

Face Detection in Complex Background Using Scale Invariant Feature Transform and Haar Cascade Classifier Methods

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Abstract: Face detection is a process by a computer system that can find and identify human faces in digital images or videos. One of the main challenges faced in the face detection process is the complex background. Complex backgrounds, such as many color combinations in the image, can interfere with the detection process. To overcome this challenge, this research uses a combination of two methods: Scale Invariant Feature Transform (SIFT) and Haar Cascade Classifier. Scale Invariant Feature Transform (SIFT) is a method used in image processing to identify and describe unique features in an image. The SIFT method looks for keypoint descriptors in images that can be used as a reference in comparing different images. After the keypoint descriptor is found with SIFT, the Haar Cascade Classifier method is used to detect faces in the image. Haar Cascade Classifier is a practical algorithm for object detection in images. After facial features are extracted with these two methods, the results are compared with the K-Nearest Neighbor (KNN) approach. This research involves the introduction of 28 color images with complex backgrounds. The results of combining these two methods produce an accuracy of 81.75%. This shows that combining these two methods effectively overcomes complex background challenges in face detection.

Keywords: Complex Background, Face Detection, Haar Cascade, Image, SIFT

INTRODUCTION

Computer vision is a branch of Artificial Intelligence (AI) that trains computers to recognize things in images. Computer vision works almost identically the human vision process to specify so that it can be recognized (Tirajoh, 2020). One of the popular and valuable applications of computer vision is face detection. Face detection is the primary step for carrying out facial identification, and facial analysis, including facial recognition (Cahyo et al., 2023; Kristanto et al., 2023; Mataram, 2020; Prasetyawan & 'Uyun, 2020).

Computers can be programmed to have intelligence similar to humans, such as detecting faces, making it easier for humans to work more systematically. This system can be applied to human activities that coexist with facial detection systems, such as unlocking devices, banking transactions, presence in various sectors, and so on (Arifin, 2022; Ayu et al., 2023; Salamah et al., 2022; Yanto et al., 2022). This technology increases security and comfort in daily human activities and makes it easier to access information technology for further advances in artificial intelligence (AI), especially in computer vision systems.

In processing face detection, a level of background accuracy is required, which will be used when there are many objects or colors or a mismatch between the object and the background is necessary (Fansyuri & Yunita, 2023; Sistem, 2021; Wang et al., 2020). Face detection with complex backgrounds requires extracting facial features obtained by separating facial images to avoid background abstraction by narrowing the detected face region (Kuddus, 2021).

In previous research by Munawir et.al (2020) concerning face detection in the context of student attendance, which was carried out using the Haar Cascade Classifier approach, which resulted in an accuracy of 76%, while using many faces resulted in an accuracy of 33%. Research conducted by Heryana et.al (2020) developed an application to identify features on human faces using the Viola-Jones approach, which includes the Haar-like Feature method, integral image, Adaboost, and Cascade of Classifier, achieving an accuracy of 75% with a simple background.

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Saputra et.al (2023) used a combination of the Kalman Filter and Scale Invariant Feature Transform (SIFT) methods to improve the spherical object detection system in robotics and automatic control technology. Saputro & Prayudi (2022) research on object match detection using the SIFT algorithm utilizes images from CCTV for digital forensics needs, with an accuracy value of 100%. Miftahuddin et.al (2021) examined the detection and classification of heavy vehicles on highways using the SIFT algorithm, resulting in an accuracy of 78%. Pratama et.al (2022) researched traffic sign identification using the ADAS approach with SURF. Then Faturohman et.al (2020) compared object detection via CCTV using the SIFT, SURF, and ORB algorithms, with the SIFT method obtaining the most excellent accuracy results of 89.67%.

Therefore, this research tries a new approach to detecting faces by combining two methods, namely Scale Invariant Feature Transform (SIFT) and Haar Cascade Classifier. The SIFT approach may identify and describe local characteristics in images, indicating the existence of keypoint descriptors that can be used to compare different images. Meanwhile, the Haar Cascade method can also detect human faces. The combination of two methods in this research seeks to provide a new alternative to overcoming the challenge of detecting faces with complex backgrounds. For this reason, the differences between previous and current research are in the method, time and place of research, and research objects.

METHOD

Face detection in complex backgrounds requires several stages of research. Stages in the research include data collection, pre-processing (converting RGB images to grayscale), and face detection using SIFT and Haar Cascade methods (Yulina, 2021). Subsequently, match the two facial feature extraction results. Figure 1. illustrates the stages of this research.

