Use of a Fuzzy Logical Apparatus in Primary Processing Text Manuscript Recognition

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Abstract: In recognizing texts manuscripts, fuzzy algorithms have been used to remove blurring in the image and increase the efficiency of recognition. The recognition emphasizes the effectiveness of the simultaneous use of FCM and Gaussian filtering, median (3x3) algorithms to increase the brightness of an image in a fuzzy logic apparatus to sharpen a black and white image.

Keywords: filtration, fuzzy logic, Gaussian filtering, fuzzy FCM filtration

1. Introduction

For primary processing algorithms, it is usually assumed that we process the image and clean it from the noise. Many fuzzy algorithms are used in resolving filtration problems. These algorithms serve for effective removal of noises in the image. In recent years, the research on the use of fuzzy methods in image has been carried out in developed countries around the world, it is connected with the following:

1) These methods serve as powerful tools of reflecting and processing the knowledge;

2) They can effectively manage uncertainty and fuzziness.

Many image processing programs require expert knowledge to overcome some difficulties (e.g., object recognition, scene analysis). Unclear sets theory and fuzzy logic have powerful tools for reflecting and processing human knowledge as unclear IF rules. On the other hand, many difficulties in image processing are due to the randomness and inaccuracy of the data used in the problems under consideration.

The fuzzy logic apparatus uses the method of emphasizing the blurred features of a gray image, which can be used to increase the contrast of that image. Improving the quality of the original image is usually one of the first stages of computer visual problems. Image quality improvement techniques typically remove noise, smooth areas where grayscale levels do not change significantly and highlight abrupt changes in grayscale levels.

The fuzzy logic apparatus is very suitable for creating an image enhancement system because it allows the introduction of heuristic knowledge about its specific application in the form of rules.

This has led to the development of various image enhancement methods based on the fuzzy logic. Below we will briefly review some of them.

[2] proposed a filter to dynamically reduce the narrowing of the range of brightness values and increase the contrast using an ambiguous rule approach. The method is based on the algorithm given in [3]. [4] proposed a linear blur filter for image processing. Average filters are known by effective removal of Gaussian noise and and filters based on systematic statistics, such as the average filter, are used effectively to eliminate impulse noise. The fuzzy logic is used to combine these two filters [5].

2. The main part.

Images entered into a computer are often low-contrast, meaning that their changes in brightness are small compared to their average value. In this case, the brightness changes from gray to slightly darker gray but not from black to white. That is, the actual range of brightness turns out to be much lower than the allowable one (gray scale). The task of increasing contrast is to “stretch” the brightness of the image to the full scale.

The essence of image processing on the elements should be as follows $f(x,y)$ va $g(x,y)$ and these are values of the initial brightness and the values obtained after image processing.

The frame point obtained in accordance with the Cartesian coordinates corresponds to x – the row number and y – the column number.

Rational processing of an element means that there is a functional relationship between this brightness, i.e.

$$g(x,y) = F(f(x,y)) \qquad (1)$$

allows you to determine the value of the output signal with the original signal value.

The contrast function is connected with improving the fit of the image to the dynamic range and the screen that displays it. If 1 byte (8 bits) of memory is allocated for the digital display of each image sample, then the input or output signals can take one of 256 values. Usually, the operating range is 0 .. 255, 0 corresponds to the black level during the display and the value of 255 corresponds to the white level. Let's say, the original image and its values $f_{\min}$ and $f_{\max}$ are equal to the minimum and maximum brightness, respectively.

If these parameters or one of them differ significantly from the limit values of the brightness range, then the displayed image looks like an awkward, blurred observation.

It is often convenient to view an image as the execution of an obscure random process. The random output function is represented by a continuous image current function $f(x,y)$, where the spatial coordinates of the two variables are x, y.

Tasodifiy vazifasini chiqarish uzluksiz tasvir joriy $f(x,y)$ funksiya bilan ifodalanib, bu erda ikki o'zgaruvchilar fazoviy koordinatalarini x, y. The random process $f(x,y)$ is fully characterized by the joint probability of the density $P[A]$

This problem can be solved by the element-by-element variation of the linear opposition, i.e.:

$$g(x,y) = af(x,y) + b, \qquad (2)$$

so we got a and b, which leads to vague values of field clarity to some standard values.

