GRID APPROACH FOR X-RAY IMAGE CLASSIFICATION

Bertalya [1], Prihandoko [2]
[1,2] GunadarmaUniversity
Jl. Margonda Raya 100, Pondok Cina
Depok 16414 - Indonesia
bertalya@staff.gunadarma.ac.id [1], pri@staff.gunadarma.ac.id [2]

ABSTRACT

The process of medical image classification is still carried out manually using the knowledge of the physician or radiologist, which leads to inaccurate and slow process of object identification. Thus, we need an automatic system that can classify medical images, accurately and faster from query images into one of the pre-defined classes.

In this research, we are dealing with the classification of medical image to the image classes that are defined in the database. We focus on using the shape of X-ray image to carry out the classification process and to use the Euclidean distance and Jeffrey Divergence techniques to measure image similarity. In this paper, we use a grid approach to simplify the shape of X-ray images to obtain a better recognition rate. Our experiment shows that this approach gives a higher recognition rate.

Keywords : grid, classification, x-ray image, similarity

1 INTRODUCTION

The large amount of digital images produced in hospitals requires an automatic mechanism to store and retrieve images from database. This system can be used to group the images into some categories.

At present, the process of classification is still carried out manually using the knowledge of the physician or radiologist, which leads to inaccurate and slow process of object identification. To solve this problem, it needs an automatic system that can classify medical images, accurately and faster from query images into one of the pre-defined classes.

A number of researchers have proposed various methods to deal image classification [1,2,3,4,5,6]. In IRMA (Image Retrieval in Medical Applications) project [1,2], a classification is an important step for content-based image retrieval. This step aims to determining the imaging modality and it's orientation as well as the examined body region and functional system for each image query. A detailed classification scheme has been developed to encode medical images according to their contents.

According to [1,2,3,4], classification of medical images means the grouping of medical images into a predefined image class. Jain [7] defines an automatic classification is like a mapping of images into their classes. This involves three basic principles: (1).representation, i.e. the extraction of appropriate features to describe the image content. Feature extraction is the process of calculation and extraction of the image features, such as color, texture, shape and spatial information. A set of global features is combined to a feature vector. A global feature means that only a small number of numerical values are used to describe the entire image. (2) adaptation, i.e. the selection of the best feature subset regarding discriminative information, and (3) generalization, i.e. the training and evaluation of a classifier.

Most of the researchers in the medical images use the texture feature to classify the medical images. Texture feature is used to describe the characteristic of the entire image or region of interest of an image by extracting structurally and statistically [8].

Paredes [6] proposed classification method by using local representations of medical images, which are small square windows taken from the images. He could classify 1617 images with a leaving-one-out procedure and reported an error rate of 8 %. The advantage of this method is that it used only few parameters in computation. But, it took too many overlapping local representations for each image that leads to complex computations.

Pinhas and Greenspan [5] proposed a classification method by representing the radiological images in blobs. Blob is extracted from the image based on 4 features, i.e. intensity, texture, spatial information (x, y). They reported an error rate of 1% to classify 851 radiological images into eight classes by using a leave-one-out procedure. The advantage of this method is an objective object representation which each blob represent each part of the object image, but this blob, probably is not relevant to classify the X-ray image.

Lehmann and Guld in IRMA project [3,4] classified 6231 images to 81 categories by rescaling representation of the images and obtained a recognition rate of 76 % using a 1-NN algorithm. The recognition rate increased to 85 % using parallel combination; Tamura texture and Image Distortion Model (IDM). However, due to the texture extraction globally on the X-ray image, the method could calculate an irrelevant pixel.

In this paper, we propose an X-ray image classification by implementing a transformation process utilizing Freeman Code to represent the shape of an image. To improve the accuracy and to speed up the process, we proposed the use of grid. This grid approach is significant in accelerating the recognition rate.

In addition, the process of image similarity measurement uses Euclidean distance and Jeffrey Divergence techniques [8].

