Texture-Based Eyebrow Recognition

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Abstract: Recent studies show that eyebrows can be used as a biometric or soft biometric for recognition. In some scenarios such as partially occluded or covered faces, they can be used for recognition. In this paper, we study eyebrow recognition using texture-based features. We apply features which have not been used before for eyebrow recognition such as 3-patch local binary pattern and WLD (Weber local descriptor) features. Also, we use more conventional features such as uniform LBP (Local binary pattern) and HOG (Histograms of oriented gradients). Methods are tested on both small- and large-sized datasets of images taken from FRGC database. Our experiments show that using some of these texture-based features together increases the performance significantly. We achieved more than 95% recognition accuracy for left and right eyebrows.

Keywords: eyebrow recognition, texture-based, local descriptor, HOG, LBP, 3-patch LBP, 4-patch LBP, WLD

1 Introduction

Face recognition systems have become more popular due to the improvements in hardware and software components. However, although the hardware and software are more robust in handling problems such as low resolution or blurring, they are not capable of identifying people accurately in some cases. For instance, when a person's face is partially occluded or covered with a balaclava, face recognition systems may easily fail. For that kind of challenging cases, one can think to use only some region of the face instead of using the whole face. Compared to other parts of the face (eye, eyelids or lip etc.) eyebrows might be more robust to different conditions such as different facial expressions. In recent years, the periocular region (eye, eye surroundings, and with or without eyebrow) is studied extensively as an alternative to iris biometrics and it is effective to identify a person. The eyebrows cover a small area on the face but it still might be very effective as a periocular region to identify a person.

There are some difficulties regarding the eyebrow biometric. With makeup or cosmetic operations (e.g. botox, plucking, tattoos), eyebrow shape or texture can be altered. If the contrast between eyebrow hair and skin is low, it is difficult to detect them and extract enough features. However, these situations are not frequent, so the eyebrow modality still might be useful biometric.

Eyebrows provide high-contrast lines which make them very noticeable, but also they might be detected even from long distances unless they are very thin. Besides, being easily

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detected, they also provide high-quality features to discriminate people. Eyebrows have shape-related characteristics such as thickness, length, and arch type. To discriminate a person using this kind of basic properties, they have to be determined very precisely, so accurate eyebrow segmentation is needed. Since it is a challenging problem itself (Dong et al.[DW11] use shape features; however, they segment eyebrows manually.), using texture information is easier and more convenient for eyebrow biometrics. In this paper, we focus on texture features of the eyebrow and propose a method for eyebrow recognition using multiple texture features. Even though 3-patch LBP and WLD features were successfully applied in face recognition and promising results were acquired, they have never been used in eyebrow biometrics before. We are the first to apply 3-patch LBP, 4-patch LBP, and WLD features in eyebrow recognition. Our proposed method achieved 'state-of-the-art' performance. Moreover, our experiments illustrated that eyebrows themselves can be as effective as a whole periocular region for identification.

This paper is structured as follows. In Section 2, we review related work. In Section 3, we describe the methods in detail. Then, we mention datasets and experiments in Section 4. We give the results and discuss our findings and compare with previous works in Section 5 and draw a conclusion in Section 6.

2 Related Work

The research in eyebrow biometrics is still limited even though some previous works such as [SJS03] and [RCA14] showed that eyebrows are one of the most important features for face recognition systems. Dong et al.[DW11] investigated the shape-based eyebrow features for biometric recognition and gender classification. Shape-based features were extracted from manually segmented eyebrow regions and grouped into three categories such as global shape features, local area features, and critical point features. They used three different classifiers: Minimum Distance Classifier (MD), Linear Discriminant Analysis Classifier (LDA), and Support Vector Machine Classifier (SVM). Best recognition rates obtained were 89%, 91% on MBGC dataset and 78%, 72% on FRGC dataset for the left and the right eyebrows respectively. In [LL07], Li et al. proposed a HMM-based eyebrow recognition system. They used Fourier coefficients as features and constructed recognition system using K-means classifier and HMMs. The proposed method tested on a small database which includes 54 eyebrow images from 27 subjects. The method achieved the highest accuracy of 92.6%. [Xu12] integrated Radon transform and SPP (sparsity preserving projections) and showed the feasibility and validity of their method by conducting an experiment on BJUT eyebrow database (The highest recognition rate of 87.2% was reported.). [YHZ13] showed that eyebrows may have the potential to be used in the real world security applications. They designed an eyebrow recognition system via fast template matching and Fourier spectrum distance. The proposed method achieved an accuracy of 98.6% on the BJUT eyebrow database. [JS11] focused on partial face. They divided the face into 6 regions (strips) and used eyebrow, eye, nose, and lip strips for recognition. Features were extracted by using LBP, WHT-LBP(Walsh-Hadamard Transform-LBP), DCT-LBP, and DFT-LBP. Unlike previous works, they used a large dataset and followed NIST's FRGC EXPERIMENT 4 protocol which involves matching 8K uncontrolled images to

