

# Identifying Useful Features for Recognition in Near-Infrared Periocular Images

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**Abstract**—The periocular region is the part of the face immediately surrounding the eye, and researchers have recently begun to investigate how to use the periocular region for recognition. Understanding how humans recognize faces helped computer vision researchers develop algorithms for face recognition. Likewise, understanding how humans analyze periocular images could benefit researchers developing algorithms for periocular recognition. We presented pairs of periocular images to testers and asked them to determine whether the two images were from the same person or from different people. Our testers correctly determined the relationship between the two images in over 90% of the queries. We asked them to describe what features in the images were helpful to them in making their decisions. We found that eyelashes, tear ducts, shape of the eye, and eyelids were used most frequently in determining whether two images were from the same person. The outer corner of the eye and the shape of the eye were used a higher proportion of the time for incorrect responses than they were for correct responses, suggesting that those two features are not as useful.

## I. INTRODUCTION

The periocular region is the part of the face immediately surrounding the eye. While the face and the iris have both been studied extensively as biometric characteristics [1], [2], the use of the periocular region for a biometric system is an emerging field of research. Periocular biometrics could potentially be combined with iris biometrics to obtain a more robust system than iris biometrics alone. If an iris biometrics system captured an image where the iris image was poor quality, the region surrounding the eye might still be used to confirm or refute an identity. A further argument for researching periocular biometrics is that current iris biometric systems already capture images containing some periocular information, yet when making recognition decisions, they ignore all pixel information outside the iris region. The periocular area of the image may contain useful information that could improve recognition performance, if we could identify and extract useful features in that region.

A few papers [3], [4], [5], [6] have presented algorithms for periocular recognition, but their approaches have relied on general computer vision techniques rather than methods specific to this biometric characteristic. One way to begin designing algorithms specific to this region of the face is to examine how humans make recognition decisions using the periocular region.

Other computational vision problems have benefitted from a good understanding of the human visual system. In a recent book chapter, O’Toole [7] says, “Collaborative interactions between computational and psychological approaches to face

recognition have offered numerous insights into the kinds of face representations capable of supporting the many tasks humans accomplish with faces” [7]. Sinha et al. [8] describe numerous basic findings from the study of human face recognition that have direct implications for the design of computational systems. Their report says “The only system that [works] well in the face of [challenges like sensor noise, viewing distance, and illumination] is the human visual system. It makes eminent sense, therefore, to attempt to understand the strategies this biological system employs, as a first step towards eventually translating them into machine-based algorithms” [8].

In this study, we investigated which features humans found useful for making decisions about identity based on periocular information. We found that the features that humans found most helpful were not the features used by current periocular biometrics work [3], [4], [5], [6]. Based on this study, we anticipate that explicit modeling and description of eyelids, eyelashes, and tear ducts could yield more recognition power than the current periocular biometrics algorithms published in the literature.

The rest of this paper is organized as follows. Section II summarizes the previous work in periocular biometrics. Section III describes how we selected and pre-processed eye images for our experiment. Our experimental method is outlined in Section IV. Section V presents our analysis. Finally, Section VI presents a summary of our findings, a discussion of the implications of our experiment, and recommendations for future work.

## II. RELATED WORK

The work related to periocular biometrics can be classified into two categories. The first category includes initial research in segmenting and describing periocular features for image classification. This research used features to determine ethnicity or whether an image was of a left or right eye. The second category includes recent research that has analyzed periocular features for recognition purposes.

### A. Periocular Feature Extraction for Image Classification

A classifier to determine whether an eye image is a left or right eye is a valuable tool for detecting errors in labeled data. One preliminary method of differentiating between left and right eyes used the locations of the pupil center and the iris center [9]. The pupil is often located to the nasal side of the iris rather than being directly in the center. An accurate tear duct detector could also be used as a right/left classifier. Abiantun and Savvides [9] evaluated five different methods

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Table I: Periocular Research

