Geometrical Normalization and its Effects on facial Recognition

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Abstract— it is obvious that face recognition performance is greatly affected by the face cut. There are major databases for the face recognition evaluation, which use their own cut models. Therefore, there is no standard method for the face cut. There are many face recognition researches, which focus on feature extraction, pre-processing such as illumination, pose correction, and feature classification. However, there are very few research works done for investigating the effects of different face crops. Hence, we conducted a research on face cut models. In this paper, we study the several face cuts from the major databases, mainly yale face cut, frgc face cut, Cas-peal face cut and our proposed cut style called Ayo-cut and compare their performance differences with existing face recognition algorithms. The face images are cut based on yale standards or face recognition grand challenge (FRGC) standards or caspeal standards or our own standards. After cutting, they are filtered out to eliminate the background effects and then resulting images are used for extracting the features. We perform extensive experiments on different face cut models. The results of evaluation of face cut models show that our proposed face cut model gives the best recognition rates among the other face cut models.

Keywords— feature extraction, face cropping, face recognition, face registration, geometrical normalization

I. INTRODUCTION

Face recognition has become a very popular topic during the last decades since face recognition technology has a variety of potential applications in law enforcement and public surveillances, access control [1], [2]. It is because face recognition is untouchable biometric recognition technology, which can recognize a person from the remote distance [3]. Therefore, it has taken significant attention from both the academic and industrial companies during the past twenty years. Therefore, several researches have been conducted from different aspects of face recognition. For instance, Samal et al. [4] and Valentin et al. [5] surveyed the feature-based and the neural network-based techniques, respectively. Daugman [6] gave some interesting survey results for an effective face recognition system On the other hand, Yang et al. [7] and Hjelmas et al. [8] reviewed face detection techniques, Rothkrantz et al. [9] made a survey on the automatic facial expression analysis, Zou et al. [10] presented a survey on illumination techniques for an illumination invariant facial recognition. In addition to these surveys, there are more surveys on eye detection [11], image segmentation [12], 3D face recognition approaches [13], [14] and face poses [15]. Although there are many survey studies and significant amount of works are all done in face recognition, the research on face cut is not available. Cropping a face is significantly important for face recognition. For example, one may hypothesize that including front hairs affects the face recognition performance by causing false acceptance rates. It is because hairs are represented as a feature set in subspace if the face extraction is done by using a holistic approach such as principal component analysis [16], [17]. When using feature-based approaches like Gabor wavelets, hairs are a kind of noise factor and they are formed as a part of feature sets [18]. Therefore, two people with front hairs are mixed up to each other since hairs keep some common features after Gabor wavelets. On the other hand, convolutional neural networks [19] and Active appearance model-based approaches [20] give good results if front hairs are included. In a similar way, including chin area increases the false acceptance alarms since it also increases the background noises. Cutting face from the eyebrow area decreases the false acceptances but increases the false rejection rates. There are many factors like that which affect the recognition performance. For example, cutting the face equally both in width and height causes some loss of features since long faces needs to be cut from the above of mouth to keep width and height the same. Inclusion of forehead area also causes the front hair to be included. Therefore, it is important to know which face cuts should be used and how the faces should be filtered out.

The paper is organized as follows: In section 2, we explain the previous works and in section 3, we give the principals of face cut. Section 4 gives the experimental results. The recognition rates for the different face cuts are given in this section. Section 5 concludes the work.

II. PREVIOUS WORKS

Lu worked on an image analysis for face recognition. He investigated the close-face cut and head-face cut models [21]. In his paper, close-face cut means the face area is cropped to contain only internal structures such as the eyebrows, eyes, nose and mouth, while ” head-face cut” cropping contains the entire face area. Qatawneh et al. [22] introduced 3D face

recognition technique. He mentioned about the importance of face cropping in his paper. However, he did not analyse the effects of different cuts.

