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Binary Morphological Model in Refining Local Fitting Active Contour in Segmenting Weak/Missing Edges

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Abstract— ***Medical images are known to have poor quality which leads to difficulty in vision and segmentation process. Mainly, noise and intensity inhomogeneity are two main characteristics that lead to gaps (missing at edges) at the boundary of the desired object. This paper investigated method that managed to smooth the image texture in order to overcome the gaps problem. Our method adopts the morphological closing operations using the diamond-shape structuring elements to overcome the above-mentioned problem. We applied the dilation and erosion operation to expand and later smooth the regions with gaps. Our method shows satisfaction results when dealing with binary image rather than working with gradient. The results obtained shows better accuracy as the evolving curve is following the pixels value in the binary image. The method proposed is executed based on the output from Local binary fitting energy.***

Keywords- ***Local binary fitting energy, medical image segmentation, active contour model, morphological operations.***

I. INTRODUCTION

Image segmentation is a process of partition an object into meaningful sub-region [1][2]. Currently, image segmentation is actively applied in medical images to assist experts in interpreting the image better. However, as the quality of the medical images is poor, segmentation process becomes difficult. There are many methods arising in medical image segmentation. However, among all methods, active contour model is becoming popular among the researchers as the model has a big potential in segmenting medical images.

Active contour model can be classified as edge-based and region-based active contour model [1]. The edge-based active contour models highly utilize the image's local properties which are defined highly by the gradient [2][3][4]. Methods in the edge-based are snake model, gradient vector flow (GVF) [3], geometric active contour, geodesic active contour [2] and active contour without re-initialization [4]. However, the drawback of edge-based active contour model is that the method is sensitive to image noise and could only consider segmenting the outer parts of the image. For example, segmentation of blood cell from microscopic image. One may want to investigate the structure or types of the cell image. As for that, segmentation of the internal part of the cell is considered important and these methods have failed to do so.

The active contour model without edges is one of the most typical region-based active contour models and the method is proposed by Chan and Vese [5]. This method is robust to image noise but it is sensitive to intensity inhomogeneity as the method assumed that the intensity of the object must be totally different from the background. Due to this factor, it failed to successfully segment the microscopic image of cell.

The local binary fitting energy is one of the active contour methods that implements both edge and region based. The method is using the local property to avoid the local minima problem created by most edge-based active contour model [6]. This method is proposed by Chumning Li and the method could successfully segment medical images with intensity inhomogeneity and it is robust to image noise. One of the drawbacks of this method is the method is sensitive to weak or missing edges, therefore it failed to segment the microscopic image of cells.

The objective of this paper is to investigate and develop the best solution in joining gaps between the two separate regions. We propose a method to overcome the weak or missing edges problems and our proposed method is refining the output from LBF method. The proposed method is based on morphological operation which is known in the area of image processing. The aim is to expand and merge the contour with the existing contour to overcome the gap problem.

The organization of the paper is as follows. In section 2, methods in segmenting medical images with weak or missing edges are reviewed and in section 3, discussion on morphological operation is presented. Later the proposed method is discussed. Section 4 presents the

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experiments and results and the conclusion will be stated in section 5.

II. Literature Review

In this section review on the LBF method is reported. The aim is to review its weaknesses in segmenting medical images with missing edges or gaps problem. Before that, the Chan&Vese method is also reviewed to explain on how region-based active contour model works.

A. Active Contour Model without Edges

The Active Contour without Edges (ACWE) [6] is a region-based active contour model that shows potential when segmenting the medical images. ACWE is based on two regions, the inside region and outside region. This method can detect objects where boundaries are not necessarily defined by gradient. Due to this factor, it is less sensitive to noise and its computation is fast when compared to edge-based method. The idea in minimizing the energy is simple where the fitting energy is minimized if C = C_o.

