



IMAGE RECOGNITION OF TEXT ELEMENTS BASED ON THE USE OF NEURO-FUZZY NETWORKS

Jumanov Isroil Ibragimovich,
Doctor of Technical Sciences, Professor, Department of Information
Technologies, Samarkand State University, Samarkand, Uzbekistan

Allayorov Jasur Azamat o'g'li
Graduate Student, Department of Information Technologies, Samarkand State
University, Samarkand, Uzbekistan

ABSTRACT

A technique for modeling and constructing algorithms for recognition, classification, control of the reliability of the transmission of text elements based on the mechanisms of fuzzy sets, inference algorithms, and neuro-fuzzy networks is proposed. Estimates of specific characteristics of images are obtained, which increase the accuracy of identification, recognition, segmentation, and classification of objects.

Keywords: information processing, image, text elements, identification, recognition, fuzzy model, fuzzy conclusions.

Relevance of Research

Currently, much attention is paid to the creation of various applied applications for solving intellectual problems using the theory of fuzzy sets and systems and neural networks (NN), which have shown themselves well in solving image processing problems in fingerprint identification, face recognition, hand geometry, etc. Moreover, the methods of combining the capabilities of fuzzy models and NN allow building effective computer technologies for processing handwritten characters, speech sounds, text elements, and mechanisms for identifying, recognizing, and classifying images [1,2]. So, for example, neuro-fuzzy networks (NFN) for error control in texts have a number of undoubted advantages that distinguish it from other types of systems, among which it is worth mentioning the ease of implementation, the high speed of the learning algorithms, as well as the high reliability and accuracy of recognition and classification [3,4].

This work is devoted to solving problems of improving the quality of images of objects (letters, symbols) by filtering noise components, segmentation and clustering of images [5,6].

Mechanism of Fuzzy Filtering of Images of Text Elements

A mechanism is proposed that, based on the NFN, performs fuzzy text processing, has two main features:

- The used fuzzy filter calculates the fuzzy increment in such a way that it is less sensitive to local changes in the structures and boundaries of the image;
- Membership function (FF) NFN adapts to the noise components to perform fuzzy filtering (smoothing), where it is assumed that the noise is evenly distributed throughout the image.

The principle of applying a fuzzy filter is as follows [7,8]:

- The pixel value of the image is determined depending on the values of the surrounding neighboring pixels and the filter is required to provide a high degree of discrimination between noise and image structure;
- Increments between pixels are determined for each pixel, an estimated degree is calculated, which characterizes how large or small the increment is in a certain direction;
- A small fuzzy increment corresponds to noise, a large fuzzy increment - to the boundaries of objects.

Figure 1 shows the location of a pixel relative to its neighboring pixels NW, N, NE, E, SE, S, SW, W for an image area of 3x3 pixels.

137	94	30
72	15	47
254	8	92

NW	N	NE
W	(x, y)	E
SW	S	SE

Figure 1. patches of the micro object image.

The simple increment of the central pixel (x, y) in the D direction - NW, N, NE, E, SE, S, SW, W is defined as the difference between the pixel with (x, y) coordinates and one of the adjacent pixels in the D direction. Let's denote the increments as $\nabla_D(x, y)$:

$$\nabla_N(x, y) = I(x, y - 1) - I(x, y). \quad (1)$$

$$\nabla_{SW}(x, y) = I(x - 1, y + 1) - I(x, y). \quad (2)$$

The fuzzy increment is based on the following consideration. If the object border is positioned along the SW-NE direction, then the value of increment $\nabla_{NW}(x, y)$ will be large, but the value of the increments of neighboring pixels that are perpendicular to the direction of the object border will also be large, i.e. $\nabla_{NW}(x - 1, y + 1)$ and $\nabla_{NW}(x + 1, y - 1)$ [9,10].

If it is found that two of the three increments are small, then it is considered that there are no object boundaries in the considered direction. In this case, the fuzzy increment is defined by the concept of "small", and the MF $m_k(u)$ for this concept is taken as:

$$m_k(u) = \begin{cases} 1 - \frac{|u|}{k}, & 0 \leq |u| \leq k; \\ 0, & |u| > k, \end{cases} \quad (3)$$

where k is an adaptive parameter.

The fuzzy increment value for a pixel in the NW direction is calculated using the following rule:

$$\begin{aligned} & \text{if } (\nabla_{NW}(x, y) \text{ small}) \text{ and } (\nabla_{NW}(x - 1, y + 1) \text{ small}) \\ & \text{or } (\nabla_{NW}(x, y) \text{ small}) \text{ and } (\nabla_{NW}(x + 1, y - 1) \text{ small}) \\ & \text{or } (\nabla_{NW}(x - 1, y + 1) \text{ small}) \text{ and } (\nabla_{NW}(x + 1, y - 1) \text{ small}) \\ & \text{then } \nabla_{NW}^F(x, y) \text{ small} \end{aligned} \quad (4)$$

Note that a total of eight such fuzzy rules are built, applied for each of the directions.

