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An Improved Method for Edge Detection and Image Segmentation Using Fuzzy Cellular Automata

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ABSTRACT

Image segmentation is one of the most important and challenging problems in image processing. The main purpose of image segmentation is to partition an image into a set of disjoint regions with uniform attributes. In this study, we propose an improved method for edge detection and image segmentation using fuzzy cellular automata. In the first stage, we introduce a new edge detection method based on fuzzy cellular automata, called the *texture histogram*, and empirically demonstrate the efficiency of the proposed method and its robustness in denoising images. In the second stage, we propose an edge detection algorithm by considering the mean values of the edges matrix. In this algorithm, we use four fuzzy rules instead of 32 fuzzy rules reported earlier in the literature. In the third and final stage, we use the local edge in the edge detection stage to more accurately accomplish image segmentation. We demonstrate that the proposed method produces better output images in comparison with the separate segmentation and edge detection methods studied in the literature. In addition, we show that the method proposed in this study is more flexible and efficient when noise is added to an image.

KEYWORDS

Edge detection; fuzzy cellular automata; image denoising; image segmentation

Introduction

Image segmentation is the process of partitioning an image into multiple segments (sets of pixels; Al-amri, Kalyankar, and Khamitkar 2010). Image segmentation remains one of the most challenging problems in image processing. The objective of image segmentation is to render a digital image of the objects by extracting various visual aspects such as the objects edges, homogeneous regions, and 3D objects (Safia, Oussama, and Chawki 2011). There is no ideal or optimal solution in image segmentation due to the large variety of images, their characteristics, and the type of extracted information. Using image segmentation, an image is partitioned into regions with homogenous characteristics as a means

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of separating objects from their background (Alpert et al. 2007; Choong et al. 2012). The result of segmentation is a set of components or a series of lines extracted from the image, which collectively cover the entire image.

We propose an improved method for edge detection and image segmentation using fuzzy cellular automata. The proposed method comprises three stages. In the first stage, we introduce a new edge detection method based on fuzzy cellular automata, called the texture histogram, and empirically demonstrate the efficiency of the proposed method and its robustness in denoising images. In the second stage, we propose an edge detection algorithm by considering the mean values of the edges matrix. In this algorithm, we use four fuzzy rules instead of 32 fuzzy rules as reported earlier in the literature. In the third and final stage, we use the local edge in the edge detection stage to more accurately accomplish image segmentation. We demonstrate that the proposed method produces better output images in comparison with the separate segmentation and edge detection methods as studied in the literature. In addition, we show that the method proposed in this study is more flexible and efficient when noise is added to an image.

The remainder of this article is organized as follows. In "Literature Review," we review the edge detection and image segmentation literature. In "The Proposed Method," we present a step-by-step description of the edge detection and image segmentation method proposed in this study. In "Implementation Results," we evaluate the performance of the proposed algorithm with a series of images taken from the literature. In "Discussion," we discuss our findings and finally, we present our conclusions and future research directions.

Literature Review

Image segmentation is a fundamental and challenging problem in computer vision and image processing. In particular, it is an essential process for many applications such as object recognition, target tracking, content-based image retrieval, and medical image processing, etc. The overall goal in image segmentation is to partition an image into a certain number of pieces that have coherent features (color, texture, etc.) and in the meanwhile to group the meaningful pieces together for the convenience of perception (Peng, Zhang, and Zhang 2011).

Zhang, Zhong, and Zaho (2007) presented a new improved edge detection algorithm based on cellular automata. Their method uses fuzzy logic and a defuzzification procedure to process direction information and edge order measures, develops a direction-measure matrix and detects edges by automatic evolution of cellular automata. This method is applied on noisy images, and it was shown that edges are still sufficiently detected and maintained when noise is added to the image. One of the advantages of the proposed method is the capability to use fuzzy logic, but it needs to be tested with human beings.

Over the past three decades, a variety of denoising methods have been developed in the image processing and computer vision research centers (Chang and Vetterli 1997; Pesquet 1997; Chen, Vemuri, and Wang 2000; Wei 2009; Hedjam and Cheriet 2010; Dewangan and Goswami 2012; Kaur et al. 2012; Swami and Jain 2012; Gupta and Gupta 2013; Gupta and Meenakshi 2014). Although each is unique, they all share the same property: to preserve the meaningful edges and remove the less meaningful ones (Liu et al. 2008).

Wang et al. (2009) proposed a new method that combines the theory of cellular automata and fuzzy rules to establish a model of fuzzy cellular automata. Thus, the pixels whose gray level is between the object and the background can be analyzed in an appropriate manner resulting in a good image segmentation. This method solves the difficult problem of follicle recognition in ultrasonic image processing of ovaries. It also resolves many of the ambiguities caused by the complexity and incompleteness of the system.

Zirari, Mammass, and Ennaji (2011) presented a new method of separating text from image. The method is based on a statistical analysis of texture and morphological operations. Initially, the energy for each pixel is calculated by using a method to extract features such as the co-occurrence matrix, and then the morphological operations are applied. In fact, this method allows different areas of document image (text and images) to be adequately separated. This method compares favorably with the top-down approach but it has the disadvantage of having a high processing time.

In this article, we explain the implementation of a novel technique to select the dominant colors from the input image using the information from the color histograms. The main contribution of this work is the generalization of the *k*-means algorithm that includes the primary characteristics of the color smoothness and texture complexity in the process of pixel assignment (Ilea and Whelan 2006).

