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CLASSIFICATION OF SIGNS SYMBOLS USED FOR RECOGNITION

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ABSTRACT

This paper describes some basic methods of character recognition. It is considered that the feature extraction is one of the most difficult and important tasks in pattern recognition. For character recognition can be introduced a large number of different systems of signs. The challenge was to highlight those characteristics that effectively distinguish one class of symbols from all other.

KEYWORDS: Classification of Signs, The Correlation Template, Statistical Distribution of Points, Integral Transform, Neural Network Structure

INTRODUCTION

In recent years significantly increased the interest in electronic, digital and optical image processing techniques with the aim of improving their quality. This contributed to the increase of the operation speed and reducing the cost and size of digital computers and the technical means of signal processing. Image processing techniques are already playing a significant role in scientific research, industry, medicine, and space research and information systems. Examples of these methods include transferring digital images from spacecraft, the video telephone communication through the telephone channels, increasing the clarity of images generated by an electron microscope, distortion correction of images taken from space, automatic analysis of the nature of the terrain, natural resources images transmitted from satellites of the Earth, the formation and improvement of the quality of biological and medical images, including radiographs, images, and pictures, radioisotope diagnosis, automatic mapping on aerial photographs, the detection of defects in machine parts, using industrial radiographs. There is no doubt that over time, the image processing techniques will find wider use in medicine, in many cases making it easier for doctor's diagnosis, and in technology. The actions of the robot, endowed with "vision" will be based on automatic analysis of scenes. Effective methods for encoding images, apparently, will in the future create an individual television channels of bilateral communication both personal and official use [1]. In the design and analysis of image processing systems it is convenient and often necessary to have a mathematical description of the processed images.

CORRELATION AND PATTERN MATCHING

Introduced the matrix of symbols is compared to a set of standards. Calculates the degree of similarity between the image and each of the standards. Classification of the test image occurs using nearest neighbor.

From a practical point of view, this method is easy to implement and many commercial systems use it. However, even a small dark spot caught on the outer contour of a symbol, can significantly affect the recognition result. Therefore, to achieve good quality of recognition systems using pattern matching, use other methods of comparing images [2].

One of the main modifications of the image comparison algorithm uses templates presentation templates in the form of a set of logical rules.

STATISTICAL DISTRIBUTION OF POINTS

In this group of methods for feature extraction is based on the analysis of different statistical distributions of points. The most famous methods of this group use the calculation points and calculation of intersections.

Moments of different orders are successfully used in such problems of image processing as the robots vision, detection and recognition of aircraft and ships by the images, scene analysis and character recognition. In the latter case, as signs are used, the values of the statistical moments of totality "black" points with respect to a selected center.

The most commonly used in applications of this kind are progressive, Central and normalized moments.

For digital images stored in a two-dimensional array, row-based moments are functions of the coordinates of each point in the image following:

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y)$$

where p, q=0,l,...,; M and N are the image dimensions along the horizontal and vertical and f(x, y) is brightness of a pixel at point (x, y) in the image. The Central moments are a function of the distance of the point from the center of gravity of the symbol:

$$m_{pq} = \sum\sum (x-\bar{x})^p (y-\bar{y})^q f(x,y)$$

Where x and y with a line - coordinates of the center of gravity.

Finally, the normalized Central moments are obtained by dividing Central moments to moments of order zero.

It should be noted that the string points, as a rule, provide low detection level. Central and normalized moments are preferable because of their greater invariance to transformations of the images.

In the method of intersection signs are formed by counting the number of times occurred on the intersection of image symbols with selected direct held at certain angles (e.g. 0, 45, 90, 135 degrees. This method is often used in commercial systems due to the fact that it is invariant to distortion and slight stylistic variations of characters, and has a high enough speed and does not require substantial computing resources. For example, on the market of OCR-systems based on automatic device that reads any uppercase alphanumeric characters. As the recognition algorithm used the method of intersections. There are many other methods of recognition based on selection of features from the statistical distribution of points. For example, zone method involves the separation of the square frame, enclosing symbol, region, and the subsequent use of densities of points in different areas as a set of characteristic features. In the method of the adjacency matrices as features deals with the frequency of the joint occurrence of "black" and "white" elements in different geometric combinations.

INTEGRAL TRANSFORMATION

Among modern recognition technologies, based on transformations that stand out methods that use Fourier descriptors of the characters and the descriptors of the boundaries.

The advantages of methods that use Fourier-Mellin, due to the fact that they have invariance to scale, rotation and shift of the symbol. The main drawback of these methods lies in the insensitivity to sharp jumps in brightness at the borders. At the same time, filtering noise at the boundaries of this property may be useful [3].

