Eyebrow Deserves Attention: Upper Periocular Biometrics

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Abstract: Ocular biometrics is attracting exceeding attention from research community and industry alike thanks to its accuracy, security, and ease of use in mobile devices, especially in the presence of occlusions such as masks worn during the COVID-19 pandemic. When considering the extended periocular region, eyebrows have not been getting enough attention due to their perceived low uniqueness. In this paper, we evaluate a mobile-friendly deep-learning model for eyebrow-based user authentication. Specifically, we used a fine-tuned lightCNN model for eyebrow based user authentication with promising results on a particularly challenging dataset and evaluation protocol (open-set with simulated twins). The methods achieved 0.99 AUC and 4.3% EER in VISOB dataset and 0.98 AUC and 5.6% EER on SiW datasets using closed-set and open-set analysis, respectively.

Keywords: Ocular biometrics, eyebrow biometrics, biometric recognition.

1 Introduction

Advances in deep learning has brought about remarkable improvement in the accuracy and robustness of biometric systems [Su14, PVZ15, Ng17]. Biometric systems scan a trait or modality such as face, finger or ocular region of interest in order to identify the user requesting physical or digital access. Among ocular modalities, periocular and iris have received much attention due to their accuracy and added security especially when used in smartphones [Zh18, RDR19, RD17a]. Despite advances in face recognition, there are pressing applications calling for ocular biometrics, such as users wearing face masks for safety reasons due to the recent COVID-19 pandemic. The non-touch nature of ocular biometrics adds to its utility for the aforesaid use case. However, studies have also revealed challenges related to iris and periocular recognition, including occlusions and image artifacts due to eyelids and cosmetic contact lenses, glasses, eye movements, and makeup [Bh10, MRD19, RD17b, RRD20].

Expanding the periocular region, especially towards the upper region, one may consider eyebrows and their possible utility as a biometric modality. Eyebrows, as a biometric trait, have not been well studied despite several prior works indicating their potential [Zh18, MRD19, JXS11]. Eyebrows may be used to supplement other ocular modalities such as iris in cases when the eye is closed or off-axis (Figure 1). Furthermore, eyebrow recognition can be achieved in RGB using the ubiquitous front-facing (selfie) mobile cameras,

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eschewing the need for dedicated near-infrared cameras and illumination necessary for iris recognition. Due to its lower uniqueness, eyebrows are usually categorized as a soft-biometric trait [Da11]. However, thanks to their texture and morphology consistency, at least for short term mobile use cases, eyebrows maybe used for continuous user authentication or re-identification [MRD19, JXS11].

Moving from modalities to processing methods, deep learning based methods have brought about significant improvement in ocular recognition. However, many prior works in [Al18] use large neural network models, such as VGG-16 [SZ14] and ResNet [He16]. Despite advancements in mobile hardware technology, especially in inference speed, it is prudent to use models with smaller computational footprint for lower CPU and battery usage (especially for high frequency applications), faster real-time operations, and smaller download size. In this work, we employ lightCNN, a light weight convolutional neural network which uses Max-Feature-Map activation to suppress the feature map output after every convolutional layer in order to obtain compact (256-dimensional) but yet robust and accurate feature vectors for eyebrow recognition.

Fig. 1: Scenarios where eyebrow maybe preferable over iris for user authentication.

The aim of this work is to demonstrate capabilities of an efficient mobile eyebrow-based recognition system utilizing a single eyebrow as input for user verification under a challenging protocol including near identical eyebrows (simulated twins) and open-set evaluation. The three main contributions of this work are:

1. Establishing the utility of eyebrows as a stand-alone biometric for human recognition using smartphones' front facing cameras in presence of very challenging samples.
2. Fast and efficient end-to-end eyebrow based deep learning system including an efficient feature extraction using a light-weight CNN.
3. A thorough evaluation of the aforementioned system using open and closed set protocols on VISOB [Ra16] and SiW [LJL18] datasets, captured under different lighting conditions, along with simulated twins.

