Cerebellum and Frontal Lobe Segmentation Based on K-Means Clustering and Morphological Transformation

Rakha Asyrofi
Informatics Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
asyrofi.19051@mhs.its.ac.id

Yoni Azhar Winata
Informatics Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
yoniwinata.19051@mhs.its.ac.id

Riyanarto Sarno
Informatics Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
riyanarto@if.its.ac.id

Aziz Fajar
Informatics Department
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
azizfajar519@gmail.com

***Abstract*—K-means clustering can be used as an algorithm segmentation that can split an area of interest from the image into several different regions containing each pixel based on color. Nevertheless, the result of the color division of the clustering has not been able to display clean segmentation because there are still pixels that connect each other and produce pixel noise or unwanted pixels. In this work, we propose a technique where it can select four dominant colors from the k-means clustering results then display it as digital image output. In our approach, the proposed method can separate the cerebellum and frontal lobe from the background of the brain after several operations of morphological transformation. In implementing this method, three samples of the brain from different people were tested. From the experimental results, the DSI produces a value of 0.72 from 1 for the frontal lobe and 0.86 from 1 for the cerebellum. It means that the proposed method can segment the desired part of the brain properly.**

Keywords— Brain MRI; Brain image segmentation; Morphological transformation; K-Means clustering

I. Introduction

A clustering method aims to group the number of objects into groups so that each cluster that is arranged will contain objects that are as similar as possible. K-means is an unsupervised clustering algorithm method and is widely used to segment brain digital images [1]. It can cluster the data provided in several K clusters [2]. Wei Liu et al. [3] describe that the selection of the number of groups in the k-means method has a significant impact on the results of brain tissue segmentation, especially on the efficiency and accuracy of segmentation factors. Brain tissue can be divided into four classes during the segmentation process. The types are grey matter, white matter, cerebrospinal fluid, and background. Their study also tested, using k-means clustering in which their technique divides the class of brain tissue into 5-10 categories. As a result, four cluster classes are the best of all, so that the number of clusters is the most appropriate to implement. In this study, k-means clustering was applied to divide brain image digital into four cluster classes or regions. From the division process result, the cluster region, which has the dominant area, is selected to obtain the part of the brain that is desired to be displayed.

In the last years, morphological transformation is also widely used to be applied in image processing as part of brain medical image segmentation [4]–[6]. Morphological transformation is a renowned digital image processing operation [7], where it uses a set of mathematical morphological operations. It depends on image shapes based on the features of pixel values, and it is implemented in the form of binary images [5], [8]. Morphological transformation operations require two image inputs. It calls as operands. The first input is the original digital brain image that has not been processed by digital images processing, and the second input is an image of kernel convolution that can be represented in the form of binary numbers. The kernel convolution is a structuring element made of a set of several discrete points for image recognition and analysis. However, the increasing use of morphological transformation encounters noticeable challenges to which operators should be used to get precise segmentation.

Based on k-means clustering, we propose a function where it serves as a color extraction technique from the results of k-means clustering. In our approach, the color divider function selects the four most dominant color and then displays it as an output of image segmentation. Furthermore, with several

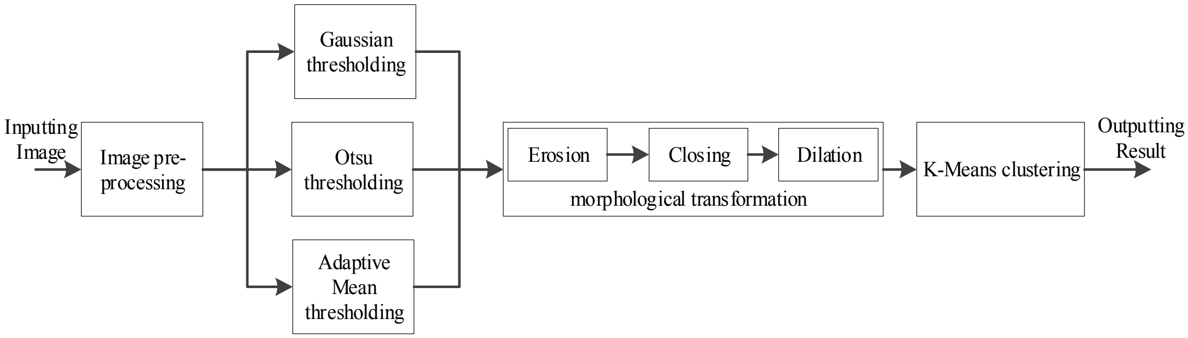


Fig.1. An overview of the proposed algorithm to extract frontal lobe.

