Unsupervised Method for 3D Brain Magnetic Resonance Image Segmentation

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***Abstract*— Research at Digital Imaging and Communication in Medicine (DICOM) is very useful research in the field of health. In brain images, the problem encountered is when you want to divide or segment each part of the brain. In previous studies, some of research are still segmenting from 2-dimensional images, where the results will be different for each image slice. Therefore, in this research, we conducted the Magnetic Resonance Image (MRI) segmentation of the brain from the 3-dimensional plane to prevent the information contained in the images from being lost. In the early stages, MRI images will be converted to NifTi format to obtain 3-dimensional volume. The pre-processing is added as a modification from previous research, such as, convert image to grayscale, bias field correction, and skull stripping method to remove the skull (non-brain tissue) so that only brain tissue remains from the human brain. The segmentation process is done using multi-otsu thresholding. The experimental result shows that our method has successfully got three different brain tissue named white matter (WM), gray matter (GM), cerebrospinal fluid (CSF)**

Keywords—DICOM, segmentation, multi-Otsu thresholding

I. Introduction

Research in the medical imagery field is one of the most widely conducted research subjects [4]. And Magnetic Resonance Imaging (MRI) images are one of the most frequently performed. Digital Imaging and Communication in Medicine (DICOM) MRI images are obtained from a machine to obtain images of the human brain. The images of the human brain obtained from MRI are divided into many slices, which are divided into 3 planes [8]. Namely the axial (from bottom to top), coronal (from front to back), and sagittal (from right to left).

Previously, research that had been done a lot was on 2-dimensional MRI brain. Namely by taking one of the slices to be processed. An example is a research conducted by Atikah et al [1]. This study segmented the MRI image by taking one of the planes, namely Sagittal. The method used is filtering, then the largest connected component is carried out to take the brain image, then segmentation is carried out using the unsupervised learning method, namely k-means. However, the disadvantage of using 2-dimensional images is the value carried by each slice is different. And the selection process must be done manually regarding which slice will be used as the initial dataset.

There are several unsupervised methods that can be used for the segmentation process. One of the segmentation methods is threshold-based segmentation [10]. And in general, the goal of segmenting brain tissue is classified brain images into three main tissue classes, which is, white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) [7]. Sakib et al. [2] conducted research on the MRI brain using the Insight Toolkit (ITK) to perform segmentation. The study conducted comparisons of 3 segmentation methods, namely Otsu thresholding, Bayesian classification, and Bayesian Gaussian smoothing. The purpose of this study was to segmented brain images into several parts (WM, GM, CSF). However, in this study researcher said that he did not do any further about preprocessing images. So that this is a weakness of the algorithm of the ITK. Because MRI can be noisy without any preprocessing method [15].

Based on these problems, this research was proposed to segment the 3-dimensional MRI image using an unsupervised approach. This research, it was done by taking the slice from the axial side. Then the conversion is done in the NifTi format to obtain 3D images. The pre-processing is added as a modification from previous research, such as gray-scaling images, bias field correction, and skull stripping method to remove the head bone so that only brain tissue remains from the human brain. The results of the skull stripping will be segmented using multi-Otsu thresholding to get three different brain tissue (WM, GM, CSF).

II. PREVIOUS STUDY

.Atikah et al, [1], using adaptive thresholding, K-means at clustering phase, and morphological operation to segmenting the brain in the corpus callosum. The adaptive threshold is used in the preprocessing phase of brain images. The purpose of adaptive thresholding is to make the skull stripping much easier. After pre-processing and get the brain, k-means is performed to divide the parts of the brain to be segmented, namely the corpus callosum. Then the noise in that phase is removed using mathematical morphology.

Sakib et al. [2] compare segmentation methods on brain tissue (GM, WM, CSF) using 3 methods, namely Otsu thresholding, Bayesian, Bayesian plus Gaussian smoothing. The brain dataset was tested one by one on the methods available at ITK. The results obtained are quite good. And CSF is the important point. In Otsu thresholding, brain tissue segmentation in CSF is superior to the other 2 methods.

Despotovic et al. [6] discuss various method to do segmentation on brain images. They use preprocessing techniques such as bias field correction, image registration, removal non-brain tissue, or many researchers call it skull stripping. And then, they also discuss MRI segmentation methods such as manual segmentation that have been done by experts, intensity-based methods (Threshold, region growing, clustering, classification), atlas-based method, surface-based method, and hybrid methods. For segmentation evaluation, this paper also mentioned Tanimoto coefficient and dice similarity coefficient.