16K controlled images from the 466 subjects. The average rank-1 accuracy from the full face was calculated as 47.9%. On the other hand, average accuracy from eyebrow was observed as 31.7%. Although eyebrow strip covers 1/6 of the full face, the average accuracy decreases by only 16.2%. They concluded that the eyebrow can be used as a stand-alone biometric.

3 Methodology

3.1 Preprocessing

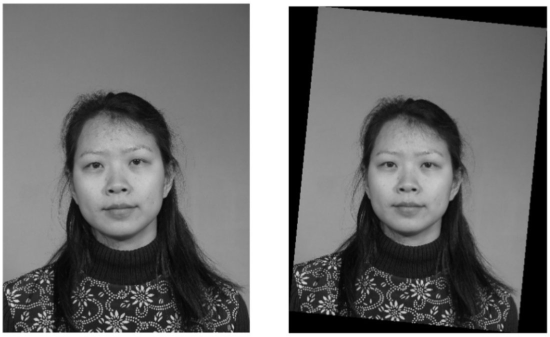
In our work, we use gray-scale images and use two different methods to obtain gray-level eyebrow images. In the first method, to align the image, an image is rotated in a way that left and right eye landmarks are aligned horizontally. Then, the image is cropped based on eyebrow landmark points (Leftmost, rightmost, topmost, and bottommost points are considered.). In the second method, we use fixed-eye coordinates. In this coordinate system, positions of eyes are constant. For instance, the xy-position of right and left eyes are (0,0) and (d,0) respectively (Here d is constant.). The image is transformed (rotation, scaling, and translation) in a way that left and right eye landmark points move to those specific positions in the space. Then, we place a fixed-size bounding box by incorporating eyebrow landmarks and crop the images. After applying both methods, the resulting images are resized to 36 by 90 pixels and used as an input image to extract features. In addition, we perform a histogram normalization in order to decrease the illumination effect before extracting features.

Fig. 1: Facial landmarks which are used in our work. There are 20 landmarks for an eyebrow and 1 landmark for an eye.

3.2 Texture Features

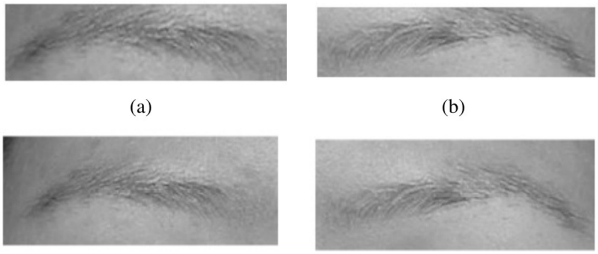
3.2.1 HOG (Histogram of Oriented Gradients) Features

The basic idea behind the HOG is local object appearance and shape can be described by local intensity gradient distributions or edge directions without knowing the edge positions [DT05]. In order to calculate the descriptor, the image is divided into small spatial regions and for each region, a local 1-D gradient histogram is calculated in a region. Then, histograms from each region are combined into a feature vector.



(a) (b)

Fig. 2: Aligning the face according to facial landmarks. (a) Original image. (b) Transformed image.