The complete equation is given by;

$$\begin{aligned} \varepsilon(\phi, c_1, c_2) &= \mu \int \delta(\phi(x,y)) \mid \nabla \phi(x,y) dxdy \\ &+ \nu \int H(\phi(x,y)) dxdy \\ &+ \lambda_1 \int_{in(C)} \mid I - c_1 \mid^2 \, dxdy \\ &+ \lambda_2 \int_{out(C)} \mid I - c_2 \mid^2 \, dxdy \end{aligned} \tag{1}$$

where the length calculation is given by $\delta(\phi(x,y)) \mid \nabla \phi(x,y) dxdy$ using the dirac function whereas the area term calculation is given by $H(\phi(x,y))dxdy$ and is using the Heaviside function. As this method assumed the inside and outside region as having homogeneous intensity, it failed to segment medical images with intensity inhomogeneity.

B. Local Binary Fitting Energy (LBF) method

Local binary fitting energy proposed by Chumning Li [3] shows better segmentation results when applied to medical images with complex scene. In the proposed model, Chumning Li introduced the region-based active contour model for image segmentation with a variational level set formulation whereby a local binary fitting is incorporated within the model. The method is able to utilize accurate local image information for accurate recovery of the desired object. It is said that the method could handle image inhomogeneity and denoising images as well. The equation of LBF method is defined as:

$$\begin{aligned} &\varepsilon_x^{LBF}(C, f_1, f_2) \\ &= \lambda_1 \int_{in(C)} K(x-y) \mid I(y) - f_1(x)\right|^2 dy \\ &+ \lambda_2 \int_{out(C)} K(x-y) \mid I(y) - f_2(x)\right|^2 dy \end{aligned} \tag{2}$$

The equation above shows the global properties of the active contour model where K is a weighting function with a localizing property that K(u) decreases and approaches zero as |u| increases and $f_1(x)$ and $f_2(x)$ are two numbers that fit image intensities near the point x which is called as centre point and is called as local binary fitting (LBF) energy around the center point x.

However, the drawback of this method is that it failed to segment medical images that have missing at edges. Figure 1 shows the output of segmentation using LBF method when applied to microscopic image of cell. The image of cell is having characteristics of intensity inhomogeneity and noise which lead to missing at certain edges at boundary of the cell. Our aim is to cover the gaps between the boundaries in the image as shown in Figure 1.

We proposed to use the concept of morphology whereby the pixels value in the cell image is structured into smaller structuring elements. From the structuring elements, we implement the dilation and erosion techniques on the image consequently. Detailed explanation on morphology of the image to fill up the gaps problems will be discussed in the next section.

III. Binary Morphological Operations

As medical images were degraded with low quality, segmenting the desired object from the background can be difficult. For example, the microcospic image of cells.The characteristics of microscopic images that made it difficult in segmentation are noise that lead to missing edges at the boundary of the cells and also having intensity inhomogeneity in the image. Due to the intensity inhomogeneity problem, Chan&Vese method failed to successfully segment the cell from the background.

However, the LBF method could segment the cell from the background but it failed to segment the boundary of the cell accurately when the contour passes by at weak or missing edges. This is due to the drawback of the method whereby its sensibility to the initial position of the contour that create two contours in the segmentation process.

a b

Figure1: The right side showing image of cell with missing at edges shown by arrow and at the left is the close up of the missing edges.

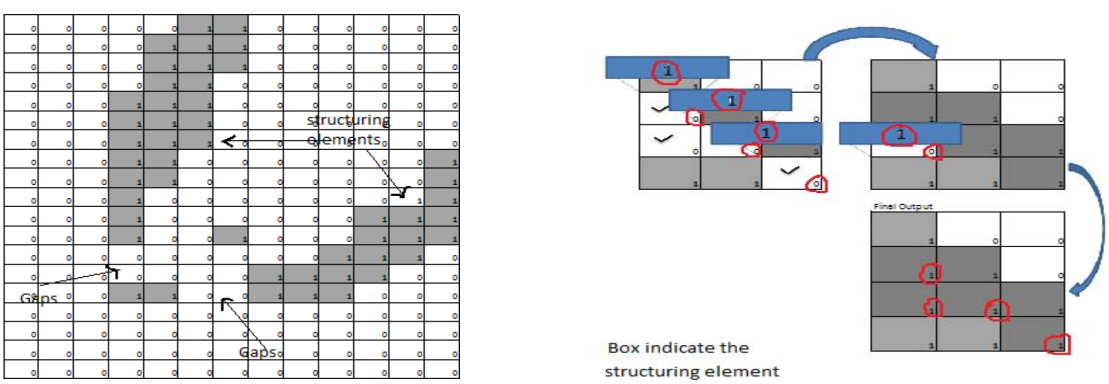
This paper proposes a method which refines the output image segmented from the LBF method. Our proposed method adopts morphological closing operator using the diamond-shape structuring elements (SE) in order to expand or to fill in the holes at the disjoint regions [7][8]. Closing operation consists of a dilation operation followed by erosion operation. The morphological closing operator adopts the dilation operation to expand and merge the separate region to produce a meaningful object that is the cell in the microscopic image. In other words, dilation could fill in holes at any gaps at the boundary. Then, the erosion operation is applied to smooth and remove unneeded pixels in the image before an outline function is applied to create an outline on the image. Between the two operations, the image is reconstructed to connect and remove several diagonal connections.

