The Results of Sulfur Print Image Classification of Section Images

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Abstract. The article deals with mathematical and algorithmic support for sulfur prints image classification based on fuzzy sets and rules of accessories using peer inspections. In the study of the causes of unambiguous classification the authors have introduced codomains of membership function form: single classification, empty set, complete absorption and unambiguous classification. The article conceived the concept of equilibrium and nonequilibrium membership functions. The results showed unambiguous classification of 100% images. The research was carried out in 2011–2015. The proposed technique is applicable to the classification of static images to assess the structure of materials using combined methods.

Key words: data validity, image classification, fuzzy sets, tenancy rules.

1 Challenge problem

One of information sources about the quality of continuously cast billet is sulfuric prints. The reliability of the information is determined by the methods of irregular shape objects recognition in the image of sulfur prints. The authors carried out the investigation for the identification of objects in an image using statistical methods [1], morphological operations [2] and adaptive fuzzy trees with a dynamic structure [3]. However, the known image recognition procedures set out in [4–6], do not provide getting accurate information without resulting images prior classification. There is an actual problem of improving the information reliability obtained during continuous casting sulfur prints recognition.

Nowadays, active research is being carried out in the field of classification of images and objects including in the structure. Among the known solutions, we can specify the results of the studies which are conducted in many countries around the world, including Russia. One of the approaches to solve the classification problem remains creating a library of images according to the categories. For example, in [7] the seven categories of images were studied to construct a vector classification system. The paper demonstrates the selection theory with linear shared objects in an optimal hyper plane. The authors conducted more than 2670 tests with classes: airplanes, birds, boats, buildings, fish, people, and vehicles. In the study the authors used Laplacian of Gaussian distribution as a core.

When constructing the classifier the authors achieved a classification accuracy of 11 to 16%. The authors in [8] suggest using Support Vector Machines (SVM) for multipoint images classification. The paper presents the method of hyper plan choice. However, the authors do not speak about the problems in methods using in increasing hyper plans number. Quite a lot of works is dedicated to the human face recognition and its elements. For this purpose the authors propose the use of automatic classification based on the map of the characteristic points. For example, in [9] we offer the use of two-dimensional wavelet transform based on the envelope wave to highlight the main points of the face. This method application resulted in 82% level of correct identification of the person's face. The disadvantage of this method is the image quality sensitivity and mimic changes of the main face elements. One of object classification methods is to define the feature points of the predetermined textures [10, 11]. In [7] the authors advance an approximate base model of image segmentation based on point's brightness assessment. The authors of the work used an algorithm to image the brain. The result was a classification of images with different textures of up to 84.4%. In [11] we considered the statistical approach to texture classification of the individual images, which is based on determining the lighting quality, camera position and image processing conditions. The method is based on the use of the filter resistant to the image rotation, the image histogram evaluation and the histogram shape evaluation. The basic decision-making procedure has been adopted the class picture k-means (k-Means), which appears sensitive to the choice of the original condensation centers. The image classification problem was solved by the same ways both with the help of fuzzy sets and fuzzy logic. The first studies on the machine use for the fuzzy image classification appeared in the late 80's and early 90-ies of the 20th century and demonstrated good recognition results of cartographic images with regularly shaped objects [12–14]. The presented fundamentals have been developed in recent studies [15–17]. However, despite many existing research the problems of classifying the image with lots of irregular shaped objects, low contrast, low quality and contrast remain unsolved [18–20].

The aim of the article is the development of software for sulfur prints image classification for the further effective application of segmentation methods.

2 Factorable image classification technique

Three stages have been included in the image classification technique. Each subsequent stage of the classification is provided to use for the images in the field of unambiguous identity in accordance with the evaluation of the previous step. Each shaped stage is different from the previous one by the number of identification codes and the complexity of the membership functions belonging to each class. The first stage uses the rules for identifying the image, built on the basis of the three formative characteristics of the histogram: the position of the threshold luminance; position of maximum brightness to the left of the threshold; position of the maximum brightness to the right of the threshold. The second stage, by increasing the number of identification codes from 3 to

256, uses three measures of similarities, describing the dispersion to evaluate the scattering distance relative to the average value of each class. The third stage is used only for the images that lacked unambiguous identity of the previous two stages. Considering lack of the possibility to identify the images on the basis of deterministic parameters of the histogram, we decided to perform linguistic variables, terms and rules to identify images into the classes. The techniques built on fuzzy rules include expert assessments and allow taking into account the insights in the process formalization.

