Automated Identification and Reconstruction of 3D Images on the Mastoid Air Cell System

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Abstract – The mastoid air cell system (MACS) protects the structures in the ear and regulates air pressure in the ear cavity. MACS segmentation is very difficult because of the many overlapping object characteristics in the temporal bone. This study aims to accurately identify and measure MACS areas from CT-scan images of mastoiditis patients. The data tested consisted of 128 CT images from 13 different patients. Images were taken using the Siemens SOMATOM Perspective CT Scanner model 10662260 axially. The extended Adaptive Threshold (eAT) method was developed to produce optimal threshold values for each test image. Furthermore, the eAT results are used to convert the test image into a binary image and then applied to the identification and extraction model automatically for reconstruction from 2D to 3D images. Smaller MACS sizes indicate inflammation of the mastoid bone and require intensive care. Thus, this research can be used to help doctors make the right decisions in carrying out further medical actions.

Keywords – Mastoid air cell system, CT-scan, extraction, reconstruction.

1. Introduction

The application of information technology in medical image processing has had a significant impact on medical experts in diagnosing and taking treatment.

The mastoid air cell system (MACS) protects the structures in the ear and regulates air pressure in the ear cavity [1]. Mastoiditis is caused by an infection that occurs in the cavity of the mastoid bone, thus affecting the size of the MACS of the temporal bone [2], [3]. This infection can spread to all surfaces of the temporal bone and is difficult to identify due to the overlapping surfaces [4], [5] so a digital image processing process is needed to overcome this problem.

The role of image processing in the medical field is currently very important in clinical diagnosis. Image processing can carry out a treatment plan, evaluation, and prediction of the development of a disease. These developments are presented in medical information technology media such as magnetic resonance imaging (MRI) or computed tomography scans (CT-scan). To support the examination of mastoiditis, patients carry out medical examinations through X-Ray technology such as MRI or CT-scan of the temporal bone [6]. Temporal CT-scan is a radiological examination to obtain a cross-sectional view of the mastoid anatomy [7].

Visually the information contained in the mastoid CT-scan image has helped medical experts in determining the MACS area, but in fact, it is difficult for medical personnel to determine the surface area of the MACS area. This is due to several objects that have different characteristics and overlap, making it difficult to segment the MACS area [8]. For this reason, accurate and precise image analysis is needed in measuring the MACS surface area.

Until now, there have been many studies to detect MACS sizes both normal and abnormal, including segmenting and calculating the surface area of MACS in the inner ear cavity using Image Enhancement, Image Filtering, Feature Extraction, and Skeleton Image methods on CT-scan images [9]. Research in calculating the threshold value to measure the volume and surface area of MACS based on pixel intensity using Hounsfield Unit (HU) [10]. Furthermore, the research develops automatic segmentation in identifying critical temporal bone structures with image enhancement methods and feature regions on temporal bone CT-scan.
This research results in automatic segmentation providing more precise identification than manual segmentation [11], [12]. In another study, automatic segmentation of the temporal bone structure of the micro-section of CT-scan images used method of morphological enhancement to improve image quality and Convolutional Neural Network (CNN). This research resulted in good segmentation accuracy on temporal bone structure image [13]. Subsequently, a CT-scan of the ear area was reconstructed using the global thresholding and feature region segmentation method [14]. 3D reconstruction is very necessary in providing an overview of surface conditions and area volumes as well as facilitating the process of image acquisition and analysis [15], [16].

The number of other objects that are displayed visually on the temporal bone CT-scan and the varying results of taking pictures such as the position of the shooting area, color, and brightness level [17], for this reason it is necessary to process the image and separate the objects to be identified from the input CT-scan images not required with the image segmentation method [18], [19]. The results of the automatic identification of the MACS, then a feature extraction process is carried out which aims to analyze the characteristics of the image in finding object features [20], [21], furthermore that the results of this image extraction process are used to measure the area of the MACS pixel area on each slice of each test image. This research produces image reconstruction from 2D images into 3D images to obtain the average MACS volume by combining several image slices of each patient from the image extraction process.

