# MATNNI TANIB OLISH TIZIMIDA KLETKALI AVTOMATLAR

**Umarova Benazir Botirjon qizi**
NamMTI, Avtomatika va energetika fakulteti
Informatsion texnologiyalar kafedrasi assistenti
E-mail: Benazir.umarova1225@gmail.com

## ANNOTATSIYA

Kletkali avtomatlarning afzalliklari matnni aniqlash tizimida foydali bo‘lishi mumkin. Qoidalarning soddaligi va bir xilligi bir nechta mantiqiy yoki matematik elementlarga asoslangan murakkab tizimlarni yaratish va kamroq hisoblash resurslari va xotira bilan natijalarga erishish imkonini beradi.Tadqiqot jarayonida ishlab chiqilgan g‘oyalar va algoritmlarni amalga oshirish uchun model va uning asosida dastur yaratish kerak bo‘ladi.

**Kalit so‘zlar:** Tanib olish, belgilar, belgilar xususiyatlari, tasvirni qayta ishlash, tasvirni oq-qora holati, matnni belgilarga bo‘lish, kletkali avtomatlar.

# CELLULAR AUTOMATON IN TEXT RECOGNITION

**Benazir Umarova Botirjon qizi**
NamIET Faculty of Automation and Energy
Assistant of the Department of Information Technology
E-mail: Benazir.umarova1225@gmail.com

## ABSTRACT

The advantages of cellular automaton can be useful in a text recognition system. The simplicity and uniformity of the rules allows to create complex systems based on several logical or mathematical elements and to achieve results with less computing resources and memory. To implement the ideas and algorithms developed during the research, it is necessary to create a model and a program based on it.

**Key words:** Recognition, characters, character properties, image processing, black-and-white image, segmentation of text into characters, cellular automata.

The ability to “Recognize” is the main characteristic of humans, as well as other living organisms. A symbol is a description of an object. Recognition efforts are made every minute.

The recognition of concrete symbols by a person can be considered as a psychophysiological issue related to the process of interaction of a person with a certain physical being. When a person perceives a symbol, he performs a process of inductive inference and establishes an associative connection between his perception and certain generalized concepts or "Directions" that he has established on the basis of past experience. In fact, human recognition of an image can be reduced to a question of estimating the relative chances of initial data matching one or another set of certain statistical ensembles that are determined by the individual's past experience and provide guidance and a priori data for recognition. Thus, the problem of symbol recognition can be considered as a problem of identifying differences between raw data by identifying not individual symbols, but their collections. This is done by searching for characters (invariant properties) in the set of objects that make up a particular set.

Texture recognition is one of the most important tasks in computer vision and, despite the recent success of learning-based approaches, there is still need for model-based solutions. This is especially the case when the amount of data available for training is not sufficiently large, a common situation in several applied areas, or when computational resources are limited. In this context, here we propose a method for texture descriptors that combines the representation power of complex objects by cellular automata with the known effectiveness of local descriptors in texture analysis. The method formulates a new transition function for the automaton inspired by local binary descriptors. It counterbalances the new state of each cell with the previous state, in this way introducing an idea of "controlled deterministic chaos". The descriptors are obtained from the distribution of cell states. The proposed descriptors are applied to the classification of texture images both on benchmark data sets and a real-world problem, i.e., that of identifying plant species based on the texture of their leaf surfaces. Our proposal outperforms other classical and state-of-the-art approaches, especially in the real-world problem, thus revealing its potential to be applied in numerous practical tasks involving texture recognition at some stage.

**INTRODUCTION**

Since its popularization in the sixties, chaos theory, in its modern sense, has attracted attention in numerous areas. Models for image processing and analysis have also been proposed, benefiting from tools originally developed for the analysis of chaotic systems (Gao and Yang, 2014, Rosin, 2010, Guo et al., 2010, da Silva et al., 2015, Yu, 2017).

Among the classical models of deterministic chaos, cellular automata (CA) (Wolfram, 2002) have been natural candidates to model digital images, mainly due to their intrinsic representation over a two-dimensional grid, which allows the association between pixel intensity and cell states.

Whereas the literature has presented applications of CA models in image processing (Wongthanavasu and Tangvoraphonkchai, 2007, Gao and Yang, 2014, Rosin, 2006, Rosin, 2010, Leguizamón et al., 2010, Gu and Sun, 2018) or general applications of pattern recognition (Chandramouli and Izquierdo, 2006, Guo et al., 2010), the use of CAs to provide image descriptors is still a topic little explored, at least in explicit terms.