Tan et al. [27] proposed an illumination technique to remove the illumination-related components from the face surface. Their technique normalizes the face image by applying a gamma correction and then projecting the image by Difference of Gaussians (DoG) filter technique.
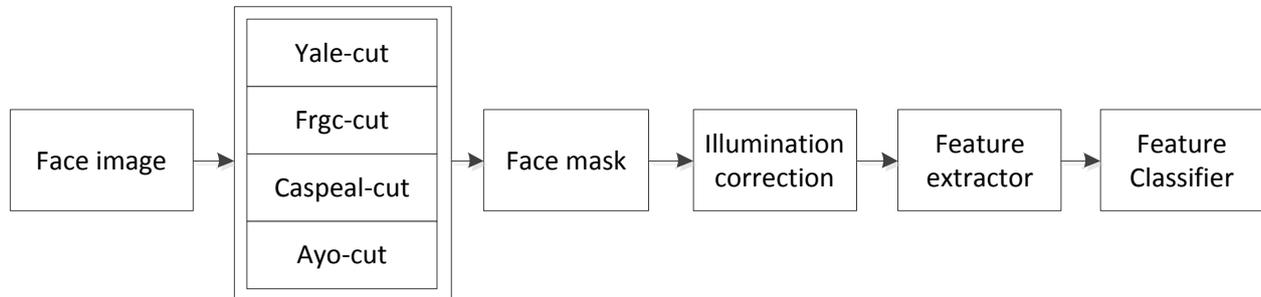
III. OVERVIEW OF THE RESEARCH

Fig. 1. Flowchart for face recognition

In fig.1, the flowchart of the system is shown. After face image is applied, the face image is cropped to include only the face region with little hair and background as fig. 2 shows (the size of the cropped face image is 50×50 for yale cut, caspeal cut, ayo-cut and 52x60 for frgc cut). In the masking step, a predefined mask is put on each cropped face image to further reduce the effect of different hairstyles and backgrounds which are not the intrinsic characteristics as fig. 2 shows. Typically, the hairstyle of a specific subject and the background

After that, illumination is corrected and feature is extracted and classified. Simple histogram equalization is used to eliminate the illumination effects. Histogram equalization is a global transform over the whole image area. Therefore, it is likely to fail when side lighting exists. Side lighting mainly causes asymmetry between the left and right parts of the face, as well as the intensity variance between the top and bottom regions.

We use feature based feature extractor as well as holistic based approaches as feature extractor during our evaluation. We choose two different approaches since the characteristics of extractors are different. For instance, holistic approach focuses on general appearance of a face and feature-based approaches work on local features such as eyes, nose, mouth, chin, cheeks. Therefore, it is very important what part from left, right, top, down we crop. In holistic approaches, this is still important but not as critical as feature-based approaches. Hence, we evaluate the cut models by using two different approaches.

A. Cut models and cut model characteristics

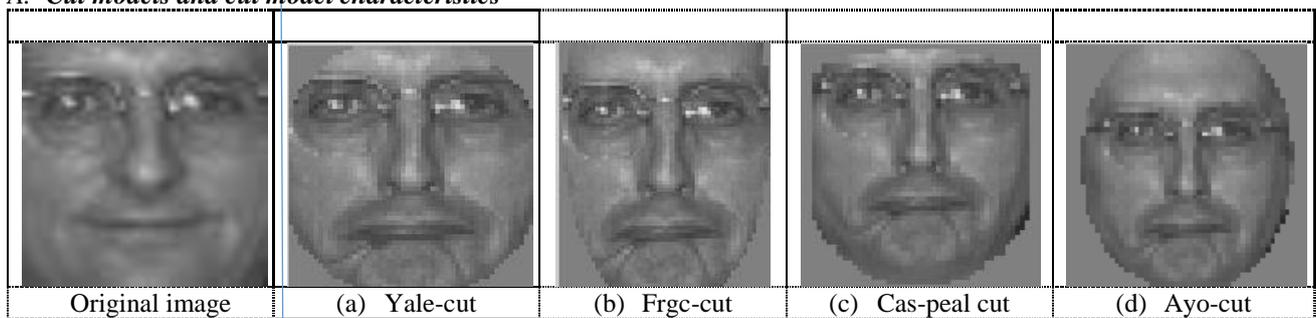| Original image | (a) Yale-cut | (b) Frgc-cut | (c) Cas-peal cut | (d) Ayo-cut |

Fig. 1. Face cut models and their masked models

In fig. 2, upper side shows the original images and lower side shows their masked images.

Yale cut is the format of the Yale database. Width and height are cut in proportion. The part of forehead and chin are left as in fig. 2(a). Frgc-cut is the cut model of the Face recognition grand challenge (FRGC). The width and height are not the same. Width is 52 pixels and height is 60 pixels in frgc-cut (fig. 2(b)). Cas-peal cut contains more chin areas compared to other three cuts as in fig. 2(c). It focuses on eliminating the forehead hairs. Finally, our proposed Ayo-cut contains more components in forehead and chin area. Therefore, more features remain as shown in fig. 2(d). Ayo-cut contains the entire head. To eliminate the background, we apply a facemask. A predefined mask is directly applied to face region by referencing the eye points. A typical ayo-cut face mask is seen in fig. 3(b). This model increases the hit rate by lowering the FAR/FRR rates [6], [13]. It is because more features are obtained from a face in this cut model.