STRUCTURAL ANALYSIS

Structural features typically used to highlight the overall structure of the image. They describe the geometric and topological properties of a character. One of the most used features are strokes and spaces used to identify the following characteristic features of the image: end points, intersections of line segments, closed loops, and their positions relative to the frame, embedding the symbol.

Let the matrix containing utonchennyh symbol is divided into a number of areas, each of which has the letters A, B, C, etc. Symbol is treated as a set of strokes. The stroke is a straight line (λ) or curves (c), and connects some two points in the drawing of the symbol [4]. The stroke is a curve if the points satisfy the following expression:

$$ABC\left|\frac{\sum_{i=1}^{n} ax_i + by_i + c/\sqrt{a^2+b^2}}{n}\right| > 0.69$$

Otherwise, this is straight line. In this formula (x_i, y_i) is a point belonging to the stroke; ax+by+c=0 is the equation of the line passing through the ends of the stroke, the coefficient of 0.69 obtained experimentally. If the introduced symbols signs symbol can be written, for example, in the form 'AλC' and 'AcD', which means that a straight line passing from region 'A' in region 'C' and the curve going from region 'A' in area 'D' respectively. The advantage of the structural characteristics in comparison with other methods will be determined by the resistance to shear, scale and rotate the symbol at a slight angle and also to possible distortions and various stylistic variations of fonts. Unfortunately, the task of feature extraction of this type is still in the research process and has a more conventional solution.

In existing systems, OCR used a variety of classification algorithms, i.e. the assignment of features to different classes. They vary significantly depending on the selected characteristics and classification rules.

COMPARISON WITH THE STANDARD

To classify characters, you must first create a library of reference feature vectors. For this stage of training the operator or the Builder enters into the system OCR a large number of samples of the font characters. For each sample, the system highlights the characteristics and stores them in the feature vector. A set of feature vectors describing a character is called a class or cluster.

In the operation of the OCR system may need to expand the knowledge base. To achieve this, some systems have the ability to geobotany in real-time. However, the training process requires human intervention and is time-consuming, though, and studies aimed at the automation of the learning process that will enable the organization to minimize the participation of the human operator. The classification problem is to define the class that owns the feature vector obtained for a given symbol Classification algorithms based on the determination of the degree of closeness of the set of attributes of the symbol under consideration each of the classes. The credibility of the result depends on the chosen metric feature space. The most well-known metric refers to the Euclidean distance:

$$D_j^E = \sqrt{\sum_{i=1}^{N} (F_{ij}^L - F_i^L)^2}$$

Where F_{ij}^L - i- th characteristic of the j-th reference vector; F_i^L - ith symptom of the tested images of the symbol.

When classifying using nearest neighbor symbol will be assigned to class, a feature vector which is closest to the feature vector of the character. Note that the cost of computation will increase with the increase in the number of used features and classes.

One of the methods to improve the metric of similarity based on a statistical analysis of the reference set of features. In the classification process more reliable indication is given greater priority:

$$D_j^E = \sqrt{\sum_{i=1}^{N} w_i (F_{ij}^L - F_i^L)^2}$$

Where w_i, - weight of the i-th symptom.

Another classification technique that requires knowledge of a priori information based on the use of Bayes ' formula. From Bayes rule it follows that the feature vector belongs to class j if the likelihood ratio by more than the ratio of prior probabilities of class j to the a priori probability of class L.

NEURAL NETWORK STRUCTURE

Artificial neural network is widely used in character recognition. The algorithms that use neural networks to character recognition are often built in the following way. Coming to recognize a character image (bitmap) is reduced to a certain standard size. Generally used a raster of 16x16 pixels. Examples of such normalized rasters are shown in Figure. 1.

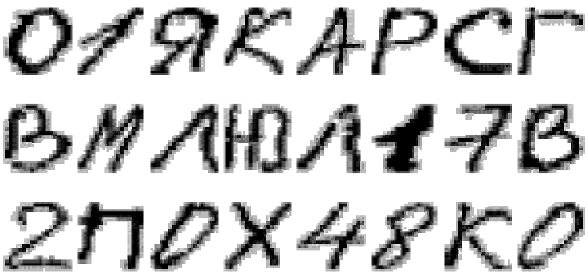


Figure 1: Bitmap

The brightness values of the nodes of normalized bitmap are used as input parameters for the neural network. The number of output parameters of the neural network equals the number of recognized characters. The recognition result is a character which corresponds to the greater of the values of the output vector of the neural network (see Figure 2, shows only a portion of the links and nodes of the raster). Improving the reliability of such algorithms is due, as a rule, either in the search for more informative input features or complexity of the structure of the neural network. The reliability of recognition and the need of a program computing resources largely depend on the choice of structure and parameters of a neural network. Image numbers are adjusted to one size (16x16 pixels). The resulting image is input to the neural network.

