Abstract—Occlusion is one of the most challenging problems for recognizing faces captured in unconstrained conditions. This paper focuses on direct detect the useful part in the face which used for features extraction process. To solve occlusion problem and detect un occluded face parts, a Non-Occluded Face Area Detection (NOFAD) method based on geometric features is proposed. The performance of the proposed method is evaluated on the SFV and MOBIO databases, and the experimental results show the outperformance of the proposed method in extracting the non-occluded facial area, realising an accuracy rate of 99.4% and 99.1%, respectively.

Keywords—Face Detection, Face Recognition, Occlusion, Geometric Features, Smartphone Database.

I. INTRODUCTION

The detection of the facial area may be insufficient to obtain useful information for face recognition. Thus, face recognition remains a difficult problem due to numerous interfering factors, which can make two images of the same face appear completely different. The most important variations are due to changes in positions, illuminations, facial expressions and occlusions. Among these challenges, facial occlusion is considered one of the most challenging problems that degrade the performance of the face recognition system. The performance of most occluded face recognition methods still has limitation in terms of accuracy and time consumption.

Occlusion increases the intra-class variation (when it is used to hide one's identity) and reduces the inter-class variation (when it is used to impersonate someone else). To make automatic face recognition more reliable, it is necessary to address the problem of occlusion or at least unintentional occlusion such as beard, moustache, hair. Improving the performance of face recognition algorithms for face images with/without unintentional occlusion is an actual problem [1]. Face recognition methods that are able to solve the problem of partial occlusion can be classified into two categories. The first category is a part based method which deals with the occlusion problem by separating the image into parts and then classifying these parts to non-occluded and occluded parts. After that, the features of the non-occluded parts are being used in the recognition process. [2] had conducted the research differently by splitting the image into fractions and classifying it using sparse representation to robustly handle occlusion which was based on the training set. While [3] proposed an approach called Psychophysically Inspired Similarity Mapping (PISIMA) to recognize occluded faces. This approach processes the local facial components instead of holistic processing. The Bayesian network model is proposed to capture the local features entailed in horizontal sub-regions of face images based on evidence collected from the psychological domain. However, this approach required many face images for training. In addition, it performed on a specific type of occlusion which did not include the unintentional occlusion. [4] divided the face image into parts and computed the intensity histogram and LBP as a texture descriptor for all patches then classified it using Support Vector Machine (SVM). The proposed approach computed the LBP for each Biometric parts to identify the test image.

The second category is feature-based methods which try to detect the occlusion parts from the local features of image.
[5] presented an algorithm that selects the best set of features or templates for each individual, and uses these distinct personal traits to boost face recognition performance even when they are partially occluded. The experiment result and comparisons show that the proposed method is effective in recognizing faces with partial occlusion and variation in expression. However, the method depended on a manually-select local features with different size.

In this research a Non-Occluded Facial Area Detection method is proposed which combined the two over mentioned categories to handle the unintentional occlusion problem by extracting a correct non-occluded area from the face using the face geometric features.

II. LITERATURE REVIEW

Although face recognition has been an active research area since the 1960s, it is still continuously evolving due to several challenges encountered by face recognition systems that heavily affect recognition accuracy. Such challenges include occlusion, varying illumination and different facial expressions. Facial occlusion, which is inherent in real-world scenarios, is considered one of the most challenging problems that degrade the performance of face recognition systems [6]. It usually emanates from wearing eyeglasses, sunglasses, hats and scarves, as well as unintentional occlusions, such as beard, moustache and hair.

In a study by [7], occlusion was detected based on skin colour. First of all, face detection was performed by using a Hough transform method followed by occlusion detection based on skin colour. For that reason, SVM classifier was used to classify skin colour and other colours in an image by training a system. During the final stage, PCA algorithm was being used for face recognition. [8] proposed a mean face image which was obtained from train image. The mean face was subtracted by test face to form an error face image. Based on the image segmentation technique, the occlusion area of the test image was obtained by using the error face image. Then, the corresponding occlusion area was being removed from the test image and finally recognition was performed by collaborative representation based classification (CRC) or robust collaborative representation based classification (RCRC). [9] proposed a face recognition method for occluded face image by detecting the occluded region using SVM classifier and processing the recognition on the non-occluded regions of image. This work did not present any quantitative results, nevertheless, the evaluation was done on controlled environment in terms of illumination and background. [10] presented an automatic and semi self-training system to detect and segment facial hair like beard and moustache simultaneously in challenging facial images. The proposed method consisted of four stages, namely superpixel generation, feature extraction, classification and refinement. The feature vector was composed of HoG and HOGG at different directions and the frequencies was extracted from both the bounding box of the superpixel and the superpixel foreground. Random Ferns and Support Vector Machine were used to build The classifier. The algorithm was evaluated on the entire MBGC, FERET database and a large subset from Pinellas database with satisfied result. However, the proposed method fails in the presence of shadows and illumination artifacts. [11]

addressed the double-occlusion problem with a limited amount of training data using a unified framework named subclass pooling. This method was introduced by dividing a face image into ordered subclasses according to their spatial locations, then a fuzzy max-pooling scheme was proposed to suppress unreliable local features from occluded regions. The results of the proposed method need to be further improved when compared to state of the art methods, furthermore, its performance degraded when there were different occlusion types for the same person.

Most of the methods mentioned above have used learning techniques to classify the occluded and useful part which is difficult to apply due to the variety of accessories that can be used for disguise or the variety of hair face features (like intensity, colour and shape differences between brow, beard and moustache). Therefore, it is difficult to model occluded parts by using a limited training database. In addition, these techniques was considered as time consuming because it requires classification of each part as a useful or occluded part [4,12,13]. In this study, the evaluation data that was used includes faces with natural occlusion like beard and moustache. An efficient method that detects a correct non-occluded face part based on the geometric features of face area was used.

