Two New Methods of Boundary Correction for Classifying Textural Images

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Abstract

With the growth of technology, supervising systems are increasingly replacing humans in military, transportation, medical, spatial, and other industries. Among these systems are machine vision systems which are based on image processing and analysis. One of the important tasks of image processing is classification of images into desirable categories for the identification of objects or their specific areas. One of the common methods is using an edge finder in image classification. Due to the lack of definite edges in many images obtained from various sciences and industries such as textural images, the topic of textural image classification has recently become of interest in the science of machine vision. Thus, in this article, two methods are proposed to detect edges and eliminate blocks with non-connected classes based on fuzzy theory and weighted voting concepts in classifying textural images. In the proposed methods, the boundaries are corrected using fuzzy theory and weighted voting concepts. Using the proposed methods can help improve the definition of boundaries and classification accuracy.

Keywords: *Textural Images; Contourlet Conversion; Boundary Correction; Fuzzy Theory.*

1. Introduction

In recent years, different methods have been proposed for automatic classification of textural images in various application domains. In common classification algorithms, each pattern is assigned only to one category, and patterns are classified into non-connected categories [1]. Thus, they have an acceptable performance in compressed and quite distinct classes. However, in most cases, especially in classifying textural images such as seabed images and distributing them into two sets, there has been an overlapping in the space of combination, and the performance of the algorithm has not been appropriate [2]. Due to the absence of definite boundaries between different sets of textural images, the problem of boundary correction has been considered in them [3]. The problem of precession is one of the challenges in the determination of boundaries in textural images and their classification. Methods proposed in this paper eliminate the problem of precession in boundary correction by the use of fuzzy theory and weighted voting concepts. The rest of the paper is organized into six sections. The related work is presented in Section 2. Sections 3 and 4 introduce the proposed methods based on fuzzy theory and weighted voting concepts, respectively. Experimental results are presented in Section 5. Comparison

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between the proposed methods is presented in Section 6. At last, conclusion is drawn in Section 7.

2. Related Work

The classification of textural images can be divided into three separate steps:

Step 1: Feature extraction: In this step, the image is first divided into m*m blocks and then features of the blocks are extracted using Contourlet algorithm.

Step 2: Block classification: In this step, the blocks with the features obtained in the first step are allocated to different classes (in other words, they are classified) using data mining algorithms. Among the studies conducted on the classification step, we can mention the following two:

In [4], the features obtained in the first step were weighed using fuzzy theory. According to the weights given to the features and using the SVM algorithm, the appropriate classification was presented.

In [5], after extracting the features in the first step, the appropriate classification was presented by combining the SVM algorithm and fuzzy neural method.

Step 3: Border correction: In this step, after executing the classification method on the blocks of a textural image, borders of the obtained image are usually blurred. The border correction method is commonly used to clarify the borders. The four-neighborhood voting method is used in the border correction step. Unfortunately, few studies have been conducted on this topic in recent years. In most of the articles mentioned in the references, the four-neighborhood voting methods are used in the border correction step. In order to indicate the importance of this step, we can mention [6], in which four-neighborhood voting method was executed in two steps on the image in order to improve the border correction step. The innovation of the present article is in the third step of classification, that is, the border correction step. In this research, the four-neighborhood voting method is investigated and a considerable progress is achieved in the border correction step using the fuzzy theory and weighing the blocks.

The main goal of studying textural images is classifying parts of the image which have different textures. For this purpose, different methods have been proposed in scientific papers, but no unified method for categorizing different textural images with an acceptable accuracy has been introduced. Thus, research is continued in this area [7, 8, 9]. Contourlet transformation has been suggested as an improvement to other transformations. It has not only all the characteristics of the wavelet transformation such as satirizing the place of frequencies and multi-resolution show, but also other characteristics such as direction and anisotropies. According to research, the accuracy of the results in Contourlet transformation is more than those in the wavelet transformation. In most papers, classification methods based on texture have been divided into supervising and un-supervising groups. There are two main steps in the classification of methods based on texture [3, 10, 11]. The first step is extracting the effective properties of the texture, and the second step is classifying the image using clustering algorithm or extracting feature [8]. There are two types of methods for textural image classification [12, 13]. The first type is based on the region, and the second is based on boundary and edges.