Here $M[f(x,y)],\ \sigma[f(x,y)],$ is estimated proximately, to get the pre-exit area option $M[\mathrm{g}(x,y)],\ \sigma[\mathrm{g}(x,y)]$ the coefficients a , b are selected:

$$\bar{g}(x,y) = \frac{f(x,y) - M[f(x,y)]}{\sigma[f(x,y)]} \cdot \sigma[g(x,y)] + M[\mathrm{g}(x,y)] =$$

$$= \frac{\sigma[g(x,y)]}{\sigma[f(x,y)]} f(x,y) + M[g(x,y)] - M[f(x,y)] \frac{\sigma[g(x,y)]}{\sigma[f(x,y)]},$$

$$a = \frac{\sigma[g(x,y)]}{\sigma[f(x,y)]};\ b = M[g(x,y)] - M[f(x,y)] \frac{\sigma[g(x,y)]}{\sigma[f(x,y)]}. \qquad (3)$$

Here

$$M[f(x,y)] = \frac{\sum_{i=1}^{k} f_i(x,y) \cdot \mu_i^f(x,y)}{\sum_{i=1}^{k} \mu_i^f(x,y)},\quad M[g(x,y)] = \frac{\sum_{i=1}^{k} g_i(x,y) \cdot \mu_i^g(x,y)}{\sum_{i=1}^{k} \mu_i^g(x,y)}; \qquad (4)$$

$$g(x,y) = F(f(x,y)) = \begin{cases} 0, & \bar{g}(x,y) < 0, \\ \bar{g}(x,y), & 0 \le \bar{g}(x,y) \le 255, \\ 255, & \bar{g}(x,y) > 255. \end{cases} \qquad (5)$$

Thus, when processing images it is necessary to select the same locations of the image based on certain features. Image processing steps reduce the impact of distortions on the recognition process.

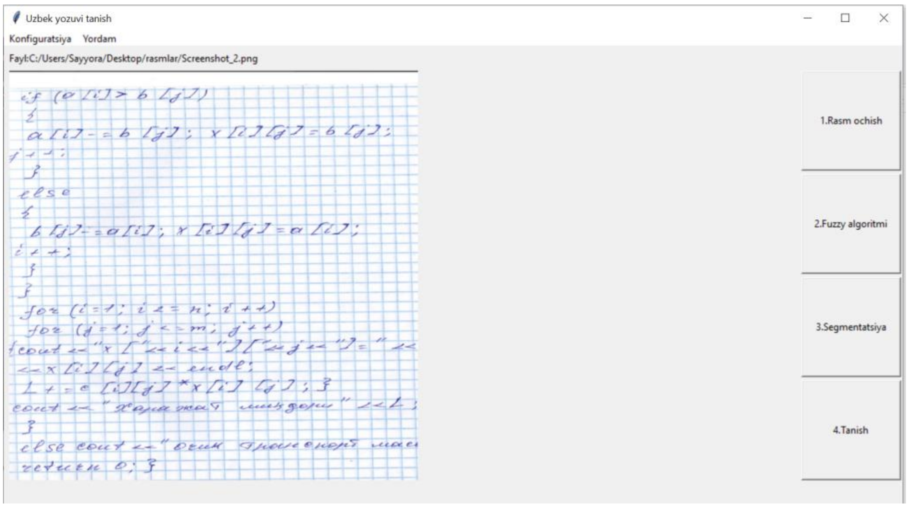

Figure 1. Input image

The result obtained after c-mean and Gaussian filtration.