Sulaiman and Isa (2010) proposed a new clustering algorithm, called *adaptive fuzzy-k-means* (AFKM) *clustering for image segmentation*. The proposed AFKM is specifically designed to incorporate both the fundamental theories of the conventional *k*-means and the MKM clustering algorithms (i.e., assigning each data to its closest center or cluster) and the conventional fuzzy *c*-means (FCM) clustering algorithm (i.e., allows the data to belong to two or more clusters or centers). The modification concept introduced in the AFKM algorithm assumes that each cluster should have a significant value of belongingness that measures the relationship strength between the center and its members. Thus, pixels with the highest degree of membership are assigned to the same cluster.

In this work, a *k*-means clustering algorithm was performed on images with new features, i.e., the use of cellular automata. In the next step, edge detection was performed using fuzzy cellular automata, resulting in an accurate image segmentation.

The Proposed Method

In the first stage, using cellular automata and dependent on the number of pixels and the neighbors in the original image, we obtained a one-dimensional vector, called the texture histogram feature. In the next step the *k*-means clustering method was applied with the new features, and the resulting matrix indicates the clustering of the pixels. In the second stage, the edge detection algorithm is presented. In the third stage, fuzzy cellular automata are used to improve the edge detection technique, and the local edges help to increase the accuracy of the image segmentation process.

Texture Histogram

In this section, we first explain the new texture histogram features that have been obtained with the help of cellular automata for each $w \times w$ neighborhood and then describe how to integrate these features with *k*-means clustering. Different stages of the procedure are summarized in the flowchart of Figure 1:

a) We assume that each image pixel is mapped to a cell in an automaton and the neighborhood relation of cells is Moore (Kumar and Sahoo 2010). This neighborhood is one of two common neighbors that are used in cellular automata. The advantage of the Moore neighborhood is its flexibility to detect the correct region for segmentation. This mapping can be seen in Figure 2.
b) In the proposed method, the neighborhood of each pixel is represented by $w \times w$. The number of repetitions of each pixel is calculated in each neighborhood based on the value of that pixel. This number is stored in the respective cell number in a one-dimensional vector. This process is repeated for each pixel of the original image with $w \times w$ and determining a one-dimensional vector for each neighborhood, i.e., the number of pixels

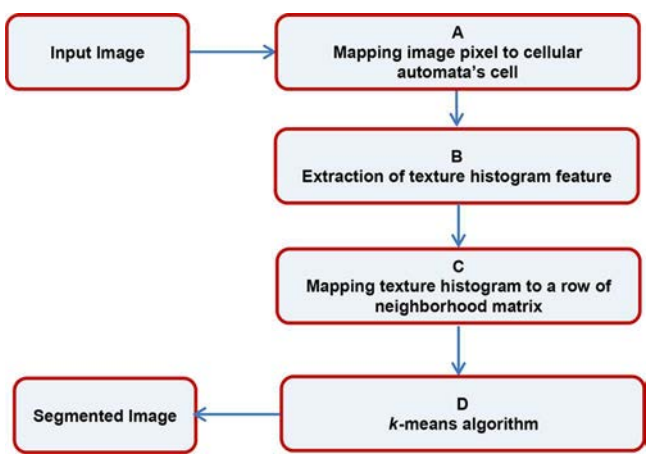

Figure 1. Flowchart of the proposed algorithm for image segmentation.

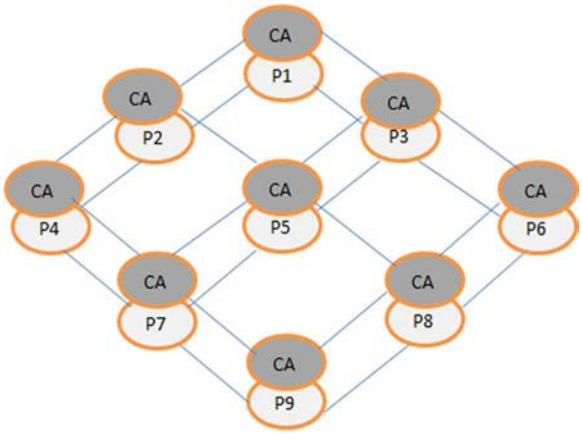

Figure 2. Mapping image pixel to cellular automata's cells.

of the original matrix. Using this one-dimensional vector, a new feature was defined called the *neighborhood histogram* for each pixel. The pseudocode is given in Figure 3.

In Figure 3, I is the input image matrix, x is the number of rows, and the number of columns. This matrix consists of pixels that are mapped into cells of cellular automata. A neighborhood vector that is initialized to zero and computed for each pixel of the input image is represented by V.

c) After calculating the new feature, each one-dimensional vector (vector) that was calculated for each neighbor is stored as a row of the new matrix called the *Neighborhood Matrix* (NM), and the number of pixels corresponding to each neighbor will be stored in another matrix. This process is represented symbolically in Figure 4.

d) In this phase we implement a k-means clustering algorithm on the calculated histogram in NM. At this stage, the k points are selected as

```
Find_ Texture Histogram(x, y)
        Set current cell to (x, y)
        Set vector V to 0
      Repeat
            Repeat
  Read I(x, y) from row (x)& column (y)
  Increase one V(I(x, y))
                                  Y + 1
            End
                  x + 1
      End
End Find_ Texture Histogram(x, y)
```

Figure 3. Pseudocode of texture histogram.

cluster centers. Pixels that have the minimum distance from the cluster center are placed in that category. All pixels belonging to one of the clusters are used to calculate the new point as the center of the cluster. This process is repeated until there is no change in the cluster centers. The number of clusters, k, represents the number of partitions of the original image.

The resulting matrix identifies the clustering of the pixels, and thus, the image is partitioned into separate segments.