2. Method

The image used as the input image is a grayscale image, still having a background and information that is not needed for further processing (noise) and makes it difficult for the segmentation process, extraction and calculation of the area and volume of the MACS, then it is done separation of unnecessary information by the cropping process.

In building a processing system for MACS identification on temporal CT-scan images of patients, a research method is needed which consists of the extended Adaptive Threshold (eAT) method which is applied to the MACS identification model to obtain MACS identification automatically as shown in Figure 1.

3. Results and Discussion

In identifying the MACS there are several stages of image processing are required. The initial stage is by inputting the Mastoid CT-Scan image, then it is processed in the pre-processing stage to improve image quality. The results of the pre-processing stages are used for image segmentation in taking the image object to be examined and eliminating other objects. The resulting eAT segmentation results will be a continuation of the extraction process. The results of the image extraction process, then a 3D image reconstruction is carried out to calculate the volume using the slice interpolation technique.

3.1. Original Image

The original image is used as data input in the form of an axial CT-scan of the temporal bone which consists of a collection of data obtained from a CT-scan with the specification Siemens SOMATOM Perspective model 10662260 X-Ray Tube 688-MV, where the conversion of the value of each pixel = 0.29 mm in RSU M. Djamil Padang, West Sumatra, Indonesia.

The dataset used in the test consisted of 13 patients with 128 slices of grayscale images in 1105x649 pixels size saved in the format *.jpg from the syngo® fastView, shown in Figure 2.
The input image presented in Figure 2, consists of many objects in the temporal CT-scan that have the same characteristics. The picture shown on the right shows MACS which is still in shape and normally black in color, while the MACS area on the left is not shaped due to infection. In this study, only one test image slice was presented out of 128 image slices with 13 different patients for MACS area segmentation, extraction, and reconstruction as well as calculating MACS volume.

3.2. Cropping Image

The image from the temporal CT-scan has many characteristics of the object displayed, it is necessary to separate the MACS area from the CT-scan input image that is not needed so that it can be processed for further processing. To eliminate these objects so that it is easier to identify MACS, a cropping process is needed on the temporal image. The cropping method is a technique for separating objects that are carried out vertically and horizontally [22], which aims to remove noise that is not needed for further image analysis [23]. The image cropping process algorithm in the form of an ellipse can be seen in Algorithm 1.

![Figure 2. One of the temporal CT slices of the original image set](image)

**Algorithm 1: Ellipse Cropping**

**Function** Mx, Px, Bx  
**Input:** Im (y, z)  
**Initialization** // Calculate sum the size and intensity pixel  
[m, n, l] = size (Im)  
p = 0  
Im1(1:m, 1:m) = 0  
C = size (Im)/2  
[y, z] =Mx (1: size (Im, 2), 1: size (Im, 1))  
Im1 = (n (2) * (y – c (1)).^ 2 + n (1) * (z – c (1)).^ 2 <= Px(p))  
Img = Bx (Im1)  
**Output:** Img (y, z)

At this stage, the results of the cropping process get an area of interest so that areas that are not needed outside the Region of Interest (ROI) studied are removed before the segmentation process is carried out. The results of the cropping process can be seen in Figure 3.

![Figure 3. Results of Cropping Image Process](image)

The results are presented in Figure 3, some objects and information that are not needed have been removed. From this cropping process, objects that are outside the ROI that are not needed for further analysis will be removed, so that a region of interest is obtained for analysis at the next stage. The results of this process emphasize the object to be analysed in the image even though there are still other objects that are not needed for further analysis.

3.3. Filtering Image

This stage aims to adjust the pixel values that can affect the quality of an image. The difference in the value of each pixel with neighbouring pixels that is too large will affect the image quality [24], [25]. The results of the filtering process can improve image quality to be processed and analysed at a later stage. The image filtering process algorithm is presented in algorithm 2.

