

Recognition of hand gestures using image with histogram feature extraction and Euclidean distance classification method

Yenni Astuti^{1*}, Sudaryanto², Indah Dwi Ariyanti³

^{1,3}Department of Electrical Engineering, Faculty of Industrial Technology, Adisutjipto Institute of Aerospace Technology

²Department of Informatics, Faculty of Industrial Technology, Adisutjipto Institute of Aerospace Technology

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ABSTRACT

Human-Computer Interaction technology allows humans to communicate with computers using natural language such as gestures. One of the gestures used by humans to communicate is hand gestures. In this research, hand gestures are recognized using images that represent pitch, roll, and yaw movement. As a feature extraction method, the histogram is used, while the classification method used is the Euclidean distance. From the experimental results, the combination of the histogram feature extraction method and the Euclidean distance classification method had an accuracy of 30 percent for images representing pitch and yaw movements, and 60 percent for images representing roll movements.



Corresponding Author:

Yenni Astuti,
Department of Electrical Engineering,
Institut Teknologi Dirgantara Adisutjipto,
Jalan Majapahit, Blok-R, Lanud Adisutjipto, Yogyakarta 55198
Email: yenniastuti@itda.ac.id

1. INTRODUCTION

Technology and knowledge are increasingly developed. One of the technologies that is currently developing is digital image processing. Image processing is the process of manipulating and analyzing images using a computer. Digital image processing studies various aspects related to image quality, such as increasing contrast and making colors sharper. In addition, image processing can also be used to select optimal image features, which are useful for analysis, data storage, and data processing [1]. Generally, image processing is used in biometrics, signature recognition, facial recognition, and hand gesture recognition [2]–[4].

Image recognition is a part of Artificial Intelligence (AI) which aims to improve and process image data [5]. In other words, image recognition aims to make images more appropriate and easier to process at subsequent stages, such as classification or object detection [6], [7]. This includes various techniques to optimize image quality, reduce noise, and identify important features so that subsequent processing and analysis can be performed efficiently and accurately.

Image recognition can also be used to recognize hand images [8], [9]. In the process of hand gesture image recognition, feature extraction is a very important process [10]. One of the popular techniques is histogram-based feature extraction [11], [12]. The histogram method is used to analyze the distribution of pixel intensity in hand images, producing a numerical representation that reflects the visual characteristics of each hand movement. Through histogram analysis, unique patterns in the distribution of light and shadow intensity in hand images can be identified, which are then used as the main features for classification purposes.

After the important features are successfully extracted using the histogram method, the next step is to classify the hand gesture image to recognize or identify the gesture it represents. One of the effective and frequently used classification methods is Euclidean distance-based classification [13], [14]. This method measures the similarity of two feature sets generated from the feature extraction method, by calculating the Euclidean distance between the feature vector of the test image and the feature vector of the training images in

the database [15]. A smaller Euclidean distance means a closer similarity between the two images, allowing the system to recognize hand gestures more accurately.

Although the histogram feature extraction and Euclidean distance classification methods have great potential, challenges in terms of accuracy and efficiency of data processing are still problems that need to be solved, especially when dealing with large and varied datasets. Therefore, this study focuses on the exploration and analysis of hand motion images to be extracted using the histogram method, as well as how to implement Euclidean distance classification effectively. The hand images to be extracted represent the pitch, roll, and yaw motions of the aircraft's center of gravity rotation.

2. RESEARCH METHOD

2.1. Flowchart of The System

To build a hand image recognition system that represents pitch, roll, and yaw gestures, a system is designed which is depicted in the form of a flow diagram as shown in Figure 1.

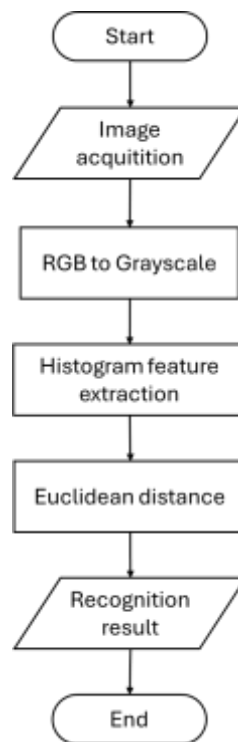


Figure 1. The system's flowchart.

From the flowchart in Figure 1, the hand image recognition process begins with taking image data or test data from the internal camera of the mobile smartphone. The next stage is to convert the image from Red-Green-Blue (RGB) to grayscale to obtain the histogram of the image. This process is followed by the process of determining the Euclidean distance. From the Euclidean distance classification method, the similarity score will be obtained to be used for recognition. The recognition result indicates that the system is complete.