Cellular automata and texture descriptors share a fundamental property: the locality. Well established texture descriptors such as Haralick features (Haralick, 1979), local binary patterns (Ojala, Pietikäinen, & Mäenpää, 2002), or bag of visual words (Varma & Zisserman, 2009), rely on the idea of a local descriptor capable of quantifying the relation among pixels within a neighborhood. In a similar way, CAs evolve in time by applying predefined rules that essentially depend on the neighborhood states. Nevertheless, CAs add an extra ingredient to the process, which is the successive application of a nonlinear operation. This approach has also recently demonstrated its powerfulness in texture recognition (Bruna and Mallat, 2013, Florindo, 2020), providing a model competitive even with the state-of-the-art learning-based methods. The utility of CA models as a robust texture descriptor has also been recently verified in (da Silva et al., 2015) and confirmed the expectations.

Therefore we propose the theoretical development and practical application of a texture descriptor that combines the pattern recognition abilities of CAs with the advantages of a texture descriptor based on the local binary patterns (LBP) theory (Ojala et al., 2002). The proposed descriptors are named Cellular Automata Texture descriptors (CATex).

The proposed methodology consists in successive applications of an LBP-based operator exploring its nonlinear characteristic. The simple successive application yields, however, a rapid increase in the global complexity of the model, as expected from chaos theory. These changes excessively disorganize the pixel patterns of the original image and in this way hamper recognition tasks. CATex descriptors circumvent this problem by introducing a control parameter that combines the cell state in the next iteration with the state in the current iteration, thus ensuring that the “chaoticization” process takes place in a controlled manner.

Four main contributions are presented in this manuscript. The first one is the introduction of a control mechanism to the CA model of a texture image, which ensures the effect of highlighting complex nonlinear patterns without an excessive disorganization of the pixel arrangement. The second novelty is the introduction of an LBP-based transition function to a CA model for texture recognition. As a third contribution, we also present a theoretical motivation for the success of the proposed solution. For that, we relate the local differences quantified by the transition function with higher order derivatives and their ability to represent texture patterns at diverse ABSTRACTion levels. A fourth relevant contribution is the development of a chaos-based framework for recognition (analysis) whereas most chaos models in image processing are employed for encryption.

The proposed CATex descriptors are tested on texture classification tasks, being compared both with classical texture features, like LBP (Ojala et al., 2002) and VZ-Joint (Varma & Zisserman, 2009), and with modern approaches, such as binarized statistical image features (BSIF) (Kannala & Rahtu, 2012), scale invariant feature transform (SIFT) combined with bag-of-visual-words (BOVW) (Cimpoi, Maji, Kokkinos, Mohamed, & Vedaldi, 2014), and convolutional neural networks (CNN) (Cimpoi, Maji, Kokkinos, & Vedaldi, 2016). Benchmark databases like UIUC (Lazebnik, Schmid, & Ponce, 2005), UMD (Xu, Ji, & Fermüller, 2009) and KTH-TIPS2b (Hayman, Caputo, Fritz, & Eklundh, 2004) are used for comparison. The developed methodology is also applied to a "real-world" problem, namely, the identification of plant species based on images of the leaf surface. The classification accuracy achieved by the proposed model attests its value as an alternative for texture recognition in general. In particular, the new method will be helpful in situations where learning-based approaches are not advantageous, for instance, when there are only few data for training, which is a common problem in several areas, for example, in medical applications.

The mixture of the contemporary social networks and the high-performance of smart-phones with built-in cameras has sparked a tremendous increase of available images. Textual information in images constitutes a very rich source of high-level semantics for retrieval and indexing. It can be acquired as scene text that was captured by a camera as part of a scene. Although after decades of research in document image processing, it has reached a satisfactory level of success.Text detection on natural scenes is still a hard task to solve.

State of the art research on scene text detection can be roughly split in two categories: region-based and texture-based. Region-based methods group pixels that belong to the same character based on the colour homogeneity, the strong edges between characters and background or by using a stroke filter. Then, the detected characters are grouped to form lines of text according to colour, size and geometrical rules. Texture-based algorithms scan the image at different scales using a sliding window and classify image areas as text or non-text based on features that rely on texture information.

Searching for symbols is one of the most important steps in the process of identifying symbols, especially symbols.

Before the process of character feature extraction, it is necessary to solve several problems: it is necessary to process the text image from noise, bring it to a state that allows to fulfill the conditions of recognition algorithms, and extract individual character images from it.

**IMAGE PREPROCESSING**

Image processing is a matter of changing the features of an image so that the algorithms involved in text recognition perform better with fewer errors. In addition, the number of cell states (point colors) of an image is a very important element to improve the efficiency of cell automata involved in recognition.