2 THE PROPOSED METHOD

The process of X-ray image classification consists of six stages, i.e. object segmentation, identification of the object boundary, transformation using grid approach, representation using Freeman Code, calculation and matching process, as shown in Figure 1.

2.1 Object Segmentation and Identification

A segmentation process is a process where the goal is to obtain the region of the object by separation the region of the object from its background. Actually, our goal is not to have the region of the object but a boundary of the object.

This segmentation process is performed by following the five steps; thresholding, edge detection, dilation, filling, erosion and cleaning. Thresholding is a conversion from a monochrome image to a binary image. The technique of thresholding is based on the histogram defined by Otsu [9]. Then, the edge of the image object is identified by using Canny operator to obtain the lines of the border of the object, as shown in Figure 2.b. Canny operator is chosen from the other operators, because this operator can detect more lines of the border of the object.

The result of edge detection, which is in binary image, will then be dilated by using the morphological image processing concept [9]. This process aims to dilate the lines so that between one line and the others can be merged to be one object boundary, as shown in Figure 2.c.

Then, the hole that appeared inside of the object boundary is filled by applying the filling and cleaning processes to obtain the entire region of the object [9]. The result of this process is shown in Figure 2.d.

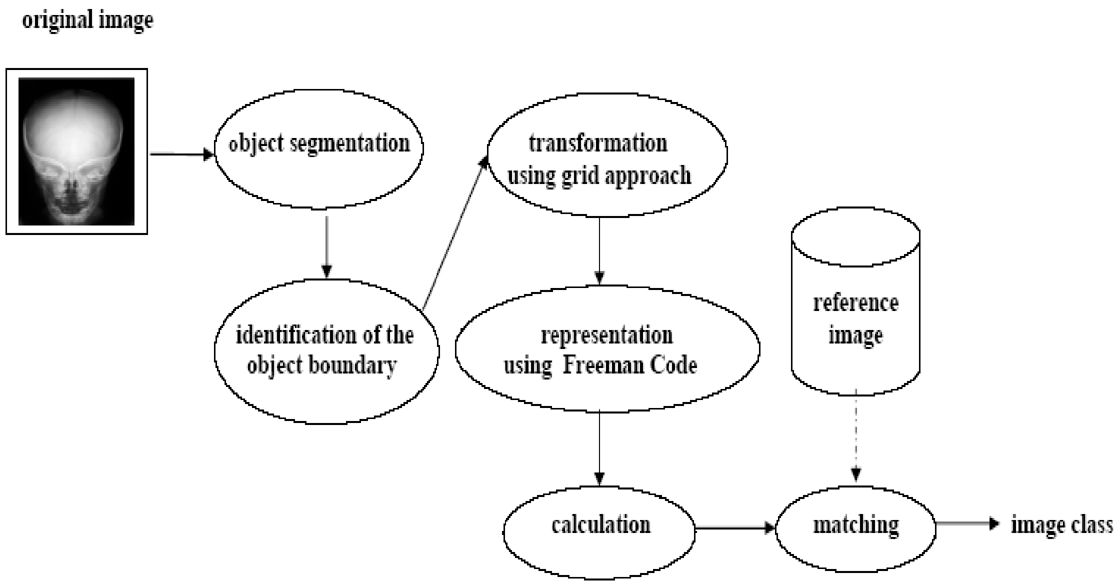

Figure 1. Schema of classification method using grid approach

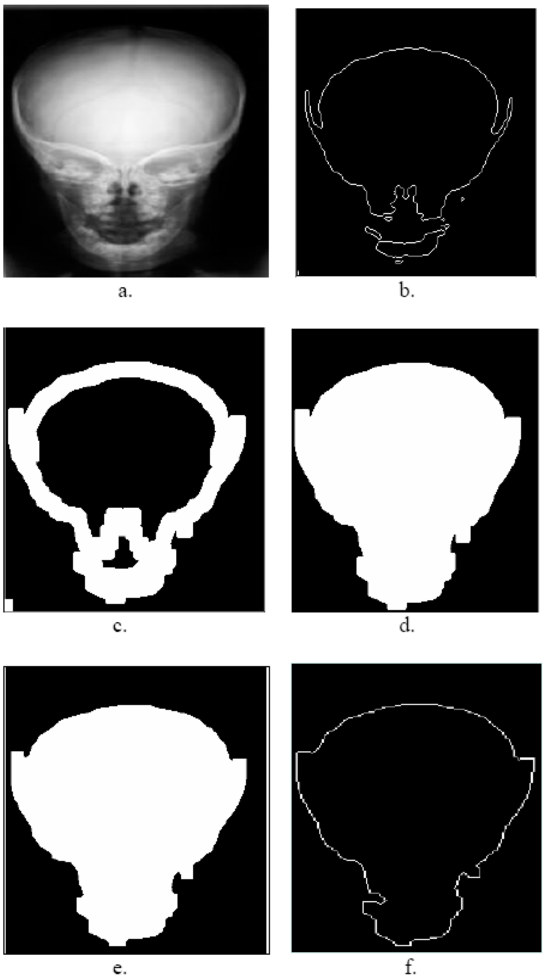

Figure 2.
a. Original image b. Result of edge detection