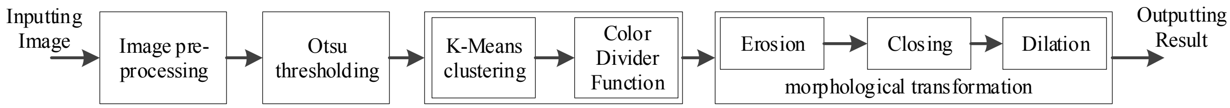


Fig.2. Colour divider function is an algorithm, and it is implemented after a digital brain image is clustered

methods in morphological transformation, the proposed method can segment the Frontal lobe and cerebellum. The Frontal lobe is a part of the brain that functions to help focus, plan something, pay attention to something, and move specific body parts. Meanwhile, the cerebellum is a part of the brain that functions to coordinate body movements. In this study, segmentation has worked on several stages of the method. The methods used include thresholding, morphological transformation, and LCC or Large Connected Component (LCC).

II. Method

A. Thresholding Techniques

Thresholding is an image segmentation method where an object can be separated from the background. It can be categorized into the most straightforward segmentation process. How thresholding works is to convert images into binary images. The result of the image is a greyed-out image. Later, models that tend to be dark should make the intensity value 0, or close to dark. Conversely, colors tend to be bright intensity value is made to 1 or close to be light [9]. Thresholding, besides being called the most uncomplicated process in segmentation, it is also the technique most often used in segmentation [10].

Otsu threshold has been widely used in various studies because it is simple and effective for discriminant analysis dividing the image into background and foreground [9][11]. Other than that, there are also adaptive thresholding where the focus of the problem case is the image has varying illumination, and it uses small areas as threshold deduction. This thresholding is the adaptive mean and gaussian thresholding. In this study, the Gaussian thresholding algorithm can be used for the segmentation of regions of the brain that appear more substantial, such as Frontal lobes. Meanwhile, the Otsu thresholding algorithm can be used for parts of the brain that perform smaller, for example, Corpus Callosum. While the Adaptive mean thresholding algorithm, based on our experiments, has not been able to display the brain without a skull when used for segmenting the original image. For all of them, we use an ellipse convolution kernel because the shape of the kernel matches the shape of the brain.

B. Morphological Transformation

Morphological transformation is a method of processing images using shapes. This method will be useful to use when we target edge detection, which has a lot of noise because of its sensitive nature. In images that have a lot of noise at the edges of the image, this method is more responsive than the classical image gradient for edge detection such as Canny, Sobel, or Laplacian of Gaussian [4]. It is divided into Dilation, Erosion, Opening-Closing, and Gradient [5], [6], [8].

Dilation is a technique for enlarging binary images by extending the edges around an object. Erosion is the opposite of dilation, where erosion will erode the binary image by undermining the edges around the object. Images with binary label one will be narrowed, whereas, for dilation, the opposite applies. Opening and closing are methods that incorporate the dilation and erosion of the same binary elemental image structure. The difference is, the opportunity contains an erosion technique, which is then directly followed by dilation. Meanwhile, closing includes a dilation technique, which is then followed by an erosion technique [5].

C. Largest Connected Component

In image processing, connected components are binary images in the form of black and white pixels. It has the function to distinguish pixels in a picture with the same value. The input image must be converted to a grayscale image, then a binary image scanning process from all pixels is used to different connected components. White pixels will have a value of 1 and are processed, while black pixels have a value of 0 not processed. Pixels with a value of 1 are processed and labeled as the target number. After distinguishing these connected components, the highest dense part is extracted [6][12].

