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Fingerprint Identification for Attendance Using Euclidean Distance and Manhattan Distance

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Abstract: Attendance is an action to confirm that someone is present at the office, school, or event. The use of attendance in an agency or company is really important as it can improve the level of discipline and productivity. However, the traditional way of doing attendance is considered less effective, less secure, and more difficult to organize. Therefore, a modern attendance system that utilizes fingerprints can be the right solution, especially because every fingerprint is unique. In this research, we focus on designing a fingerprint identification system for attendance purposes by using two distance measure methods, namely Euclidean Distance and Manhattan Distance. The dataset used in the research contains 111 fingerprint images with 90 images for training the designed fingerprint identification system and the remaining 21 images for testing the system. Each fingerprint image has undergone image pre-processing stage before being used. We compare Euclidean Distance and Manhattan Distance based on their performances in identifying fingerprint. From the test results, the fingerprint identification accuracy obtained using Euclidean Distance is 76.19%, while the accuracy obtained using Manhattan Distance is 71.43%. In general, both algorithms succeed in providing the correct identification results. This proves that Euclidean Distance and Manhattan Distance can be utilized for fingerprint identification purposes.

Keywords: Euclidean Distance; Fingerprint; Fingerprint Identification; Image Pre-processing; Manhattan Distance

INTRODUCTION

Attendance is a data collection activity that aims to determine how many times members or employees are present at the office or event (Gifelem, Mangantar, & Uhing, 2021; Pulungan & Saleh, 2020; Ratih, 2022). Attendance is often used in an agency or company that has many members. The main function of attendance is to find out and calculate how much wages should be given to members. In addition, attendance is also used by companies to easily manage, assess, and supervise the performance and discipline of their employees (Gifelem et al., 2021; Ngurah et al., 2022; Ratih, 2022).

Every agency or company is required to be able to keep up with technology so that many are starting to switch from traditional to modern ways. This also applies in terms of conducting attendance (Gifelem et al., 2021). With the traditional or manual methods, employees can easily fake and falsify attendance data. In addition, managing a lot of attendance data can be very arduous and tends to be less accurate if done manually. Those problems are certainly obstacles in assessing employee performance (Ngurah et al., 2022). Therefore, the utilization of technology in attendance system is

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considered simpler, more effective, more accurate, and more secure (Ananta, 2022; Gifelem et al., 2021; Ngurah et al., 2022; Pulungan & Saleh, 2020; Ratih, 2022). Attendance system can utilize biometrics, such as voice, iris, face, or fingerprint (Hoo & Ibrahim, 2019). Fingerprint is basically used to identify a person because it is a physical characteristic that is unique and not influenced by age and growth (Hoover, 2023). Attendance system utilizing fingerprint identification can be the practical and right solution due to the ease of data access and information retrieval. With the fingerprint attendance system, members or employees also tend to be more disciplined so that they can be more effective and productive at work (Gifelem et al., 2021; Ngurah et al., 2022). The fingerprint identification system must be able to identify a person's fingerprint from a large set of fingerprints stored in the database. Due to the large amount of data used, this becomes a problem for the accuracy and efficiency of the identification system.

There are several previous research related to fingerprint identification. (Cao, Nguyen, Tymoszek, & Jain, 2020) designed an automated fingerprint identification system (AFIS) that can automatically cut the ROI, pre-process the latent fingerprint, and identify latent fingerprint. Conversely, (Liu, Liu, Zhao, & Shen, 2020) built an automated fingerprint recognition system (AFRS) that utilized spectral domain optical coherence tomography (SD-OCT) to extract features from hidden skin layers of fingertips. (Awasthi, Fadewar, Siddiqui, & Gaikwad, 2020) utilized back propagation neural network to identify fingerprint. The research focused on image pre-processing and minutiae extraction. (Dong, Niu, Zhang, Wei, & Xiong, 2020) created a new method for latent fingerprint identification by using a combination of R-CDs and starch as a dusting powder. The latent fingerprint images obtained with the dusting powder were pre-processed before identification. Additionally, (Win, Li, Chen, Viger, & Li, 2020) analyzed and compared algorithms used in fingerprint classification, fingerprint identification, fingerprint recognition, and fake fingerprint detection. From the survey conducted, they concluded that there are still many weaknesses and challenges in fingerprint identification so more research is needed in the future.

