Brain Segmentation using Adaptive Thresholding, K-Means Clustering and Mathematical Morphology in MRI Data

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***Abstract*— Nowadays, many methods have been applied for brain segmentation on MRI data. This paper proposes a new method for brain segmentation using Adaptive Thresholding, K-Means Clustering, and Morphological Mathematics in MRI data. The adaptive threshold was chosen because the adaptive threshold method will vary across images to suit various lighting conditions and background changes. We segment the corpus callosum. This experiment shows that with the Adaptive Thresholding, K-Means Clustering, and Mathematical Morphology to segment the corpus callosum produces the highest Dice Similarity Coefficient (DSC) value of 0.757.**

Keywords—Brain Segmentation, Adaptive Thresholding, K-Means Clustering, Mathematical Morphology, MRI data, Corpus Callosum

I. INTRODUCTION

Nowadays, unsupervised learning has been performed for medical related cases[1], [2]. Many methods have been used to segment the brain in MRI data. The various types of segmentation techniques are: (a) Edge-Based Segmentation (b) Threshold-Based Segmentation (c) Regional-Based Segmentation (d) Clustering (e) Matching. [3].

There are a lot of approaches taken by previous researchers to do brain segmentation. Blayvas *et al* [4] and Singh *et al* [5] use adaptive thresholding for image binarization. Kazi *et al* [6] combined adaptive threshold with K-Means Clustering for brain image segmentation. The K-cluster clustering algorithm used for multi-dimensional data segmentation, which is intended to approve for variants of vectors assigned to each cluster. K-Means Clustering is a partitioning method [7] . Singh and Singh [8] and Patel *et al* [9] uses K-Means Clustering for brain tumor detection. The results that interpret unsupervised segmentation methods are better than the supervised segmentation methods. Irani and Belaton [10] presents a creative general purpose segmentation system. Wu *et al* [11] use K-Means Clustering color based on brain tumor detection. The proposed method combines the use of color translation, K-Means clustering and histogram clustering to make it useful and easy to do. Meenakshi [7] proposed, a morphological image processing approach using K-Means Clustering for brain tumor detection. Ali *et al* [12], Kumar *et al* [13] conducted a study to detect tumors using Morphological Operations and K-Means. They conducted studies on preprocessing and segmentation methods available to detect tumors on MRI data. Patil [14] uses preprocessing techniques using median filters and morphological operations, and they discuss various methods that need to be discussed during MRI and CT preprocessing. Morphology is used to eliminate noise in preprocessing.

K-means is a clustering method that is widely used since it is fast. Moreover, using clustering method such as K-means does not need many data for the training purpose[15], unlike deep learning or neural networks. This clustering algorithm suitable for this research since we got only 54 data from Indonesian hospital.

Based on these literatures, we propose a new method for brain segmentation in MRI data using an adaptive threshold, K-Means Clustering, and mathematical morphology to segment the corpus callosum. Adaptive thresholding is used at the preprocessing stage, after which the image will be clustered using k-means, and to eliminate noise, mathematical morphology will be applied. Adaptive thresholds are needed to separate the main objects from the background. The adaptive threshold was chosen because the adaptive threshold method will create various local threshold throughout the image. This method works by formulating the threshold surface as each pixel has a threshold value [16]. The adaptive threshold is considered more effective for pixel classification. K-Means Clustering used to segment corpus callosum and then mathematical morphology is employed for noise removal. Finally, we discuss and compare our proposed method which used K-Means as a clustering method with Fuzzy C-Means and Active Contour Chan-Vese in discussion section to show the performance of our proposed method.

II. PREVIOUS STUDY

Blayvas *et al* [4] and Singh *et al* [5] uses adaptive thresholding for image binarization. Blayvas et al use the threshold surface are constructed with a much lower and smoother computational complexity so that the resulting binary image will be better and often have better noise resistance. Singh *et al* explain the locally adaptive thresholding technique removes the background using the mean and deviation of the local mean.

Kazi *et al* [6] proposed a new update on adaptive thresholding and K-means cluster algorithm to obtain cerebrospinal fluid (CSF), Gray Matter (GM), White Matter (WM), and others. K-Means Clustering is used to group images of the brain into desired parts by determining the value of k. Experiments on MRI data are used to measure the accuracy of the proposed algorithm.Singh and Sing [8] and Patel [9] are doing the detection of brain tumors using K-Means Clustering. The first step they do is move the brain with the skull. After that, the noise will be removed by using median filtering. Then, they use k-means grouping to segment the brain tumor. This research produced part of a brain tumor that had been segregated.

