Mandibular Image Segmentation on the CT-Scan of the head using the Active Contour Method

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Abstract: Image segmentation is one of the image processing methods with the goal of sharing the image based on uniformity, one of which is the active contour method. This method is to detect objects on a particular image by using curve evolution techniques, and can also overcome the deficiencies in the boundary method. In this study image segmentation was carried out using the active contour method to evaluate the mandible on the head CT scan. It started with a CT-Scan of the head as input data, and saved with BMP (Bitmap) format. Then initial contour mandible, and after that the next step is image segmentation with active contour chan-vese method. From the analysis and evaluation of 108 images of the mandible with *BMP (Bitmap) format we get to the average accuracy values which were 99.809%, and sensitivity value of 99,806%. The conclusion of this study is that the active contour method gives accurate results of mandibular bone segmentation on the CT scan of the head.

1 INTRODUCTION

The mandible is the bone that forms the face of a person, especially the lower third. Like other organs, the mandible may develop abnormalities such as tumors, fractures, or dislocations. Tumor abnormalities in the mandible may result in bone defects. Bone defect is a state of partial or complete loss of bone, which can cause changes in bone function and anatomy that negatively impact by psychological weakness and reduced confidence in social relations[1,2].

Therefore, mandibular reconstruction surgery is recommended immediately. One thing that can be done to optimize surgical operations is to use a 3D prototype of the dissected organ. It aims to assess the severity of bone defects, improve the accuracy of marginal resection, as an implant pre-contour plate, and can reduce surgical time[3,4].

3D prototypes are the result of the printing technology of 3-dimensional objects from combining several materials such as plastics, polymers, ceramics, liquids and living cells. Stages to obtain 3D prototypes are image acquisition, image processing, and prototype printing. For image acquisition, data input is a digital image obtained from radiology as a CT-scan image. In this study a CT scan of the head is used.

After obtaining digital image data, image processing is carried out, namely the segmentation process. The image segmentation is the process of dividing an image into a number of parts[5]. Many methods are used in the image segmentation processes, one of which is Active Contour. This method uses evolutionary curve techniques to detect objects in images[6]. The nature of this method is finding the boundary or edge of the object becomes segmented from the influence of internal energy and external energy. Internal energy regulates continuity while external energy functions to draw a curve to the edge of the target[7].

The Active Contour Method is divided into two groups: parametric and geometric. Parametric methods commonly known as deformable can segment objects with a clear boundary, one of which is the Snake Active Contour Model. While geometric method is the method that has the ability to segment objects with unclear boundaries, one of which is the Active Contour Level set model. In this study we used an active contour geometric with Chan-Vese model.

1.1 Active Contour Chan-Vese Model

One of the geometric active contours is the Chan-Vese Method, in this method the process to minimize energy is based on Region Base models[8]. Introduced by T. Chan and L. Vese in 2001, this model is an improvement from the edge based model because edge detection in an image based on curve evolution technique, Mumford-shah function for segmentation and level set[9]. This is because detection using an image gradient is less effective, because discrete gradient is limited and the stop function is not null at an edge and allows the curve to cross the existing boundary.

In Chan-Vese (C-V) models, contour initiation can be done anywhere in the image and the C-V model will automatically detect the entire contour, regardless of the location of contour initials[10]. Chan-Vese active contour method assumes images are formed from two parts. Assumed f (x, y) as a gray-level image with the domain W. Domain W can be divided into several parts W_i along the boundary C. If it is assumed that there are only two parts, those in C are called W_1 and those outside C are called W_2. So the energy model equation is shown in the equation 1[11],

$$F_1(C) + F_2(C) = \int_{w_1} |I(x,y) - I_s|^2 \, dxdy + \int_{w_2} |I(x,y) - I_s|^2 \, dxdy \tag{1}$$

In the equation above what is needed is the right C value, so that the Pas Energy value becomes minimal (equation 2)[11] as in Figure 1,

$$\inf\{F_1(C) + F_2(C)\} = 0 \tag{2}$$

Figure 1: the C curve is outside the object if F1 (C)> 0 and F2 (C) = 0.

If the C curve is inside the object it means F1 (C) = 0 and F2 (C)> 0, whereas if Curve C is inside and outside the object means F1 (C)> 0 and F2 (C)> 0. Until finally the energy fitting will be minimized if C = 0[12]

For the practicality of the Fitting Energy model, equation (2) is minimized by a regular equation such as the length (length) of the C curve and the area in the C curve to become equation (3)[11]

$$F(I_s, C) = \mu.Length(C) + \upsilon.Area(W_1) + \lambda_1 \int_{w_1} |I(x,y) - I_s|^2 \, dxdy + \lambda_2 \int_{w2} |I(x,y) - I_s|^2 \, dxdy \tag{3}$$

With $\mu \geq 0$, $\upsilon \geq 0$, and $\lambda 1$, $\lambda 2 > 0$ is a fixed parameter. In the first term, functional energy F controls the length of the contour that describes the target object. The weight of μ in this equation helps form a smooth boundary. Same with weight υ forces the total area of the foreground part of W_1 to be found in the segmentation process. Whereas the third and fourth are proportions for the gray level difference in the foreground and the background to be detected.