In this research, we design fingerprint identification system that utilizes Euclidean Distance and Manhattan Distance. Both Euclidean Distance and Manhattan Distance are distance measure methods that can determine the level of closeness or similarity between two objects (Faisal, Zamzami, & Sutarman, 2020; Mercioni & Holban, 2019; Suwanda, Syahputra, & Zamzami, 2020; Thant & Aye, 2020). We use Euclidean Distance and Manhattan Distance as the methods to recognize fingerprint patterns and match them with others. We also intend to compare the performances of both algorithms in identifying fingerprint.

METHOD

Data Acquisition

The dataset used in this research is a collection of fingerprint images. The dataset contains 111 fingerprint images and is obtained from several agencies or companies by using fingerprint scanner. All fingerprint images are in the BMP format. A total of 90 images from the dataset will be used in the training stage and the remaining 21 images will be used in the testing stage.

Fingerprint Identification System Training

Training the fingerprint identification system is done by storing fingerprint images in a database or local storage of the system. The stored images can later be used to identify the fingerprint of someone who takes attendance. The flowchart for the training stage can be seen in Fig. 1.

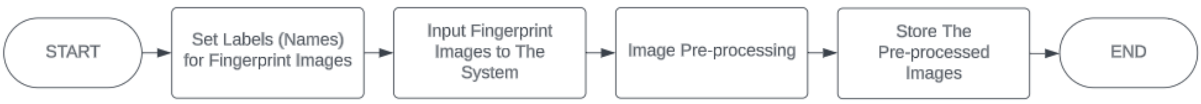

Fig. 1 Fingerprint identification system training

Each fingerprint image in this research is labeled so that the name of the fingerprint owner can be known and identified. All names that are used for labeling are just randomly obtained names because

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we want to maintain confidentiality of the fingerprint owners. Before storing the fingerprint images, image pre-processing is carried out. The aim of image pre-processing is to enhance the features or information of the image and eliminate the influence or interference of certain parts of the image (Caseneuve, Valova, LeBlanc, & Thibodeau, 2021; Devaraj, Rathan, Jaahnavi, & Indira, 2019; Madhupriya & Fairooz, 2020; Zhou, Ma, & Zhang, 2020). In this research, the image pre-processing includes image thresholding, thinning, image cropping, and resizing.

Image thresholding is also known as image binarization which aims to convert grayscale image into binary image. By applying image thresholding, the background and the main visual parts of the image can be seen more clearly due to the separation of pixel values into black pixels (background) and white pixels (foreground) (Khairnar, Thepade, & Gite, 2021; Otsu, 1979). The thresholding method used in this research is Otsu's thresholding (Otsu, 1979) which can automatically determine the proper threshold value.

The pre-processing is then continued with thinning. Thinning is the process of simplifying the image by extracting the main features and skeleton of the image to increase the effectiveness and efficiency in image recognition (Abu-Faraj, Alqadi, Al-Ahmad, Aldebei, & Ali, 2022; Zhang & Suen, 1984). The thinning algorithm used in this research is based on research conducted by (Zhang & Suen, 1984). After thinning, we determine and localize ROI (Region of Interest) that is going to be used in image cropping. Image cropping is intended to cut the image based on the ROI so that it becomes more focused on the part that is going to be recognized and analyzed.

The cropped fingerprint image is then resized to 96×103 pixels. The purpose of resizing in this research is to ensure all pre-processed images are in the same size. Additionally, we also make sure the resized images are not too small or too big. If the image is too small, some important features of the image will possibly be removed which can cause the system to inaccurately identify the image. Conversely, if the image is too big, the identification process will be inefficient and time-consuming. All steps of the image pre-processing can be illustrated as shown in Fig. 2.