Wu *et al* [11] used the K-Means Clustering method to detect brain tumors by converting gray images into color space images. MRI images of the tumor were separated by using K-Means Clustering and histogram-clustering techniques. This new algorithm is the result of several methods combined, namely, color translation, K-means grouping, and histogram grouping. this is done to make it easier to segment.

Meenakshi *et al* [7] proposed the K-Means Clustering method applied with MATLAB for detecting brain tumors. Diagnosis of brain tumors takes a long time, so it requires image segmentation techniques. Detecting brain tumors using MRI data must be done with image segmentation techniques. The results of the segmentation were store in any format that can be used for further studies in the future. The research, conducted trials on MRI analysis of brain tumors in 40-year-old men diagnosed with multicystic lesions, 30-year-old men diagnosed with glioblastoma, 40 years with normal brain, 38-year-old woman diagnosed with astrocytoma, 10-year-old boy men diagnosed with glioma, 41-year-old men diagnosed with epidermoid brain tumors, 4-year-old boy diagnosed with pediatric craniopharyngioma tumor, 42-year-old man diagnosed with ganglioglioma. The segmentation method using K-Means Clustering shows that the unsupervised segmentation method is better than the supervised segmentation method.

Ali *et al* [7] applied four different techniques to extract and calculate the tumor area for four consecutive slices from MR T2 images. To improve classification accuracy, by changing the results of Fuzzy C-means change when fuzzy is grouped with K-means using smoothing operations.

Kumar *et al* [13] extracted brain tumors using K-Means based on morphological clusters. The brain image consists of 4 regions that are determined as different classes. The four areas are gray material (GM), white material (WM), cerebral spinal fluid (CSF), and background. To get good accuracy and avoid mistakes, the elliptical combination object must be removed. After enhancement, the morphological image process is carried out to extract the required area. Furthermore, K-means with the cluster applied. It can be concluded from the results of the unsupervised segmentation method that is better than the supervised segmentation method. Because of the unsupervised nature of considerations, the proposed system is efficient and less sensitive to errors. In contrast, the supervised segmentation method requires large amounts of training data and testing data.

Patil [14] discusses various techniques that need to be discussed during MRI and CT preprocessing. They use preprocessing techniques using median filters and morphological operations. The median filter produces good results compared to the algorithm obtained. Morphological operations such as erosion and dilation also produce efficient results in skull removal from brain MRI.

III. Reseach Method

A. Block Diagram

The steps to do image segmentation in this study are illustrated by the block diagram that can be seen in Fig 1 below:

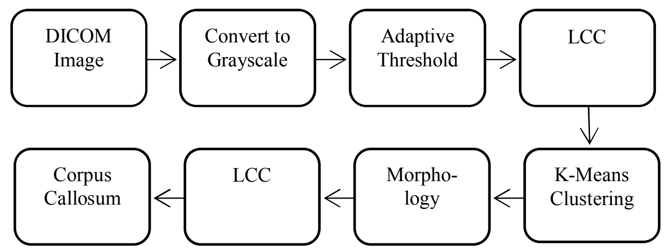

Fig 1. Block Diagram.

Fig 1 explains the steps on this study. The first step begins by loading the image. After loading the data, the image will be converted to grayscale. Then the adaptive threshold is applied. After getting the results from the adaptive threshold, the next step is to make a sizeable connected component to release between the skull and the brain. Brains that are taken part of the brain are connected. Then K-Means Clustering is applied. After getting the results of K-Means Clustering, the image still produces noise. Noise is removed by using an opening mathematical morphology so that the image will produce segmentation results consisting of the corpus callosum.