B. Proposed cut model

Our proposed cut model contains all chin and forehead area and it is targeted to keep the invariant features.

To compute the cut area, the right, left, up down areas must be calculated. Let I(x,y) be the input face image, i_w be the width and i_h be the height of the input face image before cropping,
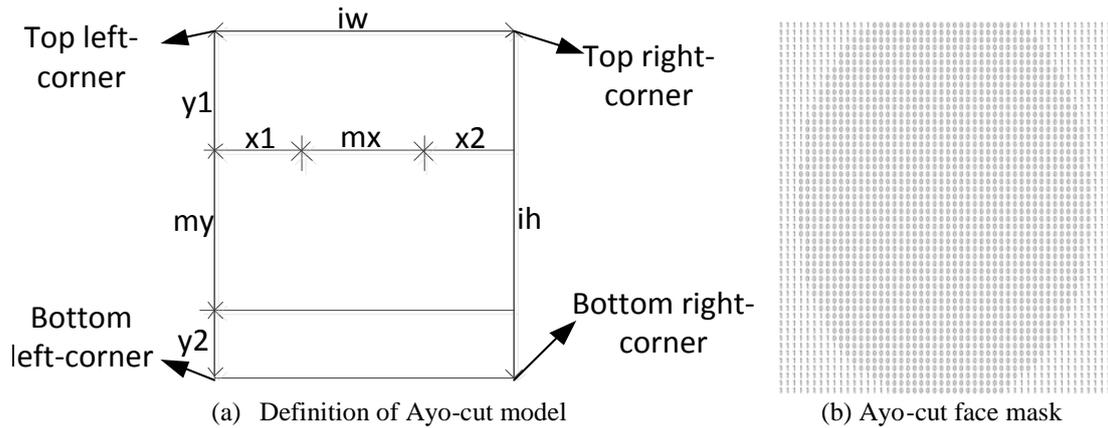
(a) Definition of Ayo-cut model

(b) Ayo-cut face mask

Fig. 3. Ayo-cut face structure

Ayo-cut cutting structure is shown in fig. 3. i_w is the width of the face and i_h is the height of the face. x_1 is the distance between the left eye and the top left corner, x_2 is the distance between the right eye and the top right corner. m_x is the distance between the eyes. y_1 is the width of the forehead. y_2 is the distance between mouth and bottom left corner. m_y is the distance between eyes and mouth. Top left-corner is the top of the left corner of a face. Top right-corner is the top of the right corner. Bottom left-corner is the bottom of the left corner of the face and bottom right-corner is the opposite side of the left-corner. These four points are automatically detected by applying the pre-trained haar-like cascades.

$$m\_x=i\_w-(x\_1+x\_2)$$
$$m\_y=i\_h-(y\_1+y\_2) \tag{1}$$

Based on above equation, the relation between m_x, x_1, m_y, y_1 is given below

$$y\_1=6/5 \ x\_1, \ y\_2=4/5 \ x\_1$$
$$x\_1=x\_2 \ , \ y\_1=(3y\_2)/2$$
$$m\_y/y\_1 =m\_x/x\_1 =4/3 \tag{2}$$

The computation is done based on two eye corners and the face coordinates. These are the only input to the cropping procedure. The equations are based on frontal face cropping. Face crop under a pose is not covered in this paper.