Edge Detection

This method improves the edge detection process by using fuzzy cellular automata. For edge detection of an $M \times N$ image, a two-dimensional cellular automata with M rows and N columns is used. Each pixel of the image is mapped on one cell of the fuzzy cellular automata (Figure 5). Each cell is then presented in Moore contiguity according to its current location. Fuzzy rules are then used to determine which of the classes, edges, or backgrounds each pixel belongs to. To determine the condition of each pixel, eight different positions in the Moore contiguity are defined.

For each of the eight positions, one value is represented by α_i, which is obtained from the crossed cells, and one value is represented by β_i, which is obtained from the colored cells. The index i represents the specific state among these eight states. These inputs are given in Eq. (1):

$$\begin{aligned} \alpha_i &= \frac{1}{5}\left(\sum_{i=\text{pertain to hatch cell}} |p - p_i|\right) \\ \beta_i &= \frac{1}{5}\left(\sum_{i=\text{pertain to fill cell}} |p - p_i|\right) \end{aligned} \tag{1}$$

In the proposed method, with inputs α_i and β_i and using the input fuzzy function (Figure 6) and with minimum and maximum values of α_i and β_i, we obtained four rules (Figure 7) instead of the 32 fuzzy rules introduced in Mirzaei, Motameni, and Enayatifar (2011). We use these four fuzzy rules

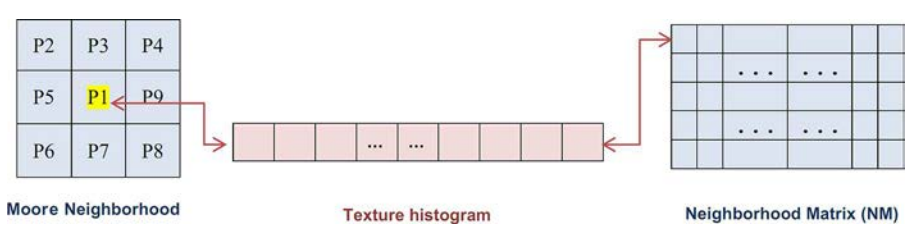

Figure 4. Mapping texture histogram to rows of neighborhood matrix.

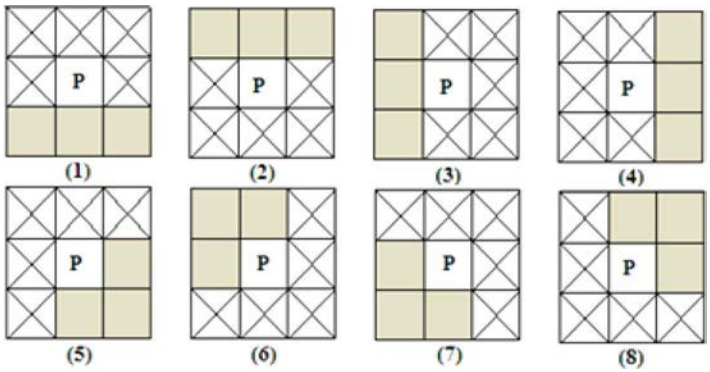

Figure 5. Converge FCA on image pixels (Mirzaei, Motameni, and Enayatifar 2011).

for α_i and β_i and extend them for other α_i and β_i. In addition, the method of conventional defuzzification, fuzzy Mamdani (Anderson and Hall 1999), and the center of gravity are used. Each "alpha" and "beta" corresponds to a specific edge value using the output fuzzy function (Figure 8), resulting in eight different edge values. The value of each entry of the edge's matrix is obtained from the mean of these eight values. This matrix displays the image edges.

Furthermore, according to Figure 8, the matrix values are obtained in the range [0,1], we assign values greater than 0.5 as 1 and less than 0.5 as 0 in a new matrix.

Image Segmentation

This method combines image edges and fuzzy cellular automata to improve the image segmentation process. In the first step, for an $M \times N$ image with Moore neighborhood and α_i and β_i inputs, edge detection is performed using the four provided fuzzy rules. In the second step, with the use of image edge detection and according to the texture histogram's feature, the average of the edges has been calculated to find the local edges. Using these local edges, we

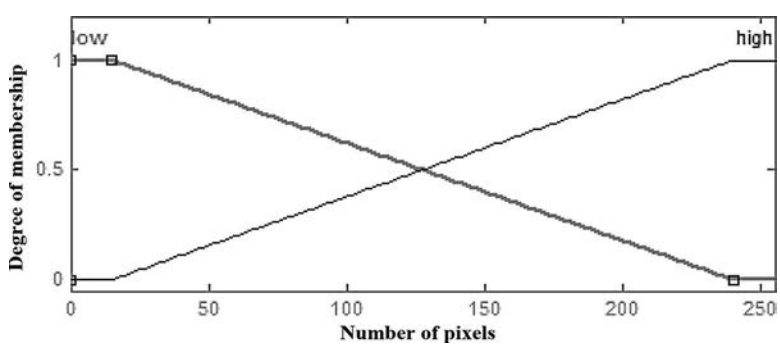

Figure 6. Input fuzzy function.

IF	THEN	Edge
A_{low} & B_{low}		Low
A_{low} & B_{high}		High
A_{high} & B_{low}		High
A_{high} & B_{high}		Low

Figure 7. Fuzzy rules database.

can find image regions for segmentation. In fact, image regions can be chosen in a simpler and more accurate way with the edge detection technique rather than the segmentation technique.

The new texture histogram's feature and fuzzy cellular automata, which are used in the combined method, result in more accurate edges of gray-level images, resulting in better image segmentation. The combination of these two methods produces better results than the separate methods of segmentation and edge detection.

Implementation Results

In order to evaluate the performance of the proposed algorithm, a series of images are taken from Zirari, Mammass, and Ennaji (2011), Senthilkumaran and Rajesh (2009), and Krinidis and Chatzis (2010) and evaluated with MATLAB. These 256×256 images have different pixel neighborhoods and clusters.