(a) (b)

(c) (d)

Fig. 3: Eyebrow images. (a)-(b) Images which are obtained by the first method. (c)-(d) Images which are obtained by the second method.

3.2.2 LBP (Local Binary Patterns) Features

The LBP is a descriptor of local spatial patterns and gray scale contrast. It was first introduced by Ojala et al.[OPH96]. Originally, each pixel in a 3-by-3 window is compared with the center pixel and labeled with 0 or 1 accordingly; then, the 8-bits binary code is obtained by concatenating all these labels in the window. The descriptor is created by calculating histograms of LBP codes in small regions. In this work, an uniform LBP which is an extension of the original LBP is used. In the uniform scheme, all the LBP codes which have more than 2 transitions (0 to 1 or 1 to 0) are assigned to one specific code.

3.2.3 Three-patch LBP Features

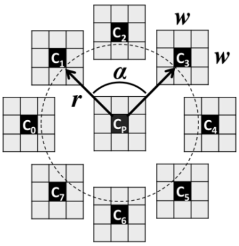
The three-patch LBP (TPLBP) descriptor is a different version of the LBP descriptor which was first introduced in [WHT08]. The way of producing each bit (0,1) in the code assigned to a single pixel differs. For each pixel in the image, a w by w patch centered on a pixel, and S additional patches distributed uniformly in a ring of radius r around the pixel are considered (see Figure 4). α is a parameter for the distance between two patches which are used at the same time. The value of a single bit is set according to which of the two patches in the ring is more similar to the central patch. The resulting code has S bits per pixel. Simply the following formula is applied to each pixel.

$$TPLBP_{r,S,w,\alpha}(p) = \sum_{i}^{S} f(d(C_i, C_p) - d(C_{(i+\alpha)\ mod\ S}, C_p))2^i \tag{1}$$

Here $d(C_i, C_p)$ is a difference between pixel values (C_i, C_p). $f(x)$ is an unit step function.

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & otherwise \end{cases} \tag{2}$$

To calculate the 3-patch LBP descriptors, the same procedure with LBP features is applied. The image is divided into m by m small equal sized regions. For each region, a histogram is obtained by using 3-patch LBP codes. Then, these histograms are concatenated. The final histogram vector is called as 3-patch LBP descriptor.



$$\begin{aligned}
&\mathrm{TPLBP}_{r,8,3,2}(p) = \\
&f(d(C_0, C_p) - d(C_2, C_p))2^0 + \\
&f(d(C_1, C_p) - d(C_3, C_p))2^1 + \\
&f(d(C_2, C_p) - d(C_4, C_p))2^2 + \\
&f(d(C_3, C_p) - d(C_5, C_p))2^3 + \\
&f(d(C_4, C_p) - d(C_6, C_p))2^4 + \\
&f(d(C_5, C_p) - d(C_7, C_p))2^5 + \\
&f(d(C_6, C_p) - d(C_0, C_p))2^6 + \\
&f(d(C_7, C_p) - d(C_1, C_p))2^7
\end{aligned}$$

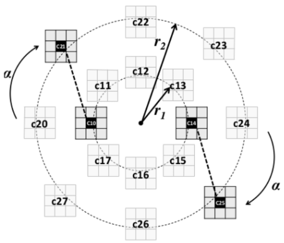
Fig. 4: 3-patch LBP process with parameters $S = 8$, $\alpha = 2$ and $w = 3$. (Courtesy [WHT08])

3.2.4 Four-patch LBP Features

The four-patch LBP (FPLBP) was first introduced in [WHT08] as three-patch LBP. For each pixel in the image, two rings of radii r_1 and r_2 centered on a pixel, and S patches of size w by w spread out evenly on each ring are considered (see Figure 5). To produce a four-patch LBP code, two center symmetric patches in the inner ring with two center symmetric patches in the outer ring positioned α patches away along the circle (say, clockwise) are compared. One bit in each pixel's code is set according to which of the two pairs being compared is more similar. Thus, for S patches along each circle, there are $S/2$ center symmetric pairs which are the length of the binary codes produced. The formal definition of the four-patch LBP is following.