c. Result of dilation d. Result of filling
e. Result of erosion and cleaning
f. Object boundary

The next step is to thin to normalize the result of the dilation by applying the erosion process. We show the result of this process in Figure 2.e. According to [9], a boundary of the region is a set of pixels in the region that have one or more neighbors that are not in the region, whereas a background point is a point that is not on a boundary or region. To identify the boundary of the object, from the result of object segmentation (Figure 2.e.), we trace the exterior boundary of the object in clockwise direction. We denote the object boundary points as 1s and the background points as 0s. We can see the boundary of the object that is resulted from the tracing process, is represented in binary image, as shown in Figure 2.f.

2.2 Transformation using Grid Approach

After the identification of the object boundary, the next process is the transformation process of the object boundary by using a grid. In Figure 2.f, we can see that the object boundary has a variety of its lines. If we use this object boundary to find a similar image, we can not get a relevant object. This problem is caused by a difficulty to match one object boundary with the other object boundary in detail lines. Therefore, we need to simplify the shape. This can be done by using a grid to obtain a general shape of the X-ray image. A grid, we define it, as a homogeneous interval for columns and rows.

For each image of the object boundary, we applied a grid with the same size. For example, if we specify that a grid is 10, it means that there is 10 pixels between 2 lines in x and y direction. In this experiment, we had already tested the process with a grid of 20, 30, 40, 50, and 60. We show the result from this experiment in Figure 3.