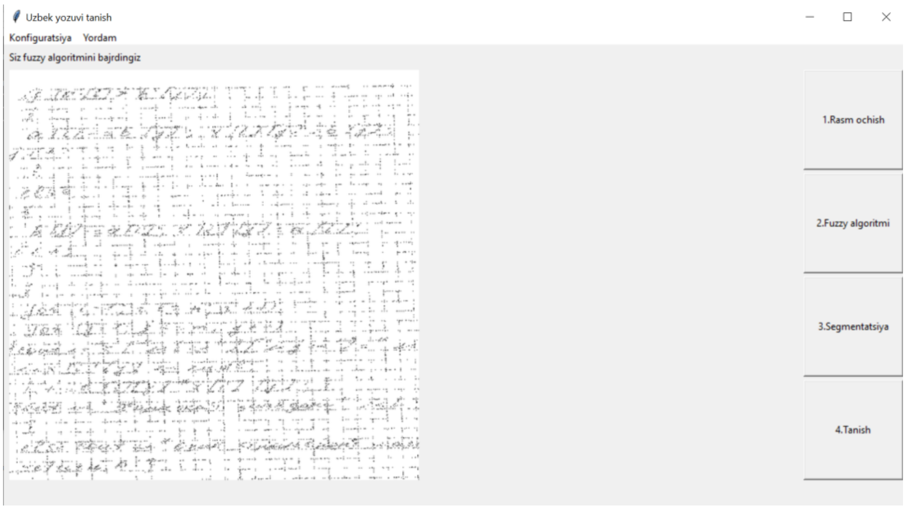

Figure 2. C-mean and Gaussian filtration result

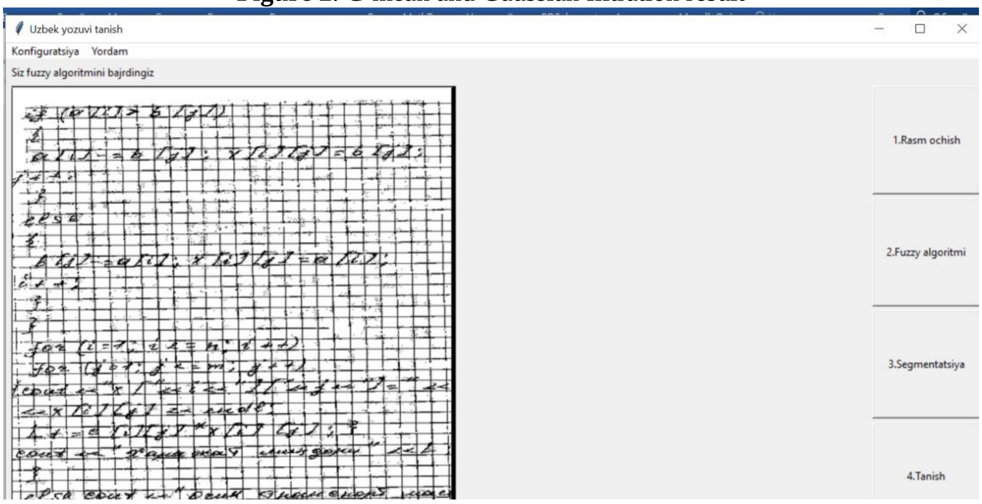

Figure 3. The result obtained after increasing the brightness.

Figure 3 shows the result of enhancing the linear contrast with an inaccurate initial data.

Segmentation based on clustering methods. The first method was the obscure clustering method Fuzzy C-tools (Fuzzy C-tools - FCM) [40, 45], which now has many modifications [1 2]. The FCM method is based on the use of mathematical apparatus of ideas and fuzzy logic. In the FCM algorithm process, each pixel of the image is assigned a vector of membership functions for each class, on the basis of which it is possible to draw conclusions about the nature of this object.

The segmentation result using the FCM algorithm depends on the selected dimension. Euclidean distance is only effective when the clusters are well positioned and their dimensions are approximately equal. Otherwise, other algorithms can be used, for instance, the algorithm proposed in [1 3] or the Gaussian mixture decomposition algorithm.

The real set and $X=\{x_1,x_2,..,x_m\}\subset R$ k the real numbers have to be given in ascending order $s_1,s_2,..,s_k$, i.e.: $s_1<s_2,<..<s_k$.

An obscure division X for a set $A_1,A_2,..,A_k$ can be organized using a triangular function *X*. When developing an obscure clustering algorithm for image segmentation, we consider membership functions first:

$$\mu_1(x)=\mu(x,s_1;s_2),$$

Here *i* = 2,3, ..., *k*−1

$$\mu_i(x)=\mu(x,s_i;s_{i-1})\wedge\mu(x,s_i;s_{i+1}),$$

$$\mu_k(x)=\mu(x,s_k;s_{k-1}). \qquad (6)$$

Functions define the division of a section $\mu_1,\mu_2,..,\mu_k$ by the following equation:

$$\mu_1+\mu_2+...+\mu_k=1. \qquad (7$$

Second, the defusion operator t (µ, g) applied to the uncertain section is determined:

$$\tau(\mu,\gamma)=(\tau_1,\tau_2,..,\tau_k), \qquad (8)$$

Here

$$\tau(x,\mu,\gamma)=\frac{\mu_i^{\gamma}(x)}{\sum_{j=1}^{k}\mu_i^{\gamma}(x)} \qquad (9)$$

v_i va F_i are defined as follows:

$$v_i(x)=\mu_i(x)\wedge\tau_i(x,\mu;\gamma), \qquad (10)$$

$$F_i(s_i)=\frac{\sum_{j=1}^{m}v_i(x_j)\cdot x_j}{\sum_{j=1}^{m}v_i(x_j)}. \qquad (11)$$

And now we will consider the following parameter constraint: $s_1,s_2,..,s_k$:

$$s_i=F_i(s_i). \qquad (12)$$

The obscure *Ai* set is determined by equation (1). s_i center belongs to the convex body of the X set and it is the fixed point for the F_i function.

