Corpus Callosum Segmentation from Brain MRI Images Based on Level Set Method

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***Abstract*— Corpus callosum integrates left and right hemispheres of human brain. There are several methods for segmenting corpus callosum, but the existing algorithms need several steps to segment images. Therefore, we propose a simple method using level set method to segment corpus callosum. We use level set method as it can handle the structure of the brain easily. This method provides a numerical solution for processing changes in topological contours by representing a curve or surface as a zero level to a higher hyper-dimensional surface. This experiment shows that by implementing level set method to segment the corpus callosum produces Dice Similarity Coefficient (DSC) value of 85.14%.**

Keywords—Unsupervised Learning, Level Set, MRI, Brain, Carpus Callosum

I. INTRODUCTION

In the human body, there are various vital organs that support humans to stay alive, one of which is the brain. With a weight of about 1.5 kg, it can be said that the human brain becomes the most complex organ in the human body itself [1]. There are several parts in the human brain, one of which is the corpus callosum. Corpus callosum, which is located in the center of the human brain, forms the largest commissure white matter bundle in the brain. Corpus callosum has a very important role in the integration of information between the left and right hemispheres [2].

In processing medical images from general human brain images to the right location of the corpus callosum, medical Image segmentation is the key and becomes an essential part of medical image processing [3]. Segmenting the brain requires a variety of information, including the intensity of the image, global brain position, position relative to neighboring brain structures, and anatomic landmarks [4]. In clinical applications, accuracy and speed are the main requirements in segmenting medical images [3], including in segmenting the corpus callosum in the human brain. So it is necessary to incorporate current technological advances, which can help researchers and doctors to analyze and diagnose the structure and function of the individual corpus callosum.

Currently, the most sophisticated imaging technique that the medical world has is magnetic resonance imaging (MRI). MRI aims to produce detailed images of the internal body by applying the imaging field. Compared to the X-ray-based medical diagnostic techniques, MRI uses radiofrequency fields to produce the images, does not use ionizing radiation [5].

Meanwhile, there have been several studies that have been carried out for MRI segmentation, especially for segmentation of the corpus callosum. Some supervised segmentation technique using deep learning have been proposed in recent studies. Hence, deep learning needs many data for the training process. Since the DICOM (DCM) data we gathered are limited and comes with various format, using deep learning approach would needs many preprocessing step and considerable amount of time.

Other approach that can be used is by using unsupervised learning such as clustering and contour evolution method which does not need many data for training process[6], [7], [8]. Instead, unsupervised learning provides a fast segmentation algorithm in image processing. Unsupervised learning has its downside such as a relatively lower accuracy compared to those of supervised learning.

In this research, we used semi unsupervised learning for our study. We propose a new approach to segment the corpus callosum from MRI using level set method. The level set is a numerical solution that is useful for processing changes in topology contours. Not only provides an accurate numerical value, but this technique also handles topology changes very easily [9]. Thus, the segmentation process would not need many data for training purpose, while still needs some supervision to select the accurate segmentation result. At the end of this study, we tried to show several unsupervised segmentation method using K-Means and Fuzzy C-Means compared to our proposed method using Level Set to show how clustering algorithm that is generally used in other research perform compared to Level Set method.

II. PREVIOUS STUDY

There are several studies to segment MRI images. Including manually segmenting corpus callosum. Gousias et al. [10] manually segmented MRI image of a newborn baby. This study produced 50 regions with comprehensive brain coverage in newborns baby. Then Vidal et al. [11] manually segmented the corpus callosum of male patients with autism. This segmentation aims to detect and map the spatial patterns of corpus callosum abnormalities in autism patients with traditional morphometric methods. The results of this study indicate that the method used by the researchers detected a significant reduction in the total area of the callosal and one-third of the anterior corpus callosum in autism patients.