Considering 31% of the images after the application of the two techniques based on the forming characteristics of histograms and distance remain in an unambiguous identity we developed the technique for sulfur print image classification based on fuzzy sets and fuzzy logic rules.

In order to solve the problem of image classification we introduce the structured linguistic variable – $Image$, which in its composition has four components: m, M, T, where T is an abscissa of the point for the position of the brightness threshold; m is an abscissa of the point of the brightness maximum to the left of the threshold; M is an abscissa of the point position of the brightness maximum to the right of the threshold. Fig. 1 illustrates the structure of the linguistic variable $Image$ indicating all the components.

A special feature of the variable *Image* is three elements describing the formative characteristics, for which the terms and the membership function should be defined. Each of the components of the linguistic variable Image takes three values: "Belongs to class A"; "Belongs to class B"; "Belongs to class C", which form a set of terms (Fig. 1).When describing the single reference histogram there are four types of regions: of unambiguous identification (Fig. 2), of multiple identities (areas overlapping Fig. 3), the region of "empty set", which does not include any of the reference images and the region "total absorption". For each of the cases the authors have written the membership function in a general form μ_i,$i = \overline{1;3}$, where i – notation for classes.

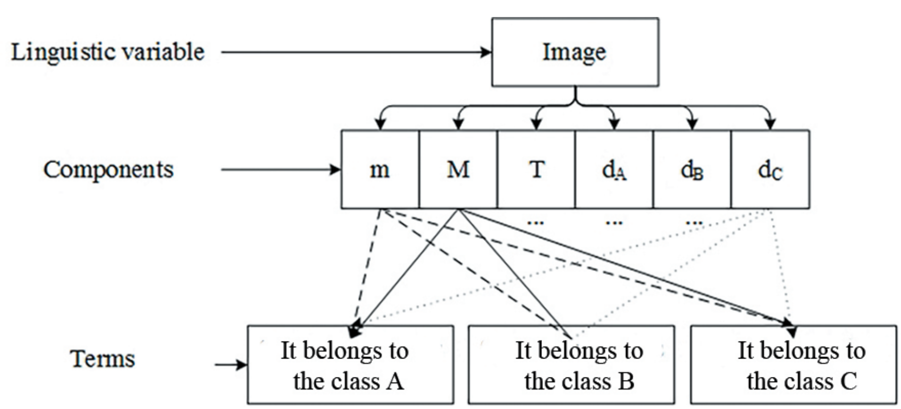

Fig. 1. Structure of the linguistic variable $Image$

If you have a unique identification of all three classes it is possible to get the pattern of membership function shown in Fig. 2. In Fig. 2 we introduced the notation: x is the considered component of the linguistic variable, [0; 255] is the domain of the membership function according to the region of the brightness histogram existence.

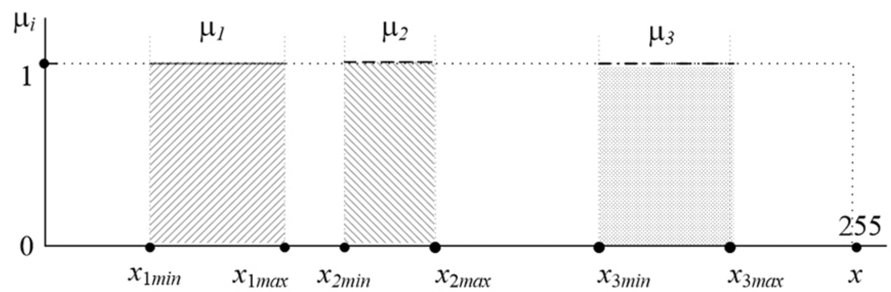

Fig. 2. Formation scheme of the membership function for the unambiguous identity areas