Evaluation of the Proposed Method for Image Segmentation

Multiple Experiments (Test 1)

In this experiment, clustering with the new texture histogram's feature was performed on images with a different number of clusters. In this experiment,

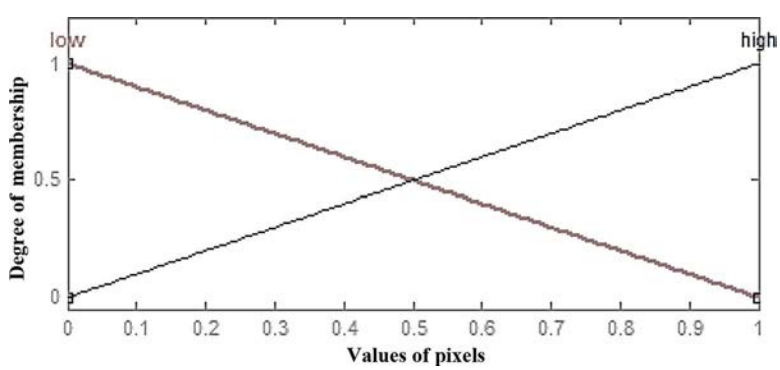

Figure 8. Edge output fuzzy function.

the neighborhood of each pixel is assumed to be 30×30. The test results are shown in Figure 9.

Resistance (Test 2)

Salt and Pepper Noise. Because of salt and pepper noise, there are some points in the picture with many colors in their surroundings. This noise causes some parts of the image to be white or black. As we can see in Figure 10, this method is robust with respect to various percentages of salt and pepper noise and has a unique solution.

To evaluate the robustness of the proposed method with respect to the noise ratio, we calculated salt and pepper error for the image with variances of 0.3 and 0.5. As seen in Table 1, when the neighborhood of the pixels decreases, the error rate is reduced.

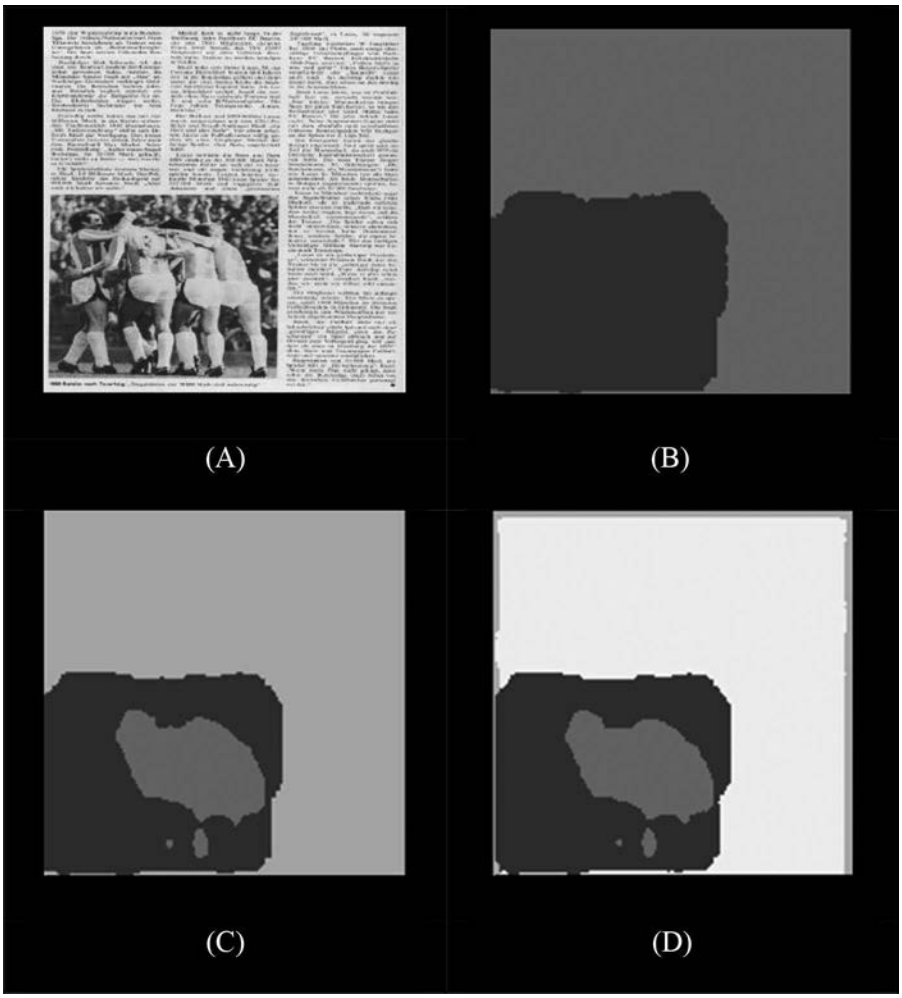

Figure 9. The proposed method applied to clusters. (A) Original image, (B) $k = 2$, (C) $k = 3$, and (D) $k = 4$.