2 Prior work

The study by Xu et al. [JXS11] was the first to compare eyebrows to face and ocular recognition over a large dataset. The comparison was performed between face, eye-band, and full eyebrow band. The authors evaluated the performance of full eyebrow band which is approximately 1/6 of the full face area using FRGC database under controlled and uncontrolled illumination settings. The study used three variants of Local Binary Patterns (LBP) for feature extraction followed by Principal Component Analysis (PCA) for dimensionality reduction. The average rank-one identification rate of the eyebrow was 31.7%.

Le et al. [LPS14] proposed an eyebrow segmentation and shape structure matching method. They used a Local Eyebrow Active Shape Model which locates 64 landmark points on the eyebrow. The model achieved 99.4% F-measure on NIST Multiple Biometric Grand Challenge (MBGC) dataset which consists of 200 images from 50 participants. For the identification task, the authors used two shape descriptors, inter-subject structure dissimilarities and intra-subject asymmetry dissimilarities, to match subjects' eyebrows. They reportedly achieved a rank one identification rate of 85.0% on a small subset and 71.3% on a large subset of the MBGC dataset.

Mohammad et al. [MRD19] investigated short-term eyebrow recognition in the presence of eyeglasses using VISOB and FERET dataset. For the short term identification using eyebrows, the authors proposed the fusion of GIST, histogram of oriented gradients (HOG), and VGG-16 features. A Support Vector Machine (SVM) classifier was used for matching. The best reported performance was 0.63% Equal Error Rate (EER) and 0.99 AUC using the fusion of the aforesaid three feature descriptors of both the eyebrows.

The summary of the state-of-the-art methods is shown in Table 1. It is worth noting that most of the existing methods used *closed-set protocol/ analysis*. Closed-set analysis, where the identities in the training and testing set overlap, usually result in higher accuracy because the system better adapts to the subject-specific peculiarities in the dataset. On the contrary, open-set evaluation identities between the training and testing set do not overlap. *To the best of our knowledge, there are no reported studies evaluating eyebrow recognition in an open-set environment, let alone with an added (simulated) twins-matching scenario*.

In order to be more relevant to real world applications at scale, the system needs to perform well in an open-set evaluation where identities in the test set are disjoint from those in the training set. Furthermore, we introduce simulated identical twin samples into our dataset, where the mirror image of users' right eyebrows are construed as new identities and matched against their left eyebrows, making our evaluation protocol even more challenging.

3 Proposed Method

3.1 Eyebrow Detection

The eyebrow region was segmented using Dlib [Ki09], an open source face landmark detection library. We used the Dlib version 19.18 that used histogram of oriented gradients (HOG) along with an ensemble of regression trees to detect 68 facial landmarks such as mouth and eye corners. We cropped the left and right eyebrow regions based on these

Tab. 1: Summary of the Prior Work on Eyebrow Recognition.

Ref	Method	Performance Metrics	Dataset	Result
[MRD19]	GIST, HOG, VGG-16, SVM	Verification rate	VISOB	99.72%
[JXS11]	LBP, WHT-LBP, DCT-LBP, DFT-LBP	Rank-1 identification rate	FRGC	31.7%
[LPS14]	Shape-Based Descriptors	Rank-1 identification rate	AR	76.0%
			MBGC	85.0%
[LLC13]	Fast Fourier Transform	Verification rate	BJUT	98.12%
			CFERET	89.22%
[LL07]	Hidden Markov Model	Verification rate	In-house	92.6%
[YXL13]	Sparsity Preserving Projection	Verification rate	In-house	92.5%