In this work, cell automaton involved in character recognition operate on the basis of two cell states corresponding to the white and black colors of the image pixels.

In the process of converting the image to black and white, the components of the dots must be separated from the background. A cell automaton can be used to solve this problem, where each cell corresponds to an image point and the local radius for the cell is zero. The automaton implements three rules: turns the color of each point of the image into gray; paints a cell black if it is darker than a certain threshold color; if it is lighter than the specified threshold, it will paint the cell white. Figure 1 shows the rules of the cellular automaton created on the basis of the modeled program presented in the work.

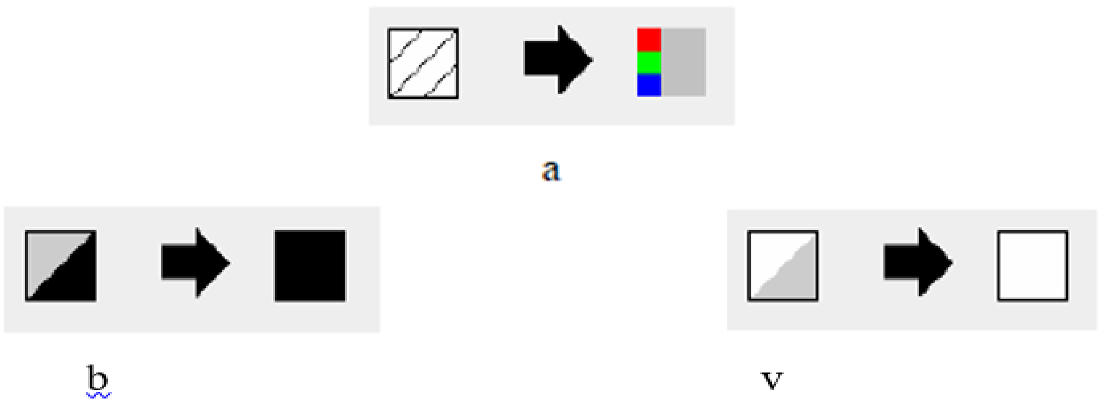



**Figure 1.** The rules of the automaton for converting the text image to black and white: a - change the point color to gray, b - paint the cell black if its color is greater than the border color, v - paint the cell white, if its color is less than the threshold color.

**Split text into characters.** Currently, one of the unsolved problems of text recognition systems is its division into characters [4].

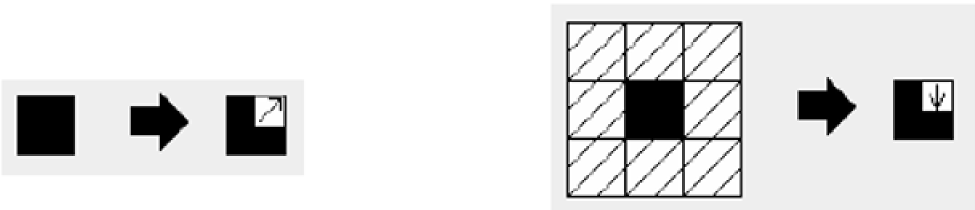
Often, this problem is solved in the system as follows: the text image is first divided into separate images of characters, and then the relationship between different images is determined by estimating the distance between them. In the recognition phase, the segmentation results of multiple captured images can be determined for further segmentation or fusion. Enhancements can be built based on context: if some characters are well known, they can indicate that they are not recognized, or they can be based on poor recognition of the image of the character appearing in the enhancement.

Cell automaton help in the initial separation of text images into character images. In this case, it is necessary to define automatic machines with a two-point cell, the rules of which are described below.

1. The first machine labels each black point of the image as a sequence of integers.

2. For each black point, the second automaton considers a local neighborhood of unit radius and itself, and places a minimal number of tags from that neighborhood. In this case, the old tag will be launched.

Figure 2 shows the scheme of the automaton created on the basis of the modeled program.



a b

**Figure 2.** Label cell automaton separating characters in the text image: a – label number generator, b – low number label search machine.

After the bots are finished, different characters are highlighted in the text image with different labels, which makes it possible to distinguish the images of individual characters.

In the case of scene text detection in natural images there is not an acceptable available solution yet. The heuristic techniques proved to be very efficient and satisfactory robust for specific applications with high contrast characters and relatively smooth background. However, the fact that many parameters have to be estimated experimentally condemns them to data dependency and lack of generality. Moreover, when background is really complex, they become computationally expensive.