III. METHODOLOGY

Most of the existing occluded face recognition methods depend on learning techniques for the detection of the occluded and non-occluded facial area. However, these methods demand training a considerable amount of data to include all accessory types or different hair intensities, which is time consuming. The present study proposes the NOFAD method to overcome the aforementioned problems by using the geometric features of the human face.

One of the advantages of NOFAD is that it does not necessitate splitting of the full image into patches nor using training data for occlusion parts. The proposed method detects the non-occluded facial area using the geometric features of the obtained face boundary from the [15]. The width and height ratio of the face boundary is used to detect the non-occluded facial area, which is unaffected by occlusions.

[16] proposed face ratio measurements and proved that the height ratio of the human face can be divided into three equal parts, as shown in Figure 1. The NOFAD method calculates the non-occluded area from the cheek because it is the clearest area unaffected by the occlusions. The non-occluded facial area is calculated depending on the measurements of
the height and width of the face boundary (see equation (1)). Figure 2 shows the non-occluded cheek area.

The selected non-occluded facial area is denoted by $U$, which starts from $(x_1, y_1)$ and ends with $(x_2, y_2)$, as shown as follows:

\[ x_1 = 0.75 u_1, \quad y_1 = 0.5 u_2, \]
\[ r = 0.33 u_2, \]
\[ x_2 = x_1 + 0.08 u_1, \quad y_2 = y_1 + 0.4 \]

where $u_1$ is the width, and $u_2$ is the height of the face boundary.

IV. EVALUATED DATABASE

To evaluate the proposed method a smartphone face video database was constructed which contains the unconstrained environment of the real world videos, in addition, the public available smartphone database MOBIO [14] was used to evaluate the NODAF method. The SFV database was captured exclusively on mobile phones (iPhone 6). Four unique video samples are available for each of the 50 male participants, that is, two videos from the front and rear cameras in an indoor environment and two other videos from both cameras in an outdoor environment with duration range of 10–15 s. The SFVs were captured at various sites over one year with people from different races, including those from the Middle East and Asia. The SFV database is complicated because most users capture photos of themselves (“selfie”) while being close to the device. In addition, the liberty to take a photo whenever and wherever introduces considerable variations among similar photographs, including image blur, angles and/or rotations and varying amounts of background, illumination and partial images. Although all these issues are prevalent in most face recognition applications, mobile devices further complicate this task due to the inability to expect consistent and cooperative behavior. In addition, both used databases include unintentional occlusion, where the users required to change their face and hair styles.

V. EXPERIMENTS, RESULT AND DISCUSSION

This section discusses the performance of the proposed NODAF method. It is evaluated on two different smartphone databases, namely, SFV and MOBIO.

The experiment presented in this section is designed to evaluate the proposed NOFAD method. The proposed method for the occlusion problem is based on the geometric facial ratio features of the face boundary obtained from face detection process. To evaluate the proposed method, the accuracy of its performance is calculated. The normalised mean $R$, $G$ and $B$ values of the obtained non-occluded area are calculated to compare them with normalised mean $R$, $G$ and $B$ values taken from the manually detected non-occluded area (ground truth). The obtained non-occluded area is considered correct if its mean $R$, $G$ and $B$ values are equal to that from the ground truth. The proposed method for detecting non-occluded facial area is evaluated on the SFV and MOBIO databases, and the accuracy rate for its performance is calculated for both databases as shown in table 1. For further evaluation, the performance of the proposed NOFAD is compared with the method of [4] on SFV and MOBIO databases. [4] proposed a method to identify biometric (useful) and non-biometric areas from the image by dividing it into patches. Therefore, the proposed patch classification algorithm in the present study aims to classify the patches into biometric and non-biometric classes. [10] proposed an automatic and semi self-training system to detect and segment the non-biometric parts. Figures 3 shows the samples of the experimental results of [4] on SFV and MOBIO databases.
VI. Conclusion

Occlusion is one of the challenges associated with face recognition. In real-world scenarios, faces are easily occluded by objects in active or passive ways. Faces may be partially occluded by the subjects themselves. For example, people wear facial accessories, such as sunglasses, hats and scarves, and may also have beard and moustache. All these occlusion types affect the face recognition performance due to their negative influence on extracting correct facial features. This study proposes the NOFAD method to extract the correct non-occluded facial area by using the geometric features of the obtained face boundary from the previous stage. The height and width ratio of the detected face boundary are used to detect the non-occluded area from the face, which is unaffected occlusions. The performance of the proposed method is evaluated on the SFV and MOBIO databases, and the experimental results show the outperformance of the proposed method in extracting the non-occluded facial area, realising an accuracy rate of 99.4% and 99.1%, respectively. In addition, the performance of the proposed method is compared with the methods of [4] and [10] for further evaluation. The comparison results show excellent performance for the proposed method in terms of accuracy rate and running time.

REFERENCES


Table 1: Accuracy Rate of NOFAD, [4] and [10] Methods

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<td>SFV</td>
<td>99.4%</td>
<td>87.5%</td>
<td>90.9%</td>
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<tr>
<td>MOBIO</td>
<td>99.1%</td>
<td>83.6%</td>
<td>87.8%</td>
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Table 2: Average Run Time (Unit: s) of NOFAD, [4] and [10] Methods

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<tr>
<td>SFV</td>
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<td>MOBIO</td>
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<td>1.6</td>
<td>2.35</td>
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