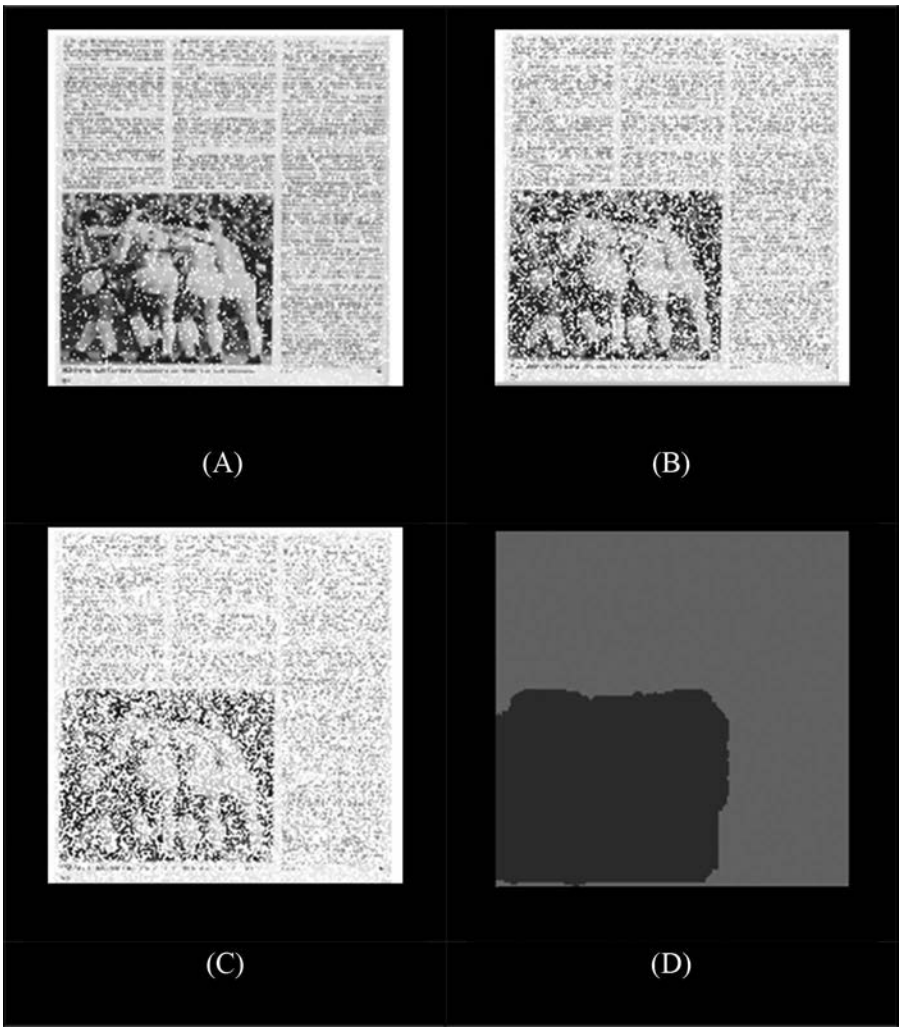

Figure 10. (A) 10% noise, (B) 30% noise, (C) 50% noise, and (D) result of applying the proposed method on noisy images with salt and pepper.

Gaussian Noise. In Gaussian noise, there is a probability that adding noise to each pixel obeys a Gaussian function. In this experiment, the neighborhood 30×30 and the image taken from Krinidis and Chatzis (2010) has been used. Initially, Gaussian noise imposed on the image and then the proposed method was applied on the noisy image. As seen in Figure 11, the proposed method improved the results given in Krinidis and Chatzis (2010), which assumed a noise-free image.

Table 1. Error Percentage in Noisy Images with Different Neighborhoods

Newspaper	$k=2$ NM $=10\times10$		$k=2$ NM $=30\times30$	
Error	$\sigma=.3$	$\sigma=0.5$	$\sigma=0.3$	$\sigma=0.5$
	13.2	15.3	18.6	24.7

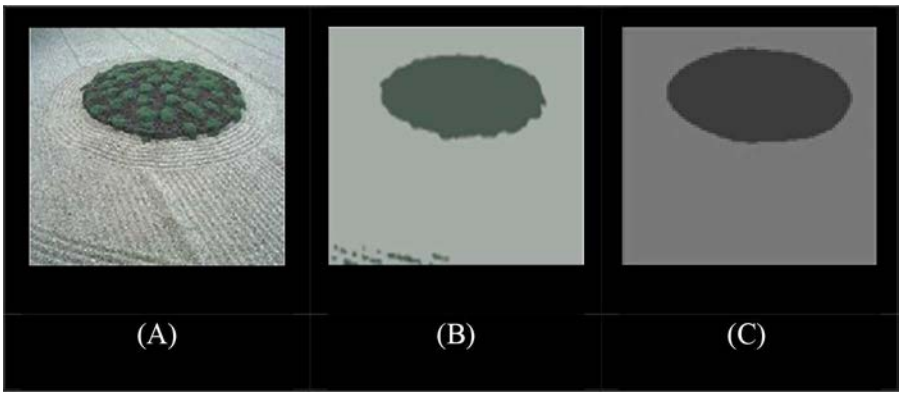

Figure 11. (A) Original image, (B) result given in Krinidis and Chatzis (2010) on the image with Gaussian noise, and (C) result of the proposed method applied on the image with Gaussian noise.

Effectiveness (Test 3)

To evaluate the effectiveness, we implement the proposed method without the new features. This means that instead of using cellular automata and neighborhood histogram, we add pixels of the original image to a new matrix, convert this new matrix to a three-dimensional matrix, and apply *k*-means clustering. The method was tested on a variety of images and, as shown in Figure 12, the result of this method is not as accurate as the proposed method.