D. Largest Connected Component

K-Means clustering [2] has been applied in this proposed work. In our approach, the initialization of the K center (centroid) cluster is random; it means the cluster centers of the image pixels are given an arbitrary initial value. The proximity of two-pixel objects is determined based on the distance of the two objects using the Euclidean distance, and the length of each data to each cluster center is also calculated. The cluster center is the average of all members of the cluster. The loop should be

executed to run until the entire cluster center cannot be changed. The similarities of the pixel are calculated as the Euclidean distance in this Equation.

$$\boldsymbol{E} = \sum_{j=1}^{k} \sum_{i=1}^{nj} ||\boldsymbol{x}_i^j - \boldsymbol{c}_j||\ ^2 \quad (1)$$

As shown in the Equation (1) above, x_i^j is the *I* pixel in the cluster to *j*, and *cj* is the centroid cluster of *j*. Meanwhile, *k* is the total number of groups, and *nj* is the number of members of cluster *j*.

Algorithm 1: K-Means Clustering

Input: Biner matrix of digital brain image, the number of cluster $K = 4$;
Output: a set of cluster *C* and clusters centroid *P*;

1. Randomly choose *K* pixel from *D* as the initial cluster centroid s;
2. Assign each pixel to the closest cluster on the basis the similarities between the pixels computed by Euclidean distance;
3. Update each cluster centroid as the mean value of the pixels in the cluster;
4. Repeat step 2 and 3 until the centroid stop changing;

Algorithm 2 shows the pseudo-code of the K-means divider function. The input of the algorithm includes seven elements, such as a, b, c, that represent the RGB color and F_1, F_2, F_3, and F_4, that represent the four divider functions. SI is the region of K-means clustering results. Here, k-means clustering could enrich the color. If the *K* gets higher, it means the color the more heterogeneous. F_1, F_2, F_3, and F_4 are sequentially representations

The output of the segmented image consists of the thresholding and morphological transformation, and its implementation can vary according to the results of the segmentation of which part of the brain is desired. To segment, the part of the brain that seems more prominent, K-Means clustering and the color divider functions are implemented at the end of the process after thresholding and morphological transformation method. Meanwhile, to segment the part of the brain that appears smaller such as the cerebellum, we implement K-Means clustering and the function of the color divider after thresholding and before the morphological transformation method.

using the Jupyter Notebook tools that are in Anaconda 3. The programming used in this study is Python 3.0.

Based on Figure 2, It is explained that our contribution to the development method, that starts with image preprocessing. The DICOM file loads it, then continues with how to use the otsu thresholding is better than other thresholding, then It proceeds

of grey matter, white matter, cerebrospinal fluid, and the background.

Algorithm 2: K-Means Color Divider Function

Input: *a, b, c*, F_1, F_2, F_3, F_4, *SI*;
Output: segmented image on RGB;
for all ($SI \rightarrow a, b, c = 0$) do
    if $SI == 0$ then
    $F_4 \leftarrow F_4 + 1$
        $F_1 \leftarrow F_1 + 1$

        $F_2 \leftarrow F_2 + 1$
        $F_3 \leftarrow F_3 + 1$
        $F_1 \leftarrow F_1 + 1$
        $F_2 \leftarrow F_2 + 1$
        $F_3 \leftarrow F_3 + 1$
if (F_1, F_2, F_3, F_4) then
    SI [*SI!* $\rightarrow a = 0$]
    SI [*SI!* $\rightarrow b = 0$]
    SI [*SI!* $\rightarrow c = 0$]
    SI [*SI!* $\rightarrow d = 0$]

To divide colors from the digital brain image processing and then retrieve them, we propose a method called the color divider function. In Figure 1, which aims to extract the region from the frontal lobe, the color divider function is not needed because after the stages of the morphological transformation; it has produced an image segmentation output. Whereas in Figure 4, which aims to extract regions from the cerebellum, a color divider is needed. Figure 1 shows the algorithm that should be applied after the K-Means clustering process to produce image segmentation.

