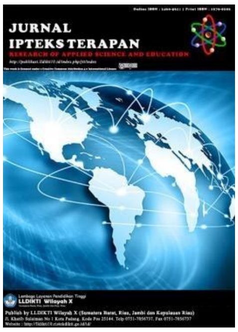

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EAR IMAGE SEGMENTATION WITH EDGE DETECTION METHOD ON CANNY AND LAPLACE ALGORITHMS

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Abstract

Technology in identifying ear shapes is the most important step in an automatic ear shape identification system. The purpose of this paper is to introduce an approach to image segmentation, color by determining the pixel values in the database and scanning results, the similarity results are formed, the error value of each image. The method used is color segmentation based on RGB(red, green, blue) values, edge detection with the canny and laplace methods and the results of the segmentation. The results obtained are that the program that has been created can identify the shape of the ear image in the database compared to the scanning results using the segmentation method and calculate the number of image pixels between the database image and the scanned image where the minimum number of pixels for the ear shape image in the database is 452 pixels, while the total the maximum pixels is 3028 pixels. For the image of the shape of the ear the result of scanning the minimum number of pixels is 419 pixels and the maximum number of pixels is 2742 pixels. The percentage of identification results for the shape of the ear has an average similarity level: 92%, the results of this study show a very high level of accuracy. The percentage of error in identifying the shape of the ear has an average error rate of: 8%, the results of this study indicate a very low error rate. a conclusion that comparing one image with another image will get a very high level of accuracy in the canny image results are better because the edge detection is clearer and the noise is less. While image laplace is worse because there is a lot of noise.

Keywords: Ear, RGB, Edge Detection ,Canny, Laplace, Segmentation.

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INTRODUCTION

In recent years, the human ear has played an increasingly important role in biometrics [1]. Ear biometrics have been considered as reliable biometrics and have received attention mainly because of their behavior that does not vary with a person's age[2]. As well as playing an important role in the forensic specialization and having a significant impact for biometric scientists and researchers[3]. Actually, many ear recognition studies show promising results, but some problems such as manual detection process, efficiency and robustness do not reach a certain level of maturity[4], The ear, nose and throat (ENT) [5] where the ear is advantageous when compared to some other biometrics such as the face. Ears have a more uniform distribution of color, are immune to changes in facial expressions, or even when wearing mustaches and spectacles. It is not affected by aging. Another feature that the ear has is that it can be captured even at a distance, causing less anxiety, unlike the eye such as retinal and iris imaging. There are several boundaries that affect the outer ear area [6].

Identification systems based on biometric features are becoming increasingly important. One of the most common biometric features is the ear. The accuracy of this system is highly dependent on the characteristics extracted from it [7]. Biometric authentication systems are currently an integral part of modern society and everyday life due to their important and potential applications in security, law enforcement, forensics and surveillance[8].

RESEARCH METHODS

The ear detection character which is very challenging because this part of the human head can be displayed on the image in various sizes, rotations, shapes and colors. In addition, images can be of varying quality, and parts of the ear can be hidden [9]. Ear recognition is a very interesting research strand in the medical field. Considering the spectrum of malformations affecting the developing anatomical regions of the first and second branchial arches (Craniofacial microsomy CFM), it was observed that some subjects had ear abnormalities affecting one or both ears. Congenital malformations that a common condition is microtia, which is the presence of an underdeveloped or absent outer ear. Malformations can affect the size, orientation, shape and position of the external ear and have a worldwide prevalence of 2.06 per 10,000 births. Several studies have addressed the problem of detection and recognition of the ear using different methods and techniques utilizing available data [10].

The Ear detection and recognition using different methods and techniques in utilizing available data [11] such as image identification data, converting images to Rgb2gray, edge detection, Imfill namely image repair / image reconstruction, Strel makes various forms of structural elements The shape determinant, imerode, is an erosion operation. The input process is a foreground/background segmentation algorithm that is recognized based on global thresholding at the optimal histogram derivative cutoff [12]. Edges are an important part of an image. Image extraction must not change any features in the extracted image. In the work we

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propose three algorithms are selected for edge detection namely the Canny and Laplace detection algorithms[13].

RESULTS AND DISCUSSION

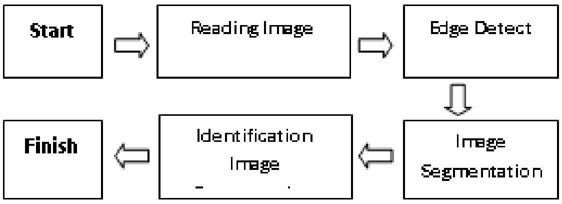
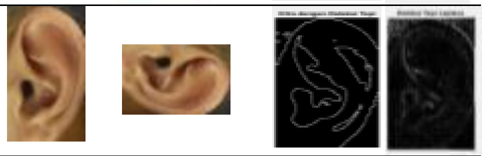
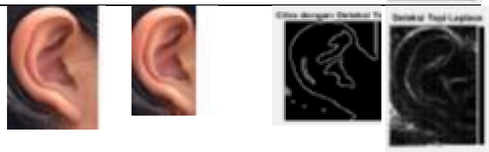
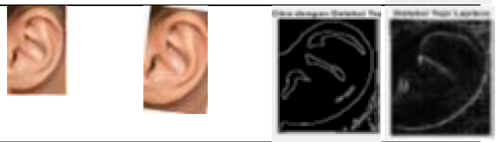
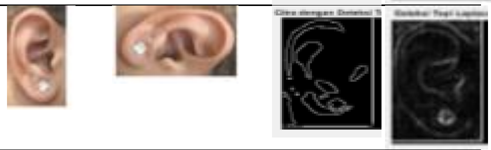
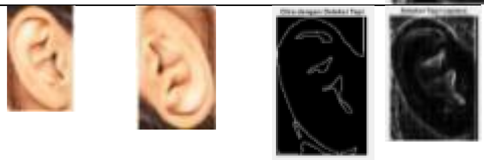


Figure 1. Data Processing Flowchart

In the edge detection process an object can be easily detected in an image if the object has enough contrast from the background. Changes in contrast can be detected by edge detection using the canny operator, which creates a binary image. To define a binary image by using the edge function.