The texture-based techniques cannot catch satisfactory text with size bigger of the sliding window. Moreover, an increase of the window make these methods quite costly. In addition, they still use empirical thresholds on specific features therefore they lack adaptability.

The proposed method address the scene text detection problem by modelling texture into cellular automata (CA) context aiming to eliminate most limitations, such as the empirical thresholds and costly operations.

CA, first introduced by von Neumann, are models of physical systems with local interactions, where space and time are discrete. CA are made for simulating physical systems perceiving the essential local features of systems in order to achieve global actions from the collective effect of locally component interaction. Complicated CA are obtained whenever the dependence from the values of each state is nonlinear [1]. As a result, on the one hand any physical system satisfying differential equations may be approximated by a CA, by introducing finite differences and discrete variables, on the other hand, CAs are one of the computational structures best suited for a VLSI realization.

**CONCLUSION**

These algorithms allow for parallel computation at critical stages of the text recognition process. In addition, the algorithms can be implemented in hardware due to the use of the cellular automata mechanism.

A model program was created to implement the developed algorithms. This made it possible to gradually evaluate the effectiveness of the created algorithms and conduct experiments on text recognition.

**REFERENCES**

1. Neumann J. Theory of self-reproducing automaton. J. Neumann. M.: Mir, 1971.
2. Wolfram S. A New Kind of Science. Wolfram Media. Inc., 2002.
3. Kolesnikov S. Pattern recognition. General information /Newspaper “Computer-Inform”. Software. http://www.ci.ru/
4. Travin A. Technologies for optical text recognition // Electronic office. 1996. November.
5. Khaikin S. Neural networks: a complete course. M.: Williams, 2006.
6. Terekhov S. A. Lectures on the theory and applications of artificial neural networks. Laboratory of Artificial Neural Networks NTO-2. Snezhinsk. VNIITF.
7. OpenCV introduction – https://docs.opencv.org/3.4.1/d1/dfb/intro.html
8. Чабан Л. Н. Теория и алгоритмы распознавания образов. Учебное пособие. – М.: МИИГАиК, 2004, 70 с
9. EmguCV references – http://www.emgu.com/wiki/files/3.4.1/document/html/8dee1f02-8c8a-4e37-87f4-05e10c39f27d.htm
10. Ту Дж., Гонсалес Р. Принципы распознавания образов // Пер. с англ. Гуревич И. Б. – М.: «Мир», 1978
11. LeCun Y. et al. Gradient-based learning applied to document recognition

//Proceedings of the IEEE. – 1998. – T. 86. – №. 11. – C. 2278–2324.
12. McCulloch W. S., Pitts W. A logical calculus of the ideas immanent in nervous activity //The bulletin of mathematical biophysics. – 1943. – T. 5. – №. 4. – C. 115–133.
13. Ojala, T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns / T. Ojala, M. Pietikainen, T. Maenpaa // IEEE Trans. Pattern Anal. Mach. Intell. – 2002. – T. 24 – № 7. – C. 971-987.
14. Wolf, L. Descriptor based methods in the wild / L. Wolf, T. Hassner, Y. Taigman // Science (80.). – 2008. – T. 6 – C. 1-14.
15. Ahonen, T. Face description with local binary patterns: Application to face recognition / T. Ahonen, A. Hadid, M. Pietikäinen // IEEE Trans. Pattern Anal. Mach. Intell. – 2006. – № 12 – C. 2037-2041.
16. O'Connor, B. Facial Recognition using Modified Local Binary Pattern and Random Forest / B. O'Connor, K. Roy // International Journal of Artificial Intelligence & Applications. – 2013. – T. 4 – № 6. – C. 1-25.
17. Trefny, J. Extended set of local binary patterns for rapid object detection / J. Trefny, J. Matas // Proc. Comput. Vis. Winter – 2010. – C. 37-43.
18. Plataniotis, K.N. Color image processing and applications / K. N. Plataniotis, A. N. Venetsanopoulos – Engineering Monograph: Springer Science & Business Media. – 2000. – 65c.
19. Cootes, T.F. Training Models of Shape from Sets of Examples // BMVC92. – 1992. – C. 1-10.
20. Cootes, T. Model-based methods in analysis of biomedical images / T. Cootes // Image Process. Oxford Univ. Press. – 2000. – C. 223-247.
21. Abdi H., Williams L. J. Principal component analysis // Wiley Interdisciplinary Reviews: Computational Statistics. — 2010. — T. 2, № 4. — C. 433—459.
22. Geurts P., Ernst D., Wehenkel L. Extremely randomized trees // Machine learning. — 2006. — T. 63, № 1. — C. 3—42.