$$FPLBP_{r_1,r_2,S,w,\alpha}(p) = \sum_{i}^{S/2} f(d(C_{1,i}, C_{2,i+\alpha\ modS}) - d(C_{1,i+S/2}, C_{2,i+S/2+\alpha\ modS})2^i \tag{3}$$

After 4-patch LBP code is calculated for each pixel, the feature vector is created by applying the same procedure with LBP and 3-patch LBP.



$$
\begin{aligned}
&\mathrm{FPLBP}_{r1,r2,8,3,1}(p) = \\
&f(d(C_{10},C_{21}) - d(C_{14},C_{25}))2^0 + \\
&f(d(C_{11},C_{22}) - d(C_{15},C_{26}))2^1 + \\
&f(d(C_{12},C_{23}) - d(C_{16},C_{27}))2^2 + \\
&f(d(C_{13},C_{24}) - d(C_{17},C_{28}))2^3
\end{aligned}
$$

Fig. 5: 4-patch LBP process with parameters $S = 8$, $\alpha = 1$ and $w = 3$. (Courtesy [WHT08])

3.2.5 WLD Features

Weber local descriptor was first introduced in [Ch08]. It is inspired by Weber's Law[NE06] which is a perceptual law and simply states that the size of a just noticeable difference (ΔI) is a constant (k) proportion of the original stimulus value (I).

$$\frac{\Delta I}{I} = k \tag{4}$$

For instance, in a noisy environment, one must shout to be heard while a whisper works in a quiet room.

This descriptor consists of two components: differential excitation and orientation. Differential excitation for each pixel is computed as following.

$$\xi(x_c) = \arctan\left(\sum_{i=0}^{p-1} \frac{x_i - x_c}{x_c}\right) \tag{5}$$

here, x_c is the central pixel and x_i is the neighboring pixel. In order to prevent differential excitation of the pixel from increasing or decreasing too quickly, the arctan function is used as the excitation function (A sigmoid function can be used as well.). The orientation component is computed as following.

$$\theta(x_c) = \arctan\left(\frac{x_{right} - x_{left}}{x_{bottom} - x_{top}}\right) \tag{6}$$

here, x_{right} corresponds to right neighboring pixel of x_c. After differential excitation and orientation are computed, two suitable bins (one for excitation and one for orientation) are assigned to each pixel in the image, so each pixel is encoded with two numbers. Then, the image is divided into m by m small equal sized regions. For each region, 2-D histogram $WLD(\xi_j, \theta_t)$ is obtained and then, the 2D histogram $WLD(\xi_j, \theta_t)$ is further encoded into a 1D histogram H by reshaping. The final descriptor is created by concatenating the histogram (H) of each region (See Figure 6).

3.3 Score Functions

To compute the similarity between different feature vectors, L2 and χ^2 distances are used which show higher performance compared to L1 and normalized cosine distances.

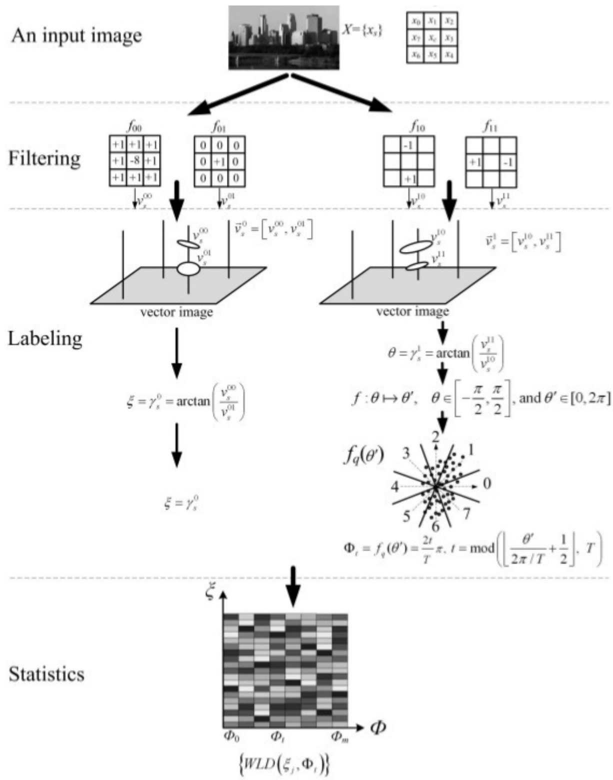


Fig. 6: Illustration of the computation of the WLD descriptor. (Courtesy [Ch10])