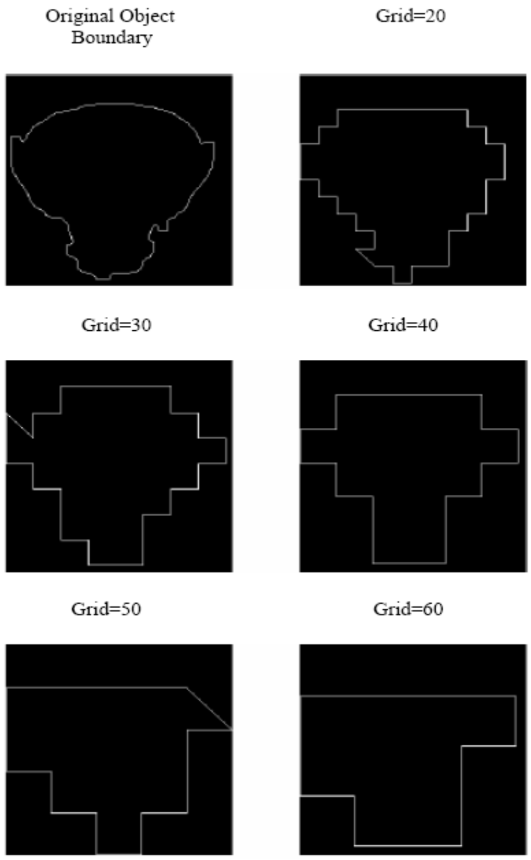

Figure 3. Object boundary of scull image with grid 20, 30, 40, 50 and 60

From this experiment, as shown in Figure 3, we found that the object boundary with grid less than 40 is still has detail lines. However, we lose the real shape of the object if we use grid more than 40. Thus, it's difficult to identify the shape of the object. So, we choose a grid with size 40 because this size is the most proportional to capture the shape of object.

As illustrated in Figure 4, the object boundary of the 'scull' image (Figure 4.a.) is applied a grid with size 40 (Figure 4.b). It means that the line in x and y direction, is separated by 40 pixels. For each point of the object boundary which is inside a grid, we assigned it to a closest grid node. A grid node is an intersection between x direction and y direction. From this transformation, we obtain a set of point of the object boundary in small variations. To represent the new shape, we connected the new points of the object boundary in clockwise direction. The result of this transformation process is illustrated in Figure 4.c.

We can see from Figure 4 that the shape of the image object in detail variations has changed to a simple shape. We believe that similar objects will have similar shapes in small variations. So, we can use this simple shape to compare between one image and the others, to find a similar image and to define an image class.

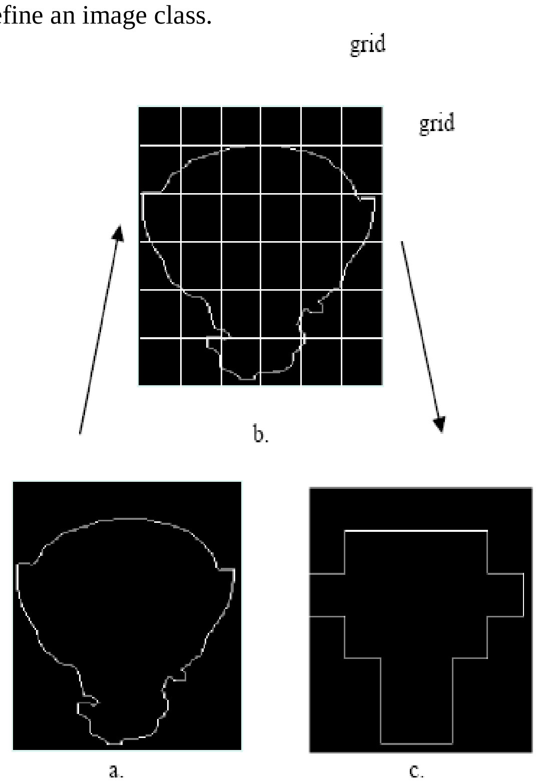

Figure 4. Transformation process :
a. Object boundary, b. Object boundary applied a grid
c. object boundary resulted from the transformation process

2.3 Representation and Calculation Using Freeman Code

This grid approach that we use to transform the image to general shape of the object, will be useful to minimize the processing time of matching between images. This happens when we are attempting to find a particular image among images in the database. But, it needs a wide space to save the image in the database. It's easy to save image by using a code. So, we have to map object boundary to a code representation.

The next step after the transformation process, we represent the new object boundary by using the Freeman Code. A new boundary of the object resulted from the transformation process, is represented based on the 8-directional Freeman Code, as shown in Figure 5.