In [14], a method has been proposed for recognizing edges based on Contourlet transform using modulus maxima theory. In this method, blocks of the received image which has been divided into m*m blocks are assessed from the upper left side. If the known block has the same category as half of its neighbors, the block will not change.

Also, in [1, 6], four- and eight-neighborhood methods have been proposed for textural image classification. They allow the analysis of images at various scales and directions, which effectively captures smooth contours that are the dominant features in seabed images.

3. The proposed Method for Classifying Textural Images Based on Fuzzy Theory Concepts

In this paper, the proposed method can eliminate the problem of precession by the use of fuzzy theory. There are problems of precession in several image classification methods such as voting of four neighborhoods [1, 6]. According to the proposed method, a membership degree is assigned to every block. Each neighbor influences the voting based on membership degree which is defined here as the membership degree of the block intended in the white class. For example, if the membership degree of a block is 0.75, the block is a member of the white class with the membership degree of 0.75, and is a member of the black class with the membership degree of 0.25. Thus, it is enough to know how much a block is a member of the white class; accordingly, the membership degree of its black class can be identified. The flowchart of the proposed method is shown in Fig. 1.

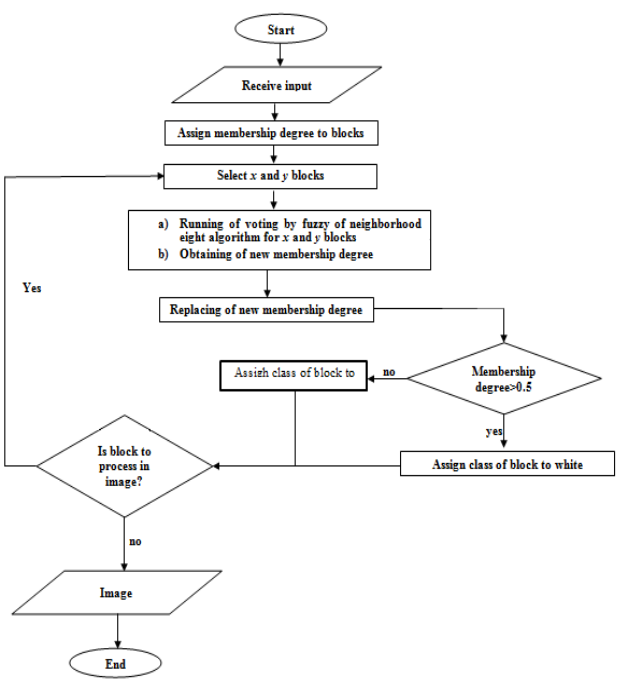

Fig. 1. The flowchart of the proposed method based on fuzzy theory concepts for textural image classification

In the proposed method, first each block with the white class is assigned membership degree 1, and then it is examined from the upper left side of the image toward its lower right. For such an investigation, membership degrees are first summed, in which the membership degree of the considered block or is also considered. To do so, the membership degree of all the neighboring blocks and the considered block are summed according to Equation 1.

$$dm = dbx + dby \tag{1}$$

where dby is the membership degree of the intended block, and dbx is the total membership degrees of neighboring blocks. Then, using Equation 2, the new membership degree of the considered block is calculated.

$$dby = dbm / (n+1) \tag{2}$$

where n is the number of neighboring blocks and dby is the new membership degree of the considered block. The proposed method continues to go to the next blocks and obtain their membership degrees. Finally, all the blocks whose membership degrees are more than 0.50 are classified as members of the white class, and the blocks smaller than 0.50 are the members of the black class. The class of the blocks with the membership degree of 0.50 remains unchanged. Below, an example of implementing the proposed method is presented in Fig. 2.