3.4 Score Fusion

Score-level fusion is used to fuse the information from different methods. Reduction of high-scores effect (RHE) normalization[He10], which is more robust compared to standard min-max normalization, is used. The normalized score x' is computed as following.

$$x' = \frac{x - X_{min}}{X^*_{mean} + X^*_{std} - X_{min}} \tag{7}$$

where x is the unnormalized score, X is the set of all the scores (genuine+impostor) and X^* is the set of genuine scores.

4 Experimental Setup

4.1 Dataset

In this work, the FRGC (Face Recognition Grand Challenge) v2.0[PF05] dataset was used. The images were taken in controlled and uncontrolled settings. Frontal images were taken into two lighting conditions with two facial expressions(smiling and neutral) from different poses. In this work, only controlled images are used. In the first experiment, 500 images have been randomly chosen from 100 subjects (50 female, 50 male), 5 images each. In the second experiment, all the controlled images with facial landmark points are used, in total 12078 images from 568 subjects. The maximum number of images per subject is 70. In order to extract the eyebrow region, the locations of the facial landmark points have been obtained from DEST (Deformable Shape Tracking) facial landmarks. There are 199 landmarks in total and each eyebrow is encircled by 20 landmark points.

Fig. 7: Example (controlled) images from the FRGC dataset.

4.2 Experiments

We conducted 2 experiments. In the first experiment, we used 5 different feature extraction techniques (e.g HOG, LBP) and 2 different matching (preprocessing) techniques for left and right eyebrow images. We did not incorporate any learning (training) procedures. To compute the similarity between different feature vectors, we used Euclidean (L2) and χ^2 distances. Both verification and closed set identification tests were performed. For verification, a similarity matrix was created by taking the multiplicative inverse of each distance. In total, 1K genuine similarity scores and 123K impostor similarity scores were obtained. The performance was evaluated in terms of EER (Equal Error Rate). For identification, 3 images for each subject were randomly selected as the gallery image and the other 2 images were used as the probe image. The performance was evaluated in terms of rank-1 accuracy. In the second experiment, we used a large data-set. We followed the same procedure with the first experiment except we used only one matching technique and only one distance (L2 or χ^2) for each feature according to first experiment results. For identification, 200K genuine and 72 million impostor similarity scores were obtained. For identification test, half of the images were randomly selected as gallery image and the remaining images were used as probe images. In both experiments, information from different sources was fused in score level and the performances are reported in the same way.

5 Results & Discussion

The results of the experiments are listed in Table I and II and IV in terms of the equal error rate (EER) and in Table III and V in terms of the rank-1 accuracy. In order to obtain high performance, parameters of each method were optimized roughly in the first experiment and in the second experiment exactly the same parameters were used. The second matching (preprocessing) technique gives better results (see Table I); therefore, for the rest of the experiments, only the second method was used. TPLBP and FPLBP features give lower EER with Euclidean (L2) distance; whereas, HOG and WLD features give lower EER with χ^2 distance; thus in the rest of the experiments, L2 distance is used for TPLBP and FPLBP features; χ^2 distance is used for the other features.

Our work shows that for eyebrow recognition using texture-based approach, transforming an image into a fixed-eye reference frame and using a fixed-size bounding box (method 2) is much better matching technique than using a variable-size bounding box according to eyebrow landmarks and re-sizing it to fixed size (method 1). Method 2 is more robust to inter-shape changes, so it provides impostor similarity distribution with lower variance. We think that the main reason that causes lower performance of method 1 is that eyebrow landmarks are not perfectly located on the boundary of the eyebrow (especially at the right and left tails of an eyebrow).