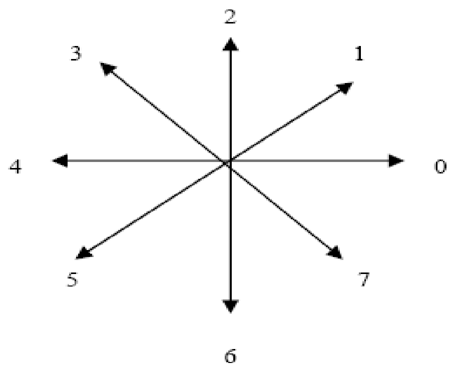

Figure 5. Schema of an 8-directional Freeman Code
[Gonzales and Wintz, 1987; Gonzales et al., 2005]

By tracing the object boundary from the start point to final point in a circular way, we obtain the Freeman Code, as ilustrated in Figure 6.

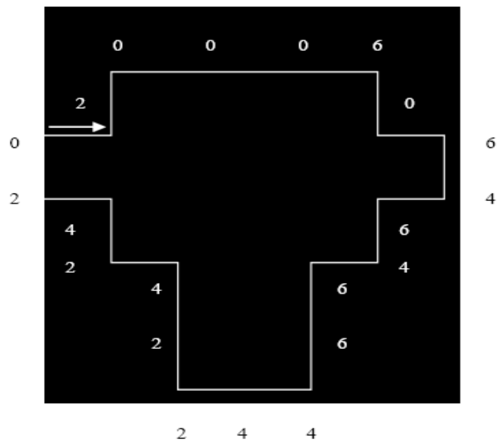

Figure 6. Determination of Freeman Code

From this process, we calculated the distribution for each Freeman code. In order to reduce an unbalanced value of the code distribution, we normalized the values between 0 to 1. The values were represented in vector. The vector resulted from the above process for 'scull' image, is illustrated in Figure 7.

Image	Freeman Code							
	0	1	2	3	4	5	6	7
scull	0.2900	0.0000	0.2219	0.0000	0.2662	0.0000	0.2219	0.0000

Figure 7. Distribution probability of Freeman Code for 'scull' image

From Figure 7, we can see that there is only Freeman Code for code 0, 2, 4 and 6. It represents the direction of the line of the object boundary based on the 8-directional Freeman Code, as shown in Figure 4. For example, a distribution probability for the Freeman Code 0 is 0.2900, code 2 is 0.2219, code 4 is 0.2662, and code 6 is 0.2219.

2.4 Matching

The last step of the classification process is matching. The aim is to compare between two images by calculating the vector distance.

By using this vector, we matched the X-ray image from the query image and reference image. The methods of the similarity measurement that we use are Euclidean Distance and Jeffrey Divergence techniques. The formula of these techniques are as follow [8] :

a. Euclidean Distance

$$D(I,J)= \sqrt{ \left(\sum_i \left| f_i(I) - f_i(J) \right|^2 \right) } \qquad (1)$$

In formula (1), D(I,J) is a distance between image I and image J, I is a query image (test image), J is a reference image in the database, and $f_i(I)$ is the number of pixels in bin i of image I. Blobworld[10], one of the image retrieval system used Euclidean Distance to compute the similarity between texture and shape features of the two images.

b. Jeffrey Divergence

$$D(I,J)= \sum_i f_i(I) \log \frac{f_i(I)}{\hat{f}_i} + f_i(J) \log \frac{f_i(J)}{\hat{f}_i} \qquad (2)$$

$$\hat{f}_i = [f_i(I) + f_i(J)] / 2$$

Jeffrey Divergence is a modification of Kullback-Leibler Divergence [8,11] which compare two empirical distributions of the two images I and J.

We used Euclidean Distance and Jeffrey Divergence to measure the similarity of test image and reference image in database by calculating the similarity between the vector of the distribution probability of Freeman Code for query image and reference image. We denoted I as a query image, J as a reference image in database, and $f_i(I)$ as a distribution probability of Freeman Code (i) for image I.

Based on the result of the similarity measurement, we found the minimum distance that indicated the class for the test image.

To describe the accuracy of this method, we calculated a recognition rate. A recognition rate means the percentage of the correct image class is divided all the images.

