation of texture allows to count up the informing features for each class only onces, where as matrix of estimations of cumulants must be counted 4 times (for each orientation).

The main disadvantage of this algorithm is little number of informing features. The dimension of Kohonen's topographic map must be increased for correcting classification attached to augmentation of amount of classes, but that is gives considerable classifier work time augmentation.

Further researches are directed to removal of disadvantages which were brought above, that can be reached by use, for example, adaptive resonance theory network (ART2).

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