ON IMPLEMENTATION OF A NEURAL NETWORK CLASSIFIER FOR SOME CLASSES OF BIOLOGICAL AND MEDICAL PREPARATION IMAGES

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Abstract

The paper is devoted to the investigation of the applicability of textural and morphological analysis to the images of some biomedical preparations.

The obtained feature vectors are input of an artificial network classifier. All the groups of images can be successfully classified by any of 3 methods considered, being for blood crystals images the morphological method is the best one.

1. INTRODUCTION

In this work we investigate the applicability of textural and morphological image analysis methods to the images of blood crystals and plant extract crystals obtained by the Pfaifer sensitive crystallization method [6,7], and brain tumor images [1].

Medical experimental research showed that structural features of blood crystals characterize both clinical signs of diseases and the presence of tendencies to get a disease. This reason stimulates designing reliable algorithms to classify such preparations images.

In the proposed implementation an artificial neural network is used as a classifier. The input of the network consists of different variants of classifying signs of analyzed images: statistical textural signs obtained with the help of the gray-tone spatial dependence matrix or Grey Level Co-occurrence Matrix (GLCM) [3], Gabor filter [2] and morphological signs (skeleton representation) [5]. For adjustment of modeled neural network parameters RProp (Resilient Propagation) algorithm that speeds up Back Prop algorithm is used [4].

Experimental data obtained for images of different classes show that the constructed model makes good progress for all the groups of features. However, the best classification results for blood crystals images are achieved when morphological signs are used.

2. IMAGES DESCRIPTION

We analyzed 3 groups of images: (1,2) were obtained by the Pfaifer sensitive crystallization method (addition a small quantity of blood or plant extract to cuprous chloride solution) and (3) is brain tumors images. All the images are supposed to be monochrome.

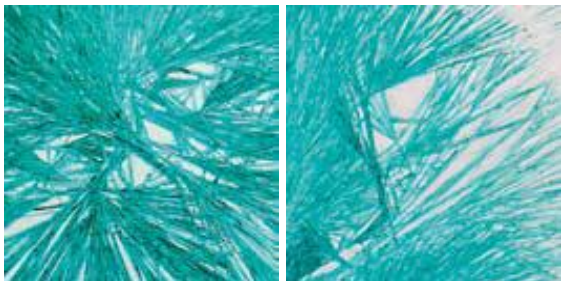
2.1. Blood images

It was revealed that in a health organism needles in crystals are radiating from the centre to periphery. In the case of a disease there is an interruption in the crystal growth, the change of its form, etc.

Moreover, it has been stated empirically that there is a relation between the position of the parts having changed form and structure and the malfunctioning an organ or the organs system.

This method helps to detect a disease on infancy, which is very important for early diagnosis. It may be useful to estimate the efficiency of taken therapeutic actions.

The next figure illustrates the following typical forms of crystals: hole structure of crystals – typical of degenerative processes (left); hollow form of the crystal with transversal structures, malignant tumor (right).



2.2. Plant extract images

We analyze the following images: orange juice, wheat flour solution and wheat extract crystalls.

2.3. Brain tumor images

Images are classified according to the tumor kind. We consider the tumors of 3 types: astrocytoma, nevrinoma, oligodendroglioma.

The images were given in [1], where the textural analysis was performed basing expert knowledge and here we used them for comparative analysis.

3. METHODS OF IMAGES FEATURES GENERATION

3.1. Gray tone spatial dependence method

GLCM is a matrix containing co-occurrence pairs of pixels of a given intensity that are in a definite spacing defined by the angle and the distance that are the matrix parameters.

We use the following texture features based on the normalized GLCM $P_{i,j}^{Norm}$ (i and j are intensities of neighboring pixels) [3].

Contrast specifies a measure of intensities contrast between a pixel and its neighbor:

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j}^{Norm}(i-j)^2$$

If all pixels have the same intensity *Contrast* =0.