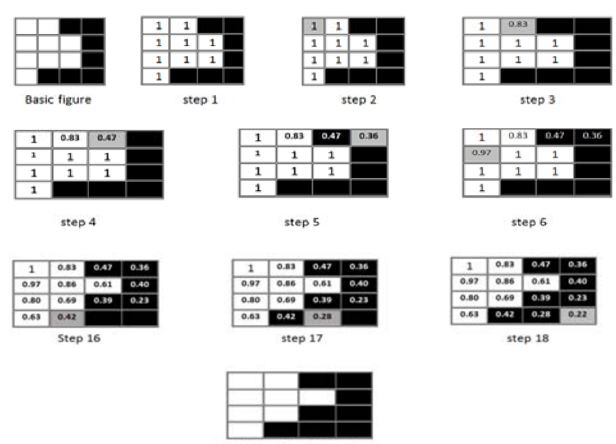

Fig. 2. An example of implementing the proposed approach

4. The Proposed Method for Classifying Textural Images Based on Weighed Voting Concepts

In voting, instead of four connected blocks which have been purified in four main directions, we can use eight neighbouring blocks. In the proposed method, recognition of boundaries is better and precession is faster. Thus, it has a higher accuracy than the four-neighbour voting method. The proposed method assigns different weights to blocks. Accordingly, weight 1 is assigned to the neighbouring blocks in four main directions, and weight 0.5 to the neighbouring blocks in four secondary directions. In voting, if the intended blocks' weight is half or more than half of the neighbours' weights, the specified block's class will not change. Otherwise, it will change. In this method, using weighed voting method, precession is eliminated and accuracy is improved. However, the effect of xy block class which has been changed could not improve the checking of blocks of the next class (right and down). For tackling this challenge, first matrix M which corresponds to the blocks is defined. In the next step, the blocks will be checked from the upper left to the lower right side, using weighted voting. If the class of the intended block does not change, routines will be performed in the same way. If the class of the intended block has to be changed, the corresponding matrix cell will be changed to the value of 1. After checking all the blocks (no block class has been changed) by referring to the matrix, any cell which becomes 1 finds the corresponding block with matrix cell and will change the intended block class. Thus, in the proposed method, the effect of block change is reduced on the next blocks as much as possible. The flowchart of the proposed method is shown in Fig. 3.