B. Adaptive Thresholding

Adaptive threshold method creates local threshold for different image regions. This is known as the local or dynamic threshold [17]. Using thresholding, the pixel value of the object image can be differentiated from the background [18]. Binary thresholding sets all pixels that have intensity values above the threshold to the foreground value, and all remaining pixels to the background value to group images. Meanwhile, the adaptive threshold will change the threshold dynamically above the image for conventional threshold operators that use global thresholds for all pixels. The adaptive thresholding algorithm works by calculating locally weighted averages along lines in an image using recursive filters [6]. The adaptive threshold is useful for pixel classification. The adaptive threshold was chosen because the MRI image data used intensity instead of RGB value for its channel. This intensity value may vary from 0-255. Thus, by employing local threshold such as adaptive thresholding, it is expected to separate the object from the background, as well as separating each boundaries of the brain anatomy. This can be achieved by formulating the threshold surface so that each pixel has its threshold value [17]. The adaptive thresholding defined as the Equation 1 [19]:

$$Th_{Gaussian} = \frac{1}{\sqrt{2\pi\sigma_{i,j}}} e^{\frac{pixel(i,j)\mu_{i,j}}{2\sigma_{i,j}^2}} \quad (1)$$

where:

i = index of column pixels
j = index of row pixels
σ = standard deviation
μ = averages

Table 1 below shows the adaptive thresholding algorithm.

TABLE 1. ADAPTIVE THRESHOLDING ALGORITHM

Adaptive Thresholding
Input: gray_img, i, j, k Output: separate background image and core object of the image

if gray_img (i,j,k) > Th_Gaussian(k)
    image (i,j,k) = (2^nBits)-1
else
    image (i,j,k) = 0;
end

Table 1 shows the adaptive thresholding algorithm. In this experiment, we use adaptive Gaussian thresholding. Gaussian filter is a local filter that smooths images from objects so that they are separated from the sides. This filter removes the high-frequency component from the image. In Gaussian filters, the adaptive threshold depends on the standard deviation value.

C. K-Means Clustering

Segmentation can be carried out using supervised and unsupervised method. K-Means is an algorithm used for unsupervised segmentation methods. The clustering method is advantageous in segmenting using MRI data. Clustering will divide pixels into classes [20]**.** The K-cluster clustering algorithm is commonly used for multi-dimensional data segmentation, which is intended to be approved for variants of vectors assigned to each cluster. The algorithm aims to minimize the objective function known as the quadratic error function as shown in Equation 2.

$$J(V) = \sum_{i=1}^{c}\sum_{j=1}^{c_i}\left\|x_i - x_j\right\|^2 \quad (2)$$

where,

$\left\|x_1 - x_j\right\|^2$= the Euclidean distance between x_i and x_i
C_i = The number of centroids.
C_j = The number of data points.

TABLE 2. K-MEANS CLUSTERING ALGORITHM

K-Means Clustering
Input: *c* (nCluster), $X = \{x_1, x_2, x_3, \ldots. x_n\}$ be the set of data points and $V = \{v_1, v_2, v_3, \ldots. v_n\}$. Output: a set of an image cluster

Begin
  Randomly select 'c' cluster centers
  if centroid found **then**
    Calculate the distance between each data point and cluster centers.
      $D(i) = arg\ min\left\|x_1 - v_j\right\|^2, i = 1 \ldots N$
    Allocate the data point to the cluster center whose distance from the cluster center is a minimum of all the cluster centers
    Recalculate the new cluster center using
      $v_i\ (\frac{1}{c_i})\sum_{j=1}^{c_i} x_i$, Where 'C_i' denotes the number of data points in the cluster.
    Recalculate the distance between each data point and newly obtained cluster centers.
 	
    if no data point was reallocated
      break
    else
      repeat find the centroid
    end if
  end if
end

Table 2 shows the K-Means Clustering algorithm. The first step, randomly selecting the center of the cluster C. Then if the centroid is found successfully, then we calculate the distance between each data point at the center of the cluster. We used Euclidean distance in this study since the data points in the image do not have specific path that needs to be calculated such as in Manhattan distance. Then, allocate data points to the center of the cluster, whose distance from the center of the cluster is the minimum of all cluster centers. Then, recalculate the cluster center and repeat the calculation of the distance between each data point and the newly obtained cluster center. This process will be repeated until there are no data points that is relocated to a different cluster center.

D. Mathematical Morphology

Mathematical Morphology aims to eliminate noise in binary images. The output generated from the Mathematical Morphology process is in the form of images obtained from the reduction of the dilation and erosion results from the original image. This paper uses Opening. The opening is an erosion process followed by dilation. Start by eroding the image, then the results are again undermined. The opening is usually used to remove small and thin objects and can make the edges of the image smoother (for large images).