The condition for the scheme existence shown in Fig. 2 appears intervals order of the selected histogram characteristics. Consequently the condition of ordering the formative characteristics is:

$$x_{1min} < x_{1max} < x_{2min} < x_{2max} < x_{3min} < x_{3max}. \tag{1}$$

The ambiguous classification cases for the two groups remain after the second stage of the classification technique. There is an interval for two overlapping areas in which there are two solutions for the variable $Image$ belonging to the considered classes. Fig. 3 illustrates a diagram of the two areas intersection in the process of image classification.

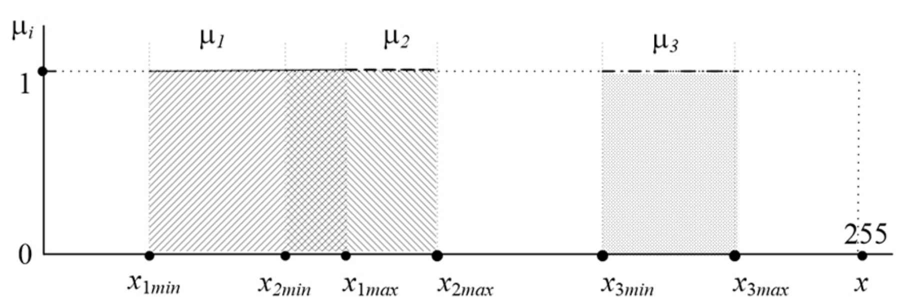

Fig. 3. The scheme of ambiguous identify region intersection

In the case shown in Fig. 3 , there is an intersection region at the range $[x_{2min}; x_{1max}]$ and the condition has been disturbed (1). Therefore, the axiomatic form of membership function must be taken for this interval.

The simplest version of the membership function form is the linear "equilibrium" model (Fig. 4a) and more complex option for strengthening the probability of membership in the class through the combination of the two quadratic functions (Fig. 4b) – "non-equilibrium" model. The point of these functions intersection is determined in the course of adaptation or learning classification system.

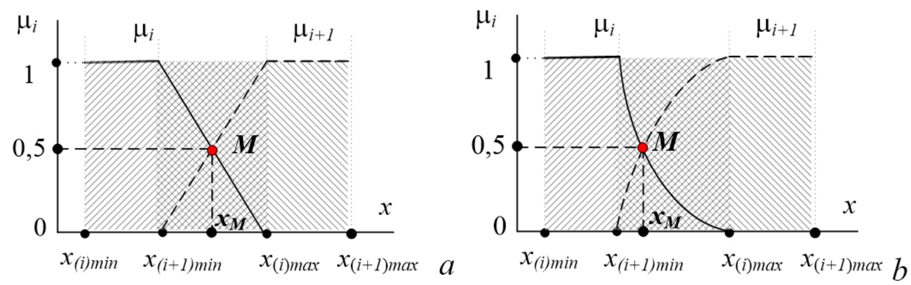

Fig. 4. The formation scheme of the membership functions for overlapping areas: a – equilibrium model; b – non-equilibrium model

Fig. 4 additionally introduces the notation: M is the membership function intersection point for the ambiguous classification region; x_M is abscissa of the membership function intersection point.

The abscissa of the point M can be displaced from its equilibrium position as to the left as to the right, keeping the ordinate. Saving the ordinate makes it possible to determine the analytical record of parabolic membership functions in the training system. We wrote the analytic form of the membership function for the equilibrium and nonequilibrium model.

For the function μ_i in the interval $\left[x_{(i+1)min}; x_{(i)max}\right]$ we try to use a canonical equation of the line passing through the two points with the coordinates $\left(\mathrm{x}_{(\mathrm{i+1})\mathrm{min}}; 1\right)$ and $\left(\mathrm{x}_{(\mathrm{i})\mathrm{min}}; 0\right)$ for the analytical records as shown in Fig. 4a.