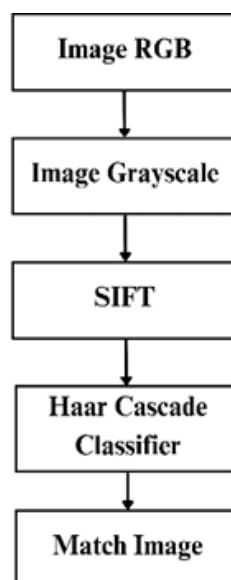


Figure 1. Research Stages

Grayscale Process

The grayscale process is a digital image processing technique used to convert color images into grayscale images (Kusnadi et al., 2022). Images that show colors are usually represented in RGB (Red, Green, Blue) format. In the Grayscale process, using certain equations, an RGB image is transformed into a grayscale image by combining each pixel's red, green, and blue color components. Grayscale processing can reduce data complexity and speed up the computing process because it only processes one color channel; handling more complex color data is unnecessary (Saraswati et al., 2023). This can make the following process easier (Andono & Rachmawanto, 2021). Equation 1 is used in this research to carry out the grayscale process.

$$gray = (R * 0.2989) + (G * 0.5870) + (B * 0.1140) \quad (1)$$

Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) is a technique for identifying and defining local features in a picture, after which a comparison of the image occurs at the level of match with the extracted image (Listiyowati et al.,

2021). The results of this feature extraction are resistant to changes in two-dimensional rotation, lighting, and three-dimensional perspective. This is supported because each local feature in the image determines a keypoint in the surrounding space. The SIFT approach has four major computational stages: scale-space extrema value detection, keypoint localization, orientation assignment, and keypoint descriptor.

The maximum and minimum values of the Difference of Gaussian (DoG) are used as keypoints (Khadapi et al., 2021). In its meaning, $L(x,y)$ represents a Gaussian filter $G(x,y,\sigma)$ with convolution of the original image $I(x,y)$.

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \tag{2}$$

$$G(x,y,\sigma) = \left(\frac{1}{2\pi\sigma^2}\right) e^{-(x^2+y^2)/2\sigma^2} \tag{3}$$

The scale-space extrema of the Difference of Gaussian function is convolved with the image $D(x,y,\sigma)$, yielding the difference between the nearest scales of the constant factor. These results are used to detect the location of stable keypoints on a spatial scale (Hidayat et al., 2023).

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma) \tag{4}$$

After getting the Difference of Gaussian (DoG) value in the previous calculation, the next step is finding the position of the keypoint extremum.

$$Z = -\left(\frac{\partial^2 D}{\partial x^2}\right)^{-1} \frac{\partial D}{\partial x} \tag{5}$$

The results of the extreme positions are determined in the manner stated in equation (5). In contrast, equation (6) calculates the keypoint value for the extreme position, meaning that D is DoG and Z is the extreme value. The following is the keypoint calculation:

$$D(Z) = D + \frac{1}{2} \frac{\partial D^{-1}}{\partial x} Z \tag{6}$$

In the orientation identification process step, each keypoint produced will show an orientation depending on its placement in the image. For this reason, keypoint results can be presented so that they do not affect image rotation and scale (Nurudin et al., 2021). The magnitude of the image sample $L(x,y)$ produced from Gaussian Blur can be calculated using the following equation:

$$M(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \tag{7}$$

Descriptors are needed to configure keypoint results from image changes by viewing angle and lighting. The keypoint descriptor is a vector from the results of the histogram orientation operation. An orientation histogram is constructed to identify the image's prevailing direction. The weight of each bin in this histogram is dictated by the Magnitude value, which was obtained before. This histogram was produced by splitting a 360-degree scale into 36 pieces or bins. The prevailing direction in the image may be identified by locating the bin with the highest value in the histogram (Wijayana et al., 2015). Figure 2 depicts the orientation histogram.