Test 4: Calculation Accuracy of the Proposed Algorithm and Comparison with Existing Methods

In Zirari, Mammass, and Ennaji (2011) clustering images were developed using the co-occurrence matrix, one of the most known methods for statistical analysis, and finally, the morphological operations were implemented. Both the

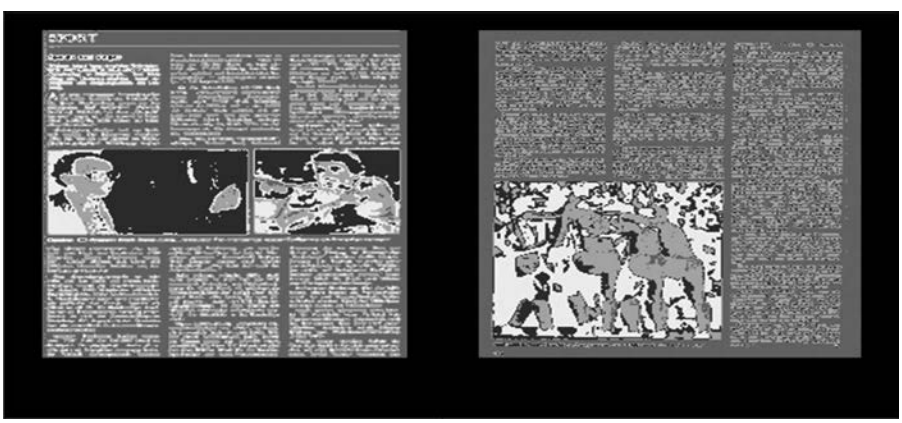

Figure 12. Applying the proposed method without new feature on the images to show the effectiveness of the proposed method.

methods proposed in Zirari, Mammass, and Ennaji (2011) and in this work changed all the context to one color and the picture to another color, but as we can see in Figure 13, the noise of the proposed method is less than that given in Zirari, Mammass, and Ennaji (2011) due to the use of the texture neighborhood histogram's feature. This shows the superiority of the texture histogram over the co-occurrence, because of local pixels.

Execution Time (Test 5)

In this test, the runtimes were calculated on different images with different numbers of clusters and neighborhoods using the proposed algorithm. The time is reduced when the neighborhood is low (with a fixed number of clusters) as well as by reducing the number of clusters (with a fixed neighborhood). We present the test results in Table 2.

Accuracy (Test 6)

To calculate the accuracy of clustering, the proposed algorithm Eq. (2) is used:

$$SA = \frac{\text{Clustering of pixels correctly}}{\text{All of pixels}} \times 100 \tag{2}$$

The accuracy of the proposed clustering algorithm was calculated using the formula SA on various neighborhoods in the original image and also for the image with Gaussian noise specifically for the picture given in Zirari, Mammass, and Ennaji (2011). Variances were assumed to be 0.3 and 0.5 for the noisy image. The test results are presented in Table 3. The results imply that for an image with a fixed number of clusters and neighborhoods, accuracy increases when the variance decreases.

Evaluation of the Proposed Edge Detection Method

Multiple Experiments

We applied the proposed edge detection method on various images. The results are shown in Figure 14. As the results show, this method reduces the error rate and increases the accuracy of the images.

Comparative Results

The proposed method for edge detection that uses cellular automata based on fuzzy logic is compared with previous methods, particularly with the fuzzy cellular automata presented in Mirzaei, Motameni, and Enayatifar (2011). We can conclude that edge detection based on the proposed fuzzy cellular automata is more suitable than other methods because it is effective in suppressing noise. However, unlike the cellular automata, it can easily identify bilevel images and reduce the error rate. The result of this comparison is shown in Figure 15.

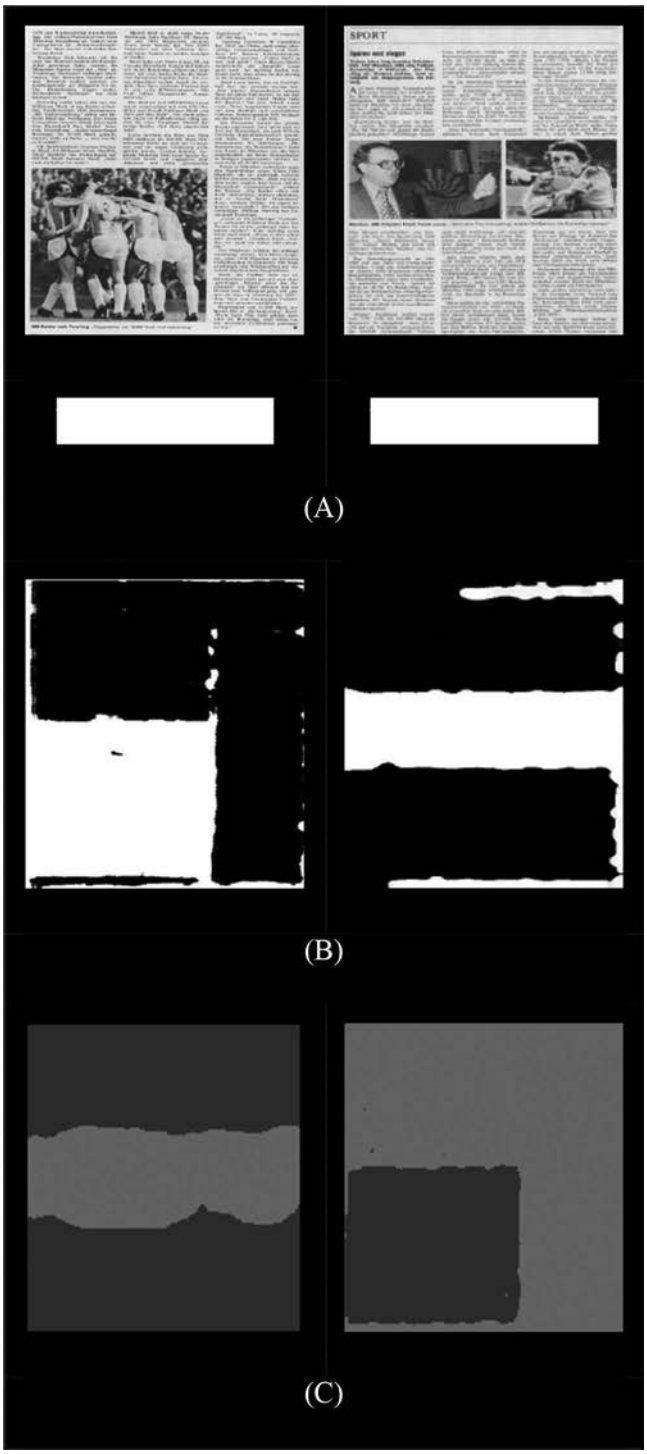

Figure 13. (A) Original image, (B) results of the clustering based on statistical analysis and co-occurrence matrix, and (C) results of clustering based on the proposed method.