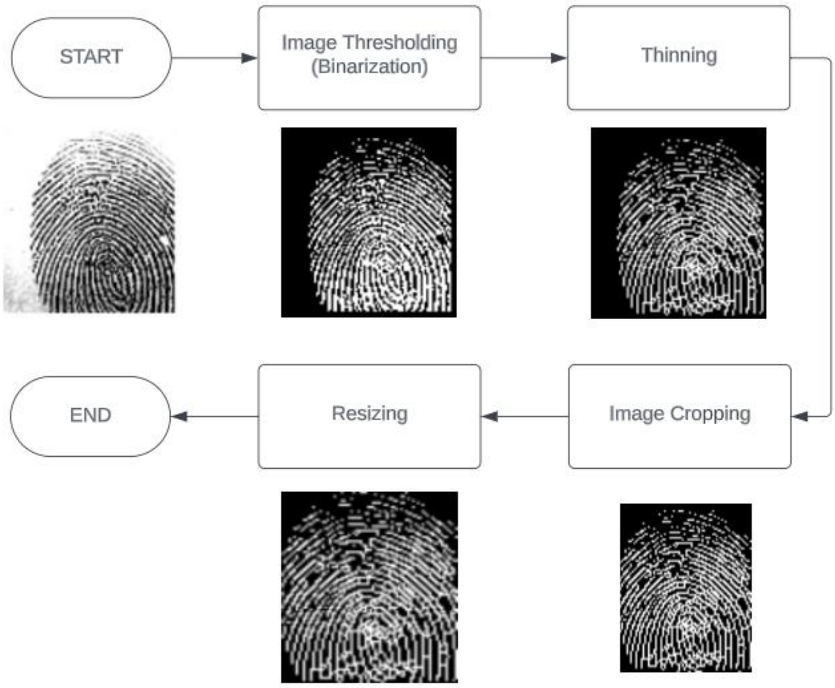

Fig. 2 Image pre-processing

Fingerprint Identification Process

The fingerprint identification system that has been built and trained must be tested to ensure the system is working as expected. The fingerprint identification process begins with inputting the fingerprint image that you want to identify. Then, the input image is pre-processed by going through image thresholding, thinning, image cropping, and resizing as done previously. Image pre-processing

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aims to remove noise and improve the quality of information that can be obtained from image so that the image is used more effectively (Caseneuve et al., 2021; Devaraj et al., 2019; Madhupriya & Fairooz, 2020; Zhou et al., 2020).

After the image is pre-processed, a comparison is made between the input fingerprint image and the fingerprint images that have been stored in the previous training stage. The comparison is carried out by utilizing distance measure method to calculate the distance or level of similarity between the compared images (Faisal et al., 2020; Mercioni & Holban, 2019; Suwanda et al., 2020; Thant & Aye, 2020). The smaller or closer the distance between the input image and the image from storage, the more similar or identical the fingerprint is. Based on the smallest distance value obtained from the distance measure, the fingerprint owner can be determined and identified. In this research, two distance measure methods are used, namely Euclidean Distance and Manhattan Distance. The flowchart of fingerprint identification process can be seen in Fig. 3.

Fig. 3 Fingerprint identification process

Euclidean Distance is the most common and frequently used distance measure method (Mercioni & Holban, 2019; Suwanda et al., 2020; Thant & Aye, 2020). Euclidean Distance basically calculates the distance between two points in a straight line based on the Pythagorean Theorem. The Euclidean Distance can be calculated by using (1).

$$d(x,y) = \sqrt{\sum_{k=1}^{m}(x_k - y_k)^2} \quad (1)$$

Description:

$d(x,y)$ = Euclidean Distance between image x and image y
k = parameter
m = number of parameters
x_k = k^{th} component of image x
y_k = k^{th} component of image y

Manhattan Distance is also known as City Block Distance which is a distance measure by summing the differences of the components (Suwanda et al., 2020; Thant & Aye, 2020). Manhattan Distance basically calculates the absolute difference between two points. The Manhattan Distance can be calculated by using (2).

$$d(x,y) = \sum_{k=1}^{m}|x_k - y_k| \quad (2)$$

Description:

$d(x,y)$ = Manhattan Distance between image x and image y
k = parameter
m = number of parameters
x_k = k^{th} component of image x
y_k = k^{th} component of image y

The fingerprint identification system will display the results of Euclidean Distance and Manhattan Distance calculation between the input fingerprint and each fingerprint from the storage. By comparing the distance values obtained, we can identify the fingerprint of a person who takes attendance.