The solution of the Is value can be approximated by the Mumford-Shah segmentation function shown in equation (4)[11],

$$I_s = \begin{cases} \text{average}(I) \text{ of } W_1 \\ \text{average}(I) \text{ of } W_2 \end{cases} \tag{4}$$

In the Chan-Vese active contour model, level-set functions are introduced to reduce functional energy F (c1, c2, C). The level-set function Φ is defined as the zero level-set in the Lipschitz function (equation 5-7)[11],

$$Inside(W_1) = \{(x,y) \in W : \Phi(x,y) < 0\}, \tag{5}$$

$$Inside(W_2) = \{(x,y) \in W : \Phi(x,y) > 0\}, \tag{6}$$

$$C = \{(x,y) \in W : \Phi(x,y) = 0\} \tag{7}$$

According to Crandall (2009), the completion of the Fitting Energy function is changed to a level-set function Φ using the Euler-Langgrange equation so that the iteration calculation can be done by solving equation (8)[13],

$$\phi(t) = d\frac{\phi}{dt} = \delta(\phi)[\mu \, div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \upsilon - \lambda_1(I, (x,y) - c_1)^2 + \lambda_2(I, (x,y) - c_2)^2 \tag{8}$$

To solve the equation (2.8) it must be discredited first, e.g. $\phi_{i,j}^n$ denoted as the value of the level-set function Φ in the pixel (i, j) in the iteration n (equation (9))[13],

$$\Delta_+^x \phi_{i,j}^n = \phi_{i+1,j}^n - \phi_{i,j}^n, \Delta_-^x \phi_{i,j}^n = \phi_{i,j}^n - \phi_{i-1,j}^n$$

$$\Delta_+^y \phi_{i,j}^n = \phi_{i,j+1}^n - \phi_{i,j}^n, \Delta_-^y \phi_{i,j}^n = \phi_{i,j}^n - \phi_{i,j-1}^n \qquad (9)$$

2 MATERIALS AND METHOD

A computer with AMD Turion (tm II) Dual Core 2.30 Gz / 2.0 GB RAM and the Matlab application (R2017a, MathWorks Inc., USA) was used in this study for simulation and analysis data. The image used is the image of the CT scan head with a 512x512 matrix size from the Brilliance CT 64 Channel (Philips medical system, Netherlands). The parameters used on the CT scan head are slice thickness of 2 mm, DFOV 360 mm, a voltage of 120 kVp and a tube current of 297 mA.

This study stage begins by collecting CT Scan images, then converts them to files with BMP extension (Bitmap), the data is called input data. The next stage is image processing where normalization will be carried out by converting input data into gray scale images, with the aim of achieving uniformity of pixel intensity. And the last stage is the process of segmentation with the chan-vese model active contour. Image results from the segmentation process will be tested with images that are manually segmented by experts (doctors). A flowchart of this study can be seen in Figure 2.
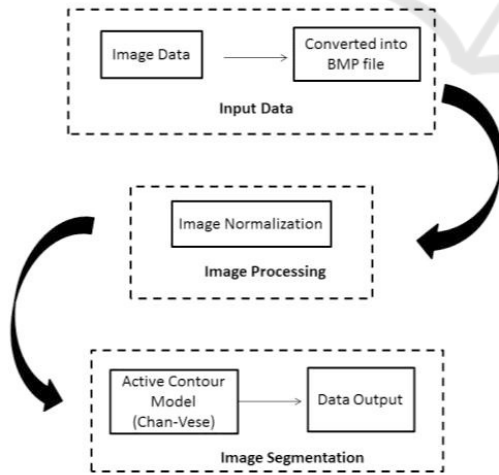

Figure 2: Flowchart of the study.

.In this study the work system is divided into several stages, namely input system, image processing and segmentation process.

2.1 Input Data

In the input system, CT scan data is obtained from scanning the head with the upper boundary of the vertex and lower limit of the base of the cranial using the MDCT 64 Slice modality (Figure 3). Data formats from CT scan have extensions *DICOM and are then converted into a file with *BMP format with a matrix size of 512 x 512. The process of converting *DICOM format to *BMP is done through the Radiant Dicom application program.
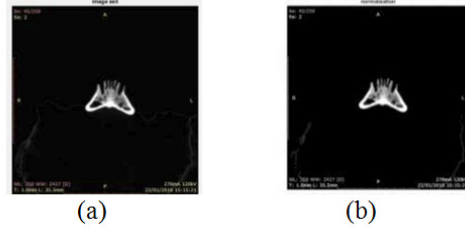

(a)   (b)

Figure 3: (a) Input data of Mandible CT, (b) Image data after normalization.