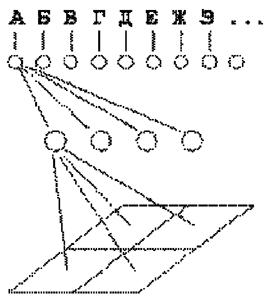


Figure 2: Part of Neural Network

As input parameters for the neural network instead of the brightness values at the nodes of a normalized bitmap can be used values that characterize the brightness difference. These input parameters allow bettering highlighting the edges of the letters. Recognition system rukopisnyh numbers, using such input parameters. Coming to recognize the images are adjusted to the size of 16x16 pixels. Then they are further processed to separate the plots with the greatest differences in brightness. One of the widely used methods to improve recognition accuracy is the simultaneous use of several different recognition modules, and then integrating the obtained results (e.g., by voting). It is very important that the algorithms used by these modules to be more independent. This can be achieved through the use of recognition modules that use fundamentally different algorithms, and a special selection of the training data.

One such method was proposed a few years ago and is based on the use of three recognition modules (machines). The first machine is trained in the usual way. The second machine is trained on the characters that were filtered the first machine so that the second machine sees a mix of characters, 50% of which was identified as the first car right and 50% wrong. Finally, the third machine is trained on the characters on which the recognition results of the 1st and 2nd machines. When testing recognized symbols are an input to all three machines. Estimates obtained at the output of all three machines are summarized. The character who received the highest total score is given as the recognition result.

POSTPROCESSING OF THE RECOGNITION RESULTS

A high accuracy OCR systems, such as, for example, reading and processing machine readable passport and visa documents, the quality of recognition obtained by recognition of the individual characters is not considered sufficient. In such systems it is necessary to use contextual information. The use of contextual information allows not only detect errors but also correct them. There are many OCR applications that use global and local positional diagrams, trigrams, n-grams, dictionaries, and various combinations of these methods. Consider two approaches to solving this problem: a dictionary and a set of binary matrices that approximate the structure of the dictionary. It is proved that dictionary methods are among the most effective in determining and correcting errors of classification of individual characters. After recognition of all symbols of a certain word dictionary is searched for this word, given the fact that it may contains error. If the word found in the dictionary, it does not mean the absence of errors. A mistake can turn one word in the dictionary to another, is also included in the dictionary. This error might not be detected without the use of semantic contextual information, only she can confirm the correct spelling. If a word in the dictionary is missing, it is believed that the word mistake. To fix resort to replacing such word for a similar word from the dictionary the correction is not made if the dictionary has found a few suitable options. In this case, the interface allows some systems to offer the user different solutions, for example, to correct the error, ignore it and continue working or make the word in the dictionary.

The main drawback in the use of the dictionary is that the lookup operations and comparisons used for error correction require significant computational cost increased with the increase of volume of the dictionary.

Some developers to overcome the difficulties associated with the use of a dictionary, trying to identify information about the structure of the words from the word itself. Such information indicates the degree of credibility of p-grams (e.g., pairs and triples of letters) in the text. N-grams can also be globally positioned, locally positioned or even re-acquisition.

For example, the reliability re-acquisition pairs of letters can be represented as a binary matrix, the element which is equal to 1, then and only then when the corresponding pair of letters in a certain word included in the dictionary. Binary positional chart B is a binary matrix, defines which pair of letters has a non-zero probability of occurrence at a particular position (i, j). The set of all positional charts includes a binary matrix for each pair of positions.

FORMALIZATION OF THE PROBLEM OF RECOGNITION OF LETTERS OF THE ALPHABET

Let's present letters in the form of a bitmap (figure 3).

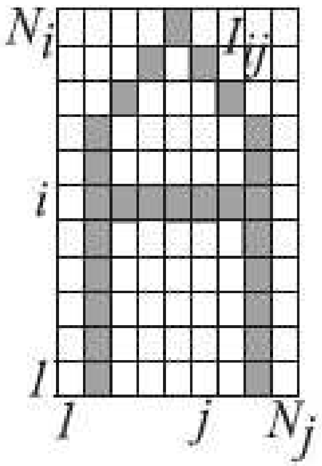


Figure 3: Bitmap

Dark cell is a pixel on the image corresponds to $I_{ij} = 1$, light - $I_{ij} = 0$. The challenge is how to define the image of the letter that was filed Build SME Ni * Nj entrances, each entry corresponds to one pixel: $x_k = I_{ij}$, $k = 1.. N_i * N_j$. The brightness of the pixels is the components of the input vector. As output signals, we choose the probability that the presented image corresponds to the letter: $y = (c_1...c_M)_T$. The network calculates the output: $(I_{ij}) \rightarrow \begin{pmatrix} c_1 \\ \cdots \\ c_M \end{pmatrix}$ where the output is C1 = 0,9 means, for example, that presented an image of the letter "A", and the network is sure of 90%, the yield of C2 = 0,1 - what image corresponds to the letter "B" with a probability of 10%, etc.