Paper	Data	Algorithm	Features
Park et al. [3]	899 visible light face images 30 subjects	Gradient orientation histograms Local binary patterns Euclidean distance SIFT matcher	Eye region with width: 6*iris-radius height: 4*iris-radius
Miller et al. [4]	FRGC data: visible light face images, 410 subjects FERET data: visible light face images, 54 subjects	Local binary patterns City block distance	Skin
Adams et al. [5]	Same as Miller et al.	Local binary patterns Genetic algorithm to select features	Skin
Woodard et al. [6]	MBGC data: near infrared face images, 88 subjects	Local binary patterns Result fused with iris matching results	Skin
This work	Near infrared images from LG 2200 iris camera 120 subjects	Human analysis	Eyelashes, Tear duct Eyelids, and Shape of eye

for detecting the tear duct in an iris image: (1) Adaboost algorithm with Haar-like features, (2) Adaboost with a mix of Haar-like and Gabor features, (3) support vector machines, (4) linear discriminant analysis, and (5) principal component analysis. Their tear-duct detector using boosted Haar-like features correctly classified 179 of 199 images where the preliminary method had failed. Bhat and Savvides [10] used active shape models (ASMs) to fit the shape of the eye and predict whether an eye is a right or left eye. They trained two different ASMs: one for right eyes, and one for left eyes. They ran both ASMs on each image, and evaluated the fit of each using Optimal Trade-off Synthetic Discriminant Filters.

Li et al. [11] extracted features from eyelashes to use for ethnic classification. They observed that Asian eyelashes tend to be more straight and vertically oriented than Caucasian eyelashes. To extract eyelash feature information, they first used active shape models to locate the eyelids. Next, they identified nine image patches along each eyelid boundary. They applied uni-directional edge filters to detect the direction of the eyelashes in each image patch. After obtaining feature vectors, they used a nearest neighbor classifier to determine whether each image showed an Asian or a Caucasian eye. They achieved a 93% correct classification rate.

These papers describe methods for extracting periocular features, but their focus is on classification, not recognition. Our paper focuses on determining which features have the most descriptive power for recognition.

### B. Periocular Recognition

The use of periocular features for recognition is a new field of research, and only a few authors have published in the area. The first periocular paper published presented a feasibility study for the use of the periocular biometrics [3]. The authors, Park et al., implemented two methods for analyzing the periocular region. In their “global method”, they used the location of the iris as an anchor point. They defined a grid around the iris and computed gradient orientation histograms

and local binary patterns for each point in the grid. They quantized both the gradient orientation and the local binary patterns (LBPs) into eight distinct values to build an eight-bin histogram, and then used Euclidean distance to evaluate a match. Their “local method” involved detecting key points using a SIFT matcher. They collected a database of 899 high-resolution visible-light face images from 30 subjects. A face matcher gave 100% rank-one recognition for these images, and their matcher that used only the periocular region gave 77%.

Another paper by Miller et al. also used LBPs to analyze the periocular region [4]. They used visible-light face images from the Facial Recognition Grand Challenge (FRGC) data and the Facial Recognition Technology (FERET) data. The periocular region was extracted from the face images using the provided eye center coordinates. Miller et al. extracted the LBP histogram from each block in the image and used City Block distance to compare the information from two images. They achieved 89.76% rank-one recognition on the FRGC data, and 74.07% on the FERET data.

Adams et al. [5] also used LBPs to analyze periocular regions from the FRGC and FERET data, but they trained a genetic algorithm to select the subset of features that would be best for recognition. The use of the genetic algorithm increased accuracy from 89.76% to 92.16% on the FRGC data. On the FERET dataset, the accuracy increased from 74.04% to 85.06%.

While Park et al., Miller et al., and Adams et al. all used datasets of visible-light images, Woodard et al. [6] performed experiments using near-infrared (NIR) light images from the Multi-Biometric Grand Challenge (MBGC) portal data. The MBGC data shows NIR images of faces, using sufficiently high resolution that the iris could theoretically be used for iris recognition. However, the portal data is a challenging data set for iris analysis because the images are acquired while a subject is in motion, and several feet away from the camera. Therefore, the authors proposed to analyze both

the iris and the periocular region, and fuse information from the two biometric modalities. From each face, they cropped a 601x601 image of the periocular region. Their total data set contained 86 subjects' right eyes and 88 subjects' left eyes. Using this data, the authors analyzed the iris texture using a traditional Daugman-like algorithm [12], and they analyzed the periocular texture using LBPs. The periocular identification performed better than the iris identification, and the fusion of the two modalities performed best.

One difference between our work and the above mentioned papers is the target data type (Table I). The papers above all used periocular regions cropped from face data. Our work uses near infrared images of a small periocular region, from the type of image we get from iris cameras. The anticipated application is to use periocular information to assist in iris recognition when iris quality is poor.

