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The Impact of Eyebrows Region on Deep Face Recognition

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***Abstract*—We investigate the importance of the information contained in the area of the eyebrows for deep face recognition. An isotropic 2D Gaussian low-pass filter of varying bandwidth is used to remove discriminative information in the probe and reference images gradually. We measure the recognition performance of two deep learning-based face recognition systems as a function of the bandwidth of the low-pass filter applied to the eyebrows. Methods are tested on the frontal face and high-resolution images from the PUT database. The results showed that even though the eyebrows are important for recognition, deep learning still works well on facial images with removed eyebrows. Furthermore, we found that the discriminative information provided by eyebrows comes from their shapes, not their textures.**

***Index Terms*—facial recognition, biometrics, eyebrows, Gaussian blur, masking, deep learning**

I. Introduction

Automatic facial recognition (AFR) is a technology that uses computer algorithms to automatically identify or verify individuals based on their facial features. AFR is a part of the biometric system that analyzes and matches facial patterns from images or video frames captured by cameras. The process of AFR involves several steps: face detection, face alignment, feature extraction, and matching or recognition. Moreover, Deep face recognition refers to the use of deep learning techniques, specifically convolutional neural networks (CNNs), to perform facial recognition tasks. Deep face recognition takes this a step further by utilizing deep neural networks to extract intricate and high-level features from facial images, enabling more accurate and robust recognition even in challenging conditions.

In the context of facial recognition, eyebrows are essential for recognizing and distinguishing individuals. They provide the unique features of a person's face and contribute to their overall appearance. The shape, thickness, and arch of eyebrows can vary significantly among individuals and are influenced by factors like genetics, age, and cultural preferences. Some people may have naturally thin or sparse eyebrows, while others may have thick and full ones. The color of the eyebrows is typically similar to the hair color of an individual, although variations are possible. Overall, eyebrows are a distinctive facial feature that serves both functional and aesthetic purposes, contributing to the overall appearance and expression of an individual's face.

There are several research focussing on eyebrow and eye regions. In [9], Park et al. presented the periocular as a standalone modality for facial recognition. In this case, the recognition must depend purely on the eyes and eyebrows. Lionnie et al. [6] compared the recognition performance between eyes and eyebrows in partial face recognition. They showed that the accuracy of eyes and eyebrows images is similar, although the eyebrows are better than the eyes. Moreover, Lestriandoko et al. [8] presented the contribution of facial components to deep face recognition using seamless morphing. They found that eyebrows produce the highest impact on deep face recognition compared to other face parts.

Even though some methods successfully localized the eyebrows area and retrained the network using this area, the understanding of the contribution of eyebrows for deep face recognition remains inadequate. In this paper, we analyze how the eyebrows region contributes to deep face recognition. Through experiments, we determine the response of the deep face recognition system to the changes in information about the eyebrows area.

The structure of the paper is as follows. The review of prior works is described in section 2. In section 3, we introduce new methods. Next, the experiments and results are presented in section 4. Finally, we draw the discussion and conclusions in section 5.

II. Prior Work

The knowledge of facial characteristics is an important part of further face recognition development. The facial features

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such as eyes, eyebrows, nose, and mouth become highlighted for the face recognition system. As in previous research, the block-based analysis was used in [5] to analyze the face parts' contribution to recognition. Still, in the same area, Tome et al. in [14] separated the face into 15 facial regions for face analysis. They showed that the nose area has an important role. However, the nose region still contained a small part of the eyes and eyebrows. A similar method was presented by Juefei-Xu and Savvides [3]. They presented the use of eyebrows as a stand-alone biometric for recognition. The comparison of the face components showed that eyebrows are a promising facial part for recognition.

Other researchers also pointed out that eyebrows play an important role in human recognition. The shape of eyebrows is characterized by high contrast lines, which can be used to discriminate people. They also have a prominent appearance in the case of a partially occluded face, for example, people who wear a mask, balaclava, or scarf. Although there are some difficulties involved in eyebrow recognition, for example, makeup, cosmetic surgery, and low contrast between hair and skin, the eyebrows might still be useful for biometrics because the occurrence of such eyebrow difficulties is low [16]. Many researchers have explored the eye region and eyebrow features as biometric or forensic attributes. In [1], researchers investigated the use of eyebrow features for facial recognition. On the other hand, the eyebrow modality based on a forensic perspective was presented in [17].

Furthermore, Sadr in [11] presented the use of the Photoshop clone function for facial part removal to determine the importance of facial parts. The results showed that the eyebrows and eyes are important. Radji et al. [10] described the importance of eyes and eyebrows on FR and showed that eyebrows affected recognition performance significantly. However, the dataset was too small so any conclusions would lack validity. In addition, the role of eyebrows was very important in traditional methods such as in [1], [11], [10], [3], and [5], especially for local features-based recognition.