III. RESEARCH METHODOLOGY

This research was conducted with the aim of segmenting several parts of the human brain on MRI images. The data used is DICOM data which consists of 500 slices from various planes. The programming language used in this research is Python. A general description of the methodology is shown in Figure 1.

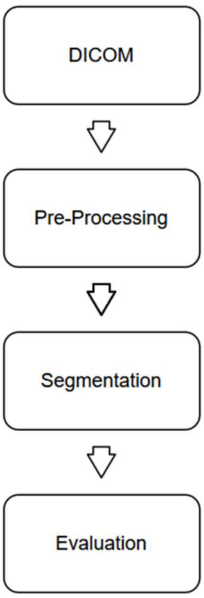


Figure 1 Research Methodology

Figure 1 describes the steps in this study. the first step is to take a image dataset. After that, the data was converted to NifTi. Then the skull stripping is done to remove the skull and leave only the tissue image of the brain. The brain images are then segmented to obtain tissue which is divided into three part (WM, GM, CSF). And CSF will be used as a dividing border to separate brain structures.

A. Dataset DICOM

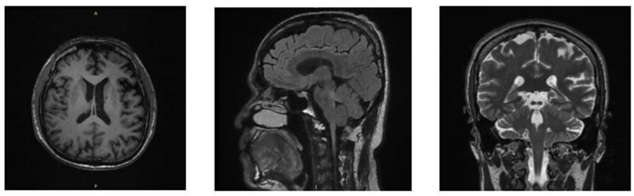
In this study, the data used were DICOM data obtained from National Hospital Surabaya. We used 2 datasets which were scanned from 2 people. Let us call it dataset A and dataset B. In the dataset, there is an MRI scan containing brain images from various planes, namely sagittal, coronal, axial. The size of each slice is 256 x 256 pixels. On MRI scan, there are several metadata used to build 3D volumes defined in Table 1.

TABLE 1 DICOM METADATA

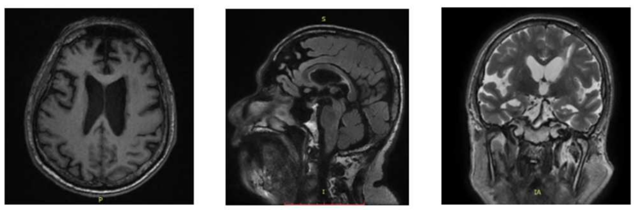
Tag	Name
(0028, 0010)	Rows
(0028, 0011)	Columns
(0028, 0030)	Pixel Spacing

Rows and Column use to defined 2 dimensional images for the X-axis and Y-axis, and Pixel Spacing for the Z-axis to perform 3D image. However, what we will process is from the axial side. An example of this dataset A and datsaet B is shown in Figure 2.

From figure 2, it is known that there is an image that is defined as the brain tissue, and there is an image that is designated as bone. The next process is to take an image of the brain with the skull stripping.



(a)



(b)

Figure 2 MRI dataset from axial plane, sagittal plane, and coronal plane in dataset A (a), and dataset B (b)

B. Pre-Processing

Preprocessing is the first step to removing irrelevant data [14] and also to improve the quality of the image to make processing much easier. There are several steps to performing pre-processing images such convert to grayscale, bias field correction, and skull stripping.

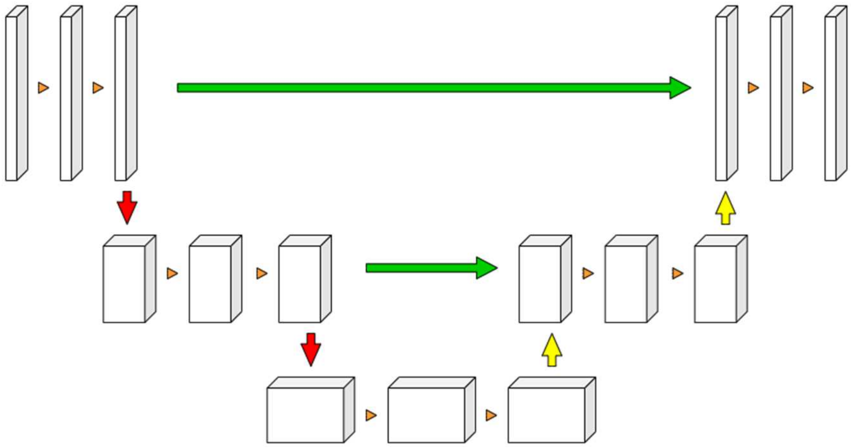


Figure 3 3D U-Net Architecture

1) Convert to Grayscale

The first step of the pre-processing image is gray-scaling. The main purpose of gray-scaling is to convert images into 1 channel so that it is easy to carry out to the next process. This 1 channel will only store pixel values from a range of 0 – 255.