Another difference between our work and the above work is the development strategy. The papers mentioned above used gradient orientation histograms, local binary patterns, and SIFT features for periocular recognition. These authors have followed a strategy of applying common computer vision techniques to analyze images. We attempt to approach periocular recognition from a different angle. We aim to investigate the features that humans find most useful for recognition in near infrared images of the periocular region.

### III. DATA

In selecting our data, we considered using eye images taken from two different cameras: an LG2200 and an LG4000 iris camera. The LG2200 is an older model, and the images taken with this camera sometimes have undesirable interlacing or lighting artifacts [13]. On the other hand, in our data sets, the LG4000 images seemed to show less periocular data around the eyes. Since our purpose was to investigate features in the periocular region, we chose to use the LG2200 images so that the view of the periocular region would be larger. We hand-selected a subset of images, choosing images in good focus, with minimal interlacing and shadow artifacts. We also favored images that included both the inner and outer corners of the eye.

We selected images from 120 different subjects. We had 60 male subjects and 60 female subjects. 108 of them were Caucasian and 12 were Asian. For 40 of the subjects, we selected two images of an eye and saved the images as a "match" pair. In each case, the two images selected were acquired at least a week apart. For the remaining subjects, we selected one image of an eye, paired it with an image from another subject, and saved it as a "nonmatch" pair. Thus, the queries that we would present to our testers involved 40 match pairs, and 40 nonmatch pairs. All queries were either both left eyes, or both right eyes.

Our objective was to examine how humans analyzed the periocular region. Consequently, we did not want the iris to be visible during our tests. To locate the iris in each image, we used our automatic segmentation software, which uses active contours to find the iris boundaries. Next, we hand-checked all of the segmentations. If our software had made an

error in finding the inner or outer iris boundary, we manually marked the center and a point on the boundary to identify the correct center and radius of an appropriate circle. If the software had made an error in finding the eyelid, we marked four points along the boundary to define three line segments approximating the eyelid contour.

For all of the images, we set the pixels inside the iris/pupil region to black. Examples of images where the iris has been blacked-out are shown in Figures 3 through 6.

### IV. EXPERIMENTAL METHOD

In order to determine which features in the periocular region were most helpful to the human visual system, we designed an experiment to present pairs of eye images to volunteers and ask for detailed responses. We designed a graphical user interface (GUI) to display our images. At the beginning of a session, the computer displayed two example pairs of eye images to the user. The first pair showed two images of a subject's eye, taken on different days. The second pair showed eye images from two different subjects. Next, the GUI displayed the test queries. In each query, we displayed a pair of images and asked the user to respond whether he or she thought the two images were from the same person or from different people. In addition, he could note his level of confidence in his response – whether he was "certain" of his response, or only thought that his response was "likely" the correct answer. The user was further asked to rate a number of features depending on whether each feature was "very helpful", "helpful", or "not helpful" for determining identity. The features listed were "eye shape", "tear duct"<sup>1</sup>, "outer corner", "eyelashes", "skin", "eyebrow", "eyelid, and "other". If a user marked that some "other" feature was helpful, he was asked to enter what feature(s) he was referring to. A final text box on the screen asked the user to describe any other additional information that he used while examining the eye images.

Users did not have any time limit for examining the images. After the user had classified the pair of images as "same person" or "different people" and rated all features, then he could click "Next" to proceed. At that point the user was told whether he had correctly classified the pair of images. Then, the next query was displayed. All users viewed the same eighty pairs of images, although they were presented in a different random order for each user.

We solicited volunteers to participate in our experiment and 25 people signed up to serve as testers in our experiment. Most testers responded to all of the queries in about 35 minutes. The fastest tester took about 25 minutes, and the slowest took about an hour and 40 minutes. They were offered ten dollars for participation and twenty dollars if they classified at least 95% of pairs correctly.

<sup>1</sup>We used the term "tear duct" informally in this instance to refer to the region near the inner corner of the eye. A more appropriate term might be "medial canthus" but we did not expect the volunteers in our experiment to know this term.