While, studies on automatic corpus callosum segmentation using MRI image, has been done by several researchers. He et al. [12] segmented the corpus callosum semi-automatically, where the user was required to initialize a seed contour consisting of four interconnected parts. The method used by researchers in this study is context-sensitive active contour. This method divides the active contours into sections and connects them to sensor points. By implementing the method and allowing the user to initialize the model, this research has lower complexity when compared to a fully automated approach. In the oher hand, Mogali et al. [13] also use semi-automatic to segment the corpus callosum. This study implements a hybrid formulation, which a restricted affine transform (RAT) constrained snake, and an unconstrained snake optimization. The formulation of the RAT in this study is used to optimize the geometry of snakes that are restricted using local contrast-based energy. Meanwhile, the unconstrained snake deformation is used to optimize snake geometry using integrated energy formulations. The application of this hybrid formula results in increased resistance to initial segmentation that will increase as well as being fast and accurate. While in fully automated, Li et al. [14] use three modules as a technique for the segmentation, adaptive mean shift (AMS), automatic CC contour initialization (ACI), and Geometric Active Contour (GAC). AMS technique in this study used to clusters all homogenous regions in the image. Then ACI achieved using the region analysis, template matching and location analysis, thus identify the CC region. And finally, to get the result of the segmentation is used the GAC technique. And based on this result, by using AMS-ACI technique, it provides an accurate initial corpus callosum. And by using AMS-ACI-GAC technique, it provide a reliable and accurate performance in corpus callosum segmentation. Then Ciecholewski et al. [15] compared the three active contour methods (ACMs) for segmenting the corpus callosum in brain MRI,. the edge-based active contour model (EM), the Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS), and the Distance Regularized Level Set Evolution (DRLSE). The result indicated that EM model is the best method based on quantitative tests of the similarity indices (SI) and overlap value (OV), where the SI of EM is 92%, and the OV is 82. Whereas Candra et al. [16] implement deep learning as an approach to segment the corpus callosum. The deep learning method used in this study is the convolutional neural networks method. The implementation of this algorithm has a promising level of accuracy that makes it popular for implementing segmentation and classification problems.

III. RESEACH METHOD

This study was conducted to segments the corpus callosum. The data used in this study are slices of MRI images in the form of DCM format from patients with normal corpus callosum conditions. We got 54 data for this study. We select the midsagittal part of the MRI images and create the ground truth data assisted by a doctor. The programming language we used to do this study is Python using cv2 library. Fig. 1 shows the system diagram of this study, starting from preparing the data for preprocessing until the accuracy calculation of the proposed method using DSC.

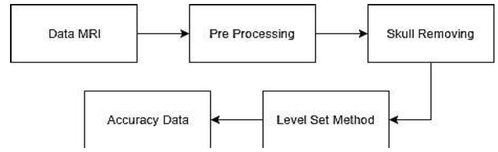


Fig. 1. System diagram.

Based on Fig. 1 shows that the first step starts by using an MRI image that has been prepared previously. Next, preprocessing the MRI image is carried out by applying several steps. After getting the results of preprocessing, the next step is to remove the skull using skull removing. Since the skull have been removed, the brain will do our segmentation method until the corpus callosum position is obtained. We used level set method in our study. The output of the implementation of this level set method is the segmented corpus callosum. The last step of our study is accuracy calculation to determine how well our method works.

A. Dataset

The data in this research were obtained from the hospital, which contained MRI images of patients who had healthy corpus callosum in the form of DCM extension files. The number of data sets used as research data is 305 images. The example of the dataset used in this research is shown in Fig 2.

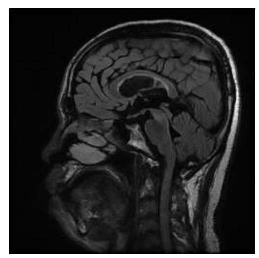


Fig. 2. MRI of human brain.

Based on Fig. 2, we know that the picture does not only contains images of the brain but also shows other organs contained in the human head. Therefore, further processing is needed so that it can focus on the organs of the human brain and find out the corpus callosum segmentation.

B. Preprocessing

Preprocessing is the initial process to eliminate irrelevant data and improve image quality so that it is easier to recognize [17]. There are two stages in preprocessing images that used in this study, i.e. resizing image and median filtering.

