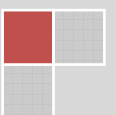


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ALGORITHM OF IMAGE TEXTURES RECOGNITION WITH THE USE OF TORQUE CHARACTERISTICS AND NEURAL NETWORK SYSTEMS

In this paper, the algorithm of texture recognition is presented, based on the application of torque characteristics, method of selection of image patches at the characteristics' extraction as well as on application of system analysis methods for problem-solving and parallel neural network architecture.

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Problems of texture recognition take special place among all the tasks of image recognition. By the construction of control systems by mobile works, image processing of aerophotography, by nondestructive testing and by searching for images in databases the necessity of image patch recognition appears, i.e. the necessity of detection of already known patches on the image including textures. The task of fast and effective recognition of image textures is one of the most difficult ones. There are different approaches to solve this problem but they are not perfect. That is the reason why the search for new ways and approaches to the solving of texture recognition tasks is still an actual problem.

In this paper, we propose a method that defines the structure of texture recognition system and algorithm of the given system functioning. Furthermore we solve the tasks of removal of neural network oversaturation at training and exact technical interpretation of input signal in the process of classification. An effective solution of these problems is a key approach to improve the quality and effectiveness of software implementation. The functional analysis instrument is used in most of the applications to interpret the response of neural network – calculation of distance, presented in the appropriate norm that has for example the following form (1)

$$\| R_i \| = \sqrt{\sum_j (D(i, j) - O(i, j))^2} \quad (1)$$

where R_i – distance between expected and observed responses, $D(i, j)$ – expected response j of neural network i , $O(i, j)$ – observed response j of neural network i .

Application of such problem-solving rule is effective because it is reliable and easy. At the same time there is an opportunity to considerably widen the mathematical tool of neural networks by implementation of a special neuronet architecture, which is adapted to the application of problem-solving from system analysis.

To develop the described algorithm we have applied the approach of data flow allocation among several neural networks in order to pass the well known problem of neural network oversaturation at the process of training for several various classes of input signals.

Neuronet system includes the number of neural networks N , each of them performs processing of one specific class of input signals (here of come class of image texture). Each of neural networks N has P inputs and M outputs (fig. 1). While $M < P$ (as the result of system performance limitations). The training process, where only one element of training selection is presented, is performed only for the neural system, which corresponds with the given class of input signals.

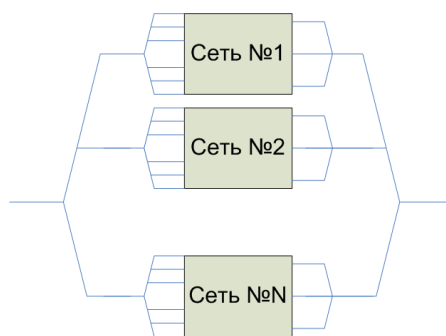


Fig. 1 – General scheme of neural processing system

To move to the task of system analysis on basis of input vector data, obtained in the process of neural networks' functioning, we build "decision matrix" system (2).

$$R = \begin{pmatrix} D(0,0) - O(0,0) & \cdots & D(0, j) - O(0, j) & \cdots & D(0, M) - O(0, M) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ D(i,0) - O(i,0) & \cdots & D(i, j) - O(i, j) & \cdots & D(i, M) - O(i, M) \\ D(N,0) - O(N,0) & \cdots & D(N, j) - O(N, j) & \cdots & D(N, M) - O(N, M) \end{pmatrix} \quad (2)$$



where R – distance matrix between expected and observed responses, $D(i, j)$ – expected response j of neural network i , $O(i, j)$ – observed response j of neural network i .

It is convenient to use risk matrix – matrix of absolute deviations of actual values, obtained as a result of neural network functioning from the values of desired response. We can easily perform the results interpretation of input vector processing with neuronet cascade by searching for the most optimal solution, presented by the acceptable risk value according to the chosen problem-solving rule. So in case of training of separate cascade neural networks with characteristics of certain image classes, the recognition task by the use of neuronet processing comes to a subtask of decision-making with the minimal risk on basis of deviation matrix of neural networks' input signals of the given cascade.