Before being processed, digital images need to be recognized by a software system that is made by reading the image so that the digital image is recognized as a matrix that is ready to be processed for the next program to process the image at the gray level, detect edges with the canny, laplace algorithm. An example of the original image can be seen in Figure 2.

Figure 2. Original Image

No	Input Image	Database Image	Channy	Laplace
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

Start Reading Image Edge Detect

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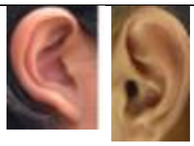
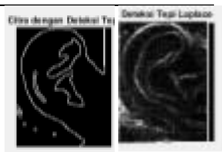
11		

Figure 3. Channy and Laplace Edge Detection

The edge detection results show that there is still a depression in the middle and unwanted image boundaries are still visible. This sometimes becomes a difficulty in image processing because the image object is not completely full and there are still unnecessary image boundaries. Therefore, to get an image that looks natural and smooth, it is necessary to do an image segmentation process. An example of the results of image segmentation and image identification segmentation is shown in Figure 4.

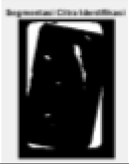
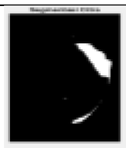
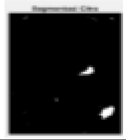
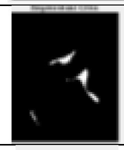
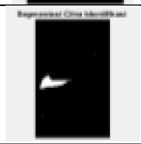
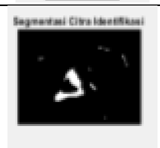
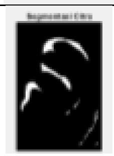
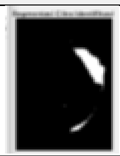
No	Segmentasi Citra	Segmentasi Citra Identifikasi
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		

Figure 4. Image Segmentation and Image Identification

From the results of Edge Detection and segmentation results from the existing image, it can be concluded in table 1 as below:

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No.	Input Image (Figure 4)	Database Image (figure 5)	Number of Ear Pixels in databases	Number of Ear Pixels Scan results	Percentage similarity (%)	ERRORS (%)	Result Identification
1	T1	T1a	2207	2207	100	0	Matching
2	T2	T2a	1956	1956	100	0	Matching
3	T3	T3a	1098	1098	100	0	Matching
4	T4	T4a	1386	1386	100	0	Matching
5	T5	T5a	2742	2742	100	0	Matching
6	T6	T6a	614	614	100	0	Matching
7	T7	T7a	779	779	100	0	Matching
8	T8	T8a	419	419	100	0	Matching
9	T2	T7	298	51	**17.11**	82.89	Not Matching
10	T1a	T1	2207	237	10.74	89.26	Not Matching
Jumlah			**13706**	**11489**	**827.85**	**172.15**	
Rata-rata			**2492**	**2088.909091**	**82.785**	**17.215**	
MAX			2742	2742			
MIN			298	51			

Table 1. Comparison Analysis Results of Input Image and Database Image

From the results of the analysis shown in Table 1. Shows the following results:

1. The program that has been created can identify the shape of the ear in the database compared to the results of scanning with the segmentation method and calculates the number of image pixels between the database image and the scanned image.
2. The minimum number of pixels for Ear shape images in the database is 452 pixels, while the maximum number of pixels is 3028 pixels. For images of the shape of the ear as a result of scanning, the minimum number of pixels is 419 pixels and the maximum number of pixels is 2742 pixels.
3. The percentage of ear shape identification results has an average level of similarity: 92%, the results of this study show a very high level of accuracy.
4. The percentage of errors in the identification of ear shapes has an average error rate of: 8%, the results of this study indicate a very low error rate.

CONCLUSION

In this paper, a new approach to identifying ear biometrics where the method proposed is by changing color images to gray values, detecting edges with the canny and laplace methods, identifying images so as to obtain a level of similarity from the given image. Where the minimum number of pixels for the ear shape image in the database is 452 pixels, while the maximum number of pixels is 3028 pixels. For the image of the shape of the ear the result of scanning the minimum number of pixels is 419 pixels and the maximum number of pixels is 2742 pixels. The percentage of identification results for the shape of the ear has an average similarity level: 92%, the results of this study show a very high level of accuracy. The percentage of error in identifying the shape of the ear has an average error rate of: 8%, the results of this study indicate a very low error rate. a conclusion that comparing one image with another image will get a very high level of accuracy in the canny image results are better because the edge detection is clearer and the noise is less. While image laplace is worse because there is a lot of noise. In future research we can compare this ear image with the edge detection method of Sobel, Prewitt, Laplace, Canny and Robert

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