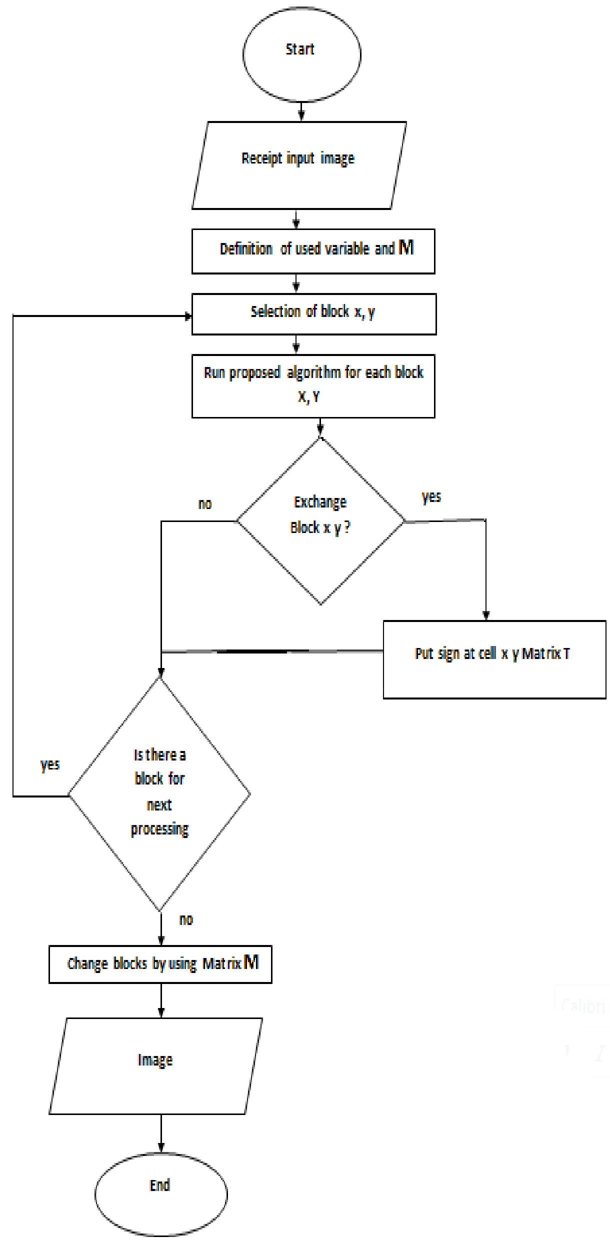

Fig. 3. The flowchart of the proposed method based on weighted voting concepts for textural image classification

An example of implementing the proposed method is presented in Fig. 4 below.

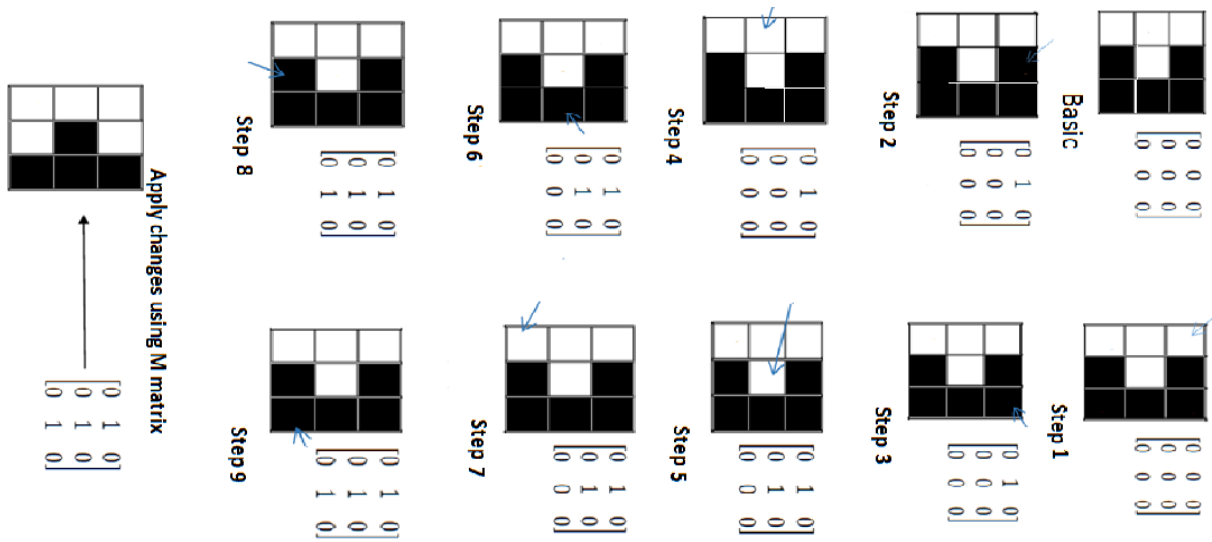

Fig. 4. An example of implementing the proposed approach

5. Experimental Results

In what follows, the experimental results are presented in two parts for the proposed methods.

5.1. Evaluation of Fuzzy Eight-Neighborhood Voting Method

To evaluate the proposed method, four-neighborhood, eight-neighborhood, and fuzzy eight-neighborhood voting methods are each implemented on 1000 images, created randomly. The images include 400 blocks of 20*20 in which the left and right blocks usually tend to the white and black classes, respectively. The least squares gradient descent backpropagation algorithm is implemented in these methods to train the parameters of membership functions. In addition, fcm genfis function is examined. Results of the evaluation are shown in Table 1. The criterion used in the comparison between methods is defined as the minimum of change and precession in images. In Table 1, the number of blocks with the changed black class is calculated, and its value is considered as variable a. The number of blocks with the changed white class is considered b. The number of changes is calculated by Equation 3.