The use of eyebrows and glasses together as soft biometrics using deep learning was proposed in [7]. Researchers compared the individual performance and the fusion performance on the VISOB dataset. Their experiments showed that eyebrows authentication using deep learning resulted in an equal error rate of between 1.26% and 6.39% under various combinations of indoor and outdoor lighting conditions. Spreeuwers et al. [13] analyzed the face part by defining 30 mask regions to cover and exclude certain kinds of variation, for example, excluding eyes and mouth. They presented a combination of regional classifiers based on the LDA approach to achieve a more robust classifier against the FR challenges. In the same area, Trigueros in [15] presented a re-train CNN architecture to improve the CNN robustness against face occlusion.

III. Methods

In this paper, we investigate how the eyebrows contribute to recognition. To achieve that goal, we ran face recognition experiments where either the identity information in the eyebrow region is suppressed or of the remainder of the face. Gaussian blur:

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

is applied to the eyebrow region or on the rest of the face to suppress the identity information, where sigma (σ) is the parameter that controls the width of the blur. The visual effect of sigma on a blurred image depends on its image resolution if the interocular distance is fixed; for example, $\sigma = 5$ will give a more significant effect on a 150x150 face box than on a high-resolution of 1024x1024. Thus, we defined a range of sigma from 1 to 10 for our database containing face images of 150x150 pixels.

The proposed methods consist of a sequence of steps: preprocessing, eyebrow masking, and feature extraction and recognition.

A. Preprocessing

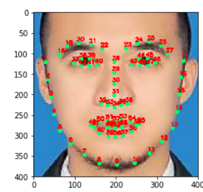


Fig. 1: The 68 points of DLIB face landmarks. We used landmarks from 18 to 27 for the eyebrows.

We apply preprocessing to facial images before they are fed into a face recognition system. The goal is to enhance the quality and consistency of facial data, making it easier for the recognition algorithm to identify and compare faces accurately.

Firstly, the face is detected and the 68 facial landmarks are obtained by the DLIB detection. Secondly, We ensured that all images were aligned before applying eyebrows masking. The alignment was based on five face landmarks that are a part of 68 DLIB face landmarks, as shown in Fig. 1. These five points are the four points of the left and right eye corners and the nose peak.

B. Eyebrows Masking

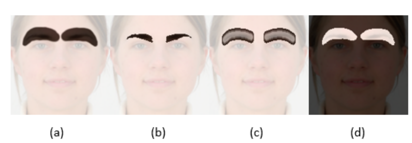


Fig. 2: Four types of mask: (a) manual mask (M); (b) automatic segmentation masking (AS); (c) gradient masking (GM); and (d) inverse manual masking (IM).

Four types of mask, as shown in figure 2, are used in our experiments to observe the impact of each eyebrow's area: (1) manual masking (M); (2) automatic segmentation masking

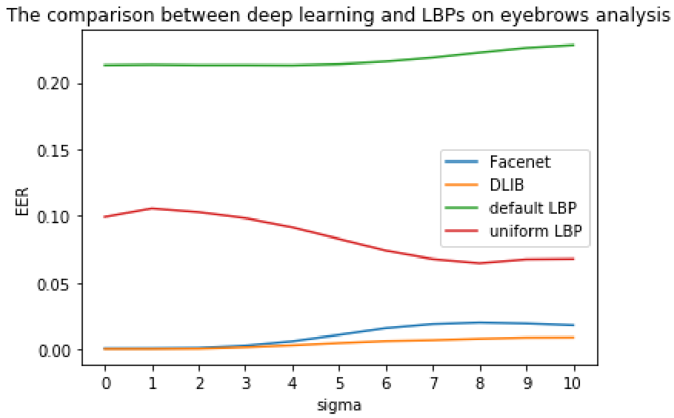


Fig. 3: The comparison of eyebrows masking analysis for various methods. There is a big gap in performance between deep learning methods (DLIB and Facenet) and classic methods(LBPs). Thus, we only use the deep learning methods for the experiments

(AS); (3) gradient masking (GM); and (4) inverse manual masking (IM). Manual masking was defined to discover the effect of removing the eyebrow and the area around it on recognition performance. The mask covered the whole eyebrows, including the area between the eyes and eyebrows.