On praxis the application of any problem-solving methods from system analysis is possible. The superiority question of any methods in the particular task is rather important and must be studied in future. In the neuronet system of texture recognition we have built, the quality of recognition, which is presented in percentage of correctly recognized images to the total size of selection, considerably differs in accordance with the chosen problem-solving method. Experience has shown that sufficient level of quality of network response interpretation is obtained by using product criterion of the form (3)

$$b_{ij} = \prod_{j=0}^M (D(i, j) - O(i, j)) \quad (3)$$

Where b_{ij} – estimation (evaluation) with respect to the chosen decision-making criterion, $D(i, j)$ – expected response j of neural network i , $O(i, j)$ – observed response j of neural network i .

At each performed experiment the following approach turned out to be more effective than the approach of image classification on basis of norm comparison of input signals of neural network (which is the most popular method nowadays), because in such way we have solved both the problem of prevention of neural network oversaturation and the task construction of parallel neuronet processing system.

The introduced approach can be used for neuronet processing of different complicated signals. By solving the task of texture recognition the subtask of particular realization of each separate neural network is also very important. On the first stage of system work the preprocessing of the image is performed. As a result the characteristics of each separate image patch are being extracted. Then these characteristics are being transmitted in specific order to the neural network for processing (training or recognition). Before the transmission of the characters to the network input they should be processed in such a way that it would enable better system functioning and training. The necessary condition for the correct object recognition is representativeness of object's characteristics used at the work of a system.

In the task of image recognition we can use for example brightness values on basis RGB in each separate image point as initial data at neuronet processing. But such conception of the image will be too much, i.e. it will contain much more information than it is actually needed. In order to remove redundancy we use the procedure of characteristics' extraction from the image. Among the most common used statistic characteristics of the image the following can be listed: mathematical expectation of brightness according to each basis color, medium linear deflection of brightness values according to each color of basis RGB from the mathematical expectation or approximate value brightness mode. By the use of these characteristics separate details of the image cannot be detected and moreover the positional relationship of image points and separate image patches is not taken in account. That leads to the loss of a big amount of information that can be used for recognition.

As characteristics in the given algorithm we use central moments of first order [2] of the form (4), which we calculate separately on each channel R, G and B.

$$\begin{aligned} \mu_{10} &= \iint_D B_R(x, y) x dx dy, \quad \mu_{01} = \iint_D B_G(x, y) y dx dy, \\ \mu_{11} &= \iint_D B_B(x, y) xy dx dy \end{aligned} \quad (4)$$

where $B_R(x, y)$ – brightness function of red component channel, $B_G(x, y)$ – brightness function of green component channel, $B_B(x, y)$ – brightness function of blue component channel.

Numerical computation of integrals in (4) is performed with the use of method described in [3].



The important feature of the given algorithm is that the computation of the moments is performed in definite image patches. These patches result from segmentation (5) of the original image into several patches, as it is shown in fig. 2.

$$W_{i+1} = \{x_{i+1} \mid x_{i+1} \in W_{i+1} : x_i \bmod p = 0\},$$

$$H_{i+1} = \{y_{i+1} \mid y_{i+1} \in H_{i+1} : y_i \bmod p = 0\} \quad (5)$$

where p – subinterval of the image, W, H – sets of segmentation points along the axes X and Y , respectively, x, y – elements of set W and H .