As a result, the membership function becomes:

$$\mu_i = \begin{cases} 1, & x \in \left[x_{(i)\,\min}; x_{(i+1)\,\min}\right]; \\ -\dfrac{1}{Q}x + L, & x \in \left(x_{(i+1)\,\min}; x_{(i)\,\max}\right); \\ 0, & x \in \left[x_{(i)\,\max}; x_{(i+1)\,\max}\right]. \end{cases}$$

Similarly, using the same notation, we obtain

$$\mu_{i+1} = \begin{cases} 1, & x \in \left[x_{(i)\min}; x_{(i+1)\min}\right]; \\ -\dfrac{1}{Q}x - R, & x \in \left(x_{(i+1)\min}; x_{(i)\max}\right); \\ 0, & x \in \left[x_{(i)\max}; x_{(i+1)\max}\right], \end{cases}$$

where $R = \dfrac{x_{(i+1)min}}{x_{(i)max} - x_{(i+1)min}}$ and $Q = x_{(i)max} - x_{(i+1)min}$.

In the case of a non-equilibrium model for the function μ_i on the interval $\left[x_{(i+1)min}; x_{(i)max}\right]$ we use the equation of a parabola through the three points with the coordinates $\left(\mathrm{x}_{(\mathrm{i+1})\min}; 1\right)$, $\left(\mathrm{x}_{(\mathrm{i})\min}; 0\right)$ and $(\mathrm{x}_\mathrm{M}; 0{,}5)$, for the analytical records as shown in Fig. 4b. The abscissa x_M is set interactively at training the classification system and it is considered known in advance.

While forming histogram there is brightness, according to which none of reference images is classified, but any new image may have the characteristics of those areas (Fig. 5). For these areas membership functions should also be recorded, which can be constructed on the same principle as that of the ambiguous identity regions. And the order of the interval boundaries must match the expression (1).

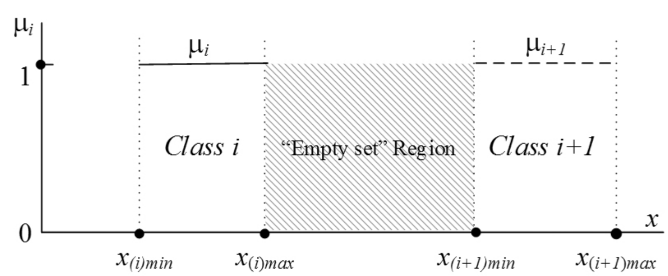

Fig. 5. Arrangement of "empty set" areas

In this case, it suffices to consider the area between the two non-overlapping intervals (Fig. 6). We wrote the analytical form of the membership function to each model.

We used the canonical equation of the line passing through two points with the coordinates $\left(x_{(i)max}; 1\right)$ and $\left(x_{(i+1)min}; 0\right)$ for the analytical records for the function μ_i in the interval $\left[x_{(i)max}; x_{(i+1)min}\right]$ as shown in Fig. 6a.

As a result, the membership function μ_i becomes:

$$\mu_i = \begin{cases} 1, & x \in \left[x_{(i)min}; x_{(i)\max}\right]; \\ \dfrac{1}{Q}x - R, & x \in \left(x_{(i)\max}; x_{(i+1)min}\right); \\ 0, & x \in \left[x_{(i)\min}; x_{(i+1)\max}\right]. \end{cases}$$

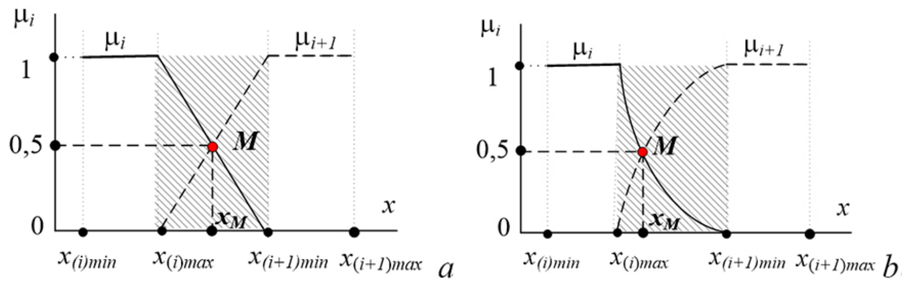

Fig. 6. The formation scheme of the membership functions for overlapping areas: a – equilibrium model; b – non-equilibrium model