The aim of morphology operation is to simplify the image, eliminate irrelevant objects and preserve the useful characteristics in an image. Morphology is an operator which is constructed with operations on set of pixels in binary image in order to extract useful component in representing an image [7]. There are two main operations of morphology; dilation and erosion are applied in our method. In our research, the applied operations will create a contour to connect the pixels to join the contour at the missing edge. This operation is also called as morphological connectivity and here we implement the 4 x 4 connectivity in the direction movement of horizontal followed by vertical or vice versa.

Morphological operation works better on binary image rather than that gray-scale image. Due to that, to perform the closing morphological operation on microscopic image of cell, first we convert the gray-scale image of cell into binary image. The advantage when working with binary image is that the speed on the evolving contour is much faster when compared with image based on gradient. Moreover, the accuracy of segmentation is better as the binary image is following the pixels value which is either value 0 or value 1. Figure 2 shows the microscopic image that was converted into binary image. Note that pixels with value of 1 are denoted as object to be segmented and are called as structuring elements (SE). Pixels with value of 0 are considered as the background. Assume that B is the binary image of the original image.

$$= B(x) - [\, B \quad A \,]\,(x) \qquad (3)$$

where A is the structuring elements (SE) and denotes morphological closing operator. This measurement represents the feature to expand the pixels value from 0 to value 1 in the dilation process. Here, we implement the morphological closing operation with flat linear SE with proper length and degree. This measurement is in a counter-clockwise direction with horizontal and vertical SE.



a b

Figure 2: The original binary image of microscopic image of cell and the dilation process

A. Dilation Operation

The dilation operation is performed by laying the structuring element A on image B and sliding it across the image in a manner similar to convolution. In a standard dilation operation, the structuring element A is moved over the binary image A. Here, in our situation the origin B intersects with black pixels in A, then we have to set all pixels covered by A in B to black as the respective pixel in A is black. At this point, the binary gradient mask is dilated using the vertical SE of B followed by the horizontal SE of B. Dilation operation is used to increase object in the image. In terms of binary image, the equation is given by:

$$\varepsilon_A(B) = \{x \mid A_x \cap B \neq \phi\} \tag{4}$$

where A_x means A translated with x, here as SE have the maximum pixel value with 1, x is translated from value of 0 to value 1. The equation (2) above can be rewritten into the unions of the translated set I_{-a}:

$$\varepsilon_A(B) = \cup_{a \in A} B_{-a} \tag{5}$$

Figure 1b illustrates the dilation process using the vertical followed by the horizontal movement. This process normally named as region filling.

B. Region filling

The region filling process is done based on set of the dilatation operations. In the dilation process, either region is filled to close small gaps or to connect the disjoint regions. Our method applied the dilation operation to fill in holes at disjoint regions and later, after the filling process, the connectivity is implemented. Assuming that the process starts with a point 't' inside the boundary of the structuring element A with black. The aim is to fill the disjoint regions with the same value of the B which is black. Here, we adopt the convention that all background points are labeled as white, later we assign a value of black to t to start filling the disjoint regions with black. Once the process is done, the connectivity begins.