The uniform LBP descriptor outperforms the rest of the descriptors in terms of both EER and accuracy. Score fusion improves the performance. Even though FPLBP does not perform very well, it is effective when it is used with other features. According to results obtained, LBP and FPLBP together are quite robust and achieve the highest performance in most of the cases. The best result obtained in the first experiment is 6.3% EER, 97.5% rank-1 accuracy and 5.7% EER, 96.5% rank-1 accuracy for the left and the right eyebrows respectively. The results of the second experiment are compatible with of the first experiment. The best result obtained in the second experiment is 9.0% EER for both eyebrow and 96.2%, 95.3% rank-1 accuracy for the left and the right eyebrows respectively.

Results of the first experiment indicate that texture features are more robust compared to shape features which are studied in [DW11]. Dong et al.[DW11] tested their shape-based method on FRGC dataset with similar dataset size (400 samples, 100 subjects) and the best performance they achieved (7.0% EER) is worse than we obtained (5.7% EER). In addition, results show that eyebrows are robust to changes in illumination, pose and facial expression. Even though eyebrows cover significantly less area than the periocular region, only small degradation occurs in recognition performance. Mahalingam et. al.[MR13] studied the LBP-based periocular recognition and they conducted experiments on the FRGC dataset with similar dataset size and similar dataset split (50% gallery, 50% probe). They achieved 97.44% rank-1 accuracy which is only 1.2% higher than our highest rank-1 accuracy.

Distance	L2 Distance				χ^2 Distance			
	Left-1	Left-2	Right-1	Right-2	Left-1	Left-2	Right-1	Right-2
HOG	10.5	8.0	11.9	8.5	10.3	**7.4**	11.4	**8.0**
LBP	10.7	**7.2**	10.1	7.5	9.5	7.7	9.4	**7.0**
WLD	14.0	11.2	13.5	10.7	10.2	**9.6**	10.5	**8.3**
TPLBP	12.8	**9.8**	11.9	**8.4**	15.7	13.2	16.4	13.1
FPLBP	12.8	**8.6**	12.5	**8.8**	13.7	9.8	13.2	10.3

Tab. 1: Equal Error Rate (EER)'s of the first experiment.

Features	H+L	H+W	W+T	W+F	W+L	T+F	T+H	F+H	L+T	L+F
Left	**6.3**	8.0	8.1	7.4	8.0	7.7	7.1	6.7	7.1	6.6
Right	6.5	7.2	7.1	6.2	7.2	6.8	6.9	6.2	6.5	**5.7**

Tab. 2: Equal Error Rate (EER)'s of the first experiment using multiple features. For suitability, only first letters of the methods are shown (H:HOG, L:LBP, W:WLD, T:TPLBP, F:FPLBP).

Features	H	L	W	T	F	H+T	H+F	H+L	H+W	W+L	T+F	L+T	L+F
Left	92.5	**96.0**	92.5	92.5	88.5	95.0	94.0	**97.5**	96.5	96.5	94.5	96.0	96.0
Right	91.5	**95.0**	92.0	90.5	87.0	93.0	93.5	96.0	94.0	95.0	92.5	96.0	**96.5**

Tab. 3: Rank-1 accuracies of the first experiment.

Features	H	L	W	T	F	H+T	H+F	H+L	H+W	W+L	T+F	L+T	L+F
Left	11.1	**10.5**	12.9	12.6	11.2	10.4	9.6	9.9	10.6	10.6	10.3	10.2	**9.0**
Right	11.3	**10.1**	12.1	12.1	12.0	10.1	9.6	9.9	10.2	10.1	10.4	9.7	**9.0**

Tab. 4: Equal Error Rate (EER)'s of the second experiment.

6 Conclusion

In this work, we studied eyebrow recognition using several texture-based descriptors. These descriptors are HOG, uniform LBP, 3-patch LBP, 4-patch LBP, and WLD. We tested our methods on a large dataset which contains more than 12000 samples and the results we obtained show that LBP is more successful for eyebrow recognition problem. Also, we achieved better results by score fusion. The best result is obtained by using LBP and 4-patch LBP together, with 96.2% and 95.3% rank-1 accuracy for left and right eyebrows respectively. It suggests these texture-based features may be used for biometric recognition applications.