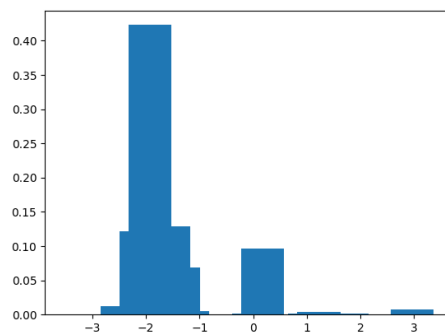


Figure 2. Orientation Histogram

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Equation 8 calculates the spatial scale of the image $L(x,y)$ produced by Gaussian Blur to get the keypoint descriptor.

$$\theta(x,y) = \tan^{-1} + \frac{L(x,y+1)-L(x,y-1)}{(L(x+1,y)-L(x-1,y))} \tag{8}$$

Haar Cascade Classifier

The Haar Cascade algorithm for object detection was first introduced by Paul Viola and Michael Jones in 2001. Haar refers to a box-shaped mathematical function known as a Haar Wavelet. Haar Cascade is a classifier created by combining Haar-like functions. The Haar-like function, commonly known as the Haar Cascade Classifier, is a rectangular function that offers precise information about a picture (Aprilian Anarki et al., 2021). The Haar Cascade classifier has black and white pixels arranged in a box. This method is repeated on each box, yielding different values to denote dark and bright areas. These data are then utilized as the foundation for picture processing (Mulyana et al., 2023). The Haar algorithm feature value calculation method reduces the pixel values in the white and black areas. This approach uses an integral depiction of a grayscale image where every pixel's value is the sum of the top left pixel value to the bottom pixel value.

The Cascade Classifier method uses several steps to determine and recalculate the Haar Feature value for more accurate results. The Cascade Classifier method has three classification stages. The first classification step includes sub-images classified with a feature. Then, the second classification consists of a classification that returns to the face image to obtain a threshold value, and the third classification includes a source of face images that will pass and approach the actual face image (Sakti et al., 2022). Figure 3 depicts the workflow of the Cascade Classifier.

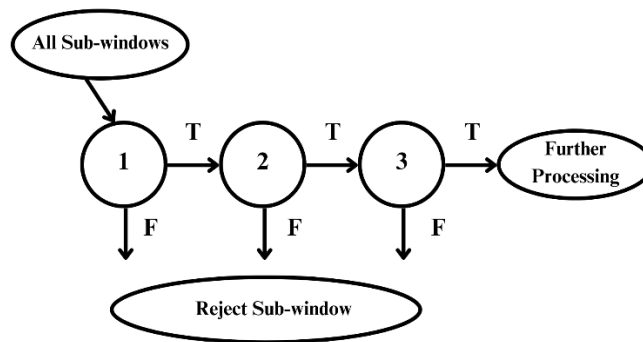


Figure 3. Workflow Cascade Classifier

Match Image

After getting the keypoint from each image and having obtained the keypoint descriptor value, the next step is to match it with the keypoints of other images. In this research, the image-matching process uses a combination of the Brute Force algorithm, KNN (*K-Nearest Neighbor*), and ratio test. The Brute Force algorithm is a form of precise (straightforward) problem-solving method, which often finds problems and involves unclear ideas (Wibawa, 2022). Using a specific distance calculation, this method compares the keypoint descriptor between one initial feature with all the different features in adjacent segments and returns the closest feature (Dewanti et al., 2020). The comparison results of the Brute Force algorithm method can be seen from the appropriate keypoint values or what is called matching keypoint, which means there is a match in the object (Saputro & Prayudi, 2022). Subsequently, the KNN algorithm and ratio test filter the Brute Force findings. The KNN classification method uses k nearest neighbor distances from an object (Riska et al., 2021). The ratio test is then used to identify pairs of descriptors that are sufficiently similar.






RESULT

The tests in this research utilized several images containing between 2 and 5 facial objects placed on a complex background. The following are the results of the images used in the research, for example, those in Table I. show images with complex backgrounds. The tests used in these images evaluate the extent to which the method can overcome existing problems in detecting faces to provide accurate and efficient results.

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Table 1. Examples of Complex Background Images

No	Images	Details
1.		Image with 1 Object
2.		Image with 2 Object
3.		Image with 3 Object
4.		Image with 4 Object
5.		Image with 5 Object

The Scale Invariant Feature Transform (SIFT) method extracts features and keypoints from images as output. The keypoint descriptor produced by the SIFT algorithm will then be used to match faces with sample facial photos. Figure 4. shows an example of a keypoint from a sample face image.



Figure 4. Image Keypoint

It was next, using the Haar Cascade method. The Haar Cascade method is an object detection technology that detects faces in images. Figure 5 shows the results of the Haar Cascade method.



Figure 5. Haar Cascade method face detection results.