Homogenity characterizes the density of distribution of GLCM elements relative to its diagonal:

$$Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}^{Norm}}{1+(i-j)^2}$$

Correlation is a correlation measure between a pixel and its neighbor:

$$Correlation = \sum_{i,j=0}^{N-1} P_{i,j}^{Norm}\left[\frac{(i-\mu I)(j-\mu J)}{\sqrt{(\sigma I^2)(\sigma J^2)}}\right]$$

where μI, μJ, σI and σJ are respectively mathematical expectation and dispersion of pixel intensities that are calculated using a current pixel and its neighbors.

3.2. Gabor filters

We introduce the 2-D Gabor function [2]:

$$g(X,Y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{(-\frac{1}{2}(\frac{X^2}{\sigma_x^2}+\frac{Y^2}{\sigma_y^2})+2\pi i\omega x)}$$

Gabor wavelets are obtained by using the generating functions:

$$g_{mn}(X,Y) = a^{-m}\cdot g(X',Y'),$$

$$X' = a^{-m}(X\cos\theta + Y\sin\theta)$$

$$Y' = a^{-m}(X\sin\theta + Y\cos\theta)$$

$$\theta = {}^{n\pi}/_{N}, a > 1,$$

where integers m, n characterize the wavelet scale and orientation: $m = 0,1,\dots,M, n = 0,1,\dots,N$ and M, N are the numbers of scales and orientations respectively.

Let $I(x,y)$ be a gray level distribution for an image. Then the image convolution with the Gabor kernel g_{mn} is defined as:

$$W_{mn}(x,y) = \int I(x,y)\, g_{mn}^{*}(x-x_1, y-y_1)\, dx_1 dy_1$$

where* denotes complex conjugation. We assume that areas with local texture are spatially homogeneous, then the mean value of the amplitude of reduction coefficient μ_{mn} and the mean-square deviation of the amplitude σ_{mn} may be used as a characteristics of the image:

$$\mu_{mn} = \iint |W_{mn}(x,y)|\, dxdy,$$

$$\sigma_{mn} = \sqrt{\iint \left(|W_{mn}(x,y)| - \mu_{mn} \right)^2 dxdy}$$

The feature vector has the form:

$$\overline{f} = [\mu_{00} \quad \sigma_{00} \quad \mu_{01} \quad \sigma_{01} \ldots \mu_{mn} \quad \sigma_{mn}]$$

3.3. Morphological Method

Mathematical morphology is a method to obtain structural components of an image that are useful for its representation and description: boundaries, skeletons and convex hulls. In this work we use so called image skeleton, which allows us to decrease the task dimension [5]. To extract the image skeleton the tools of mathematical packages are applied [8].

4. NEURAL NETWORK CLASSIFIER

In this work we use manylayered feedforward network, because it is known that such a model is sufficient for the problems of this class [4].

The number of neurons in the input layer N_{in} is defined by the feature vector size that by-turn is defined by the method of construction of the vector.

The number of neurons in the second layer N_{av} is defined as the integer part of $N_{in}/2$ (empirical recommendation).

In our experiments the number of output neurons in the third layer N_{out} is defined by the number of classes of images that are considered in each groups of test models: for medical preparations N_{out} = 5, for biological ones N_{out} = 3 and for brain tumors N_{out} = 3.

For the network training RProp (Resilient Propagation) algorithm [4] was applied. Its principal advantage over Backprop method is the simplicity, high rate of convergence and low specifications for the gradient calculating error. As opposed to Backprop based on gradient descent method, RProp uses only signs of partial derivatives but not their values to adjust weighting coefficients.

5. RESULTS OF EXPERIMENTS

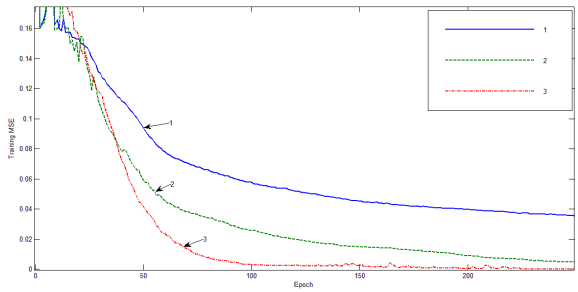
The algorithm testing was performed on the computer with Intel Core i5™ 2.27GHz processor.