**Algorithm 2: Filtering Image**

**Input:** Img (x, y)  
**Output:** Imagef (x, y)  
**Initialization**  
Get mC, mK  
Imagef= mC ⊗ mK

3.4. Image Segmentation

MACS detection is obtained through a segmentation process to get the desired area ROI [26], [27]. This stage aims to separate the object into several segments from a set of pixel values [28] by calculating the optimal threshold value automatically for each test image.
The optimal threshold value is obtained by calculating the colour intensity level value from histogram normalization divided by the number of unique pixel intensity values from the test image with the development of the extended Adaptive Threshold (eAT) method. Furthermore, the results of this eAT are used to convert the filtered image into a binary image, so that it can perform segmentation by separating the objects to be analysed in the next stage, namely for MACS detection and detection of other objects in the Axial Section Temporal Bone image. This method is applied to an image processing model that is interconnected in automatic MACS identification, where the MACS area is smaller than normal limits indicate an infection in the mastoid bone cavity. In calculating the optimal threshold value with the eAT method for each image tested, it is presented in the form of an equation (1).

$$eAT = \frac{\sum_{i,n} k_h \cdot h_i}{\sum_{i,n} p_i}$$  \hspace{1cm} (1)

Equation 1 is the process of calculating the optimal threshold value used to analyse each input image by developing the eAT segmentation method. $\sum_{i,n} k_h \cdot h_i$ is the total number of all pixel value intensities on the grey degree scale against the normalized histogram value $i$. This result is divided by $\sum_{i,n} p_i$ which is the sum of the unique values of the pixel intensity with a pixel scale value of 0-255. The stages of the eAT segmentation process are presented in Figure 4.

The next process is to change the filtered image into a binary image. The binary process uses the development of the eAT method to obtain the optimal threshold value, where the value of each pixel is changed to 1 (one) if it has a value equal to or more than the optimal threshold value, while the value below the optimal threshold is changed to a value of 0 (zero). The results of the stages of the eAT process are presented in Figure 5 with the optimal threshold value obtained 61. The results of this stage separate the object as the foreground from the background and this result still contains noise in the image which is spread irregularly.

### 3.5. MACS Identification

From the results of the process described previously, showing the change from the original image to the cropped image, then from the cropping image, a binarization process is carried out with the development of the eAT method, then the MACS detection process is carried out by separating the area in the temporal bone from some objects in the image that are not needed. The results of the MACS identification process can be seen in Figure 6.
The results of the process presented in Figure 6(a) have removed the noise from the image. After that, the image reverse process is carried out from the Identify Image (OI) object and Boundary Object Image (BOI) images, where the pixel value of the image with a value of 1 is changed to 0 and the pixel value of 0 is changed to 1 as shown in Figure 6(b). The results of this process emphasize the objects contained in the identified images as presented in Figure 6(c).

3.6. MACS Object Extraction

The results of the segmentation and morphology processes are carried out by extracting the necessary objects to obtain characteristics that can distinguish an object from other objects in the image. To find the characteristics of an object MACS image on a CT-scan of the temporal bone, an extraction process is needed by looking at the characteristics of MACS on the CT-scan of the temporal bone. These characteristics can be calculated based on the area and circumference of the object obtained from the results of the previous segmentation process [29]. MACS extraction results are presented in Figure 7.

3.7. MACS Image Reconstruction

Image reconstruction is a collection of several slices of 2-dimensional (2D) images which are transformed into 3-dimensional (3D) images. Analysis of 2D medical images often occurs in errors and requires a long process of image analysis [30]. The 3D image reconstruction process algorithm is presented in Algorithm 3.