Similarly, using the same notation, we obtain

$$\mu_{i+1} = \begin{cases} 1, & x \in \left[x_{(i)min}; x_{(i)\,\max}\right]; \\ -\dfrac{1}{Q}x - R, & x \in \left(x_{(i)\,\max}; x_{(i+1)min}\right); \\ 0, & x \in \left[x_{(i+1)\,\min}; x_{(i+1)\,\max}\right], \end{cases}$$

where $L = \dfrac{x_{(i)max}}{x_{(i)max} - x_{(i+1)min}}$ and $Q = x_{(i)max} - x_{(i+1)min}$.

In the case of a non-equilibrium model for the function μ_i we should use the range $\left[x_{(i)max}; x_{(i+1)\,\min}\right]$ as the equation of a parabola passing through the three points with the coordinates $\left(x_{(i)max}; 1\right)$, $\left(x_{(i+1)min}; 0\right)$ and $(x_M; 0{,}5)$, for the analytical records as shown in Fig. 6b. The abscissa x_M is set interactively at training the classification system and is considered known in advance.

Membership function pattern for the region of "total absorption" in accordance with the formative characteristics of the histogram. "Total absorption" area occurs during the segments order violation (1). There are two variants of the "total absorption" region creation: the overlap of the first interval (Fig. 7a) and the second interval overlap (Fig. 7b).

In this case, it is necessary to assign axiomatic value of the membership function for the absorption region. As one of the possible options, we assume that:

– when the following condition is satisfied $\left(x_{(i+1)\,\min}; x_{(i+1)max}\right) \in \left[x_{(i)\,\min}; x_{(i)max}\right]$ (Fig. 8)

$$\mu_i = \begin{cases} 1, & x \in \left[x_{(i)\,\min}; x_{(i+1)min}\right] \cup \left[x_{(i+1)\,\max}; x_{(i)max}\right]; \\ 0, & x \in \left(x_{(i+1)\,\min}; x_{(i+1)max}\right), \end{cases}$$

and

$$\mu_{i+1} = 0, \forall\, x;$$

– when the following condition is satisfied (Fig. 8) $\left(x_{(i)\,\min}; x_{(i)max}\right) \in \left[x_{(i+1)\,\min}; x_{(i+1)max}\right]$ (Fig. 8)

$$\mu_{i+1} = \begin{cases} 1, & x \in \left[x_{(i+1)\min}; x_{(i)min}\right] \cup \left[x_{(i)\max}; x_{(i+1)max}\right]; \\ 0, & x \in \left(x_{(i)\min}; x_{(i)max}\right), \end{cases}$$

and $\mu_i = 0, \forall\, x$;

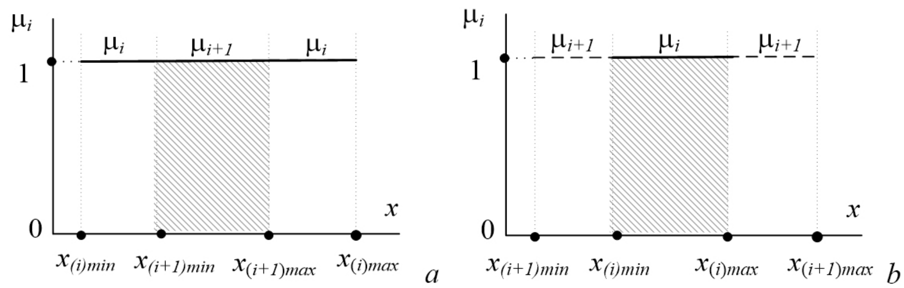

Fig. 7. Formation scheme of the "total absorption" region: a – overlapping by the first interval; b – overlapping by the second interval

In fact, zero membership function on one of the intervals excludes this area from consideration when deciding on the accessories image to one of the classes. The size of this area is less than 4% of the membership function domain. Intermittent "failure" in the values of the membership function occurs at the specified interval.