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RESULT

In this research, a dataset containing 111 fingerprint images that have been labeled is used. Each fingerprint image is processed with Otsu's thresholding (Otsu's binarization), Zhang-Suen thinning, image cropping based on ROI, and resizing to 96×103 pixels. The result of image pre-processing will look like in Fig. 4.

Fig. 4 The result of image pre-processing

The fingerprint attendance system for attendance purposes is built and trained by storing 90 fingerprint images from the dataset so that the system is able to recognize fingerprints and know their owners. The remaining 21 fingerprint images from the dataset are used to test the capability of the system to identify fingerprints by using Euclidean Distance and Manhattan Distance. Those 21 test images have also been modified and damaged in order to evaluate the algorithms used. All test images in this research are shown in Fig. 5. Each test image is compared with 90 stored fingerprint images. The identification results by using Euclidean Distance and Manhattan Distance can be seen in Table 1.

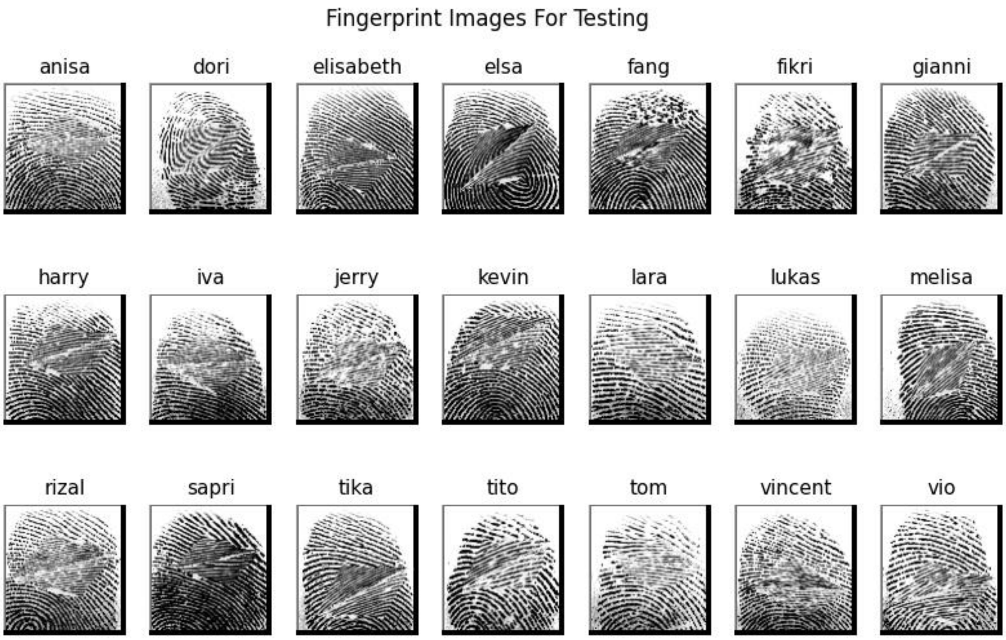

Fig. 5 The test images used in this research

Table 1
Test Results of Fingerprint Identification

Image	Euclidean Distance			Manhattan Distance		
	Label	Value	Result	Label	Value	Result
anisa.bmp	anisa	437.1338	**Correct**	anisa	238994	**Correct**
dori.bmp	dori	451.9093	**Correct**	dori	270834	**Correct**
elisabeth.bmp	fikri	873.8009	**Wrong**	fikri	930272	**Wrong**
elsa.bmp	elsa	527.4979	**Correct**	elsa	355452	**Correct**