As binary image is made up of pixels with value either 0 or 1, the pixels are always in rectangular. Due to this, the connection from one pixel to another pixel will have anti-aliasing (sharp at the corner). To smooth or to remove these diagonal connections, the translated pixels will create a contour. Our method will perform a contour evolution and is achieved by performing substitutions of 4x4 pixel patterns on the region boundary. The function applied will suppress structures that are lighter than their surroundings and are connected to the image border.

C. Erosion Operation

To complete the whole process, we implement the erosion morphological operation to smooth the image and to remove noises or unneeded components. Here, the structuring diamond elements are used. At the last stage, the outline is created. The function returns a binary image containing only the perimeter pixels of object in the input image. A pixel is part of the perimeter if it is nonzero and it is connected to at least one zero-valued pixel. In the next section, we will present the complete algorithm for the proposed binary morphological operation.

D. Binary Morphological Model

The LBF method has the potential in segmenting medical images with intensity inhomogeneity. However, it could not manage to segment medical images that have missing edges. Based on equation (2) our algorithm continued after the LBF equation. Depending on the morphological closing operation, the equation is given by;

$$[A \oplus B(X_{k-1} \oplus B) \cup A]\Theta A \tag{6}$$

The first part of the algorithm shows the dilation process whereby the SE of A is expanded with pixel B. After the dilation process, the translated pixels are filled with region. This measurement is given by;

$$X_k = (X_{k-1} \oplus B) \cup A \tag{7}$$

where k is the size of window and k = 1,2,3,4. This algorithm terminates at iteration step k if $X_k = X_{k-1}$ and A contains the filled set and its boundary. The last step in completing the whole process is to smooth and erode the image. This is represented by –A. The complete algorithm is given by;

$$\varepsilon = LBF + [A \oplus B(X_{k-1} \oplus B) \cup A]\Theta A \tag{8}$$

where the first part is the LBF method and the equation is the same as shown in (2). Once the LBF method delivered the output image, the binary morphological model will perform the morphological closing operation to close the gaps between the separate regions.

IV. EXPERIMENTS AND RESULT

This section reports on the experimental setup and the results obtained based on the model discussed in section 3. The algorithm involved in this experiment is implemented using Matlab version 2010(a). The medical image used in this experiment is microscopic image of two cells. The experiment starts with executing the image using local binary fitting energy method. This is to display the result obtained as we have mentioned earlier, our method stressed on technique that could join gaps created from previous method.

From the experiment, the result executed shows several gaps at the boundary of the two cells. Based on the output, next, we implement the binary morphological model on the image. The aim is to join the two separate regions that made up the gaps.

Figure 3a shows the results obtained when implemented with the LBF method. Figure 3b, 3c and 3d show the sequence results when we applied the binary morphological model on the microscopic image of two cells.

The result obtained from LBF method shows several gaps at the boundary of the two cells. This is one of the drawbacks with LBF method as the initial positions create two contours whereby it passes at the weak edges and creates gap. As our model is using the closing morphological operation, it starts with the dilation operation process. At this point, the dilation process will merge and join gaps at the boundary of the cell. The result of the dilation process is shown as in figure 3b. The image is often called as 'dilated gradient mask'. At this stage, the reconstruction on the image is done as explained in section 3. Here, the connectivity in joining the gaps is created and implemented. However, from the result obtained, the image is still having unneeded regions that are still being segmented by the process. To smooth the segmented image, erosion morphological operation is applied. Here, the function was set to 4 pixels in removing all diagonal connections. The erode operation is used to erode the binary image and returning the erode image again. This is shown in figure 3c where the image is now smooth and better to compare to image shown in figure 3b.

To complete the whole process, a function to create an outline on the image is presented. The function will return a binary image containing the perimeter pixels of objects in the input image (figure 3c). The complete result is shown in figure 3d. We support our findings by providing one more image for the segmentation. Now, we used the image of MRI heart.

The aim is to segment the hole at the center of the image. The result obtained when using the LBF method does not provide accurate result. When applied the binary morphological model, the segmentation by the curve is now improved. This is shown in figure 4. Figure 4 (b-d) shows the sequence results.