1) Image Resizing

Resizing the image is an important step in image processing technique, to enlarge and reduce the given image size in pixel format [17]. Resizing the image is necessary since the DCM files we got have various resolution. In this stage, the pixel value of an image will be changed so that the length and the width of the image will be 256 x 256. By changing the pixel value, it will make the object on smaller images sizes can still be detected and be segmented.

2) Median Filtering

This stage aims to improve the quality of the image by reducing noise. The pixel values of the output image are determined by the median of the image pixel of desired kernel size. In this case, we used the standard kernel of 3x3. Meanwhile, the median value is the middle value obtained by sorting the pixel value of the mask. [18]

C. Skull Removing

We do a process called thresholding that change image color into only 2 class, background (black) and foreground (white). Thresholding was basic segmentation image method. In this study, we implemented Otsu Thresholding as a method for removing the skull. The Otsu method of thresholding is a method proposed by Otsu in 1979. This method is applying the global thresholding process. The output value depends on the gray value of an image [19]. Otsu Thresholding analyze the discriminant variable by defining a variable that able to determine 2 or more classes. This discriminant analysis maximize the variable to determine background and foreground of an object. Otsu Thresholding is defined in (1).

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \quad (1)$$

The weight of ω_0 and ω_1 in (1) are the probabilities of the two classes by threshold t. While σ_0^2 and σ_1^2 are the variances of these two classes.

After the Otsu thresholding method have been applied, we used Largest Connected Component (LCC) as a method to extract the brain. Since the brain is the largest component that we got in the image, using LCC will be an effective method to remove the skull.

D. Level Set Method

The level set method is a method that implements a surface value that is equivalent to zero. This algorithm was first introduced by Osher and Sethian in 1988 [20]. The basis of this method is that the curve or surface $(\emptyset)$ that is represented as the zero levels $(\emptyset = 0)$. Implementing a level set will provide a more accurate numeric value while still making it easier to handle topology changes [9].

At first, we initialize the segmentation boundary as part of surface where the level is 0. Let the function $\emptyset(x, y, t)$ stands for the surface evolution. Therefore, the level of a boundary evolution is directly influenced by how many time (t) the boundary may evolve. We define a Signed Distance Function (SDF) on the surface shows in (2).

$$\emptyset(x, y, t = 0) = \pm d \quad (2)$$

Where the value of x, y in Equation (2) is the position of the a point in the image and t is the time. The value of d is obtained by calculating the shortest distance between the point (x, y) and the boundaries. The value of d will be negative if the point x, y is outside the initial boundary and positive if the point x, y is outside the boundary when $t = 0$. Then the points are processed in the whole evolution of the curve shown in (3).

$$\emptyset(x, y, t) = 0 \quad (3)$$

And the movement formula is shows in (4).

$$\emptyset_t + F|\nabla\emptyset| = 0 \quad (4)$$

F in Equation (4) is a function of speed, which depends on the characteristics of the evolving surface, the characteristics of its image and the ideal value which is zero on the edge of the target.

E. Dice Similarity Coefficient

We employ Dice Similarity Coefficient (DSC) to measure the segmentation results. DSC calculate the number of pixels from Corpus Callosum segmentation results compared to the pixel counts of those in the ground truth. The formula we use for DSC for this experiments are shown in (5).

$$\frac{2|X \cap Y|}{|X| + |Y|} \quad (5)$$

IV. Result and Analysis

In this section, we will show how our proposed work performed for corpus callosum segmentation.

A. Preprocessing

At this stage, the images from the training data are improved and the variables are equalized. First, the MRI image, which has the DCM format, was changed to the PNG format.

1) Image Resizing

The first step in this study is converting DCM images into PNG format. Hence, images that have been converted to PNG format have different image sizes. Therefore, resizing images are needed so that the results of segmentation can be more accurate. The result of this step shown in Fig. 3.

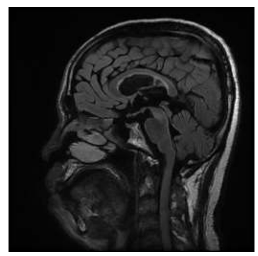


Fig. 3. Image after resizing process.