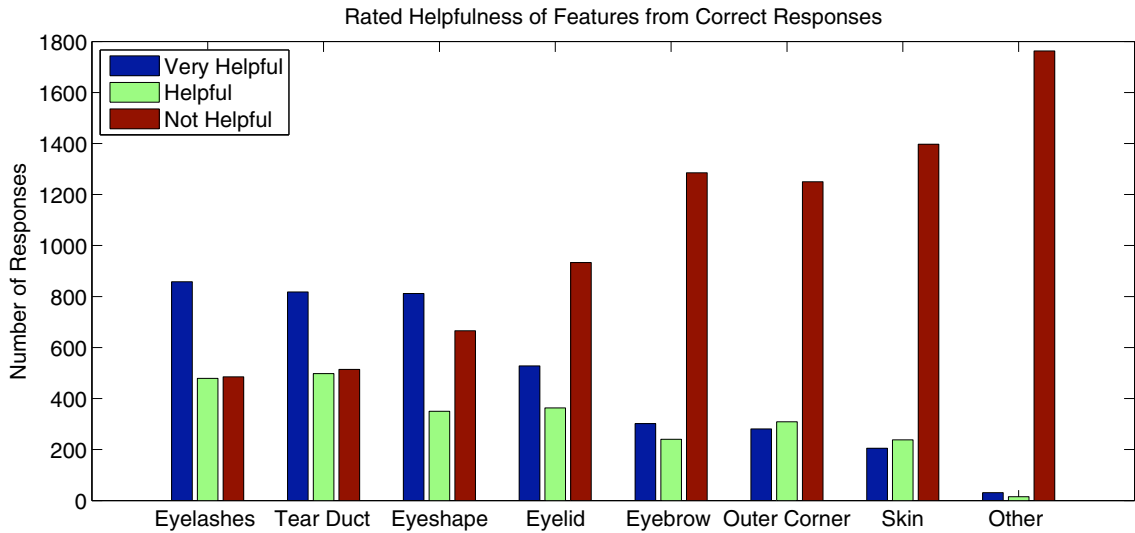


Fig. 1. Eyelashes were considered the most helpful feature for making decisions about identity. The tear duct and shape of the eye were also very helpful.

## V. RESULTS

### A. How well can humans determine whether two periocular images are from the same person or not?

To find an overall accuracy score, we counted the number of times the tester was “likely” or “certain” of the correct response; that is, we made no distinction based on the tester’s confidence level, only on whether they believed a pair to be from the same person, or believed a pair to be from different people. We divided the number of correct responses by 80 (the total number of queries) to yield an accuracy score. The average tester classified about 74 out of 80 pairs correctly, which is about 92% (standard deviation 4.6%). The minimum score was 65 out of 80 (81.25%) and the maximum score was 79 out of 80 (98.75%)

### B. Did humans score higher when they felt more certain?

As mentioned above, testers had the option to mark whether they were “certain” of their response or whether their response was merely “likely” to be correct. Some testers were more “certain” than others. One responded “certain” for 70 of the 80 queries. On the other hand, one tester did not answer “certain” for any queries. Discounting the tester who was never certain, the average score on the questions where testers were certain was 97% (standard deviation 5.2%). The average score when testers were less certain was 84% (standard deviation 11%). Therefore, testers obviously did better on the subset of the queries where they felt “certain” of their answer.

### C. Did testers do better on the second half of the test than the first half?

The average score on the first forty queries for each tester was 92.2%. The average score on the second forty queries was 92.0%. Therefore, there is no evidence of learning between the first half of the test and the second.

### D. Which features are correlated with correct responses?

The primary goal of our experiment was to determine which features in the periocular region were most helpful to the human visual system when making recognition decisions. Specifically, we are interested in features present in near-infrared images of the type that can be obtained by a typical iris camera. To best answer our question, we only used responses from cases where the tester *correctly* determined whether the image pair was from same person. From these responses, we counted the number of times each feature was “very helpful” to the tester, “helpful”, or “not helpful”. A bar chart of these counts is given in Figure 1. The features in this figure are sorted by the number of times each feature was regarded as “very helpful”. According to these results, the most helpful feature was eyelashes, although tear duct and eye shape were also very helpful. The ranking from most helpful to least helpful was (1) eyelashes, (2) tear duct, (3) eye shape, (4) eyelid, (5) eyebrow, (6) outer corner, (7) skin, and (8) other.

Other researchers have found eyebrows to be more useful than eyes in identifying famous people [8], so the fact that eyebrows were ranked fifth out of eight is perhaps deceiving. The reason eyebrows received such a low ranking in our experiment is that none of the images showed a complete eyebrow. In about forty queries, the two images both showed some part of the eyebrow, but in the other forty queries, the eyebrow was outside the image field-of-view in at least one of the images in the pair. On images with a larger field of view, eyebrows could be significantly more valuable. We suggest that iris sensors with a larger field of view would be more useful when attempting to combine iris and periocular biometric information.