2) Bias Field Correction

Bias field correction is the step to removing intensity inhomogeneity that coming from the magnetic field, sensitivity variation of the coil, and interaction between human and magnetic field [9]. Bias field correction also makes the difference of brain tissue clearer.

3) Skull Stripping

Skull stripping is performed to remove bones from the head. The purpose of the skull stripping is to simplify the next segmentation process, leaving only brain tissue [8]. At this stage, it is done using the open-source python code called deep-brain from PyPI online python repository. It uses a convolutional neural network based on 3D U-Net. The 3D U-Net architecture can be seen in figure 3.

Figure 3 explains that in the 3D U-Net architecture there are several stages. There are 4 types of arrows (orange arrow, red arrow, yellow arrow, and green arrow), each of which represents the convolution process, max pooling, upsampling, and concatenation from each step. The convolution process is carried out with a kernel size of 5 and using the activation function named Rectified Linear Unit (ReLU). The process of convolution itself will increase the depth of the images. So the image is getting thicker. Max pooling, reduces image size by half because it taking the important feature of the image. In the upsampling phase, the image size is expanded and concatenation is then carried out from the previous phase.

This model trained with already segmented brain images (CC359 dataset, NFBS dataset, and ADNI dataset). This training process produces weight and bias value that saved on pb file format. So, this model performed segmentation of brain tissue using the probability of each image voxel to generate brain masking. The voxel is selected based on probability which larger than same p (0.5 as default)

C. Segmentation

Thresholding is commonly used in image segmentation, both in medical [1,12] or non-medical [10]. And the popular one is Otsu thresholding. In this segmentation section, Brain data that previously passed the skull stripping stage will be segmented using multi-Otsu thresholding. Otsu [11] mention that multi-Otsu thresholding is a renewal of thresholding that can accommodate more than 1 threshold. This method, maximizing variance between classes to obtain an optimal threshold [13]. Multilevel threshold is good to segment the image brightness into several regions [10], which correspond to several objects and background. The method works very well for objects of various colors. On which bi-level thresholding fails to produce satisfactory results. For example, in the case of 4 class, it is assumed we have 3 thresholds: $1 <= t_1 <= t_2 <= t_3 < L$, to separate 4 classes, C0 for $[1, ..., t_1]$, C1 for $[t_1 + 1, ..., t_2]$, C2 for $[t_2 + 1, ..., t_3]$, and C3 for $[t_3 + 1, \ldots, L]$. Then the interclass variance is maximized by using the equation (1).

$$\sigma_B^2(t_1^*, t_2^*, t_3^*) = \max_{1 \le t_1 \le t_2 \le t_3 \le L} \sigma_B^2(t_1, t_2) \quad (1)$$

Where :

σ = variant of each class

L = level of each pixel

t = level of a specified threshold.

Table 2 show the basic algorithm of multi-Otsu thresholding.

This multi-Otsu thresholding will be used to segment the brain tissue to obtain WM, GM, and CSF. The goal is to get the brain structure (WM and GM), and the border (CSF) that is used as the basis of segmentation.

TABLE 2 MULTI-OTSU THRESHOLDING ALGORITM

Multi-Otsu Thresholding
Input : gray_images (a,b,c) **Output :** image with 4 main class (background, WM, GM, CSF)
If gray_images (a, b, c) < t_1 gray_images (a, b, c) = 0 **If** gray_images (a, b, c) < t_2 and If gray_images (a, b, c) > t_1 gray_images (a, b, c) = 1 **If** gray_images (a, b, c) < t_3 and If gray_images (a, b, c) > t_2 gray_images (a, b, c) = 2 **Else** gray_images (a, b, c) = 3

D. Evaluation

Evaluation of segmentation process is done using dice similarity coefficient (DSC). DSC, also known as the Dice coefficient, is a tool with based on statistical method that measures the similarity from two sets of data [4]. This the most popular tool to validate the algorithms of image segmentation. Not only the image, but this also can be applied with several dataset and application including natural language processing. The DSC formula is defined (2).