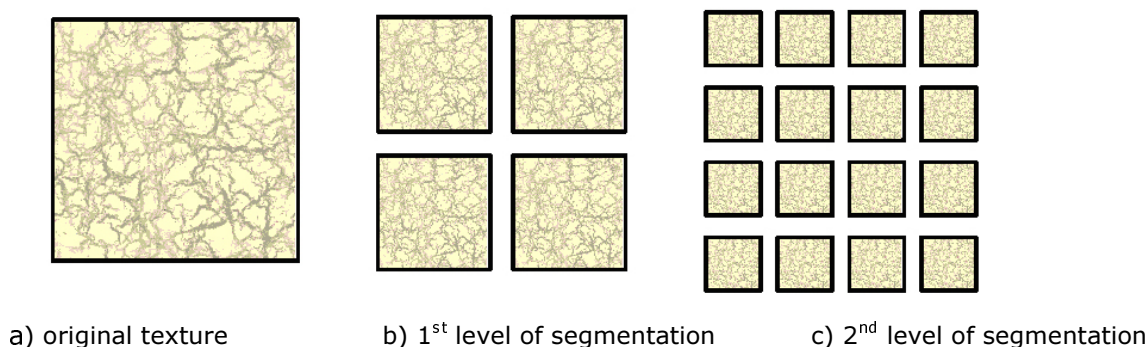


Fig. 2 – Image segmentation scheme

In the given example the image is divided into 4 subareas on the first level of segmentation (fig. 2b) and into 16 subareas on the second level of segmentation (fig. 2c). If we continue dividing the image, it will lead to the significant increase in amount of calculation and at the same time to the decrease in information value of characteristics of each area. That's why the process of segmentation into areas ends on the second level.

On each level of segmentation in every subarea the moments of first order are being calculated according to the formula (4) for every color channel. As a result we get vector of signals, which is then transmitted to the input of neural network for training or recognition. Such an approach allows the global characteristics on the first level of segmentation to be considered, and then local characteristics for each area on the second level of segmentation. It is important to consider the positional relationship of image elements is important, as such opportunity is explained by the connection existence among image subareas and synaptic inputs of neural network. As there is a one-to-one matching between the number of image subarea and the number of synaptic input (fig. 3), associative memory of neural network considers automatically the positional relationship of characteristics' channels. Neural networks (being presented as separate independent modules) can use one or another architecture in accordance with the required result.

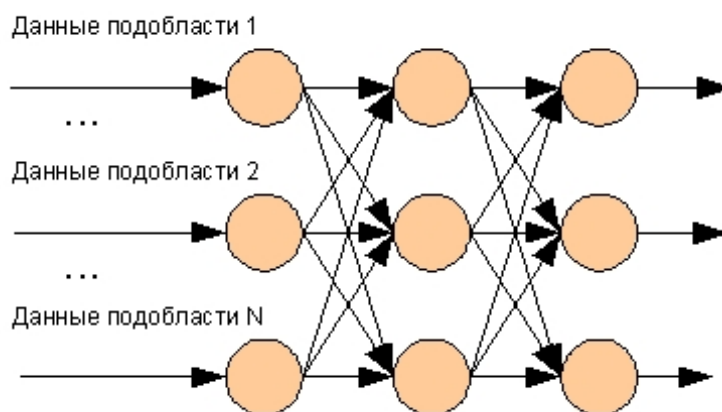


Fig. 3 – Correspondence of image subareas and synaptic inputs



This is an important factor that gives the ability to study the behavior of different neural networks at solving the task of image recognition. That provides the opportunity to choose optimal architecture of each separate computing element. As a computing element we used a fully connected neural network with sigma function of activation of the form (6) with a random starting distribution of synaptic weights in the interval $[-0.5, 0.5]$.

$$\text{Sigm}(x, c) = \frac{1}{1 + e^{-cx}} \quad (6)$$

where x – point of function evaluation, c – parameter that sets sigmoid slope.

To train the network we used gradient method of optimization with the step 0.01 and required error rate 0.1. This choice of the required error rate is a result of necessity of neural network oversaturation removal at the process of training with a big number of dissimilar examples. In general, depending on the number of objects' classes, different ways to choose this parameter are possible. The use of full connected configuration of neural network is connected with the fact that its advanced reliability has been found experimentally. We throw out insignificant synaptic connections by the chosen configuration by assigning insignificant weight coefficients. More complicated configurations of neural networks, as, for example, FNN – configuration (fast neural networks), are degenerate case of full connected network and can be obtained by the process of reducing weight coefficients of the neurons of full connected network. The disadvantage of the use of full connected network is smaller speed of data processing, which can be ignored by performing experiments, and also in order to increase system reliability.