The low ranking for “outer corner” (sixth out of eight) did not surprise us, because in our own observation of a number of eye images, the outer corner does not often provide much

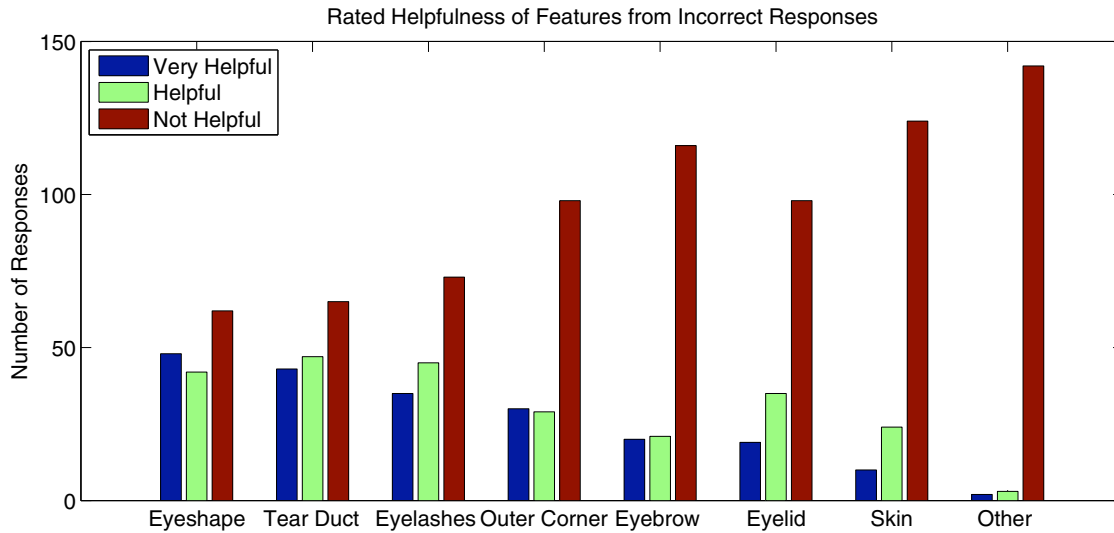


Fig. 2. We compared the rankings for the features from correct responses (Fig. 1) with the rankings from incorrect responses. The shape of the eye and the outer corner of the eye were both used more frequently on incorrect responses than on correct responses. This result suggests that those two features would be less helpful for making decisions about identity than other features such as eyelashes.

unique detail for distinguishing one eye from another. There were three queries where the outer corner of the eye was not visible in the image (See Figure 6).

Skin ranked seventh out of eight in our experiment, followed only by “other”. Part of the reason for the low rank of this feature is that the images were all near-infrared images. Therefore, testers could not use skin color to make their decisions. This result may not be quite as striking if we used a data set containing a greater diversity of ethnicities. However, we have noticed that variations in lighting can make light skin appear dark in a near-infrared image, suggesting that overall intensity in the skin region may have greater intra-class variation than inter-class variation in these types of images.

#### E. Which features are correlated with incorrect responses?

In addition to considering which features were marked most helpful for correct responses, we also looked at how features were rated when testers responded incorrectly. For all the *incorrectly* answered queries, we counted the number of times each feature was “very helpful”, “helpful”, or “not helpful”. A bar chart of these counts is given in Figure 2. We might expect to have a similar rank ordering for the features in the incorrect queries as we had for the correct queries, simply because if certain features are working well for identification, a tester would tend to continue to use the same features. Therefore, rather than focusing on the overall rank order of the features, we considered how the feature rankings *differed* from the correct responses to the incorrect responses. The ranking from most helpful feature to least helpful feature for the incorrect queries was (1) eye shape, (2) tear duct, (3) eyelashes, (4) outer corner, (5) eyebrow, (6) eyelid, (7) skin, and (8) other. Notice that “eye shape” changed from rank three to rank one. Also “outer corner”

Table II: Summary of Tester Responses to an Open-Ended Request to list Most Useful Features