2) Median Filtering.

In this study, implementing median filtering provides better results in reducing noise compared to other methods. Fig. 4 shows the result of the median filter process.

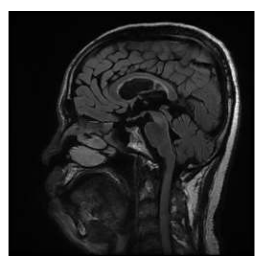
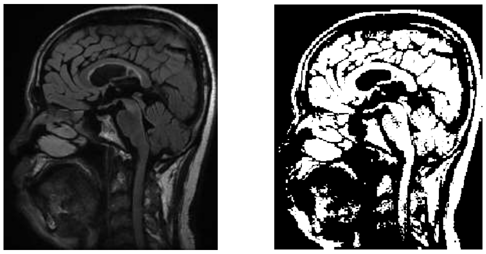


Fig. 4. Image after median filter process.

B. Skull Removing

Skull removing aims removing the skull and other organs except the brain itself. We implement Otsu thresholding before removing the skull using LCC. Fig 5 shows the result of Otsu thresholding



(a) (b)

Fig. 5. (a) Image before implementing Otsu thresholding. (b) Image after implementing otsu thresholding.

As we seen in Fig. 5, the images in Fig. 5 (b) has become an image with 2 color, black and white. Otsu Thresholding decide the class based on the color of original image. If a pixel values have not exceeded the threshold value, then it is turned to black and vice versa. We need to remove skull in the image result. The purpose of skull removing step is to aid the computer easier to detect brain segment. We use LCC to find the biggest component, and then remove the others so it left only the biggest component. LCC is a method to find pixels that have the same neighboring value and the most linked to each other. After finding the largest component using LCC, the other component will be removed and left the brain part since it is the largest component that has been found. The result of LCC is shown in Fig. 6.

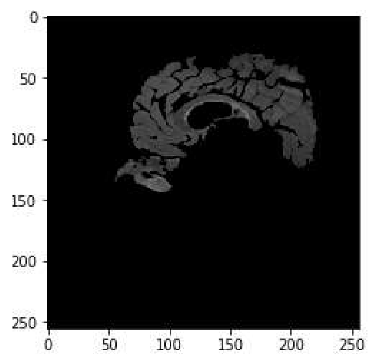
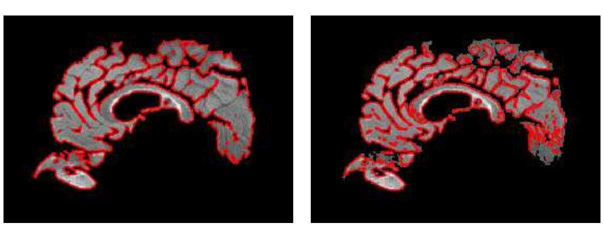


Fig. 6. Result of skull removing stage.

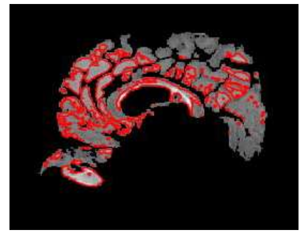
Fig. 6 shows the brain only without skull or any smaller component. It removed small part in the brain and left only the biggest. Every image have different result of skull removing based on how big the biggest part is.

C. Level Set Method

We implement the level set method to find the boundaries of brain segment. Level set method produce many segments of brain. We have to determine the level to define how many times the boundary may evolve. Different level have different result, and it is possible for the corpus collosum to not be found when some level are used.



(a) (b)



(c)

Fig. 7. Implementing the level set method in brain MRI. (a) Level =40, (b) Level=56, (c) Level=70.

As we seen in Fig. 7 (a), with level = 40 shows only outer boundaries but didn't get much detail of the brain anatomy. It needs bigger levels to make the contour have more details of the brain anatomy. Fig. 7 (b) uses level = 56, it shows more detail. Fig. 7 (c) shows more detail uses level = 70, but the results shows that brain parts are not well covered as in (b). If the level used is too big, then the boundaries may evolve too many times. Thus, it will search for more detail.

