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Image Segmentation and Contour Recognition Based on Mathematical Morphology

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Abstract**—**In image segmentation contour detection is one of the important pre-processing steps in recent days. Contours characterize boundaries and contour detection is one of the most difficult tasks in image processing. Hence it is a problem of fundamental importance in image processing. Contour detection of an image decreases the volume of data considerably and useless information is removed, but the structural properties of the image remain same. In this research, a robust and effective contour detection technique has been proposed using mathematical morphology. Three different contour detection results are obtained by using morphological dilation and erosion. The comparative analyses of three different results also have been done.

Keywords**—**Image segmentation, contour detection, mathematical morphology.

I. Introduction

IMAGE SEGMENTATION is the process of partitioning a digital image into multiple regions or sets of pixels. We can partition the image into several objects, where each object has same texture or color. Process of classifying and placing sharp discontinuities in an image is called the contour recognition [1]-[4]. In pixel concentration, if we make some immediate changes it is called discontinuities which distinguish boundaries of objects in a scene. The contour representation [5], [6] of an image significantly reduces the quantity of data to be processed [7], [8].

A nonlinear branch of signal processing is mathematical morphology, where the set theory concepts are incorporated in image analysis. Many morphological techniques have been proposed in the published or online literature [9]-[11] for the segmentation and contour detection of digital images. Morphological image segmentation methods have found wide applications [12]-[14]. In this research paper an effective approach for image segmentation and contour detection based on mathematical morphology is presented. This approach is mainly based on image erosion and image dilation. Three different results have been obtained with the proposed approach and comparative analyses (subjective analysis and statistical analysis) also have been done to show the effectiveness of the results. The performance of proposed approach is carried out for three digital images by using MATLAB R2014a software.

For better understanding, the present research paper has been divided into five sections: Section II introduces the comprehensive theoretical and mathematical morphological concepts that are applied in the proposed approach. In Section III the proposed approach has been thoroughly discussed with suitable flow diagram. Section IV presents the experimental results and discussion and Section V presents the conclusion.

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II. Image Dilation and Erosion

Erosion and dilation are two fundamental operations in morphological image processing from which all other morphological operations are based. At the beginning, it was defined for binary images, but later it is extended to grayscale images also. In an image if pixels are added to the boundaries of objects, it is called dilation. In the contrary, if pixels are removed from the boundaries of an object, it is turned as erosion. With the help of erosions and dilations, we can design more complicated morphological operators. Using a structural element (set) *B* on the shape (set) *A*, the processing is done.

$$A \oplus B = \{x | (\hat{B})_x \cap A \neq \emptyset\} \tag{1}$$

$$A \ominus B = \{x | (B)_x \subseteq A\} \tag{2}$$

From dilation, we can have the original set along with an extra boundary. The size and shape of the structural element decides what the size and shape of the boundary will be. Erosion decides whether the structuring element is present in the original set. Erosion removes the outer boundary of the original shape. The relation between dilation and erosion is dilation and erosion is complement operations.

$$\begin{aligned}(A \oplus B)^c &= \{x | (B)_x \subseteq A\}^c = \{x | (B)\_x \cap A^c = \emptyset\}^c \\ &= \{ x | (B)\_x \cap A^c \neq \emptyset\} = A^c \oplus \hat{B}\end{aligned} \tag{3}$$

For a symmetric structuring element:

$$(A \ominus B)^c = A^c \oplus B \tag{4}$$

III. Proposed Approach

The proposed image segmentation approach is competent to segment the digital images with minimum drawbacks of over segmentation. The steps of the proposed approach are shown in Fig. 2. In first step, a color image is chosen for the processing purpose and converted into gray scale image in the second step. In third step, the contrast is enhanced for the gray scale image. In fourth step, the contrast enhanced image is dilated followed by erosion in next step. The gray scale erosion and dilation is performed using flat structural elements. A plus structural element is applied for the dilation and erosion purpose in this proposed approach. In next step, three different results have been achieved using contrast enhanced image (A), dilated image ($A \oplus B$) and eroded image ($A \ominus B$). B is the structural element, operator '$\oplus$' denotes dilation and operator '$\ominus$' denotes erosion. In first result, eroded image is subtracted from contrast enhanced image (A-(A⊖B)) and the contours are extracted. In second result, the dilated image is subtracted from contrast enhanced image ((A⊕B)-A) and the contours are extracted. In third result, dilated image is subtracted from eroded image ((A⊕B) -(A⊖B)) and the contours are extracted.