$$T = a + b \qquad (3)$$

According to the results, the average number of changes is 74.70 in the proposed method, whereas the average number of changes is 72.40 in the four-neighborhood voting method. In fact, the number of changes depends on the distribution of classes of blocks in the image. The amount of precession in images is calculated by Equation 4.

$$P = a - b \qquad (4)$$

Where, parameter P is the amount of precession. The left-side class at the top usually has precession to the right-side class at the bottom. In the proposed method, the amount of precession is calculated as 0.016 in the experimental method, while it is 0.038 in the four-neighborhood voting method. In Fig. 4, a comparison is presented between values of P and T parameters in the proposed method based on fuzzy theory concepts (FENV), four-neighborhood voting method (FNV), and eight-neighborhood voting method (ENV).

Table. 1. Results of the comparison for the proposed approach

Method	a	b	*T*	*P*	T/(20*20)	P/(20*20)
Four-neighborhood [1]	43.82	28.58	72.4	15.24	0.181	0.038
Eight-neighborhood [6]	54.42	33.98	88.4	20.44	0.22	0.051
Proposed method	40.71	33.99	74.7	6.72	0.186	0.016

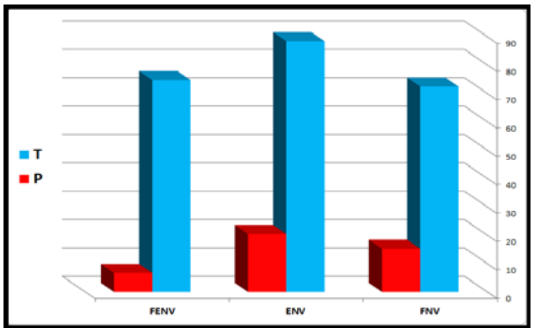

Fig. 5. Comparison between methods based on values of P and T parameters

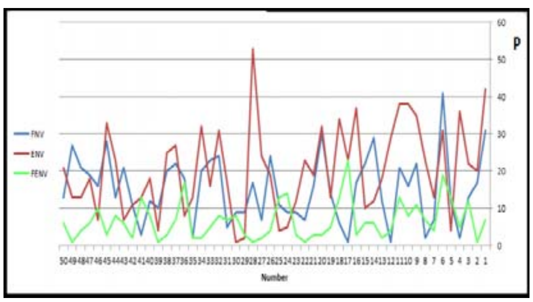

Fig. 6. The linear diagram of P parameter in 50 primary samples

In Fig. 5, the mean of results for parameters P and T is shown in 1000 examples of images. Results have been obtained with running of four-neighborhood, eight-neighborhood, and the proposed method, using Matlab. T parameter is the number of changes of block target. P parameter is the average amount of precession in 1000 images. The proposed method has shown a more appropriate result.

In Fig. 6, a linear diagram is shown that indicates P parameter in 50 primary samples. In Fig. 6, the blue line indicates the result of running in 50 first samples using the four-neighborhood voting method. The red line shows the result of running the eight-neighborhood voting method in 50 first samples. Fig. 5 demonstrates that the amount of precession is more in eight-neighborhood voting method than the four-neighborhood voting method. The result of edge correction is weak in sample images using eight-neighborhood voting method, because it has voted from eight blocks which are neighbours. The green line indicates the result of running the proposed method in 50 first samples. The amount of precession is reduced since fuzzy voting is used in block selection.

5.2. Evaluation of Weighted Voting Method

Results of the evaluation are shown in Table 2. The criterion used for the comparison between methods is defined as the minimum of changes and precession in images. In Table 2, the number of blocks with the changed black class is calculated and its value is considered *a*. The number of blocks with the changed white class is considered *b*.