From 3 levels that we try, we found level = 56 have most detail result among the others so we choose to use this level for the next step.

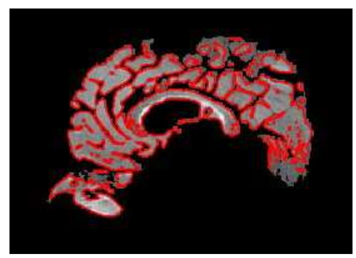
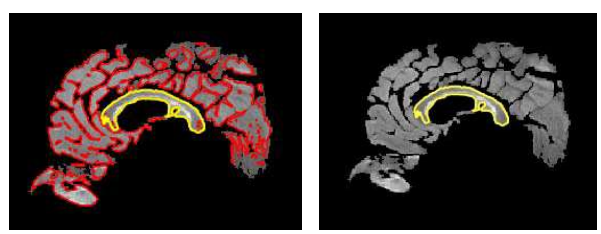


Fig. 8. Contour created by level set method.

In Fig. 8 shows many contours are created, but we only extract the corpus collosum so we need to look for which part is the corpus collosum. The results of level set method are several contours that have been evolved and bounded the brain anatomy. Every levels have different amount of contours, for level = 56, there are 105 contours that are created. Thus, we can find the corpus collosum by selecting the right contour. Fig. 9 shows the selected corpus collosum.



(a) (b)

Fig. 9. Result by using level set method. (a) Marking boundary of corpus callosum. (b) Marking only the corpus callosum.

Fig. 9 (a) shows how level set algorithm create boundaries around brain anatomy, (b) marks the corpus collosum without other segment. Fig. 10, shows the extracted corpus collosum.

Fig. 10. The extracted of corpus callosum.

D. *Proposed Method Performance*

By implementing the formula of Equation (5) in this experiment, it was found that applying the level set method for corpus callosum segmentation had DSC value of rate of 0.8514. This accuracy value is obtained by comparing the pixel count of the segmentation result and the ground truth pixel count.

Then, we compare the result of our proposed method using level set with clustering algorithms such as Fuzzy C-Means and K-means. We compare level set method with fuzzy C-means and K-means to show how unsupervised method such as level set method which follows the contour of the brain slices performed to clustering algorithm which groups each pixel to a corresponding cluster. Table 1 shows the DSC result of the proposed method compared to other algorithms.

TABLE 1. PERFORMANCE COMPARATION

Method	**Mean DSC (%)**
Fuzzy C-Means	66.7
K-means	75.79
Level Set	85.14

Table 1 shows the DSC of the proposed method is 85.14%. our proposed method performed better than the other unsupervised algorithm since our proposed method employ the level set method. Using level set method, we placed a plane which then intersect with the brain image and creating boundaries based on the intersection. Since level set method does not need to optimize the centroid like K-Means and Fuzzy C-Means, level set method can create a fine boundary of each brain anatomy easier. Resulting to a better anatomy form.

On the other hand, clustering algorithms such as K-Means and Fuzzy C-Means need an initial centroid based on the intensity of the pixels and the centroid selected might change when the cluster is optimizing. Therefore, clustering algorithms results in inaccurate clustering of the pixel values.

The proposed method used level set to evolve the initial contour based on the time which shows where the plane position is. The contour produced by the algorithm can detect the border of each brain anatomy, resulting in much better segmentation result. Moreover, this method can provide a more precise result compared to the clustering methods. Since clustering methods such k-means rely on the initial centroid.

V. CONCLUSION

This study used level set method for brain segmentation. In this research we only segment corpus collosum. The number of contours is determined by the level used in level set method. The level used in level set method shows how many times the plane which intersect with the image moves. If the levels is too high, the plane might not intersect with the boundary of the corpus callosum. If the levels is too low the plane might not reach the target anatomy.

Segmentation using level set created many segments. Thus, we must find which one is the corpus collosum. When compared with other methods such as K-Means and Fuzzy C-means, level set method achieves the best DSC values. It is possible for future work or experiment to find another part of brain using this method.

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