3 RESULT AND DISCUSSION

In our experiment, we have evaluated the utilization of the Freeman Code representation for classification of the X-ray image. We used 8 X-ray images in different classes as reference images, and 35 X-ray images as test images. But, these images have limitations, i.e. low contrast and noisy.

Table 1 presents the result of the recognition rate for the similarity measurement using Euclidean distance and Jeffrey Divergence for 35 X-ray images that was compared to 8 X-ray reference images.

Table 1. Recognition rate of the classification method using Freeman Code representation

Euclidean Distance	**Jeffrey Divergence**
57%	66%

As shown in Table 1, we obtained the recognition rate of 57 % for the Euclidean Distance and 66 % for the Jeffrey Divergence. As a similarity measurement, Jeffrey Divergence is better than Euclidean Distance. This is because Jeffrey Divergence more accurate than Euclidean Distance [8]. With the same images, we applied a proposed method by using grid approach.

The shape of the X-ray image object that we obtained from the segmentation process was transformed to a simple shape by using a grid with size 40. Next, the new shape of the object resulted from the transformation process is represented in Freeman Code. The result of the similarity measurement by using grid approach, is presented in Table 2.

Table 2. Recognition rate of the classification method using grid approach

Euclidean Distance	Jeffrey Divergence
69%	83%

With a grid 40, we improved the recognition rate from 66 % to 83 %. It is better than if we only use the detail object shape without a grid. The result for Jeffrey Divergence is better than Euclidean Distance because Jeffrey Divergence technique is an enhanced technique of similarity measurement based on Euclidean Distance technique [8].

4 CONCLUSION

In this paper we have shown that our proposed method for image classification process by using grid approach is able to get a better recognition rate. It because by using a grid, we obtained a more simple object shape which lead to a more accurate classification process. The result of our experiment for a number of images shows that there is a different score for Euclidean Distance and Jeffrey Divergence techniques of similarity measurement. The recognition rate of Jeffrey Divergence is better than Euclidean Distance.

REFERENCES

[1] Lehmann, TM, et al, (2000), “Content-Based Image Retrieval in Medical Applications: A Novel Multi-Step Approach”, International Society for Optical Engineering (SPIE), volume 3972 (32),, pp:312-320

[2] Lehmann, TM, et al, (2004), “Content-based Image Retrieval In Medical Applications”, Methods of Information in Medicine, 43,, 354-361

[3] Lehmann, TM, et al, (2005), “Automatic Categorization of Medical Images for Content-based Retrieval and Data Mining”, Computerized Medical Imaging and Graphics,29, , 143-155

[4] Guld, MO, (2004), “Comparison of Global Features for Categorization of Medical Images”, Proc. SPIE, 5371,, 211-222

[5] Pinhas A and H Greenspan, (2003), “A Continuous and Probabilistic Framework for Medical Image Representation and Categorization”, Proceeding SPIE, 5371, 230-238

[6] Paredes,R, (2002), “Classification of Medical Images Using Local Representation”, In Meiler M, Saupe D, Kruggel, Handels H, Lehmann TM (Hrsg) Bildverarbeitung fur die Medezin, Springer-Verlag, Berlin;, 171-174

[7] Jain AK, (2000), “Statistical Pattern Recognition: A Review”, IEEE Transactions on Pattern Analysis and Machine Intelligence 22(1), 4-36

[8] F. Long, H. Zhang and DD. Feng, (2003),“Fundamentals of Content-Based Image Retrieval”, Multimedia Information Retrieval and Management: Technological Fundamentals and Applications

[9] Gonzales, Rafael C, (2005), Digital Image Processing Using MATLAB, Pearson Education, India,

[10] Carson, C., (1999). “Blobworld : A System for Region-based Image Indexing and Retrieval”. Procs.3rd Int. Conf. On Visual Information System. Springer-Verlag. Amsterdam.

[11] Rubner, Y., (2000). “The Earth Mover’s distance as a metric for image retrieval”. International Journal of Computer Vision. 40(2): 99-121