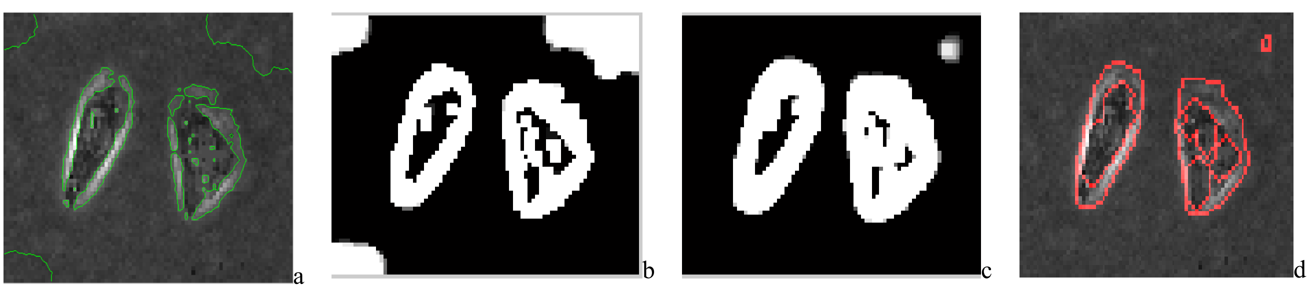
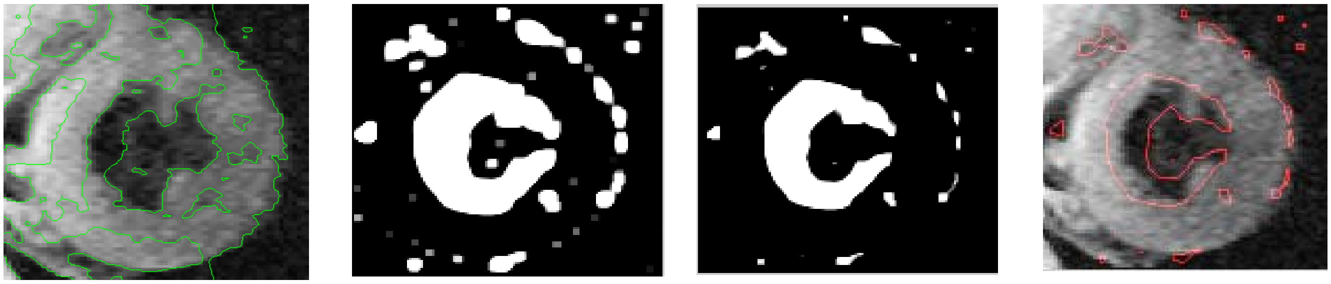


Figure 3: The sequence results obtained from the experiments using to different images; (a) shows the results obtained from LBF method;(b-d) show the results obtained when implemented using the binary morphological model.



a b c d

Figure 4: The sequence results obtained from the experiments using to different images; (a) shows the results obtained from LBF method;(b-d) show the results obtained when implemented using the binary morphological model

III. CONCLUSION

This paper investigates and reports on the importance of morphological operation in the field of image segmentation. As medical images were degraded with lots of noise, most segmentation models failed to accurately segment the desired object from medical images especially those with the missing at edge or gaps problem. The gaps problem occurred as medical images were affected with lots of noise and the intensity distribution in the image is not homogenous.

As mentioned earlier, active contour models shows satisfaction results when dealing medical images. The models can be classified as edge-based and region-based. However, neither edge-based or region-based failed to accurately segment the medical image especially medical images with severe intensity inhomogeneity. The combination of edge and region-based shows potential in overcoming the intensity inhomogeneity problem but the gaps problem remained unsolved.

This paper proposed to refine the LBF method that could not really join the missing boundary at certain part. Our method executed from the output produced based on the LBF method. Our method adopts the morphological closing operations using the diamond-shape structuring elements to overcome the above-mentioned problem. We applied the dilation and erosion operation to expand and later smooth the regions with gaps.

Based on the experiments executed on microscopic image of cell, our proposed method shows accuracy in results whereby the algorithm works better on the binary image as it follows the pixel value rather than the gradient of the image. In future, we might consider incorporating the morphological operation within any active contour methods rather than refining the method. We might also consider applying the morphological operation on gray-scale image rather than on binary image.

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