Furthermore, the automatic segmentation masking used ten points of eyebrow landmarks from 18 to 27 to automatically isolate and segment the eyebrows. So, each image will produce a different eyebrow mask, depending on its eyebrow landmark. The goal was similar to the previous experiment, namely, to find out the effect of removing eyebrows but only focused on the inner area of eyebrows. We determined the best auto segmentation of our dataset, that is, the segmentation applying an automatic local threshold and a concave-convex mask. For the concave-convex mask, the local threshold presented a good segmentation because it covered eyebrows precisely in almost all images.

Next, gradient masking is defined to analyze the impact of information removal on a certain area of eyebrows and smooth the boundary effect on the mask. We create three layers of a mask containing different values of σ at each mask layer. The outer layer was set to smaller σ to prevent the boundary effect, i.e., σ = 1, 2, and k, respectively, with k in the range 1 to 10. Next, we observed the contribution of the inner layer to deep face recognition. In contrast, inverse masking is used to find out the importance of the remaining face area outside the mask by applying Gaussian blur to the whole image except the mask area. This experiment produced the opposite behavior to that of the previous eyebrows masking experiments. The mask area was then blurred using various σ in the range from 1 to 10.

C. Feature Extraction and Recognition

There are various deep-learning methods for face recognition. One example of deep learning that is widely used in FR is ResNet architecture. For our experiments, we chose an implementation of ResNet that is straightforward to use, such as Facenet and DLIB. Facenet was developed using inception Resnet that produced 512 features. The network consists of a batch input layer and a deep CNN followed by L2 normalization [12]. Unlike Facenet, DLIB is a ResNet network with 29 convolution layers, which is a modified version of the ResNet-34 network [2] and produces 128-dimensional features.

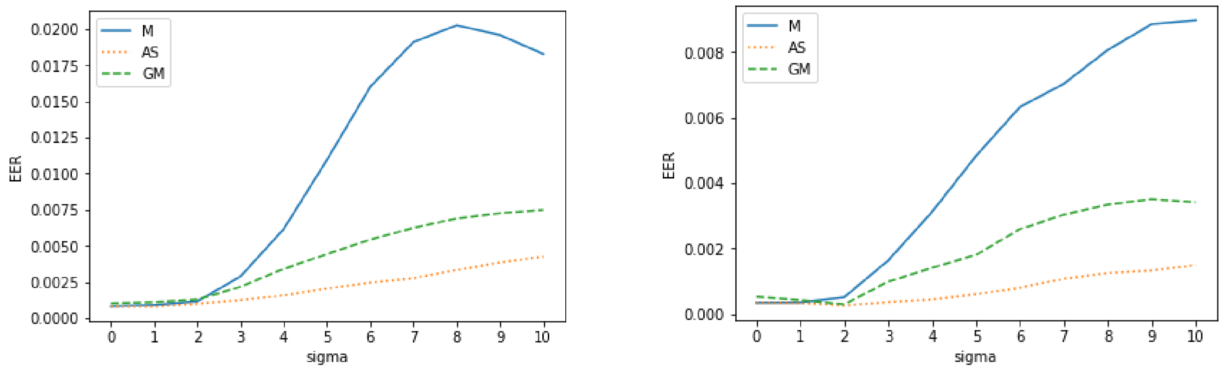
IV. Experimental Results

For the experimental setup, we chose the PUT dataset [4]. PUT provides high-resolution images, controlled settings, and the frontal faces that are needed for this work. The frontal faces contained slight poses. For testing, we used 2200 images from 100 persons.

A. Eyebrows Masking Results

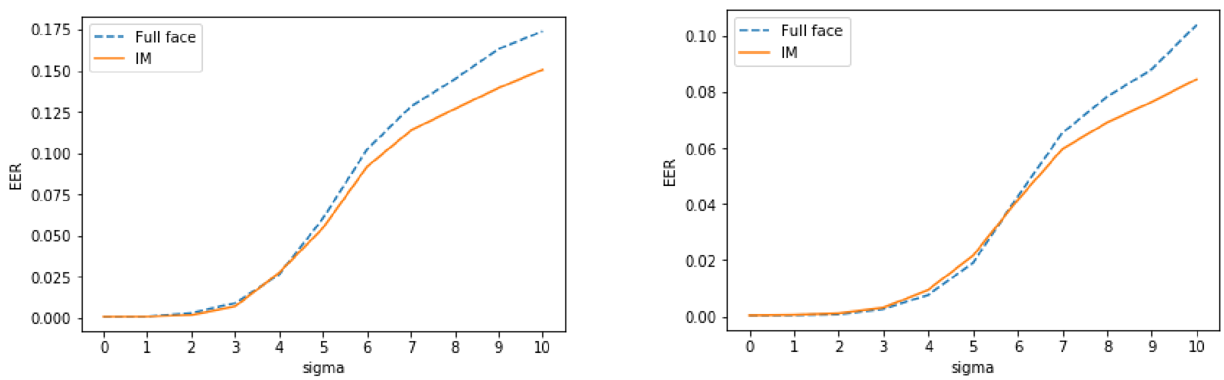
The comparison of eyebrows analysis when using various methods, i.e., Facenet, DLIB, LBP, and uniform LBP, is shown in Fig. 3. This shows that there is a big gap between classic and modern methods in eyebrows analysis performance. The behavior of the Gaussian blur impact is similar between default LBP and deep face recognition, except for the uniform LBP. The uniform LBP performance increased until $\sigma = 8$, then decreased slightly. It is caused by the encoding in the uniform LBP that gets an advantage from the smoother effect of blurring. However, deep learning still produced a good performance on eyebrows masking; even when we removed the eyebrows identity using high sigma blur, the error rate was still less than 2%. Because of the high differences in performance, we only focus on deep learning methods in the next part of the paper.