The opening is a process erosion and followed by dilation as shown in the Equation 3 below:

$$A \circ B = (A \ominus B) \oplus B \qquad (3)$$

Equation 3 shows the equation of morphology opening. $\ominus$ and $\oplus$ denote erosion and dilation, respectively. The erosion of A by B obtains the opening of A by B, allowed by dilation of the resulting image by B. The Morphology opening algorithm can be seen in Table 3 below:

Table 3. Opening Morphology Algorithm

Opening Morphology
Input : $A \circ B \lrcorner A$ Output : $A \circ B$
$A \circ B \lrcorner A$ **if** $A_1 \lrcorner A_2$, **then** $(A_1 \circ B) \lrcorner (A_2 \circ B)$ $(A \circ B) \circ B = A \circ B$ **End**

Table 3 shows the algorithm of morphology opening. The opening is an erosion process that is followed by dilation. The notation A $\lrcorner$ B is used to indicate that domain A is part of B and A (x, y) • B (x, y). The effect that results from the opening morphology is to eliminate small and thin objects, break objects at weak points, and generally smooth the boundaries of large objects without significantly changing the object's area.

E. Dice Similarity Coefficient

Each experiment requires accuracy calculations to measure the proposed method performance. The formula we use to calculate the accuracy values from the tests we do is as follows on the Equation 4:

$$\frac{2|X \cap Y|}{|X| + |Y|} \qquad (4)$$

Equation 4 shows how DSC are calculated. To calculate the DSC for this experiment, we take the number of pixels in the segmentation results (X) that is also in the ground truth (Y).

IV. Result and Analysis

A. Result

In this paper, we apply the adaptive threshold, K-Means Clustering, and mathematical morphology for brain segmentation on MRI data. We use DICOM slices of MRI data. We get data records from hospitals in Indonesia. For this study, we got 54 data in the form of slices of DICOM images. Then, we choose the midsagittal part of each patient, and process it using Python and cv2 library.

1) Convert to Grayscale

The first step in the experiment is to change the DICOM image to the grayscale image so that the image can be processed by thresholding to the next level. The results of converting the DICOM image to grayscale image can be seen in Fig 2 below:

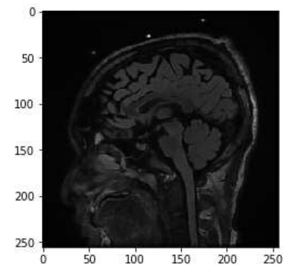

Fig 2. Convert image to grayscale

Fig 2 shows the results of the DICOM image that is converted to grayscale. We change the image that we use to the grayscale images to simplify the next preprocessing step because the image is converted to images with 1 channel.

2) Adaptive Threshold

The next step after changing the image to the grayscale image, we apply the adaptive threshold. Adaptive thresholds are needed to separate the target objects from the background. The results of adaptive thresholding can be seen in Fig 3.

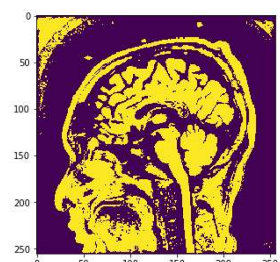

Fig 3. Adaptive Thresholding

Fig 3 shows the results of the adaptive thresholding. We chose to use the adaptive threshold because the adaptive threshold method will be better than Otsu thresholding in separating brain anatomy. Since, adaptive thresholding employs local pixel threshold, instead of global pixel threshold of the image.

3) Largest Connected Component

After getting an image of the adaptive threshold, the picture of the brain will be separated from the skull. We use largest connected components. The results of largest connected components can be seen in Fig 4.

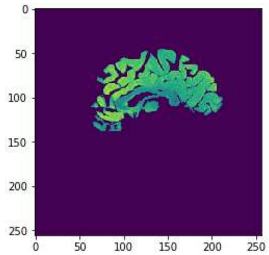

Fig 4. Large Connected Component

Fig 4 shows the results of the large connected component process. Large connected component aims to separate the brain from the skull and take parts of the brain that are connected to each other, so the pixel of the brain image which is the most connected component of the whole image will be separated from the image that is less connected to each other. The results of the largest connected component will facilitate the corpus callosum segmentation process.

4) K-Means Clustering

Since the results of a largest connected component have been obtained, the next step is to apply the k-means grouping. K-Means Clustering is used to divide pixels into classes. The results of K-Means Clustering can be seen in Fig 5.