Based on the output results of the SIFT algorithm in the form of various keypoint descriptors, the Brute Force method is used to compare each keypoint descriptor from one image with all keypoint descriptors from another image. Subsequently, KNN (K-Nearest Neighbor) will match each descriptor with the k nearest descriptor. This study uses a *k* value of 2, meaning each keypoint descriptor will be matched with the two closest keypoint descriptors from other images.

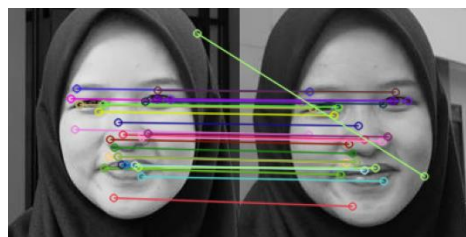


Figure 6. Keypoint matching results

Figure 6. depicts the line connecting the sample image and the test image, representing the result of keypoint matching between the two images. The ratio test is used to filter good matching results. In this research, the threshold value used for the ratio test is 0.75, meaning that if it is found that the distance between the first keypoint is more than 75% of the distance between the second keypoint, then the keypoint pair is considered suitable. The minimum number of keypoint descriptor pairs considered as good or matching in this study is 30, which yields a *MATCH* value.

Each test was carried out on individuals seven times with different partners, so 28 tests were obtained. To assess the level of testing accuracy, it can be seen in:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

Table 2. contains further information regarding the accuracy of the results of this test.

Table 2. Image Testing Results

No	Images	TP	TN	FP	FN	Recall	Precision	F1-Score	Accuracy
1.	Image with 2 Object	6	1	0	0	100%	100%	100%	100%
2.	Image with 3 Object	4	2	0	1	80%	100%	89%	85%
3.	Image with 4 Object	1	5	0	1	50%	100%	67%	85%
4.	Image with 5 Object	1	3	0	3	25%	100%	40%	57%
Average						63,75%	100%	74%	81,75%

Based on the data presented in Table 2. This research achieved a recall value of 63.75%, precision of 100%, f1-score of 74%, and accuracy of 81.75% in detecting faces in images. The research results show the effectiveness of the combined Scale Invariant Feature Transform and Haar Cascade methods in detecting faces in images. However, some factors can influence the results.

The factor influencing the results of detection is the quantity of facial objects present in the image. The intricacy of face detection escalates with the increase in the number of facial objects within an image. This is evident in Figure 5, which encompasses five facial objects. The test results show that the more facial objects in the picture, the more complex the process of detecting each face (Abdullah & Stephan, 2021; Sriyati et al., 2020).

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DISCUSSIONS

Based on the research results, combining the SIFT and Haar Cascade methods can produce accurate and effective values in detecting facial objects with complex backgrounds. The accuracy obtained was 81.75%, indicating that the combination of these two methods could be an alternative for solving the problem of detecting facial objects that have complex backgrounds.

In the context of an Image with 5 objects, face detection accuracy may decrease as the number of faces in the image increases. This is due to the increased complexity of the detection task, as the system must correctly identify and locate a larger number of faces. The Haar-like feature detection operation, which involves moving a fixed-sized sub-window pixel by pixel across the original image, can struggle to accurately detect all faces when the image contains many faces of different sizes. To address this, the image pyramid method is used to detect faces of various sizes. This method involves creating several reduced versions of an image and performing detection operations on each (Choi et al., 2022). Consequently, as the number of facial objects in an image increase, the detection process becomes more complex due to the need to recognize and differentiate between each face.

The research results (Munawir et al., 2020) regarding face detection using the same method, namely Haar Cascade, produced an accuracy of 76%. Other research was also carried out by Sakti et.al (2022) regarding face recognition in images using the Haar Cascade and Facenet methods, achieving a success rate of 80%. Thus, combining the two SIFT and Haar Cascade methods is an alternative for dealing with complex background problems in face detection.

CONCLUSION

In this research, the main objective expected by researchers is to overcome the problem of face detection in images with complex backgrounds. This is a problem that is a challenge in the field of image processing and pattern recognition. This research uses and tests a method that combines the Scale Invariant Feature Transform (SIFT) method and the Haar Cascade Classifier method to detect faces in images. The method used in this research has produced an accuracy value of 81.75% in face detection. Nonetheless, the quantity of facial objects within an image continues to be a factor that impacts the accuracy of face detection outcomes. Suggestions for further research further optimize the two methods used in this research and can adapt them to various conditions and adequate applications. Apart from that, further research examining face detection can provide efforts to create new techniques and algorithms to increase precision and efficiency in the face detection process.

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