For the future work, we will test our method under non-ideal imaging conditions. In this work, we used pre-defined facial landmark points to extract the eyebrow regions, so in order to create a complete recognition system, we are planning to construct an automatic eyebrow detector.

References

[DW11] Dong, Yujie; Woodard, Damon L.: Eyebrow shape-based features for biometric recognition and gender classification: A feasibility study. Biometrics (IJCB), 2011 International Joint Conference on. IEEE, 2011.

[Ch10] Chen, Jie, et al.: WLD: A robust local image descriptor. IEEE transactions on pattern analysis and machine intelligence 32.9, pp: 1705-1720, 2010.

[WHT08] Wolf, Lior; Hassner, Tal; Taigman, Yaniv : Descriptor based methods in the wild. Workshop on faces in'real-life'images: Detection, alignment, and recognition. 2008.

[JS11] Juefei-Xu, Felix; Savvides, Marios : Can your eyebrows tell me who you are?. Processing and Communication Systems (ICSPCS), 2011 5th International Conference on. IEEE, 2011.

Features	H	L	W	T	F	H+T	H+F	H+L	H+W	W+L	T+F	L+T	L+F
Left	92.3	**95.0**	90.0	90.3	86.7	93.7	93.0	95.8	94.7	95.4	93.3	94.7	**96.2**
Right	90.8	**93.3**	90.8	89.0	84.4	92.0	91.6	94.5	93.4	94.4	92.2	93.8	**95.3**

Tab. 5: Rank-1 accuracies of the second experiment.

[PF05] Phillips, P.J.; Flynn, P.J.; Scruggs, T.; Bowyer, K.W.; Chang, J.; Hoffman, K.; Marques, J.; Min, J.; Worek, W.: Overview of face recognition grand challenge. IEEE Conference on Computer Vision and Pattern Recognition, 2005.

[DT05] Dalal, Navneet; Triggs, Bill : Histograms of Oriented Gradients for Human Detection. Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on. Vol. 1. IEEE, 2005.

[OPH96] Ojala, Timo; Pietikinen, Matti; Harwood, David: A comparative study of texture measures with classification based on featured distributions. Pattern recognition 29.1, pp: 51-59, 1996.

[YHZ13] Yujian, Li; Houjin, Li; Zhi, Cai : Human Eyebrow Recognition in the Matching-Recognizing Framework. Computer Vision and Image Understanding 117, pp: 170-181, 2013.

[He10] He, Mingxing, et al.: Performance evaluation of score level fusion in multimodal biometric systems. Pattern Recognition 43.5, pp: 1789-1800, 2010.

[NE06] Nutter, Forrest W.; Esker, Paul D. : The role of psychophysics in phytopathology: The Weber-Fechner law revisited. European Journal of Plant Pathology 114.2, pp: 199-213, 2006.

[MR13] Mahalingam, Gayathri; Ricanek, Karl : LBP-based periocular recognition on challenging face datasets. EURASIP Journal on Image and Video processing 2013.1, 2013:36.

[LL07] Li, Yujian; Li, Xingli : Hmm based eyebrow recognition. Intelligent Information Hiding and Multimedia Signal Processing, 2007. IIHMSP 2007. Third International Conference on. Vol. 1. IEEE, 2007.

[Xu12] Xu Xiaojun, Yang Xinwu, Li Yujian, and Yang Yuewei: Eyebrow recognition using radon transform and sparsity preserving projections. In Automatic Control and Artificial Intelligence (ACAI 2012), International Conference on, pages 1028â1033, March 2012

[SJS03] Sadr, Javid; Jarudi, Izzat; Sinha, Pawan : The role of eyebrows in face recognition. Perception 32.3, pp: 285-293, 2003.

[RCA14] Radji, Nadjet; Cherifi, Dalila; Azrar, Arab : Effect of eyes and eyebrows on face recognition system performance. Image Processing, Applications and Systems Conference (IPAS), 2014 First International. IEEE, 2014.

[Ch08] Chen, Jie, et al.: A robust descriptor based on weberâs law. Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on. IEEE, 2008.