Query Type	Helpful Features	Unhelpful or Misleading Features
Match Queries	clusters of eyelashes single “stray” eyelashes eyelash density eyelash direction eyelash length eyelash intensity tear duct eyebrow unusual eye shape slant of eyes amount the eye was open contacts make-up	glare shadow different lighting different angle of eye different eye shape amount the eye was open hair in one image contact lens vs. no contact lens make-up vs. no make-up
Nonmatch Queries	lashes in tear duct region eyelash density eyelash direction eyelash length eyelash intensity tear duct eyebrow eyelid eyeshape crease above the eye contacts make-up	glare make-up

changed from rank six to rank four. This result implies that eye shape and outer corner are features that are less valuable for correct identification. On the other hand, “eyelashes” and “eyelid” both changed rank in the opposite direction, implying that those features are more valuable for correct identification.

### F. What additional information did testers provide?

In addition to the specific features that testers were asked to rate, testers were also asked to describe other factors they considered in making their decisions. Testers were prompted to “explain what features in the image were most useful to you in making your decision”, and enter their response in a text box.

Table II summarizes testers’ free-responses. Only responses from queries where they got the answer correct are listed. Testers found a number of different traits of eyelashes valuable. They considered the density of eyelashes (or number of eyelashes), eyelash direction, length, and intensity (light vs. dark). Clusters of eyelashes, or single eyelashes pointing in an unusual direction were helpful, too. Contacts were helpful as a “soft biometric”. That is, the presence of a contact lens in both images could be used as supporting evidence that the two images were of the same eye. However, no testers relied on contacts as a deciding factor. Two of the eighty queries showed match pairs where one image in the pair showed a contact lens, and the other did not. Testers did well for both of these pairs: the percents of testers who classified these pairs correctly were 92% (23 of 25) and 96% (24 of 25).

Make-up was listed both as “very helpful” for some queries, and as “misleading” for other queries. When a subject wore exactly the same type of make-up for multiple acquisition sessions, the make-up was useful for recognition. Alternatively, when a subject changed her make-up, recognition was harder. One of the eighty queries showed a match pair where only one of the images displayed make-up. Although 24 of 25 testers still correctly classified this pair, every tester who provided written comments for this pair remarked that the presence of mascara in only one of the images was distracting or misleading.

### G. Which pairs were most frequently classified correctly, and which pairs were most frequently classified incorrectly?

There were 21 match pairs that were classified correctly by all testers. One example of a pair that was classified correctly by all testers is shown in Figure 3. There were 12 nonmatch pairs classified correctly by all testers. An example is shown in Figure 4.

Figure 5 shows the match pair most frequently classified incorrectly. Eleven of the 25 testers mistakenly thought that these two images were from different people. This pair is challenging because the eye is wide open in one of the images, but not in the other. Figure 6 shows the nonmatch pair most frequently classified incorrectly. This pair was also misclassified by 11 testers, although the set of 11 testers who responded incorrectly for the pair in Figure 6 was different from the set of testers who responded incorrectly for Figure 5.

## VI. CONCLUSION

We have found that when presented with unlabeled pairs of periocular images in equal numbers, humans can classify the pairs as “same person” or “different people” with an accuracy

of about 92%. When expressing confident judgement, the accuracy is about 97%. We compared scores on the first half of the test to the second half of the test and found no evidence of learning as the test progressed.

In making their decisions, testers reported that eyelashes, tear ducts, shape of the eye, and eyelids were most helpful. However, eye shape was used in a large number of incorrect responses. Both eye shape and the outer corner of the eye were used a higher proportion of the time for incorrect responses than they were for correct responses, thus those two features might not be as useful for recognition. Eyelashes were helpful in a number of ways. Testers used eyelash intensity, length, direction, and density. They also looked for groups of eyelashes that clustered together, and for single eyelashes separated from the others. The presence of contacts was used as a soft biometric. Eye make-up was helpful in some image pairs, and distracting in others. Changes in lighting were challenging, and large differences in eye occlusion were also a challenge.

Our analysis suggests some specific ways to design powerful periocular biometrics systems. We expect that a biometrics system that explicitly detects eyelids, eyelashes, the tear duct and the entire shape of the eye could be more powerful than some of the skin analysis methods presented previously.