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fang.bmp	fang	446.5064	**Correct**	fang	234144	**Correct**
fikri.bmp	fikri	515.9060	**Correct**	fikri	332589	**Correct**
gianni.bmp	gianni	472.0053	**Correct**	gianni	269639	**Correct**
harry.bmp	harry	478.5290	**Correct**	harry	301624	**Correct**
iva.bmp	vio	830.4469	**Wrong**	tito	882191	**Wrong**
jerry.bmp	jerry	449.8566	**Correct**	jerry	236461	**Correct**
kevin.bmp	kevin	511.0254	**Correct**	kevin	331997	**Correct**
lara.bmp	tom	809.7074	**Wrong**	tito	801641	**Wrong**
lukas.bmp	lukas	498.2820	**Correct**	lukas	293721	**Correct**
melisa.bmp	melisa	455.1055	**Correct**	melisa	246105	**Correct**
rizal.bmp	rizal	534.1030	**Correct**	rizal	344124	**Correct**
sapri.bmp	tom	863.5039	**Wrong**	florian	970536	**Wrong**
tika.bmp	tika	836.1944	**Correct**	tika	878533	**Correct**
tito.bmp	tito	463.9644	**Correct**	tito	263123	**Correct**
tom.bmp	tom	787.2554	**Correct**	mikey	767349	**Wrong**
vincent.bmp	fikri	824.3331	**Wrong**	jerry	829850	**Wrong**
vio.bmp	vio	500.7395	**Correct**	vio	301906	**Correct**

Based on Table 1, by using Euclidean Distance, 16 correct fingerprint identification results are obtained, whereas by using Manhattan Distance, 15 correct fingerprint identification results are obtained. The accuracy of each algorithm can be calculated with (3).

$$Accuracy = \frac{number\ of\ correctly\ identified\ images}{number\ of\ test\ images} \times 100\% \qquad (3)$$

By using (3), the accuracy of Euclidean Distance for fingerprint identification is 76.19%, while the accuracy of Manhattan Distance is 71.43%. The accuracies show that both Euclidean Distance and Manhattan Distance are able to identify the test images well.

DISCUSSIONS

The traditional way of doing attendance is often an obstacle and difficulty for agencies or companies. Therefore, the utilization of fingerprint in the attendance process can be a solution to solve problems regarding dishonesty in attendance. This is because every person has a unique fingerprint biometric. In addition, with the fingerprint identification system, managing attendance data can be easier and more accurate.

In this research, a fingerprint identification system is successfully designed by utilizing the Euclidean Distance and Manhattan Distance algorithms. We also focus on image pre-processing techniques to make sure the features of the fingerprint image are clear and useful. From the testing stage, we obtain the accuracies of Euclidean Distance and Manhattan Distance in identifying fingerprint which are 76.19% and 71.43% respectively. The accuracy of Euclidean Distance is slightly higher than the accuracy of Manhattan Distance. Moreover, the fingerprint identification system still can wrongly identify fingerprint, especially if rotation or translation is applied to the fingerprint image. On the whole, the test results prove that the designed fingerprint identification system is able to identify fingerprint well even though the fingerprint image has been modified or damaged.

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CONCLUSION

This research successfully demonstrated that the Euclidean Distance and Manhattan Distance algorithms can be utilized to identify fingerprint. The fingerprint identification system in this study was trained by storing 90 fingerprint images that have been labeled and pre-processed. The image pre-processing that we carried out included thresholding, thinning, cropping, and resizing. After that, 21 test images were pre-processed and compared with all fingerprint images that had been stored previously. The test results showed that Euclidean Distance and Manhattan Distance are able to identify fingerprint well which means the fingerprint identification system is suitable for attendance purposes.

After conducting this research, we have several suggestions and recommendations for future research:

1. Using other methods and algorithms in fingerprint identification.
2. Using other datasets for the fingerprint identification system designed in this research.
3. Collect and add fingerprint images to the dataset used in this research to improve the identification capability of the designed system.

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