Algorithm 3: 3D Reconstruction Image

\[ \text{Input: } \text{Img} (y, z) \]
\[ \text{Input: } \text{A} (y, z) \]

\text{Initialization}
\begin{align*}
\text{Get} & \quad \text{NI}=10; \text{NA}=1; \text{Vol}=0; i=1; \text{NB}=\text{NI}-\text{NA}+1 \\
[m, n, l] & =\text{size} (\text{Img}) \\
\text{for} & \quad i = \text{NA} \text{ to } \text{NI} \text{ do} \\
\text{Vol} & = \text{i: img} \\
\text{end for} \\
\text{Output: } & \quad \text{Img} (y, z)
\end{align*}

The results of image extraction from the eAT process are applied to the automatic identification model, then used for the 3D image reconstruction process which consists of 10 image slices. The reconstruction stage is carried out by combining several image slices obtained from the MACS extraction. The process of image reconstruction from 2D to 3D is done using interpolation. Interpolation works by using known data to estimate values at unknown points. The purpose of image reconstruction is to obtain the MACS volume identified by connecting the image points from several image slices. The results of the 3D image reconstruction can be seen in Figure 8.

Figure 7. MACS object extraction

Figure 8. MACS 3D image reconstruction process
(a) Image merger illustration, (b) MACS 3D image reconstruction results
The reconstruction results are presented in 3D images for the volume of the MACS which consists of 10 (ten) slices, where one slice and the other are arranged with the interpolation technique as presented in algorithm 3 and can be shown by MACS visualization. Figure 8 shows the results of a 3D image reconstruction for a MACS volume of 5.63 cm$^3$ which consists of ten slices, where one slice after another is arranged together and can be displayed visually the surface area of the MACS. The results of calculating the surface area and volume of MACS are presented in Table 1.

Table 1. MACS area and volume calculation results

<table>
<thead>
<tr>
<th>Slice of Image to</th>
<th>Pixel Area (px)</th>
<th>Large of Area (cm$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slice-1</td>
<td>3040</td>
<td>8.816</td>
</tr>
<tr>
<td>Slice-2</td>
<td>2827</td>
<td>8.198</td>
</tr>
<tr>
<td>Slice-3</td>
<td>2657</td>
<td>7.705</td>
</tr>
<tr>
<td>Slice-4</td>
<td>2399</td>
<td>6.957</td>
</tr>
<tr>
<td>Slice-5</td>
<td>1992</td>
<td>5.777</td>
</tr>
<tr>
<td>Slice-6</td>
<td>1681</td>
<td>4.875</td>
</tr>
<tr>
<td>Slice-7</td>
<td>1388</td>
<td>4.025</td>
</tr>
<tr>
<td>Slice-8</td>
<td>1229</td>
<td>3.564</td>
</tr>
<tr>
<td>Slice-9</td>
<td>1143</td>
<td>3.315</td>
</tr>
<tr>
<td>Slice-10</td>
<td>1040</td>
<td>3.016</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>56,248</strong></td>
<td><strong>5,625</strong></td>
</tr>
</tbody>
</table>

The results in Table 1 show that MACS OII was identified with very good accuracy, this is indicated by the correct MACS surface area. The identified surface area can be used to calculate the MACS volume. MACS volume size, which is smaller than the normal size indicates inflammation of the mastoid bone and requires intensive care. Thus, this research can be used to help doctors make the right decisions in carrying out further medical actions.

4. Conclusion

From the results of processing the axial CT-scan of the temporal bone, it produces very good results for automatic identification of the MACS area. From the identification results, extraction was carried out to calculate the MACS area in pixels, where from the test image data consisting of 10 image slices for each patient, the smallest MACS area was 3.016 cm$^2$ and the largest was 8.816 cm$^2$. Furthermore, reconstruction and visualization of 3D images from the results of 2D image extraction is carried out by combining several image slices for each patient to get the average volume. The results of the 3D reconstruction visualization and the volume area of the image data that have been analyzed obtained an average MACS volume of 5.625 cm$^3$. The results of this volume calculation can assist doctors in making quick decisions in carrying out further medical actions.

References