III. Experiment And Analysis

In this study, we used an MRI brain dataset in the form of a Dicom file from different MRI images of three different people. We used samples of 14 slices for each person using a sagittal plane. This plane divides the brain into right and left parts and only takes image slices that show the corpus callosum. The dataset is kept secret due to the privacy and provided by a hospital in Surabaya, Indonesia. Dicom or Digital Imaging and Communications in Medicine is an image data storage format in the medical world. DICOM files will be processed as a matrix

with K-Means clustering to produce color divider. After that Morphological transformation process that consists of erosion, closing & dilation morphology to provide the brain segmentation.

In Figure 3, It is explained how the process is carried from previous research. That starts from taking pictures from the

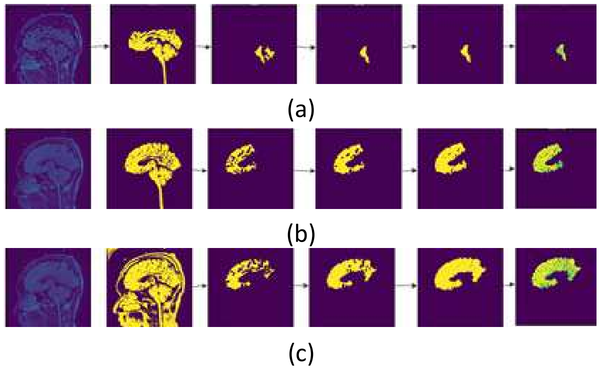
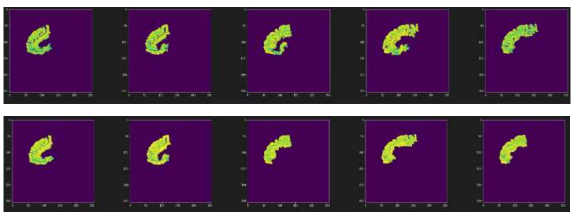


Fig.3. Experiments step number 1 using different thresholding: (a) using otsu thresholding, (b) using gaussian thresholding, (c) using adaptive mean thresholding



DICOM File, then proceeding the operation of various thresholding, starting from otsu, gaussian, and adaptive mean, then proceed with the morphology process, i.e., erosion and dilation process. Then the process of K-means clustering to get color quantization.

A. Experiments of Frontal Lobe Segmentation

We have experimented with frontal lobe segmentation in this section. As shown in Fig.3, we used otsu thresholding, gaussian thresholding, and adaptive mean thresholding. Firstly, the raw image of the brain was turned in to an integer of 8 bits, which contains the number from 0 to 255. After that, the brain image will be the erosion process. The function of this erosion is to erode certain parts of the painting according to the given iteration if given a lot more iterations are eroded. At this stage, we did four iterations. Closing morphology and dilation were added into the step. At this stage, we did one iteration. At the end of the action, we used clustering using K-means clustering and get color quantization in the image. This entire stage uses the ellipse kernel. From this experiment, the following image segmentation results are obtained:

As shown in Figure 3, The 42 slices of brain images were tested for our method for frontal lobe segments. In our approach, K-Means clustering and morphological transformation are suitable for segmenting brain images from the dataset provided, only for certain angles of segmentation that have not got a satisfactory result.

B. The Experiment of Cerebellum Segmentation

The experiment of cerebellum segmentation has done in this section. As shown in Fig.5, we have done the Otsu thresholding experiment and get the connected component using four masks.

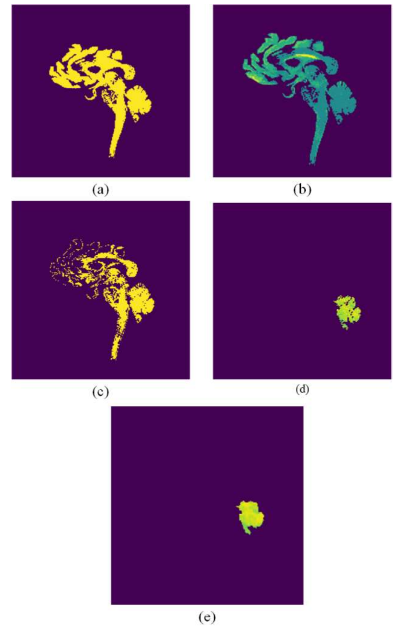


Fig.5. The segmented MRI brain images of cerebellum Cerebellum: (a) brain image withous without a skull, (b) k-means clustering implemented, (c) get the value of smallest region colour, (d) segmented image, (e) dilation operation