2.2 Image Processing

After obtaining an image with BMP file format, the next process is image normalization. This process aims to change the pixel intensity of values. The initial pixel intensity value ranges from 22-255 to 0-255 (Figure 3).

The result of normalization is an image that has a gray level with an intensity range of 0-255. Image segmentation is the next step.

2.3 Segmentation Process

The segmentation system stages using Chan-Vese active contours are as follows:
1. Determine the control parameter initialization, weights or constants of both internal energy and external energy.
2. Determine the edge image as external energy by determining the image gradient.
3. The next step is to determine the initial contour, adjust the initial contour according to the original image (Figure 4a-4b).
4. And determine total energy value.
5. If the total energy has reached the minimum, the iteration will stop and will form a contour according to the input data (Figure 4c).
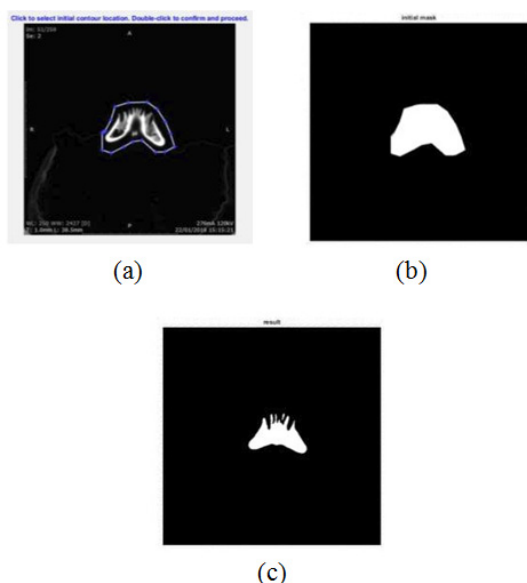6. Segmentation results are output data.

(a)

(b)

(c)

Figure 4: (a) select initial contour, (b) result initial contour, (c) result post segmentation process.

3 RESULT

The image data used in this segmentation process is 108 images. The analysis used in this study is by comparing program segmentation results with results of expert segmentation (doctor). From this comparison value will be obtained, TP: True Positive, FN: False Negative, TN: True Negative, and FP: Wrong Positive, which is calculated based on the number of pixels (Figure 5). Based on this analysis we can measure the value of sensitivity and accuracy with the equation (9-10) (Table 1).

Accuracy= $Acc = \dfrac{(TP+TN)}{(TP+TN+FP+FN)} x100\%$ (9)

Sensitivity: $TPR = \dfrac{TP}{(TP+FN)} x100\%$ (10)
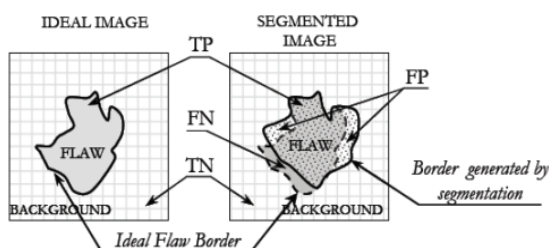

Figure 5. Analysis method of segmentation results data

Table 1: Result of accuracy and sensitivity data

Name	TP	TN	FP	FN	Acc	TPR
BMP0001	223	92488	0	58	0.99937	0.79359
BMP0002	620	92062	45	42	0.99906	0.93656
BMP0003	942	91750	0	77	0.99917	0.92444
BMP0004	1221	91468	0	80	0.99914	0.9381
...	...	...	...	...	...	...
...	...	...	...	...	...	...
...	...	...	...	...	...	...
BMP0105	5211	87505	43	10	0.99943	0.99808
BMP0106	5173	87541	39	16	0.99941	0.99692
BMP0107	5184	87519	59	7	0.99929	0.99865
BMP0108	5217	87504	36	12	0.99948	0.99771
			Evarage		0.99809	0.96806

From the above calculations it can be seen that with image segmentation using the Chan-Vese active contour method, the average accuracy value is 99.809% and the sensitivity value is 96.806%.

4 DISCUSSION

Image segmentation method is proposed using the method of active contour, as active contours always provide sustainable sub-region boundaries, so as to increase the final results of the image analysis. Mathematical implementation of the proposed active contour models is achieved using the level set method. The proposed image segmentation of this method allows us to increase the detection of mandibular bone in the image of the CT scan of the head.

In this study the segmentation program has not been able to distinguish solid and hollow bone tissue considering the bone structure is not all solid. And as this study is still using only one patient, it is expected that further research can use more data.

5 CONCLUSION

Referring to the level of accuracy segmentation results, the results of this study are quite accurate and can be used as an alternative method of mandibular bone segmentation on CT scan images to be used as data input in the subsequent process of making a 3-dimensional mandibular prototype for mandibular reconstructive surgery.

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