3 The results of the membership function construction

Using membership functions we perform their construction for the classification of images that were not clearly classified in the first two stages. After the two stages there were cases of ambiguous image classification between classes A and C, B and C. We will consider each case individually for each component of the variable Image.

Let us build the membership functions for the classes A and C. The membership function for the parameters on the left maximum and a brightness threshold is characterized by the presence of three areas of "empty set", which do not cause ambiguous identity of the image (Fig. 8), and allow you to uniquely classify new images coming in the system. In Fig. 9 we can observe μ_{MC} function failure of the range $M \in (M_{Amin}; M_{Amax})$. Thus, the membership functions are:
– membership function for a maximum on the left (Fig. 8):

$$\mu_{mC} = \begin{cases} \dfrac{1}{147}m, & 0 \le m < 147; \\ 1, & 147 \le m \le 185; \\ -\dfrac{1}{49} + 4{,}78, & 185 < m < 234; \\ 0, & 234 \le m \le 255, \end{cases}$$

$$\mu_{mA} = \begin{cases} 0, & 0 \le m < 147; \\ \dfrac{1}{49}m - 3{,}78, & 185 \le m \le 234; \\ 1, & 234 < m < 239; \\ -\dfrac{1}{16}m + 15{,}94, & 239 \le m \le 255, \end{cases}$$

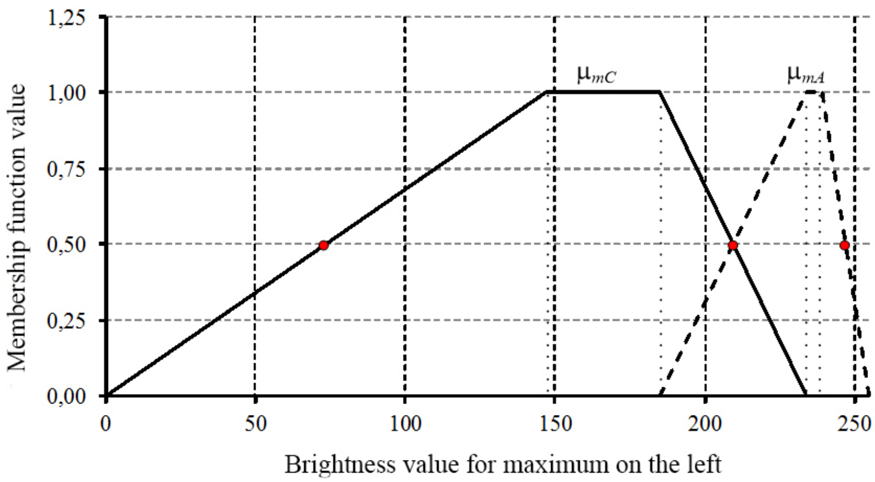

Fig. 8. Equilibrium membership function pattern for the brightness maximum on the left

– membership functions for the brightness threshold (Fig. 9):

$$\mu_{TC} = \begin{cases} \dfrac{1}{193}T, & 0 \le T < 193; \\ 1, & 193 \le T \le 207; \\ -\dfrac{1}{30}T + 7{,}9, & 207 < T < 237; \\ 0, & 237 \le T \le 255, \end{cases}$$

$$\mu_{TA} = \begin{cases} 0, & 0 \le T \le 207; \\ -\dfrac{1}{30}T - 7{,}9, & 207 < T < 237; \\ 1, & 237 \le T \le 240; \\ -\dfrac{1}{15}T + 15, & 240 < T \le 255; \end{cases}$$