The most helpful feature in our study was eyelashes. In order to analyze the eyelashes, we first would locate and detect the eyelids. Eyelids can be detected using edge detection and Hough transforms [14], [15], a parabolic “integrodifferential operator” [12], or active contours [16]. The research into eyelid detection has primarily been aimed at detecting and disregarding the eyelids during iris recognition, but we suggest detecting and describing eyelids and eyelashes to aid in identification. Feature vectors describing eyelashes could include measures for the density of eyelashes along the eyelid, the uniformity of direction of the eyelashes, and the curvature and length of the eyelashes. We could also use metrics comparing the upper and lower lashes.

The second most helpful feature in our study was the tear duct region. Once we have detected the eyelids, we could extend those curves to locate the tear duct region. This region should more formally be referred to as the *medial canthus*. A canthus is the angle or corner on each side of the eye, where the upper and lower lids meet. The medial canthus is the inner corner of the eye, or the corner closest to the nose. Two structures are often visible in the medial canthus, the *lacrimal caruncle* and the *plica semilunaris* [17]. These two features typically have lower contrast than eyelashes and iris. Therefore, they would be harder for a computer vision algorithm to identify, but if they were detectable, the sizes and shapes of these structures would be possible features. Detecting the medial canthus itself would be easier than detecting the caruncle and plica semilunaris, because the algorithm could follow the curves of the upper and lower eyelids until they meet at the canthus. Once detected, we could measure the angle formed by the upper and lower eyelids and analyze how the canthus meets the eyelids. In Asians, the epicanthal fold may cover part



Fig. 3. All 25 testers correctly classified these two images as being from the same person.

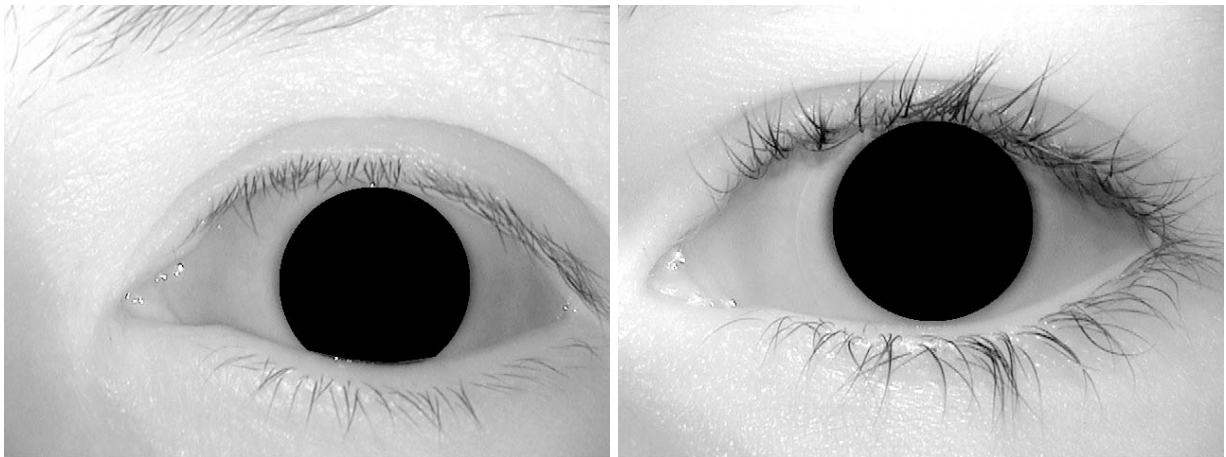


Fig. 4. All 25 testers correctly classified these two images as being from different people