Further 1 denotes medical preparation images, 2 – biological preparation images, 3 – brain tumor images.

5.1. GLCM based method

Let the number of directions to a neighbor pixel be 3 ($0°, 45°, 90°$), the number of distances to a neighbor pixel be 10 (i.e. distances = 1,2, …, 10), the number of textural features – 3 (Contrast, Homogenity, Correlation), then the number of input neurons $N_{in} = 3 \cdot 10 \cdot 3 = 90$ [har]. Hence N_{av} = 45. The size of GLCM (64x64) was defined by the given number of gray levels N=64.

For 3 groups of images the graphics of the dependences network parameter training mean-square error (MSE) σ on the number of iteration N are shown below.



The time of the construction of feature vectors and the network training is shown in the table below.

Image group number	Feature vector generation time (sec)	Network training time (sec)	Summary time (sec)
1	10.619	9.437	20.056
2	10.239	4.701	14.940
3	35.607	4.901	40.508

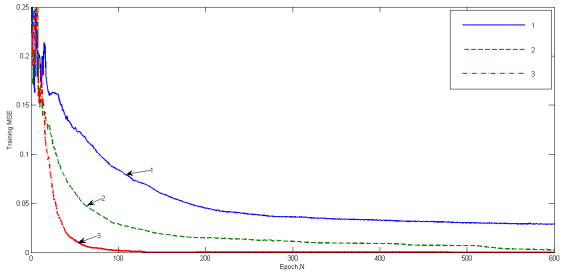
It takes 2-4 sec for the trained network to classify different images by this method.

5.2. Gabor filter

Let the number of wavelet scales be 8, the number of wavelet orientation — 5 and the number of used textural features (mathematical expectation and mean-square deviation) – 2. Then

$$N_{in} = 8 \cdot 5 \cdot 2 = 80, N_{av} = 45.$$

The graphics of the dependences network parameter training MSE σ on the number of iteration N are:



The time of the construction of feature vectors and the network training is shown in the table below.

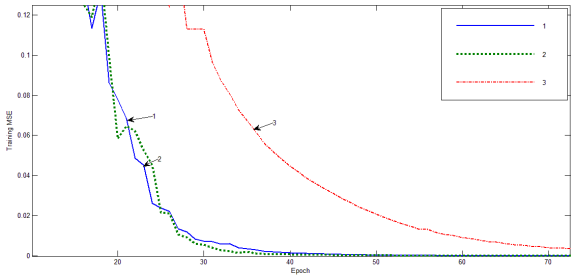
Image group number	FV gene-ration time (min:sec)	Network train-ing time (min:sec)	Summary time (min:sec)
1	14:17.964	2:31.928	16:49.892
2	14:34.104	0:6.554	14:40.658
3	26:45.027	0:4.099	26:49.126

It takes 3-4 min for the trained network to classify different images by this method.

5.3. Morphological method

Here N_{in} depends on the image size and equals 1/100 image height multiplied by image width (pixels). If N_{in}>4096 the image is partitioned into small areas.

The graphics of the dependences network parameter training MSE σ on the number of iteration N are:



The time of the construction of feature vectors and the network training is shown in the table below.

Image group number	FV gene-ration time (min:sec)	Network training time (min:sec)	Summary time (min:sec)
1	0:5.397	0:30.735	0:36.132
2	0:8.519	17: 12.592	17:21.111
3	1:02.447	39-59 min	40-60 min

Classification time is 3-4 min.

6. CONCLUSION

To summarize, in accordance with accuracy criteria all the groups of images can be successfully classified by any of 3 methods. As for time criteria, the best results for the first group of images were obtained by the morphological method and by GLCM method for group 2 and 3.

Acknowledgements

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