The training process with a separate example is performed in the system parallel on each computing element with the use of various final signals. As an input signal of neural network we use those image characteristics, obtained with the help of aforementioned scheme. As a final signal of neural network we use values vector in the interval $[0, 1]$, that describes the estimated value of belonging probability of the image to a certain class, presented with a current computing element.

The described algorithm has been implemented on program with the use of Microsoft Visual C++ and COM technology. In program implementation is the system the possibility of step modification of image segmentation is provided in order to study the influence of image segmentation methods on the process of characteristics' extractions. The program complex is implemented taking in account the application possibility of different configurations of neural network in the system working process. Architecture of texture recognition system is shown in fig. 4. Let's take a look at the basic components of the texture recognition system.

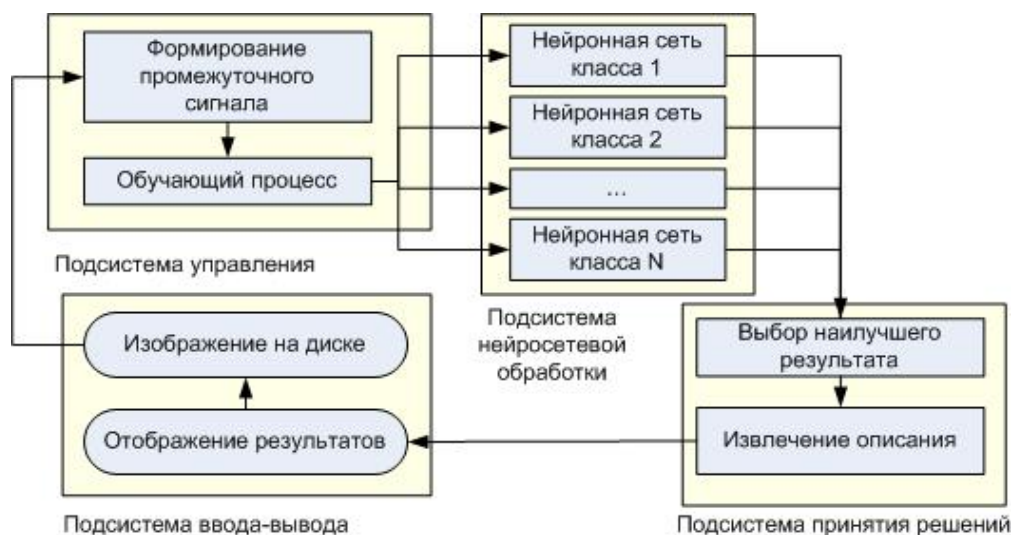


Fig. 4 – functional scheme of structural organization of image recognition system

Subsystem of input-output implements data storage on the data carrier and operations on file input-output, image storage and transformation, displaying working data to user, and also forms a set of input signals, which are a set of characteristics of this image used later at the neural network functioning. Control subsystem controls the process of training and formation of input and desired signals. Subsystem



of neuronet processing performs all the operations connected with neuronet processing, including training and calculation of the result of input signal processing. Subsystem of decision-making performs the interpretation of network output signal in the recognition process and makes decision in choosing the best (the most probable from the network point of view) class on basis of the results obtained in neuronet processing.

Testing of the program implementation of the developed algorithm has shown, that average time of system training with one master image is 3 seconds, and average time of recognition is 0,5 seconds. To perform system testing we used the selection of texture images consisting of 4000 full-color images. The number of texture images that was recognized correctly was 93%. These results indicate of practical value of the texture recognition algorithm with the use of torque characteristics and also of the fact that it is sufficient to continue studying this algorithm.

The developed algorithm of texture recognition is an effective method to solve the tasks of texture image recognition. That is performed due to the use of: torque characteristics, method of image patches selection by the extraction of characteristics, methods of system analysis for decision-making, parallel neuronet architecture.

The described algorithm helps to obtain the following results: possibility of the effective use of the easiest neuronet architectures, which do not give sufficient level of accuracy at the standard construction of neural systems; adaptation of neuronet architecture for the parallel neuronet processing, which increases the speed of system response in recognition mode; simplification of formalization process of decision-making in neuronet systems.

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