The functioning of the image filtering algorithm is to identify the boundaries of the structure of objects in the form of implementations of a fuzzy increment [12].

Segmentation and selection of object image contours

For segmentation and selection of object image contours, a multilayer NN is used, which performs image segmentation by extracting adaptive thresholds using fuzzy labels. The output of the network is described as a fuzzy set and an error function of the segmentation process [13,14].



Note that in the process of segmentation, the image is divided into constituent objects. Here the following formal definition is used. Let F be the grid of all image pixels, i.e. set of all pairs:

$$F_{M \times N} = \{(i, j)\} : i = 1, 2, \dots, N; j = 1, 2, \dots, M.$$

Herewith

$$\bigcup_{i=1}^n F_i = F, F_i \cap F_j = 0, i \neq j.$$

The fuzzification of the input image is done using the pixel values. The HNN performs adaptive multilevel segmentation using labels obtained by fuzzy filtering. Training is carried out without a teacher, i.e. the network learn to find signs of class generalization in the input information [15,16].

The NN output is described by a fuzzy distribution and a fuzzy classification error.

The general algorithm for the functioning of the NNS includes the following steps.

Stage 1. Forming a histogram of the input image and counting the number of pixels with certain intensities.

Stage 2. Finding fuzzy labels.

Stage 3. Cluster validation, where the main element is a self-organized NN. The peculiarity of such an NS is as follows.

The input of the NN receives normalized information in the range [0,1], which is proportional to the intensity of the pixel. The outputs of each neuron have a value in the range [0,1]. During training, an error is calculated at each iteration, which is used to update the weights. Training continues until the minimum error is reached or the maximum training iteration is reached. The output of the system at this stage will be a set of segmented images.

Stage 4. Determination of the segmentation error function. First, the input image is phasified, and then the error function is calculated by determining the level distribution of each hue with respect to the fuzzy entropy.

Stage 5. Adaptive thresholding. This stage consists of the thresholding system itself, the fuzzy entropy calculation unit, and the learning and adaptation algorithm. In this case, adaptive thresholding is based on the following provisions. The network consists of input, hidden and output layers. Each layer consists of $M \times N$ neurons, each neuron corresponds to an image pixel, and each layer neuron is connected only to the corresponding neuron of the previous layer, as well as to neurons with a neighborhood degree d .



There is no connection between neurons of the same layer. The NN weights cannot be initialized with a random number, they are all set to 1.

In order to provide more than two stable states of the neuron at the output, a special activation function has been developed, which consists of a set of sigma-like functions with multiple levels.

Stage 6. Defuzzification. At the same time, the NN works with pixel intensities, and not with fuzzy MF values. The output of the NN is initially considered in terms of gray, which is further converted to fuzziness to determine the error.

Algorithm for fuzzy control of the reliability of texts

Let's start with image recognition of text elements. It is required that the unknown object U be recognized reliably, for which the fuzzy representation U is compared with each fuzzy model by determining the measure of similarity. An unknown object is considered to be recognized reliably when it belongs to class C with the highest measure of similarity [17].

In this case, for each instance of the object i , a bounding mask is defined (for example, the minimum rectangle or oval), which is parallel to the coordinate axes and contains an instance of i . Let's denote the horizontal and vertical spaces by the dimensions of the bounding mask containing the i instance. The recognition and classification algorithm includes the following steps.

Step 1. A fuzzy division of the horizontal and vertical spaces into T and K intervals is made, where $T \neq K$.

Step 2. Based on the values of T and K , the size of the intervals is optimized in such a way as to highlight those structures of the object that are most important for fuzzy modeling of the same object.

Step 3. For horizontal and vertical spaces, a triangular MF is constructed for each interval extremum, which is the modal value of the fuzzy set, i.e. it is assumed that the value of the MF at this point is equal to 1. Each MF covers two neighboring intervals, the only exceptions are the first and last interval of each space, for which the MF is purely its own.

Step 4. A label is determined for each fuzzy set. Note that the distribution of the point of the object $p = (h_p, v_p)$, used for the structural model of the object, has the greater value, the closer the horizontal coordinate h_p is to the modal value of the fuzzy set.



Step 5. Modal values are selected in such a way as to emphasize the important values of the points of the object, which are determined based on the proximity of the coordinates of these points to the moral values. Note that the number and arrangement of modal values should be optimized so that they truly reflect the key characteristics of the object.