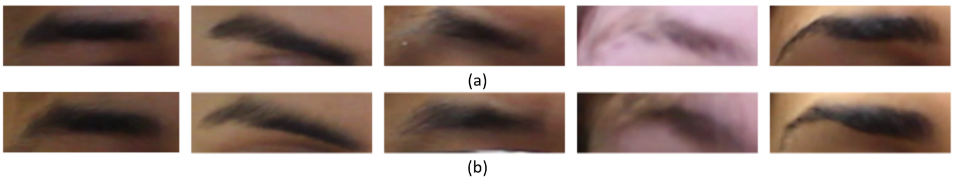

Fig. 2: Eyebrow images in SiW dataset: (a) original left eyebrow and (b) mirrored right eyebrow

landmarks. The right eyebrow crop is mirrored horizontally to synthesize a new ”twin” subject given face’s reflective symmetry, making for a challenging case similar to biometric identification of identical twins. Besides the landmarks, Dlib also provides a bounding box around the detected face.

3.2 Feature Extraction

We used lightCNN [WHS15] which has been widely used for face recognition. The general architecture of lightCNN is shown in Figure 3. The model heavily applies Max-Feature-Map (MFM) operation (see equation 1) instead of ReLu activation. This acts as feature filter after each convolution layer. The operation takes two feature maps, eliminates the element-wise minimum, and returns element-wise maximum. By doing so across feature channels, only 50% of the information-bearing nodes from each layer reach the next. Consequently, each layer is forced to preserve compact feature maps during training. The general architecture is shown in Figure 3. During the training on VISOB dataset, we added a softmax layer for classification. This layer was then removed and the remaining 256 dimensional output in MFM_fc1 was used as the feature vector representing the input identity. Two versions of lightCNN were used in this work: a 9-layer and a 29-layer lightCNN. The details of the two models can be found in [WHS15]. Thanks to their low dimensional outputs and small computational footprint for inference, both the models are suitable for mobile deployments.

$$\hat{x}_{ij}^{k} = max(x_{ij}^{k}, x_{ij}^{N}) \quad (1)$$

3.3 Matching

Cosine similarity is used extensively in deep-learning based biometric matchers such as face recognition systems. As such, we used this metric to generate eyebrow match scores between enrollment-verification feature vector pairs obtained from our lightCNN models. The function is given below:

$$d_{cos}(A,B) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (2)$$

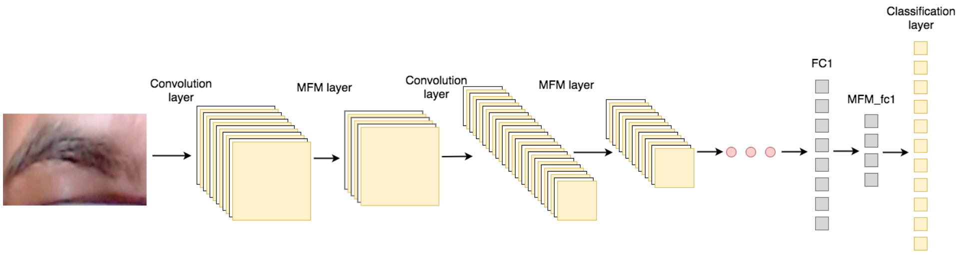

Fig. 3: Architecture of the lightCNN model used in this study.

4 Experimental Evaluation

4.1 Data and Experimental Protocol

Here we used VISible light mobile Ocular Biometric (VISOB) [Ra16] and Spoofs in the Wild (SiW) [LJL18] face anti-spoofing database to evaluate our models.

VISOB Database This database consists of eye images of about 550 healthy adults captured using three different mobile phones in three different lighting conditions. The three smartphones used in data collection are: OPPO N1, iPhone 5s, and Galaxy Note 4. During the data collection, the volunteers were asked to take selfie-like images during two visits (Visit 1 and Visit 2), 2-4 weeks apart. During each visit, images were captured in two sessions 10-15 minutes apart, and under three illumination conditions: regular office light, dim indoors, and natural daylight. In this experiment, we only used the images from OPPO device under office and natural lighting conditions.