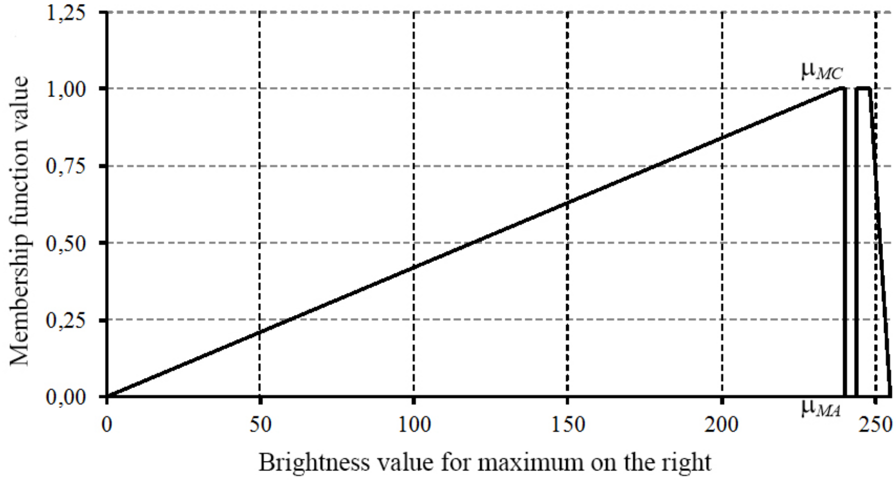

Fig. 9. Equilibrium membership function pattern for the brightness maximum on the right

– membership functions for maximum brightness on the right:

$$\mu_{TC} = \begin{cases} \dfrac{1}{238}T, & 0 \leq M < 238; \\ 1, & 238 \leq M < 240 \text{ or } 244 < M \leq 248; \\ -\dfrac{1}{7}T + 36{,}43, & 248 < M < 255; \\ 0, & 240 \leq M \leq 244, \end{cases}$$

$$\mu_{MA} = 0, \, \forall M \in [0; 255] \, .$$

For each component of the variable $Image$ let us accept membership rules:

the Image belongs to class K_i, if the membership function value for the class K_i is at least 0.5.

For each variable $Image$ we obtain values of three components, which include the picture to one of two classes according to the introduced rule.

Table 1 defines decision rules in the image classification according to membership between classes A or C. Table 2 shows an example of calculation and the membership conclusion of one of the images, which was originally, identified ambiguously, to classes A and C. After applying the technique based on fuzzy sets and expert decision rules we adopted an unambiguous solution concerning the image membership to class A.

In the tables class 0 is entered to indicate the interval of “total absorption”. Tables are filled in a survey of experts – specialists in the evaluation of the work piece quality during the training of decision-making on sulfur print images classification.

Table 1. Decision rules in ambiguous classification between A and C

Rule number	Class me mbership according to the component			Conclusion
	m	T	M	
1	A	A	0	A
2	A	C	0	A
3	C	C	0	C
4	C	A	0	A
5	C	C	C	C
6	C	A	C	C
7	A	C	C	C
8	A	A	C	A

Table 2. Example of making decisions based on the rules of Table 1

Component	Notation	Function value		Class	Conclusion
		μ_A	μ_C		
m	237	1	0	A	A
T	200	0,31	0,69	C	A
M	242	0	0	0	A

4 Conclusions

In order to resolve ambiguous sulfur prints image classification the authors proposed the technique of stage classification, which includes three stages of decision-making according to the formative characteristics of the brightness histogram, to the distance measures up to the reference histograms and fuzzy membership function with the use of expert logic inference rules. Each subsequent stage is used in the presence of ambiguous classification in the previous step. The authors offered the technique based on the theory of fuzzy sets for complex-structured linguistic variable comprising three components: a brightness maximum on the right, brightness threshold, and a brightness maximum on the left to resolve ambiguous identity regions of the image. Term-sets, which define entered membership classes, have been introduced for each component. The proposed mathematical software in describing the membership functions introduces the notions of equilibrium and non-equilibrium models, it performs a generalized technique of these models construction and its application in sulfur prints image classification. When constructing membership functions of fuzzy sets the authors conceived the concept of “empty set” and “total absorption” areas, which allowed identifying ambiguously the images from the new retrospective dataflow.

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