IV. EXPERIMENTAL RESULTS

The performance of the different face cuts by using holistic and feature-based feature extractors is evaluated and their results are given in table 1. We performed our experiments on FRGC database [23], Yale face database B [24] and CMU-PIE database [25]. The yale database contains images of 10 people at nine different poses and 64 illuminations per pose. We used all illuminations for 10 individuals in a single pose. The CMU-PIE database contains 68 individuals. We performed experiments on a set of 4,488 images, which contains 68 subjects, three poses for each subject, and 22 different illuminations for each pose. We used FRGC-DB 2.0 ROC-III protocol. It has various facial expressions (e.g., happiness, surprise). The subjects in ROC-III are 57% male and 43% female, while the age distribution is 65% 18-22 years old, 18% 23-27 and 17% 28. For testing, we used Yale Face Database B, which contains faces which are not used during the training process. Despite Yale's relatively small size, this database provides images that sample sufficiently the whole illumination space and has therefore become a testing standard for variable illumination recognition methods. In addition to this, we used the CMU-PIE database, which provides images of both pose, and illumination variation. We used frontal images for training and testing. Training images and testing images had similar illumination images. We also performed different cuts on a subset of CMU-PIE database. We used a subset of 1,496 images, which contains 68 subjects and 22 different illuminations for each pose. We chose several training images from the CMU-PIE database and used the rest of the images for the testing. Their results are given in table 1 and table 2.

Table 1 Face cut evaluation by using FRGC-DB

Feature extractor	Face cut type	Face size	Recognition rate	FAR	FRR	EER
Local-binary-patterns	Yale cut	50x50	80.4%	1%	9.99%	5.87%
	Frgc cut	52x60	90.2%	1%	8.51%	5.27%
	Cas-peal cut	50x50	92.4%	1%	7.97%	4.53%
	Ayo-cut	50x50	91.4%	1%	7.37%	4.85%
Gabor-wavelet	Yale cut	50x50	90.7%	1%	7.55%	4.93%
	Frgc cut	52x60	92.1%	1%	6.43%	3.76%
	Cas-peal cut	50x50	83.3%	1%	10.09%	6.78%

	Ayo-cut	50x50	94.3%	1%	5.30%	2.86%
Sparse-representation	Yale cut	50x50	91.5%	1%	7.20%	4.10%
	Frgc cut	52x60	94.8%	1%	4.63%	2.4%
	Cas-peal cut	50x50	90.3%	1%	6.45%	5.44%
	Ayo-cut	50x50	97.4%	1%	2.76%	1.87%

Table 1 shows the recognition rates and error rates. Recognition rates are calculated by the closest distance to the matching score. EER is computed when FAR is equal to FRR. We evaluated the different face cuts by using FRGC-DB. According to the results, PCA results are worse than Gabor wavelets. In PCA, Cas-peal cut model gave the best equal error rate (EER) with the best recognition rate. However, Gabor gave the best results by using Ayo-cut model. The EER was 2.86% in Gabor and 4.85% in PCA. The reason for that is considered due to the forehead area. PCA rather focuses on the general appearance and it is highly affected by face hair. In Gabor, face hair is minimized by changing filter magnitudes and orientation angle.

Table 2 Effect of Illumination normalization techniques on LBP by using Ayo-cut model

Illumination technique	Database	Recognition rate	Error rate(EER)
Histogram equalization		90.7%	4.93%
Tan&Triggs		92.2%	4.04%
Weberfaces	Yale-DB	88.2%	6.92%
Spherical harmonics[22]		95.5%	3.87%
Self-quotient image		89.6%	5.43%
Dog filters		90.0%	4.54%

In table 2, the effect of various illumination techniques has been investigated. We used 6 different illumination normalization algorithms as a pre-processing step to Local Binary patterns (LBP) which is used for the evaluation. According to the results, Spherical harmonics based illumination gave the lowest EER rate. Dog filters gave similar results with histogram equalization. Tan&Triggs gave the better results than histogram equalization but the results of all illumination techniques except Spherical harmonics are near to each other.

V. CONCLUSION
In this paper, we investigated different face cuts from major databases and proposed a new face cut. We demonstrated that new face model (Ayo-cut) gives significant improvements on recognition rates.
The proposed method is compared with the other cutting models and then a comparative study between the proposed face cut and other face cuts is done to see the effectiveness of the proposed method. In this research, we investigated and compared the different cuts. In this paper, we conducted testing by using frontal face images. We will do more researches on different cut models on angular face images. We plan to integrate head pose estimation methods [23] for understanding the face angle and dynamically choose and apply a different cut, which is appropriate to certain face poses. A combination of different cuts in face recognition needs more research works. All face recognition researches focus on single face cut. Some face recognition techniques are using fusing techniques by using multiple algorithms. It is obvious that one single cut is not perfect for all algorithms. If face cut is automatically adjusted depending on the face pose, feature extractor and classifier, the recognition rate will significantly improve. We keep this as future works. Furthermore, we do not consider angular face cutting in this paper. Since the cutting under a certain angle is completely different, we consider it for the future researches.

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