SiW Database SiW consists of up to 8 live and 20 spoof videos from 165 participants collected at various distances, poses, illuminations, and with different facial expressions. In our experiment, we only used live videos to harvest frames. We generated more than $100,000$ images from live videos by extracting one still frame from every 10 consecutive video frames. We chose the SiW dataset for our experiment because of two reasons: the rather large number of participants and the variations in eyebrow resolution. Based on the size of the detected faces' bounding boxes as delivered by Dlib, we divided the dataset into low and high resolution subsets. An eyebrow was deemed as high resolution if the pixel count in the corresponding face bounding box was larger than 200k, and considered as low resolution if such pixel count was in the 50k to 80k range.

Enrollment and Verification Data: We arranged for a total of 7 different experiments with different enrollment and verification data divisions shown in Table 2. To maintain consistency between comparisons, a single model (trained on VISOB visit 1, session 1, daylight) was used across all the experiments. In VISOB experiments, identities in the training set re-appear in testing set, thus it follows a closed-set protocol. However, all the experiments on the SiW dataset follow an open-set protocol (disjoint training-testing identities).

Data Processing and Experimental Protocol: During model training, single crop eyebrow input images were resized to 144×144 then randomly cropped to 128×128 to fit the model input size while presenting translation variations (data augmentation). For image matching in validation and testing, we resized the image to 128×128. We trained the models with the initial learning rate of 1e-3 for a maximum of 200 epochs and used the weights from the epoch that yielded the best validation loss (early stopping). The momentum and weight decay parameters were set to 0.9 and 10e-4, respectively.

Tab. 2: List of Experiments Conducted for Eyebrow Recognition Across Lighting, Image resolution and Time Lapse.

Dataset	Experiments	Enrollment	Verification
VISOB	Short term (Visit 1) (a)	Daylight, Session 1	Daylight, Session 2
	Short term (Visit 2) (b)	Daylight, Session 1	Daylight, Session 2
	Long term (c)	Daylight, Session 1, Visit 1	Daylight, Session 2, Visit 2
	Different illumination (d)	Daylight, Session 1, Visit 1	Office, Session 2, Visit 1
SiW	High vs. high (e)	High resolution	High resolution SiW
	Low vs low (f)	Low resolution	Low resolution SiW
	Low vs. high (g)	Low resolution	High resolution SiW

4.2 Experimental Protocol

In this study, we reflected the right eyebrow image across face's longitudinal median to double the number of identities in a way that makes the comparisons quite difficult. Given face's reflective symmetry in the sagittal plane, such augmented dataset is similar to that of identical twins, a challenging case for face and eyebrow matching. Figure 2 shows examples of (a) left eyebrow images, (b) mirrored right eyebrow image processed using Dlib [Ki09]. Table 2 list the details of all the seven experiments conducted in this study. As mentioned earlier, we only used VISOB data collected in session 1 of visit 1 under natural light to train our model with 80% set for training and the remaining 20% for validation. We evaluated the trained models in various experiments. We used Equal Error Rate (EER) and Area Under the Curve (AUC) from ROC analysis to report classifier performance for each of the experiment in Table 2. The letter next to each experiment in table 2 indicates the corresponding ROC curve in the figure 4.