Next, the decrease in recognition performance is shown in figure 4. For the manual masking (M), the EER increased significantly after $\sigma = 2$. However, the response on Facenet was slightly different from that of DLIB; the EER became saturated more quickly than DLIB at Sigma equal to eight. These behaviors indicated that this area contains important information for recognition. On the other hand, the disadvantage of this manual masking was the lower covering accuracy



(a) (b)

Fig. 4: The impact of eyebrows masking. Focusing on gradual sigma at the inner layer (GM) resulted in a lower decrease in the equal error rate than manual eyebrows masking (M). However, segmented masking (AS) still has the lowest EER. (a) FACENET and (b) DLIB.



(a) (b)

Fig. 5: Full-face blur vs. inverse manual mask on (a) FACENET and (b) DLIB. The contribution of other face parts was still significantly more important than for eyebrows only.

than auto-masking based on eyebrow landmarks. We found the mask also covered the eyelids and eyes in some images.

Moreover, the EER of the automatic segmentation masking (AS) was almost flat because the performance decreased slightly. This behavior indicates that the inner eyebrow contains hardly any important recognition information.

For the gradient masking, figure 4 also shows that the inner layer produced less recognition contribution than the manual eyebrows mask. That means that there is important information in the outer layer. Although the inner layer did not cover the eyebrows perfectly, most of the inner layer area was related to the texture/pattern of eyebrows and partial eyebrows shape. On the other hand, the outer layer covered the shape of the eyebrows. This analysis supports the previous masking analysis that the shape is important for recognition.

B. Inverse Manual Masking Results

The inverse manual masking blurred the whole face and left the eyebrows originally. Fig. 5 shows that the performance of Facenet and DLIB decreased almost as much as for the full-face blur.

Table I shows the comparison of all methods at $\sigma = 10$ on Facenet and DLIB. Based on the comparison, the gap between IM and others was very wide. For example, on Facenet, The IM produced 15.067% EER closer to full-face (EER=17.403%) than another eyebrow masking. Similar behavior is also presented in DLIB. This behavior indicated that the role of the remaining parts is essential for recognition.

Methods	Full face	IM	M	GM	AS	Original
Facenet	17.403	15.067	1.828	0.748	0.426	0.083
DLIB	10.404	8.46	0.897	0.341	0.148	0.034

TABLE I: The Equal Error Rate (%) at $\sigma = 10$

V. Discussion and Conclusion

We have investigated the contribution of eyebrows to deep face recognition. We analyzed the effect of Gaussian blur on a specific area around the eyebrows. We further established some experiments to reach the goal: (i) manual eyebrows masking analysis; (ii) automatic segmentation masking; (iii) gradient masking; and (iv) inverse manual masking. In the first experiment (i), the Gaussian blur removed the identity at a higher sigma. The comparison between deep learning and LBPs showed that there was a big gap between classic methods (LBPs) and deep learning-based methods (DLIB and Facenet). Moreover, experiment (ii) suggested that the important information about the eyebrow is contained in its shape, not in its pattern or texture. Removing the inner part of the eyebrow does not have a big impact on recognition. Furthermore, the gradient masking behavior (iii) is also consistent with previous experiments, but with a lower error rate than for manual masking and a worse error rate than for auto segmentation masking. Supporting the segmented eyebrow analysis, the gradient sigma analysis showed that the area around the eyebrow shape is more important for deep face recognition than the pattern of inner eyebrows. Otherwise, based on experiment (iv), we see that the role of other face parts is highly important for recognition. The decrease in inverse manual masking is almost as high as for the full face. Therefore, we conclude that the use of single-modality in deep learning is not sufficiently good as a substitute for the full face, even if the facial part, such as eyebrows, contains important information for recognition.

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