2.2. Histogram Feature Extraction

Previously, some image data are placed in a directory or folder called the training sets. Then the Python program is stored in a directory or folder so that the program can read the image data. The process of processing data into a histogram can be seen in the following syntax.

```

import cv2 as cv
from matplotlib import pyplot as plt
mage = cv.imread("PITCH 1.jpg")
gray_image = cv.cvtColor(image, cv.COLOR_BGR2GRAY)
print(gray_image)
cv.imshow('PITCH GRAYSCALE', gray_image)
plt.hist(image.ravel(), bins=256, range=[0, 256])
  
```

```
plt.xlabel("Nilai Intensitas")
plt.ylabel("Jumlah Piksel")
plt.show()
cv.waitKey(0)
cv.destroyAllWindows()
```

In the syntax, there is `image = cv.imread("PITCH 1.jpg")` where this command is to call the image in the computer directory. After the image is called by the Python program, the image will continue to the next process, namely with the command `gray_image = cv.cvtColor(image, cv.COLOR_BGR2GRAY)` where this command is to change the RGB image to a grayscale image. Then the program will display a histogram graph with the command `plt.hist(image.ravel(), bins=256, range=[0, 256])`.

2.3. Euclidean Distance Calculation

After the histogram of the image data is obtained, the following process is to compare the histogram values one by one from all image data. The syntax can be seen as follows. The syntax will determine the Euclidean distance value of the image contained in the computer directory.

```
def euclidean_distance(histogram1, histogram2):
    d1 = math.sqrt(sum((x - y) ** 2 for x, y in zip(histogram1, histogram2)))
    d = d1/1000
    return d
distance1 = euclidean_distance(histogram1, histogram2)
print(f"Euclidean Distance: {distance1:.4f}")
```

3. RESULTS AND DISCUSSION

3.1. Histogram of Pitch

Figure 2 shows the program output in the form of a grayscale image of Pitch 1 and a histogram graph. The grayscale image can be seen in Figure 3.



Figure 2. Grayscale of *Pitch 1*.

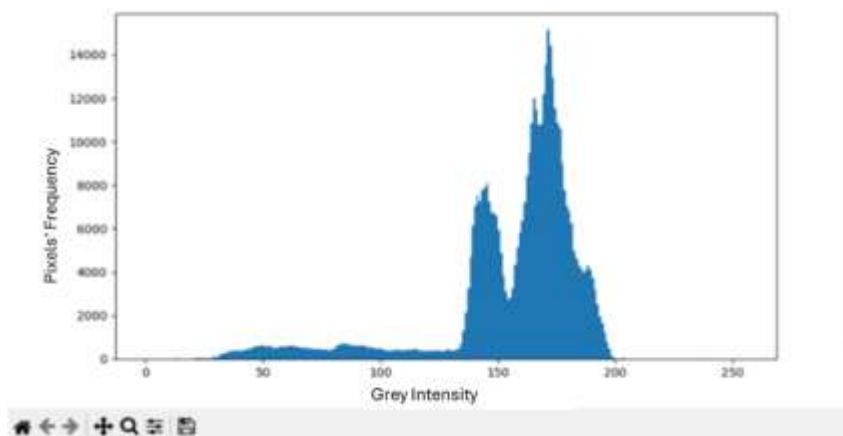


Figure 3. Histogram of *Pitch 1*.

The horizontal axis of the histogram in Figure 3 shows the range of pixel intensity values in the image, which usually ranges from 0 (black) to 255 (white) for grayscale images. While the vertical axis shows the number of pixels that have a certain intensity value. In the graph, most pixels have an intensity value of 171 and a pixel count of 15,137. While the least with an intensity value of 12.58 and a pixel count of 0.7.

3.2. Histogram of Roll

Figure 4 shows the grayscale image of Roll 1. Furthermore, Figure 5 shows a histogram graph of Figure 4. The horizontal axis of Figure 5 shows the range of pixel intensity values in the image ranging from 0 (black) to 255 (white) for grayscale images. The vertical axis shows the number of pixels that have a certain intensity value. In the graph, most pixels have an intensity value of 172.3, and the frequency of the pixels is 9,505. While the least with an intensity value of 27.50, and the frequency of the pixels is 4.



Figure 4. Histogram *Roll 1*.

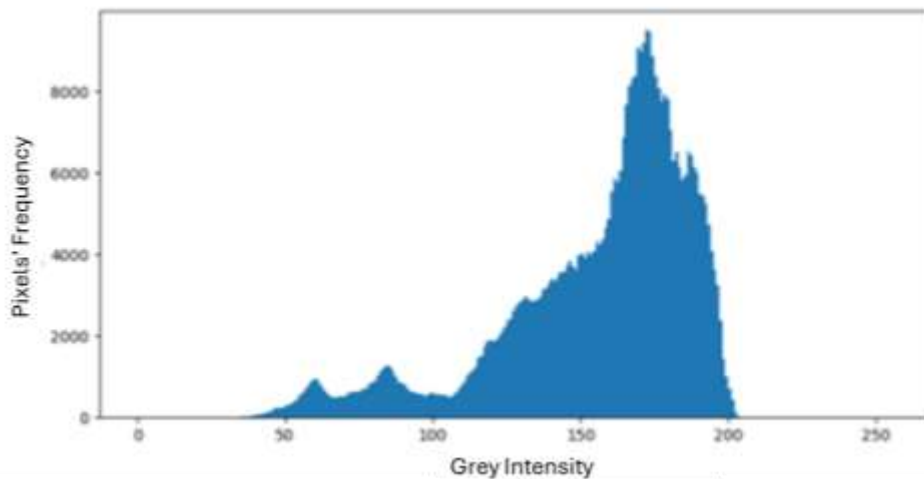


Figure 5. Histogram *Roll 1*.