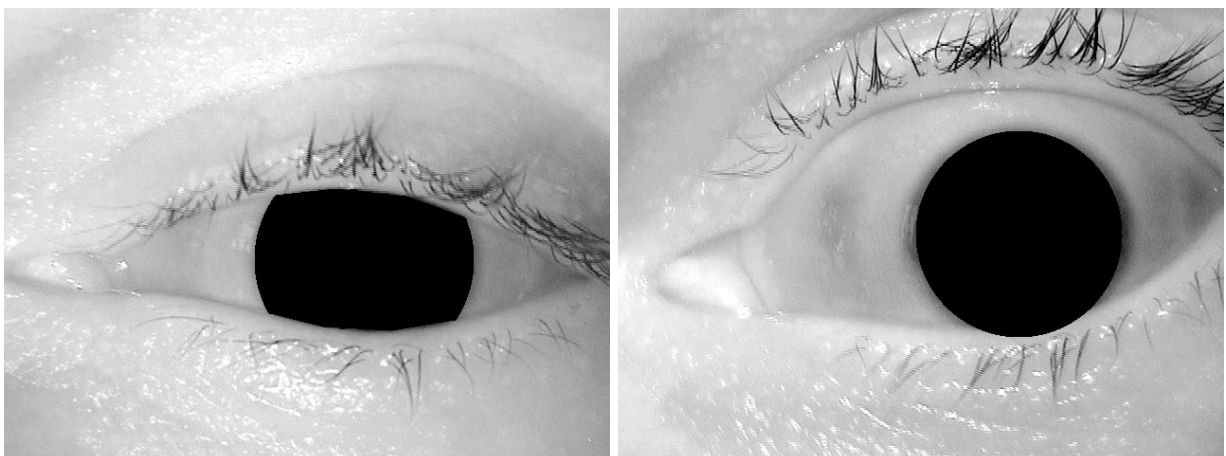


Fig. 5. Eleven of 25 people incorrectly guessed that these images were from different people, when in fact, these eyes are from the same person. This pair is challenging because one eye is much more open than the other.

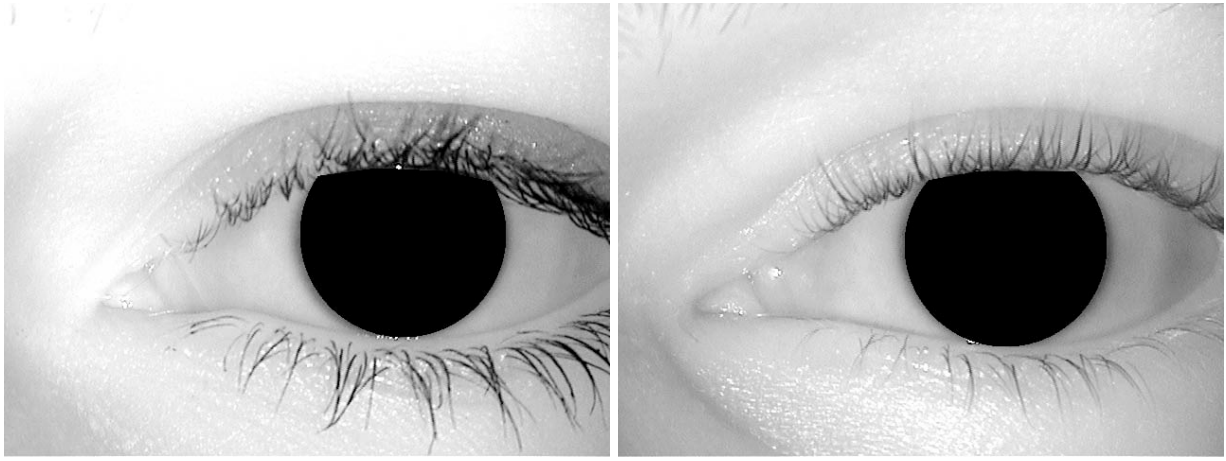


Fig. 6. Eleven of 25 people incorrectly guessed that these images were from the same person, when in fact, they are from two different people.

of the medial canthus [17] so that there is a smooth line from the upper eyelid to the inner corner of the eye (e.g. Figure 3). The epicanthal fold is present in fetuses of all races, but in Caucasians it has usually disappeared by the time of birth [17]. Therefore, Caucasian eyes are more likely to have a distinct cusp where the medial canthus and upper eyelid meet (e.g. Figure 5).

The shape of the eye has potential to be helpful, but the term “eye shape” is ambiguous, which might explain the seemingly contradictory results we obtained about the helpfulness of this particular feature. To describe the shape of the eye, we could analyze the curvature of the eyelids. We could also detect the presence or absence of the *superior palpebral furrow* – the crease in the upper eyelid – and measure its curvature if present.

Previous periocular research has focused on texture and key points in the area around the eye. The majority of prior work [4], [5], [6] masked an elliptical region in the middle of the periocular region “to eliminate the effect of textures in the iris and the surrounding sclera area” [4]. This mask effectively occludes a large portion of the eyelashes and tear duct region, thus hiding the features that we find are most valuable. Park et al. [3] do not mask the eye, but they also do not do any explicit feature modeling beyond detecting the iris. These promising prior works have all shown recognition rates at or above 77%. However, we suggest that there is potential for greater recognition power by considering additional features.

## VII. ACKNOWLEDGEMENTS

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