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

Where :

X = set 1

Y = set 2.

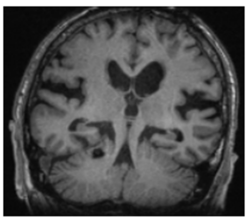
A set with vertical bars either side refers to the cardinality of the set, i.e. the number of elements in that set, e.g. |X| means the number of elements in set X. ∩ is used to represent the intersection of two sets, and means the elements that are common to both sets.

IV. RESULT AND ANALYSIS

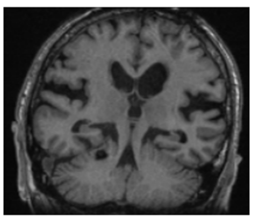
A. Pre-Processing

In the first stage, images are converted into grayscale with the range of pixel values between 0 – 255. This will make the image easy to process. The second step is performing bias field correction. Bias field correction is done to remove the magnetic field to make brain tissue clearer. The bias field result can be seen in figure 4.

After that, skull stripping was performed on the dataset. the purpose of this process is to get a brain image for further processing. The skull striping is done using 3D U-Net from the previous section. the results of skull stripping can be seen in the figure 5.



(a)



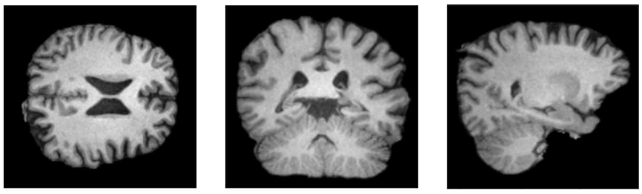
(b)

Figure 4 Brain image with bias field (a), and without bias field

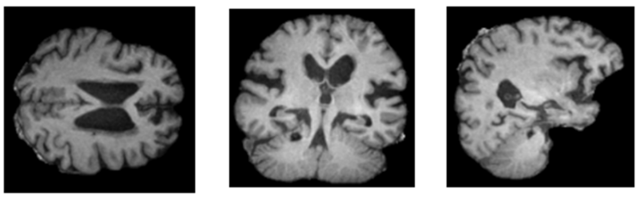
Figure 5 Brain Masking

The figure 5 shows the result of the skull stripping. From this process, we get a mask whose size matches the size of the brain in the DICOM dataset. This mask contains a Boolean value, True and False. White region on the brain has True Boolean value, and the black region has False Boolean value. Furthermore, the mask will be fit to the original brain images. The results of applying masking to the brain can be seen in the Figure 6.

From figure 6, we can see that the brain mask is fits with the brain image to get only the brain images. After this step, non-brain tissue is removed from the brain image, only the brain tissue remain.



(a)

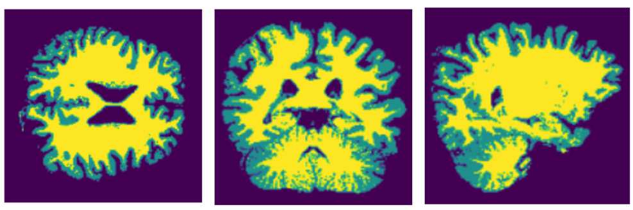


(b)

Figure 6 Applying Brain Masking to dataset A (a), and Dataset B (b)

B. Segmentation

In general, segmentation of the MRI brain image is done to obtain brain tissue. Brain tissue is divided into 3 main parts, namely gray matter (GM), white matter (WM), cerebrospinal fluid (CSF). at this stage, it is done by using multi-Otsu thresholding. The results of this stage can be seen in the Figure 7.



(a)

(b)

Figure 7 Result of WM, GM, CSF dataset A (a), and dataset B (b)

Figure 7 shows that the brain has been divided into several regions based on the threshold results. the yellow region is WM, the blue region is GM and CSF.

V. CONCLUSION

This paper uses an unsupervised approach to segment the brain images from MRI data. Three parts of brain tissue such as WM, CSF, GM were successfully segmented by this method. The preprocessing process is done by grayscaling to make the segmentation process easier by changing the pixel value to 0 - 255. Skull stripping using 3D U-Net is used to eliminate non-brain tissue to prevent segmentation error. And then, multi-Otsu thresholding is used to separate the three brain tissue classes.

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