Table 2. Runtime(s) Based on the Number of Clusters and Neighborhoods

image	$k=2$ 10×10	$k=3$ 10×10	$k=2$ 30×30	$k=3$ 30×30
Newspaper	98.89	104.52	141.59	151.48
Cameraman	108.47	109.29	136.49	146.41
Katrina	136.04	167.13	179.22	182.09

Table 3. Accuracy of the Proposed Algorithm for Different Neighborhoods on the Original Image and the Image with Gaussian Noise with Different Variances

Newspaper	$k=2, NM=10\times10$		$k=2, NM=30\times30$	
Original Image	81.57		73.5	
Noisy Image	$\sigma=0.3$	$\sigma=0.5$	$\sigma=0.3$	$\sigma=0.5$
	76.8	74.7	71.4	65.3

Figure 14. Applying the proposed edge detection method. (A) Original image and (B) image of edge detection.

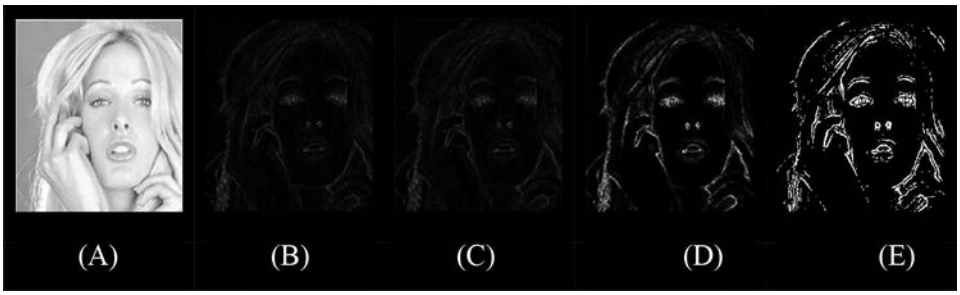

Figure 15. (A) Input image, edge detection based on (B) Roberts, (C) Sobel, (D) fuzzy cellular automata of Mirzaei, Motameni, and Enayatifar (2011), and (E) the proposed improved fuzzy cellular automata.

Evaluation of the Proposed Image Segmentation Method

The first step in image analysis is image segmentation. We often require segmenting the object from the background in order read the files correctly and recognize the image content.

Accuracy of the Proposed Combined Algorithm

In the edge detection method, the minimum and maximum values of the new matrix that is obtained based on the means of edges are calculated. Using the average of the minimum and maximum values of this matrix, the threshold is obtained for image segmentation. Next, the matrix values of the original image that are obtained based on improved fuzzy cellular automata are compared with this threshold. With these comparisons, the edge's values and background are made clearer. In fact, the related pixel can now be determined to be either part of the object or the background. The segmentation method with texture histogram feature is then applied to the image so that its edge is detected, resulting in a more accurate image segmentation process. The results of the applied proposed hybrid method are shown in Figure 16.

Most texture images are clear by existing edges. In Kaur (2012), a two-dimensional discrete wavelet transform was used to extract text information from complex images. In this article, by choosing an appropriate threshold and eliminating nonuseful edges of the component parts, image segmentation was performed. As is observed in Figure 17, the combined method of this study can offer more accurate image segmentation with lower noise by selecting local edges instead of the threshold and by using fuzzy cellular automata.

We use Eq. (2) to show the accuracy of the proposed method for image segmentation based on edge detection using fuzzy cellular automata. We assume the image size to be 30×30 with two sections. As can be seen from the results, using the feature of fuzzy cellular automata for finding local edges improves the accuracy of the segmentation process and removes more noise. The results of the calculations are given in Table 4. As can be seen, the proposed hybrid algorithm segmentation has more accuracy than the separate segmentation