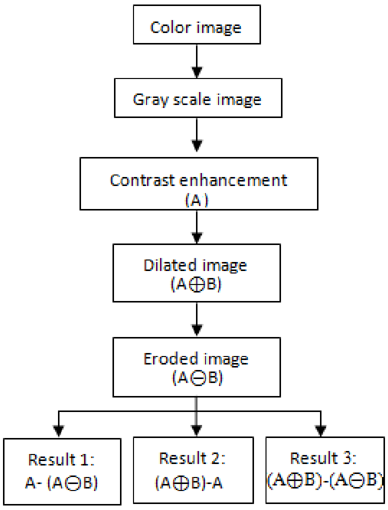

Fig. 1 Flow diagram of proposed approach

IV. Experimental Results and Discussion

Three real life images have been chosen to carry out the image segmentation and contour detection task using mathematical morphology. The original images are shown in Fig. 2. The grayscale images are shown in Fig. 3. The contrast enhancement is done on the gray scale images and accordingly shown in Fig. 4. In Fig. 5, the morphologically dilated images have been shown. In Fig. 6, morphologically eroded images have been shown. The 1st resultant images using A-(A⊖B) are shown in Fig. 7. The 1st result have produced dark shed images, i.e., the gray level of the pixel have been lower down and also the contours in the images are not very sharp. The 2nd resultant images using (A⊕B)-A) are shown in Fig. 8. The results have produced more or less same results like previous result. On the other hand, the 3rd results have given rise to images of more whitish appearance. In this case the contours and boundaries of the images are also seen to be more prominent and clear with better contrast and the images are shown in Fig. 9. Thus, in this research work, the proposed approach has been produced better results in respective of the statistical analysis and human perception. The statistical measurements with entropy, PSNR and MSE are also calculated for segmented images using conventional watershed approach applied on noisy grayscale images which are shown in Fig. 5 and final segmented images which are obtained by proposed approach applied on same grayscale noisy images and accordingly shown in Fig. 7. Image entropy refers to a measure which describes how much information has to be used to code a compression algorithm. Image entropy is calculated with the formula

$$Entropy = \sum_i P_j log_2 P_j \tag{5}$$

The Peak Signal to Noise Ratio (PSNR) is the value of the noisy image with respect to that of the original image. The value of PSNR and MSE (Mean square Error) calculated by using (6) and (7) and show in Table I.

$$PSNR(Img, Org) = 10log10_{10} \frac{S^2}{MSE(Img,Org)} \tag{6}$$

$$MSE(Img, Org) = \frac{(\Sigma c{=}1 \Sigma i{=}1 \Sigma j{=}1 [Org(i,j,c) - Img(i,j,c)]}{3NM} \tag{7}$$

Fig. 2 Sample colored digital images

Fig. 3 Gray scale images of original ones

Fig. 4 Contrast enhanced images

Fig. 5 Dilated images

Fig. 6 Eroded images

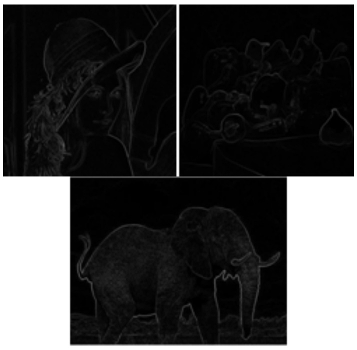

Fig. 7 Experimental results 1. (A- (A⊖B))

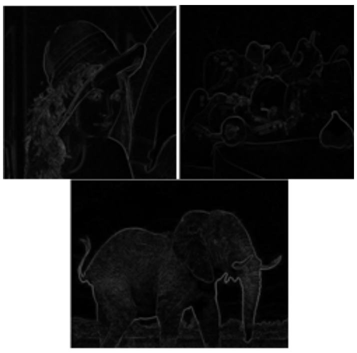

Fig. 8 Experimental results 2 ((A⊕B)-A)

Fig. 9 Experimental results 3 ((A⊕B) - (A⊖B))

TABLE I
STATISTICAL MEASUREMENTS

Figure No.	Image Name	Entropy	PSNR	MSE
Fig. 7 A- (A⊖B)	Lena	4.6744	6.2215	1.5522e+004
	Fruits	3.4835	9.1033	7.9937e+003
	Elephant	4.7711	4.0750	2.5444e+004
Fig. 8 (A⊕B)-A	Lena	4.7322	6.1484	1.5785e+004
	Fruits	3.5105	9.0549	8.0833e+003
	Elephant	4.7836	4.0694	2.5476e+004
Fig. 9 (A⊕B) - (A⊖B)	Lena	5.5785	6.6501	1.4063e+004
	Fruits	4.3864	9.9094	6.6396e+003
	Elephant	5.7985	4.2136	2.4644e+004

V. CONCLUSION

Mathematical morphology is widely in use for image segmentation purpose in recent days. An effective methodology for digital color image segmentation has been publicized in this paper with three different results. The proposed approach is fully developed using mathematical morphology and has been applied to three color digital images with almost similar objects and the segmentation results are found to be very efficient and encouraging. The experimental results and statistical measurements confirm the efficiency of the proposed approach.

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