The raw image of the brain was turned in to an integer of 8 bits, which contains the number from 0 to 255. After that, we implemented clustering with K-means Clustering. The centroid is three, the number of iteration is 1000, and the number of clusters is four. In this stage, the color divider function should get the group. After clustering, the process was followed with erosion, then closing the brain image. The scene was ended with dilation. This entire stage uses the ellipse kernel. This experiment produced a cerebellum segmentation. From this experiment, the following image segmentation results were obtained:

C. Evaluation

Dice Similarity Index (DSI) is a geometric volumetric similarity measure used to determine the extent of spatial overlap or the degree of overlap of two sets of contours between two images. Based on research from Min Li et al. [6] segmentation that is considered good value will produce a value of more than 0.7 from 1, meanwhile based on previous research in the study of Anantharaman Ayyalusamy et al. [13], it is said that a DSI value of more than 0.8 from 1 is considered as good matching criteria.

$$DSI = \frac{2(S \cap T)}{(|S| + |T|)} \quad (2)$$

Where S is the representation of the gold standard, and T is the segmentation output representation. Meanwhile, $S \cap T$ is the intersection of sets S and T. The DSI score was calculated and analyzed for segmentation output from the frontal lobe and cerebellum.

As shown in Tables I & II of DSI value measure above, the experiments the results obtained differed DSI values for each

TABLE I. DSI VALUE MEASURE COMPARISON OF FRONTAL LOBE

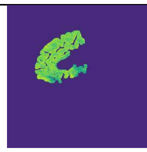
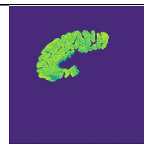
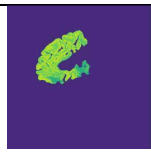
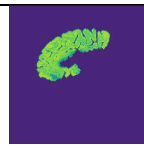
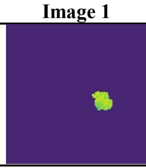
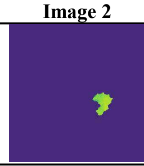
Method	Gaussian Threshold	Adaptive Mean Threshold	DSI
Morphology 1 (Erosion & Dilation)			0.75
Morphology 2 (Erosion, Closing & Dilation)			0.72
DSI	0.99	0.97	

TABLE II. DSI VALUE MEASURE COMPARISON OF FRONTAL CEREBELLUM

Method	Image 1	Image 2	DSI
Otsu threshold			0.86

test. If the image has the same DSI value, the cost will be close to 1; on the other hand, if the image has a different DSI value, the value is close to 0. The amount of DSI in this study can be close to 1 because the comparison between segmentation slices results with other segmentation slices. While a comparison with ground truth cannot be made, this is due to metadata differences that produce pixel calculation values result in the error output. We take the array value of an average brain image pixel of 30. For each pixel-calculation provides several less than 20,000. By comparison, this DSI value can be interpreted that the color dividing algorithm can work on image slices from just a few sagittal planes. In contrast, some slices of other images cannot be segmented yet. As an example is cerebellum segmentation, our approach can only make segmentation of only two of all slabs.

In Table I it is explained that the comparison of the previous method is done by only using morphology 1 (erosion and dilation), while we add the closing morphology in the morphology 2 section. So that it enriches the contours of the image to determine the Frontal Lobe.

While in Table II, we explained that only using otsu thresholding can produce the cerebellum images. While another threshold results were not obtained significantly.

IV. CONCLUSIONS

In this study, we have proposed a method to segment the frontal lobe and the cerebellum of brain image digital based on morphological transformation and k-means clustering. In this approach, the DSI measurement can have a value of 0.72 from 1 for the frontal lobe and 0.86 from 1 for the cerebellum, which is a good result. We have also implemented our method and applied it sequentially to make a precise segment region of the brain.