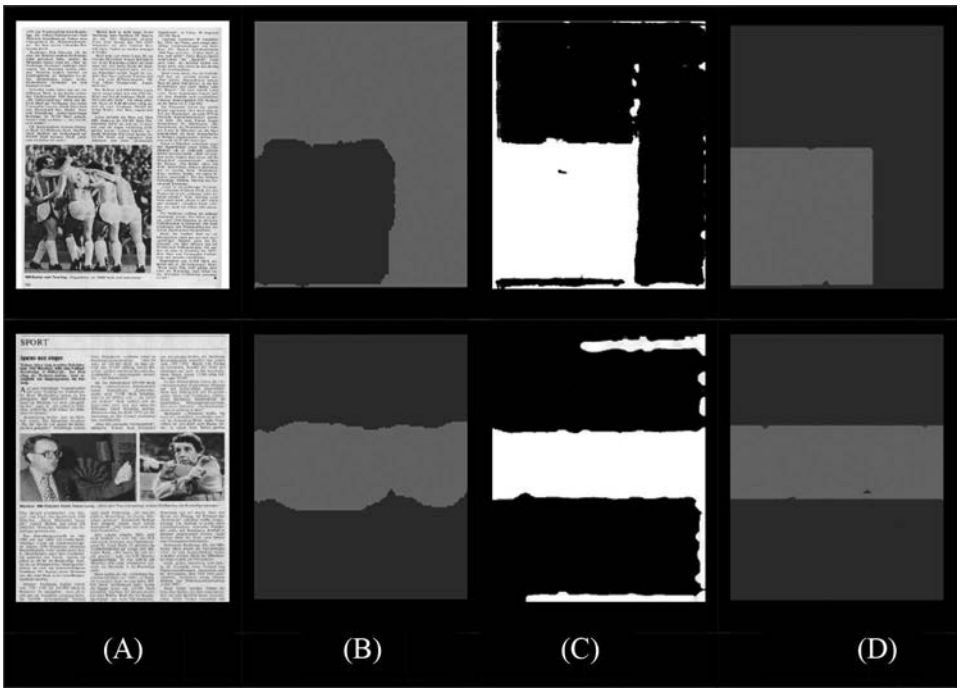

Figure 16. Hybrid method for image segmentation using fuzzy cellular automata. (A) Original image, (B) image obtained by the proposed image segmentation method, (C) image obtained based on the proposed method in Zirari, Mammass, and Ennaji (2011), and (D) the result of applying the image segmentation algorithm using fuzzy cellular automata.

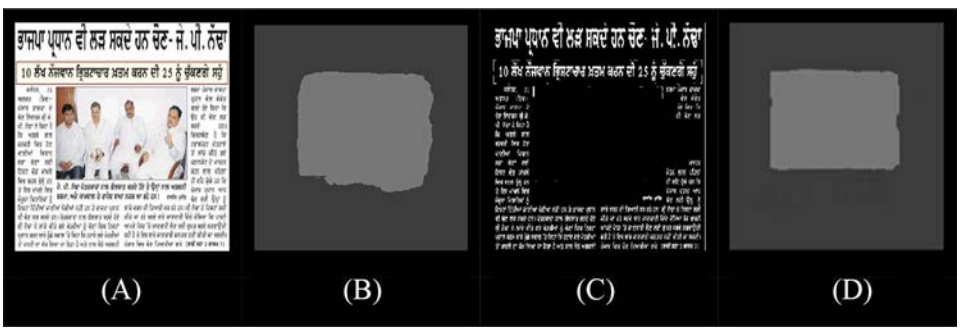

Figure 17. The result of hybrid method for image segmentation compared to the discrete wavelet method. (A) Original image (Newspaper3), (b) image obtained by proposed method of "Evaluation of the Proposed Method for Image Segmentation," (C) image obtained based on the proposed method by Kaur (2012), and (D) image obtained by applying image segmentation algorithm using fuzzy cellular automata.

Table 4. Percentage Accuracy of the Proposed Hybrid Method for Different Images

Newspaper	Related Article Method	Image Segmentation Method	Proposed Hybrid Method
1	71.1	81.57	92.8
2	89.2	73.9	91.08
3	59.64	69.81	90.74

method that was performed in "Evaluation of the Proposed Method for Image Segmentation," and the methods given in Zirari, Mammass, and Ennaji (2011) and Kaur (2012).

Discussion

Image segmentation is performed by a set of techniques and its aim is to divide the image into a shape that is more conducive for analysis. Any technique should preserve the essential properties of the images; otherwise, there could be serious errors of analysis.

Common edge detection methods use algorithms that were developed by Prewitt, Sobel, Mar, and Canny (Senthilkumaran and Rajesh 2009), but these classical methods work well when part of the image is variable. The result is an image converted to a binary image by a simple threshold. But these calculations not only have some problems, such as operator and filtering scale of choice, they also neglect the neighbors around the edges. To solve these problems, this article proposes an improved edge detection method using fuzzy cellular automata.

The superiority of the proposed improved fuzzy cellular automata for edge detection is because the decision whether the pixel is edge or image is made simultaneously, and the use of fuzzy cellular automata improves the readability of the image and decreases the noise. Actually, in previous methods, edge detection is performed after noise has been removed by filtering. But in this method, the position of each pixel (either edge or background) is decided according to fuzzy rules, and each pixel is situated in such a way that it is easy to determine its location. The method combines texture histogram features and the mean of the local edges, resulting in more accurate image segmentation.

Conclusion

In this study, we developed an improved method for edge detection and image segmentation using fuzzy cellular automata. We introduce a new edge detection method, based on fuzzy cellular automata, called the texture histogram and empirically demonstrated the efficiency of the proposed method and its robustness in denoising images. We also propose an edge detection algorithm by considering the mean values of the edges matrix. In this algorithm, we used four fuzzy rules instead of 32 fuzzy rules reported earlier in the literature. Finally, we used the local edge in the edge detection stage to more accurately accomplish image segmentation.

We carried out several experiments and compared the method developed in this study with the existing methods reported in the literature. We demonstrated that the proposed method produces better output images in comparison with the separate segmentation and edge detection methods studied in the literature. We also showed that image segmentation based on edge detection

using fuzzy cellular automata provides more accurate and efficient results compared with separate methods of edge detection and segmentation. The accuracy of the proposed method obtained by applying the relevant tests on the image is 92.8%.

One of the advantages of the proposed method compared with other methods is that the proposed algorithm creates a denser cluster that results in a more accurate segmentation based on edge detection and a more accurate resolution of the images.

Another advantage of the proposed algorithm is that its efficiency is preserved when noise is added to the image because of the use of cellular automata and the local histogram for segmentation. The amounts of error obtained when adding noise to the image, with the neighboring 10×10 with variances of 0.3 and 0.5, are 13.2 and 15.3, respectively.

One of the weaknesses of our algorithm for document image is the assumption that all the text are in the same direction (the horizontal direction is assumed by default). Therefore, these algorithms cannot be applied to documents with multiple design styles.

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