Alternatively, the inputs of the network are selected, and the output - only one, room m presented letters. The network learns to give the value of m according to the shown image I:

In this method, there is a lack of: letters with similar numbers m, but different image can be switched by the network during recognition.

There is no fixed procedure for selecting the number of neurons and number of layers in the network. The more the number of neurons and layers, the greater the opportunity network, the slower she is trained and works and, moreover, can be nonlinear dependence of input-output.

The number of neurons and layers are linked:

- with the complexity of the task;
- with the number of training data;
- with the desired number of inputs and outputs of the network;
- Available resources: memory and performance on the machine where the simulated network; There have been attempts to write empirical formulas for the number of layers and neurons, but the applicability of the formulas was very limited.

If the network has too few neurons or layers:

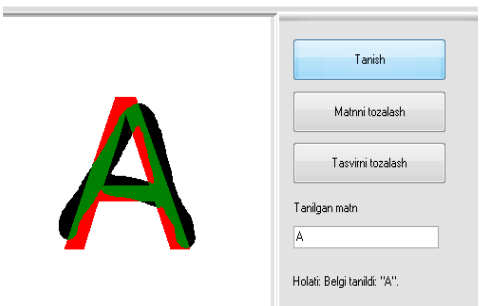
- network is not trained and a bug in the network will remain high;
- At the network egress will not be transferred to sharp fluctuations of the approximated function y(x).

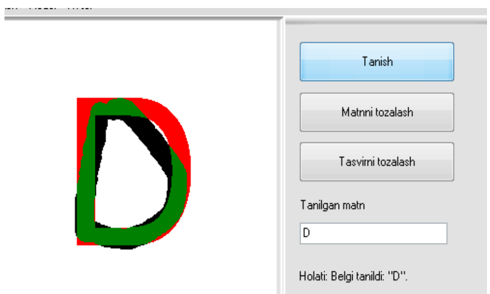
The excess of the required quantity of neurons also interferes with network operation.

If neurons or too many layers:

- performance will be low, and memory will require a lot on the von Neumann computer;
- the network will retrain: the output vector will transfer insignificant and irrelevant details in the study of the dependence y(x), for example, noise or erroneous data;
- the dependence of output to input will be sharply non-linear, the output vector will be substantially and unpredictably change with a small change of the input vector x; 4) the network will be incapable of generalization in the region where there is no or little known points of the function y(x) output vector will be random and unpredictable, will not be sufficient resamay task.

A program was written to partially implements the main blocks of the automatic recognition of letters





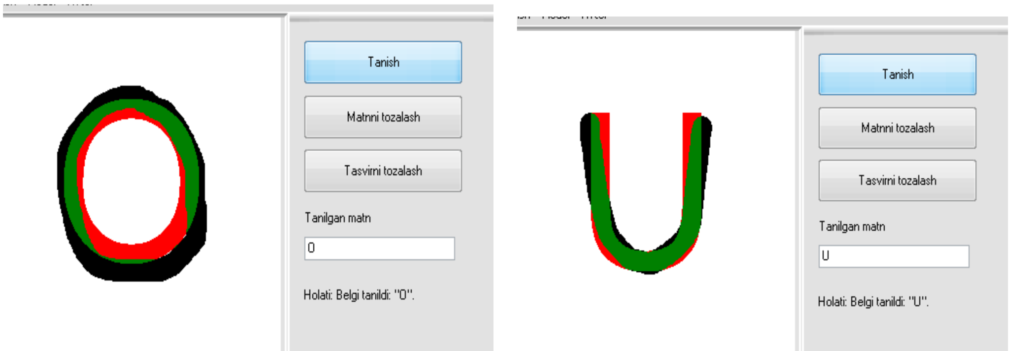


Figure 4

CONCLUSIONS

Thus, when imaging characters required for some signs to identify some homogeneous areas of the image. The stages of image pre-processing can reduce the influence of distortion on the recognition process. On the basis of the obtained results we can conclude that the proposed approach introduces a new potential in solving various problems of image processing, as it offers a flexible and adaptable way of handling the uncertainty present in digital images.

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