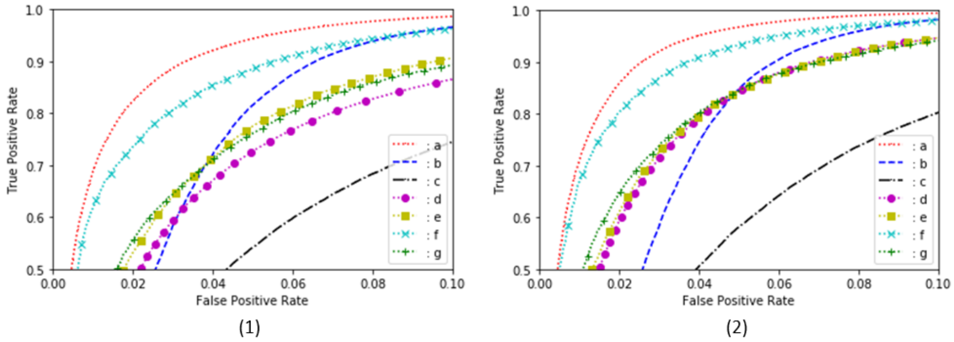

Fig. 4: ROC curves of our study's 7 experiments using (1) 9-layer and (2) 29-layer lightCNN. (a): short term verification (VISOB visit 1), (b): short term verification (VISOB visit 2), (c): long term verification, (d): different illumination, (e): high resolution vs high resolution, (f): low resolution vs low resolution, (g): low resolution vs high resolution. See Table 2 for details.

4.3 Results and Discussions

Fig 4 shows the ROC curves of the seven experiments we conducted using the 9 and 29 layer lightCNNs. As expected, both models yielded their best results on short term verification (VISOB dataset). The performance for long term verification is the worst, indicating that eyebrow is not biometrically stable over time. Cosmetic manipulation of eyebrows may also have played a role in the performance degradation. During our three experiments using SiW dataset, the low resolution versus low resolution outperformed the other two configurations. This might be due to SiW motion blur issues that are better masked in the lower resolutions.

Table 3 shows the resulting EERs [%] and AUCs (in [0,1] range). The 29-layer lightCNN yielded better results compared the 9-layer version in all the 7 experiments, meaning that the former extracted more discriminative features. Best results came from VISOB's short term verification test with the 29-layer lightCNN (EER, 4.3%, AUC, 0.990). The same network provided a 13.2% EER for VISOB long-term comparison. The 29-layer lightCNN also achieved a better EER when enrollment and verification images came from different lighting conditions (7.9% compared to 11.4% for the 9-layer model). The best open-set re-

Tab. 3: EERs and AUCs of all the Experiments in Table 2 using 9 and a 29-layer lightCNN models.

Model		LightCNN_9		LightCNN_29	
Dataset	Experiment	EER(%)	AUC	EER(%)	AUC
VISOB (Closed Set)	Short term (visit 1)	5.2	0.987	4.3	0.990
	Short term (visit 2)	7.4	0.967	6.8	0.970
	Long term	15.1	0.922	13.2	0.934
	Different illumination	11.4	0.950	7.9	0.971
SiW (Open Set)	High vs high resolution	9.7	0.963	8.0	0.973
	Low vs low resolution	7.0	0.980	5.6	0.986
	Low vs high resolution	10.3	0.960	8.2	0.973

sults (SiW dataset) show a 5.6% EER and a 0.986 AUC. Considering the especially challenging nature of our *simulated identical twins* data augmentation, these numbers show promise for eyebrows as a biometric.

One important finding from the aforementioned seven experiments is the consistency of the results across different dataset. As expected, motion blur, long term comparisons, and open set protocol did have detrimental effects on the accuracy but to a limited and reasonable extent; showing the robustness of the studied modality and matching methods.

5 Conclusion and Future Work

In this paper, we demonstrate the viability of an eyebrow recognition system that employs a light-weight deep learning model and operates on selfie-like captures. We do so using a challenging data augmentation pipeline akin to comparing identical twins, and extend our experiments to long term, open set protocols to show the resiliency of the proposed modality and matching method. Such non-touch ocular methods are especially important during challenging times such as the recent COVID-19 pandemic that has rendered ubiquitous face recognition systems into a hassle for large swaths of users wearing protective face masks. Eyebrows do deserve our attention. As a part of the future work, we would like to evaluate our pipeline with different datasets using different deep learning models in fully open-set environment. Further, eyebrow recognition will be compared with other periocular regions such as iris. Lastly, an adaptive system will be proposed to fuse eyebrow with other intra-ocular regions to further enhance the performance.

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