Table. 2. Results of the comparison for the proposed approach

Method	a	b	*T*	*P*	T/(20*20)	P/(20*20)
Four-neighborhood [1]	43.82	28.58	72.4	15.24	0.181	0.038
Eight-neighborhood [12]	54.42	33.98	88.4	20.44	0.22	0.051
Proposed method	45.03	35.97	81	9.06	0.2	0.022

The number of changes and the amount of precession are calculated by Equations 3 and 4, respectively. According to the results, the average number of changes is 81 in the proposed method, whereas the average number of changes is 72.40 in the four-neighborhood voting method. In fact, the number of changes depends on the distribution of classes of blocks in the image. In this method, the amount of precession is calculated as 9.06 in the experimental method, while it is 15.24 in the four-neighborhood voting method. Fig. 7 presents a comparison between the values of P and T parameters in the proposed method based on weighted voting concepts (ENVW), four-neighborhood voting method (FNV), and eight-neighborhood voting method (ENV).

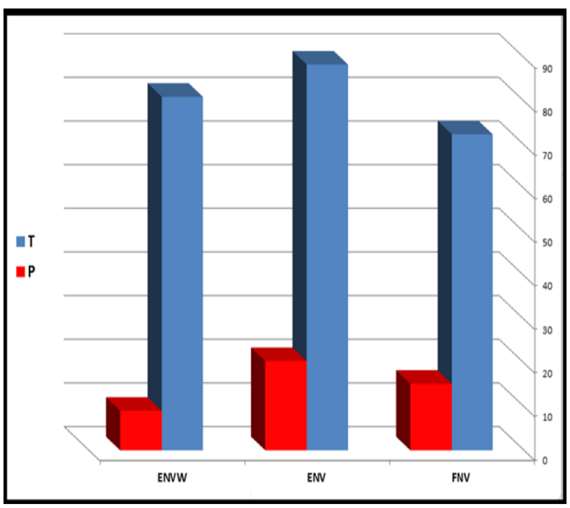

Fig. 7. Comparison between methods based on the values of P and T parameters

In Fig. 7, the mean of results for parameters P and T is shown in 1000 example of images. Results have been obtained with running of four-neighborhood, eight-neighborhood, and the proposed method, using Matlab. T parameter is the number of changes of block target. P parameter is the average amount of precession in 1000 images. The proposed method has shown a more appropriate result.

6. Comparison Between Methods

In this section, a comparison is done between the new method, four-neighborhood voting method, and eight-neighborhood voting method. Results of the comparison are shown in Table 3. The performance of T parameter is low in the weighted voting method. The P parameter is an indicator of the amount of precession and is more important than the T parameter. This parameter is improved significantly in the weighted voting method compared to the four-neighborhood voting method. Moreover, the T parameter is improved in the proposed method based on fuzzy theory compared to the weighted voting method. In the proposed method, the effectiveness of the main and secondary neighbors is the same based on fuzzy theory. Voting error is reduced because the proposed methods have used the eight-neighborhood method in voting.

Table. 3. Results of the comparison for the proposed approach

Method	**a**	**b**	***T***	***P***	**T/(20*20)**	**P/(20*20)**
Four-neighborhood [1]	43.82	28.58	72.4	15.24	0.181	0.038
Eight-neighborhood [6]	54.42	33.98	88.4	20.44	0.22	0.051
Weighted voting	45.03	35.97	81	9.06	0.2	0.022
Fuzzy theory	**40.71**	**33.99**	**74.7**	**6.72**	**0.186**	**0.016**

7. Conclusion and Future Studies

In this paper, two new methods for boundary correction have been proposed based on fuzzy eight-neighborhood voting and weighting concepts. There are often overlaps in textural image classification, and the edges between different classes are not explicitly definable in the hybrid space. Thus, edges should be corrected in the classified areas. On the other hand, there have been precession challenges in previous studies, such as voting by the four-neighborhood method. Thus, in this paper, two new methods have been proposed that improve edging accuracy by eliminating precession challenges in textural image classification.

In the proposed method, the effectiveness of the main and secondary neighbors is same based on fuzzy theory. The distinction between the primary and secondary neighbors can lead to a better boundary correction. Therefore, it can be a challenge, and will be discussed in future studies.

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