The results are obtained using the following obscure clustering algorithm.

Step 1. Number of clusters k, defuzzification parameter g, parameter stop mode d, repetition index l = 0 starts from the centers of the pile. Next, $\mu_1^{(0)}$, $\mu_2^{(0)},..,\mu_k^{(0)}$ vague membership functions and $\tau_1^{(0)},\tau_2^{(0)},..,\tau_k^{(0)}$ is a function of defuzzification components.

Step 2. The repetition rate is increased: $l \to l+1$ We calculate the functions of clusters' centres $s_1^{(l)} = F_1(s_1^{(l-1)}),\ s_2^{(l)} = F_2(s_2^{(l-1)}),....,s_k^{(l)} = F_k(s_k^{(l-1)})$, indefinite membership functions $\mu_1^{(l)},\ \mu_2^{(l)},..,\mu_k^{(l)}$ defuzzification components $\tau_1^{(l)},\tau_2^{(l)},..,\tau_k^{(l)}$ va $v_1^{(l)},v_2^{(l)},..,v_k^{(l)}$.

Step 3. $d = \sum_{i=1}^{k} \left| \mu_i^{(l)} - \mu_i^{(l-1)} \right|$ is calculated. If $d > \delta$, then return to the 2nd step, otherwise go to the 4th step.

Step4. Save the data and go up to the end.

These filtration algorithms are used in the primary processing of the image and are important in increasing the percentage of recognition. We achieved effective results in removing a lot of noises in ancient manuscripts.

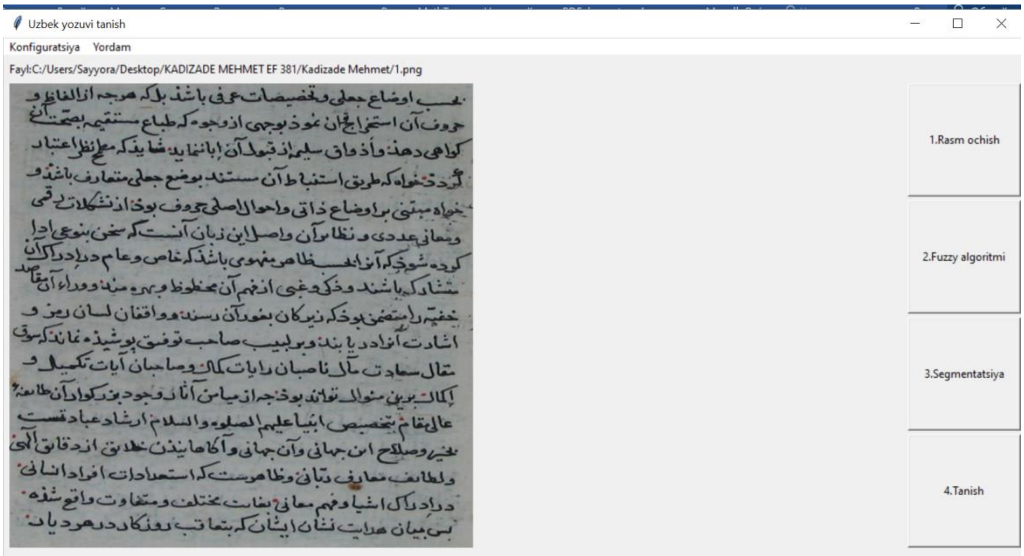

Figure 4. The original image

Figure 5. The results obtained in increasing the brightness by simultaneous use of obscure logic apparatus, FCM and Gaussian filtration, median filtration (3x3)

3.Conclusion.

When processing images, one cannot always get the required image. We can achieve the normal form using different processing algorithms. Increase in brightness was normalized based on the algorithms used in conjunction with the fuzzy logic apparatus, FCM filtration, Gaussian filtration. Using median filtration, the writing form was thickened. Images in teaching and cognitive images must be filtered. The removal of excess noise reduces the error in the process of calculations. It leads to high results in recognition issues

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