In the future, we are going to develop better segmentation using other datasets and more experiments, including improving the stages of the segmentation process so it can be adaptive to all types of datasets. By implementing adaptive segmentation, the sagittal plane of the brain's raw image at different angles can produce the output of the part of the brain that wants to be displayed as a result of segmentation.

ACKNOWLEDGMENT

The authors would like to sincerely thank Institut Teknologi Sepuluh Nopember, the Directorate of Higher Education, Indonesian Ministry of Education and Culture, and LPDP through RISPRO invitation Program for funding this research

REFERENCES

[1] L. Jia, M. Li, P. Zhang, Y. Wu, and H. Zhu, "SAR Image Change Detection Based on Multiple Kernel K-Means Clustering with Local-Neighborhood Information," *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 6, pp. 856–860, 2016.

[2] C. Guan, K. K. F. Yuen, and Q. Chen, "Towards a Hybrid Approach of K-Means and Density-Based Spatial Clustering of Applications with Noise for Image Segmentation," *Proc. - 2017 IEEE Int. Conf. Internet Things, IEEE Green Comput. Commun. IEEE Cyber, Phys. Soc. Comput. IEEE Smart Data, iThings-GreenCom-CPSCom-SmartData 2017*, vol. 2018-Janua, no. 2, pp. 396–399, 2018.

[3] J. Liu and L. Guo, "A new brain MRI image segmentation strategy based on wavelet transform and K-means clustering," in *2015 IEEE International Conference on Signal Processing, Communications and Computing, ICSPCC 2015*, 2015.

[4] M. Y. Kamil, "Morphological gradient in brain magnetic resonance imaging based on intuitionistic fuzzy approach," *Al-Sadiq Int. Conf. Multidiscip. IT Commun. Tech. Sci. Appl. AIC-MITCSA 2016*, pp. 133–135, 2016.

[5] D. Selvaraj and R. Dhanasekaran, "Segmenting internal brain nuclei in MRI brain image using morphological operators," *2010 Int. Conf. Comput. Intell. Softw. Eng. CiSE 2010*, pp. 1–4, 2010.

[6] M. Li, X. Zheng, X. Wan, H. Luo, S. Zhang, and L. Tan, "Segmentation of brain tissue based on connected component labeling and mathematic morphology," in *Proceedings - 2011 4th International Conference on Biomedical Engineering and Informatics, BMEI 2011*, 2011, vol. 1, pp. 482–485.

[7] C. Varma and O. Sawant, "An Alternative Approach to Detect Breast Cancer Using Digital Image Processing Techniques," *Proc. 2018 IEEE Int. Conf. Commun. Signal Process. ICCSP 2018*, pp. 134–137, 2018.

[8] J. Angulo and S. Velasco-Forero, "Structurally adaptive mathematical morphology on nonlinear scale-space representations," *Proc. - Int. Conf. Image Process. ICIP*, vol. 1, pp. 121–124, 2010.

[9] H. El Khoukhi, Y. Filali, A. Yahyaouy, M. A. Sabri, and A. Aarab, "Method for Skin Cancer Image Segmentation," *2019 Int. Conf. Wirel. Technol. Embed. Intell. Syst.*, pp. 1–5, 2019.

[10] R. Uthayakumar and A. Gowrisankar, "Generalized Fractal Dimensions in Image Thresholding Technique," *Inf. Sci. Lett.*, vol. 3, no. 3, pp. 125–134, 2014.

[11] C. Sha, J. Hou, and H. Cui, "A robust 2D Otsu's thresholding method in image segmentation," *J. Vis. Commun. Image Represent.*, vol. 41, pp. 339–351, 2016.

[12] E. Hossain and M. A. Rahaman, "Detection & Classification of Tumor Cells from Bone MR Imagery Using Connected Component Analysis & Neural Network," *2018 Int. Conf. Adv. Electr. Electron. Eng. ICAEEE 2018*, pp. 1–4, 2019.

[13] A. Ayyalusamy *et al.*, "Auto-segmentation of head and neck organs at risk in radiotherapy and its dependence on anatomic similarity," *Radiat. Oncol. J.*, vol. 37, no. 2, pp. 134–142, 2019.