Conclusion

A technique has been developed for constructing a neuro-fuzzy system for checking the reliability of text elements based on fuzzy recognition and classification mechanisms, which make it possible to provide: improving the quality of the transmitted image by filtering noise components; segmentation and clustering of objects present in the image; classifications at the Representative and Application layers of the OSI model. It has been determined that the proposed methods and algorithms for fuzzy inference and NN are powerful tools for building hardware-software systems for monitoring and processing text messages.

References

1. Jumanov, I. I., Safarov, R. A., & Xurramov, L. Y. (2021, November). Optimization of micro-object identification based on detection and correction of distorted image points. In AIP Conference Proceedings (Vol. 2402, No. 1, p. 070041). AIP Publishing LLC.
2. Jumanov, I. I., Djumanov, O. I., & Safarov, R. A. (2021, November). Mechanisms for optimizing the error control of micro-object images based on hybrid neural network models. In AIP Conference Proceedings (Vol. 2402, No. 1, p. 030018). AIP Publishing LLC.
3. Жуманов, И. И., & Шарипова, М. (2013). Оптимизация контроля орфографии узбекского языка основе моделей стохастического поиска. In *СОВРЕМЕННЫЕ МАТЕРИАЛЫ, ТЕХНИКА И ТЕХНОЛОГИЯ* (pp. 129-133).
4. Jumanov, I., Djumanov, O., & Safarov, R. (2021). Improving the quality of identification and filtering of micro-object images based on neural networks. In *E3S Web of Conferences* (Vol. 304, p. 01007). EDP Sciences.
5. Djumanov, O. I., Kholmonov, S. M., & Shukurov, L. E. (2021). Optimization of the credibility of information processing based on hyper semantic document search. *Theoretical & Applied Science*, (4), 161-164.



6. Жуманов, И. И., & Каршиев, Х. Б. (2019). Основе базы электронных документов и особенностей правил контроля базы знаний. Проблемы вычислительной и прикладной математики, (3), 57-74.
7. Жуманов, И., & Каршиев, Х. Методы повышения достоверности информации механизмами использования специфических характеристик и текстурных особенностей электронных документов. 2· 2019_, 44.
8. Isroil, J., & Khusan, K. (2020, November). Increasing the Reliability of Full Text Documents Based on the Use of Mechanisms for Extraction of Statistical and Semantic Links of Elements. In 2020 International Conference on Information Science and Communications Technologies (ICISCT) (pp. 1-5). IEEE.
9. Jumanov, I., Bekmurodov, Z. T., & Jumayozov, U. Z. (2018). Optimization of latent properties extraction and data processing of non-stationary objects on the basis of fuzzy genetic algorithms. Chemical Technology, Control and Management, 2018(1), 124-131.
10. Жуманов, И. И., & Бекмуродов, З. Т. (2018). Оптимизация прогноза нестационарных объектов на основе интеллектуального регулирования значений переменных. Проблемы вычислительной и прикладной математики, (3), 111-126.
11. Ibragimovich, J. I., Isroilovich, D. O., & Makhmudovich, X. S. (2020, November). Effective recognition of pollen grains based on parametric adaptation of the image identification model. In 2020 International Conference on Information Science and Communications Technologies (ICISCT) (pp. 1-5). IEEE.
12. Israilovich, D. O., Makhmudovich, K. S., & Uktomovich, Y. F. (2021). Increasing The Credibility Of Forecasting Random Time Series Based On Fuzzy Inference Algorithms. International Journal of Progressive Sciences and Technologies, 26(1), 12-15.
13. Djumanov, O. I., Kholmonov, S. M., & Shukurov, L. E. (2021). Optimization of the credibility of information processing based on hyper semantic document search. Theoretical & Applied Science, (4), 161-164.
14. Холмонов, С. М., & Абсаломова, Г. Б. Методы и алгоритмы повышения достоверности текстовой информации электронных документов. SCIENCE AND WORLD, 43.



15. Холмонов, С. М., & Абсаломова, Г. Б. (2020). Повышение достоверности текстов на основе логических критериев и базы знаний электронных документов. In *Технические науки: проблемы и решения* (pp. 15-19).
16. Ахатов, А. Р., & Жуманов, И. И. (2007). Алгоритм контроля качества текстов в системах электронного документооборота. *Журнал «Вестник ТУИТ», (2), 68-72.*
17. Zhumanov, I. I., & Karshiyev, K. B. (2013). Methods of ensuring authenticity of e-documents on the basis of structure redundancy and lexicological synthesis. *Science and world, 51.*