3.3. Histogram Yaw

Figure 6 shows the grayscale image of Yaw 1. In addition, Figure 7 shows the histogram graph of Figure 6. The horizontal axis of Figure 7 shows the range of pixel intensity values in the image ranging from 0 (black) to 255 (white) for the grayscale image. The vertical axis shows the number of pixels that have a certain intensity value. In the graph, most pixels have an intensity value of 173.41 and a pixel count of 9,893. While the least with an intensity value of 0.47 and a pixel count of 1.02.



Figure 6. Histogram *Yaw* 1.

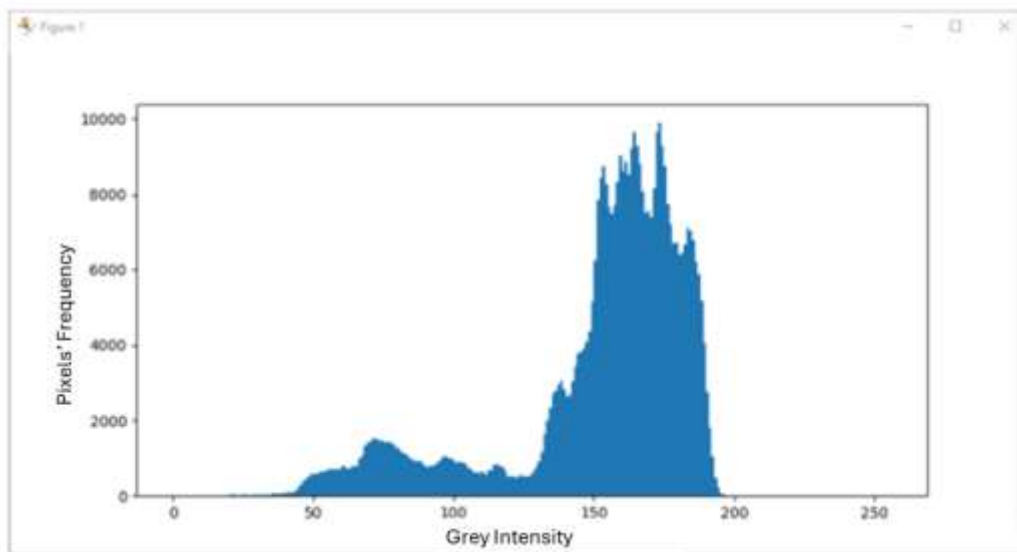


Figure 7. Histogram *Yaw* 1.

3.4. Accuration of The System

Based on the test and training data as many as 30 image data, contain 10 data pitch images, 10 data roll images, and 10 data yaw images. There are 21 image data that are successfully recognized, as shown in the graph in Figure 8.

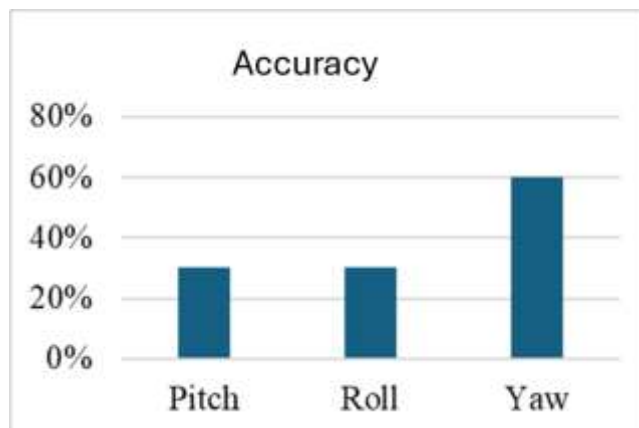


Figure 8. Accuracy percentages of images represent pitch, roll, dan yaw.

4. CONCLUSION

Based on the experiment of the hand gesture recognition system using the histogram feature extraction method and the Euclidean distance classification method, the following conclusions can be drawn.

1. The test image data uploaded to the Python application displays grayscale images, histogram graphs, and histogram values for comparison of training data and test data uploaded by the system. From these values, the system will calculate the Euclidean distance value as a similarity score of the image test.

2. Based on the results of the study using 10 Pitch test data, 10 Roll test data, and 10 Yaw test data, the accuracy of 30% for Pitch images, 60% for Roll images, and 30% for Yaw images were obtained. The failure in recognition experiments was caused by the number of gray values between the training data and test data that were not similar.

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