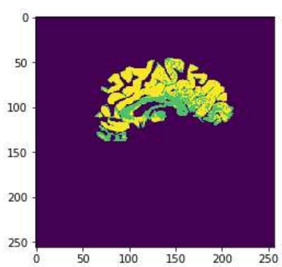

Fig 5. K-Means Clustering

Fig 5 shows the results of K-Means Clustering. This clustering aims to cluster the pixel values that have the closest similarity to each other calculated using Euclidean distance. In this study, we used the pixel values and cluster them into 3 clusters.

5) Get the pixel values of a cluster

After clustering the pixels using K-Means Clustering, we choose the cluster which contains the pixel of corpus callosum in the image. The results of the process can be seen in Fig 6.

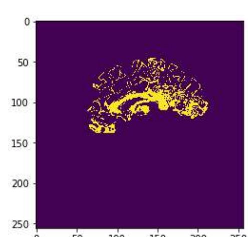

Fig 6. Get the smallest value

Fig 6 shows the corpus callosum produced by our proposed method, along with some small parts. These small parts must be removed so that the corpus callosum is better segmented.

6) Mathematical Morphology

Since we have chosen the cluster that contains corpus collosum pixels in it, mathematical morphology is then applied. We use the morphological opening. The results of the morphological opening process can be seen in Fig 7.

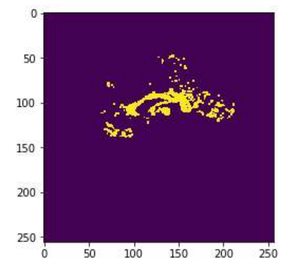

Fig 7. Mathematical Morphology

Fig 7 shows the results of the morphological opening. Mathematical morphology aims to eliminate the remaining noise to get the perfect segmentation results. The opening is an erosion process that is followed by dilation. Start by eroding the image, then the results are again undermined.

7) Segmented Image

After eliminating noise by applying a morphological opening, the segmented image still has noise. Therefore, noise elimination needs to be done again. In this experiment, to eliminate the last stage noise, the large connected component process is used. The results of the second large connected component can be seen in Fig 8 below.

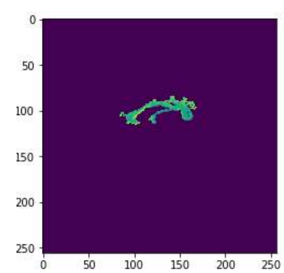

Fig 8. Segmented corpus callosum

Fig 8 shows the results of the second LCC. Since the small part of the brain image have been removed, using LCC in this step will be very reasonable since we get the largest part of the image.

B. Discussion

In this paper, we conducted several experiments on different sample images that are midsagittal part of the brain of random patients selected to segment the corpus callosum. From these trials, we calculated the DSC of each segmentation result. The highest DSC value is 0.773, and the lowest DSC value shows the number 0.728.

Our proposed method employs K-Means as the clustering method which groups the anatomy of the brain based on intensity value of the pixel. Thus, we tried to substitute the method with Fuzzy C-Means as another clustering method and Active Contour Chan-Vese as a contour evolution method. The performance of our proposed method using K-Means compared to other methods can be seen in Table 4.

TABLE 4. DSC VALUES OF VARIOUS METHODS

Method	Mean DSC
Fuzzy C-Means	0.667
Active Contour Chan-Vese	0.721
K-means	0.757

Table 4 shows the results of the DSC values from various method. Using our proposed method, K-means provide the best result. Using active contour Chan-Vese, the segmentation results shows many parts of the brain that does not have a fine boundary will be segmented as part of the corpus callosum. Thus, DSC value of the active contour method is not as good as K-means. Thus, to use active contour Chan-Vese, more preprocessing is needed. Fuzzy C-Means (FCM) in the other hand, uses the probability membership of each data points. Therefore, even if FCM uses Euclidean distance as used in k-means, the result may be different.

V. CONCLUSION

This paper uses adaptive thresholding, K-Means Clustering, and mathematical morphology to brain segmentation in MRI data. Corpus callosum was successfully segmented by applying the method. The preprocessing uses adaptive thresholding because it is considered more effective for pixel classification. K-means is used to determine each pixel cluster. Thus, from those clusters we can find which cluster contain the corpus callosum. Then to remove the remaining noise, morphology opening was applied. We conducted these experiments and compare it to the other method such as FCM and Active Contour Chan-Vese. the results show that k-means used in this study provide better segmentation results compared to FCM an active contour Chan-Vese with mean DSC value of 0.757.

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