Eyelash Removal using Light Field Camera for Iris Recognition

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Abstract. Eyelash occlusions pose great difficulty on the segmentation and feature encoding process of iris recognition thus will greatly affect the recognition rate. Traditional eyelash removal methods dedicate to exclude the eyelash regions from the 2D iris image, which waste lots of precious iris texture information. In this paper we aim to reconstruct the occluded iris patterns for more robust iris recognition. To this end, a novel imaging system, the microlens-based light field camera, is employed to capture the iris image. Beyond its ability to refocus and extend the depth of field, in this work, we explore its another feature, i.e. to see through the occlusions. And we propose to reconstruct occluded iris patterns using statistics of macro pixels. To validate the proposed method, we capture a unique light field iris database and implement iris recognition experiments with our proposed methods. Both recognition and visual results validate the effectiveness of our proposed methods.

Keywords: iris recognition, eyelash removal, light field, occlusion

1 Introduction

Iris recognition [1] is one of the most popular biometrics due to the stableness and uniqueness of iris patterns. However, there still exist several issues that severely affect the recognition procedure. The occlusions of eyelashes is one of them, it will pose great difficulty to the process of segmentation and feature encoding and finally degrade the overall recognition rate.

Traditional researches on eyelash removal methods [3] [4] [5] try to remove the eyelash region from the acquired image with rule based methods. Although they can facilitate improvement in the recognition rate, they sacrifice too much precious iris information(iris patterns occluded by eyelashes), so they are less reliable in practical use. However, in this paper we aim to find solutions that can reconstruct occluded iris information rather than exclude them from the recognition process. The thriving of the computational photography offers us a chance to effectively achieve that goal. Nowadays, there exist more options of devices for iris image acquisition, especially some device with the ability to capture the light field [15]. One of the device that come to our attention is the microlens-based light field camera.

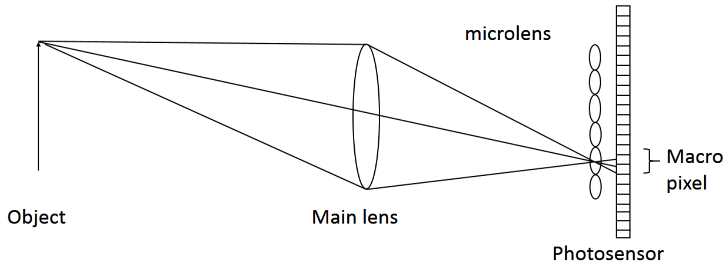
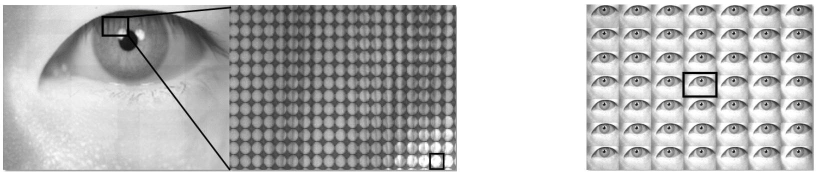


Fig. 1. Microlens-based light field camera model.

The microlens-based light field camera (LFC) which was introduced in 2006 by Ng [7] with a microlens assembled between the main lens and photo sensor of a conventional camera can capture 4D light field. The captured image (Fig.2(a)) consists of microlen images or may be called macro pixels (marked in a black rectangle) which correspond to pixels underneath each microlens that represent the directional information of the ray in space. The raw light field can also be represented using a 4D representation [7] as illustrated in Fig.2(b). Each image in 4D light field represents an image taken from a certain viewpoint and it is called the sub-aperture image. According to Ng [7], the LFC have two features compared to conventional cameras: (1) extended depth of field (DoF) with decoupled trade-offs between DoF and aperture size; (2) generating photos focused at a range of depth after the photo was taken (also known as refocus). Researches on biometrics with LFC [6] [13] [14] verify that the camera's feature on extended DoF and flexible refocusing may actually benefit the biometrics application. However, the LFC have much more potential to be explored on biometric research.

The superiority of the LFC relies on its ability to capture the 4D light field or the additional directional information. Using similar imaging system, researchers in the synthetic aperture [2] and integral imaging [9] [10] [11] [12] community try to use this kind of additional information to see through occlusions and reconstruct occluded information. Inspired by their work, in this paper, we dedicate to explore the LFC's ability on eyelash removal to benefit the iris recognition task. Unlike previous work [9] [11] [12] which implement the reconstruction mainly based on stereo matching of sub-aperture images, we propose a novel method based on the observation of the refocusing process and the prior knowledge of eyelash occlusions. Specifically, we explored other statistics of macros pixels rather than the mean, which is utilized by the refocus process, to reconstruct iris information occluded by eyelashes. To evaluate the proposed method, we capture a near infrared (NIR) light field iris database using a microlens-based LFC, and implement iris recognition test with the proposed method on this database. Compared to previous works, this paper has three major contributions: (1) we propose to address the eyelash occlusion problem with a novel camera model, i.e. the LFC, breaking through the limitations of conventional camera; (2) we



(a) raw LF image (b) 4D representation

Fig. 2. Two types of representation for LF images.

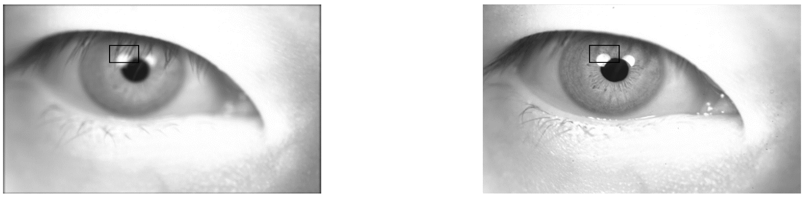
explore to process the captured light field image in a novel way compared to previous work [6] [13] [14] to reconstruct the occluded iris information; (3) we capture a unique light field iris database to evaluate our proposed methods. To the best of our knowledge, this is the first work that try to address eyelash occlusions in iris recognition with a LFC. Our work proves that LFC is a promising trend for the acquisition of iris images in iris recognition and there's more to expect about its potential.

2 Related Works

In the research of eyelash removal, most algorithms follow the procedure of firstly detecting the eyelash regions and then excluding them from iris recognition. Many rule-based methods have been proposed to detect the eyelash regions. Kong and Zhang [4] categorized eyelashes into two groups, and they adopted 1-D Gabor filter and the variance of intensity in a small window to detect separable and multiple eyelashes respectively with database dependent thresholds. Kang and Park [3] introduced the measurement of focus score to decide an adaptive threshold. He et al. [5] proposed a statistically learned prediction model to get the adaptive thresholds. Those methods all aimed at detecting the eyelash regions and excluded them from the recognition procedure, which is a great waste of information. However, we try to find ways to reconstruct occluded iris patterns using novel acquisition devices.

Recently, LFC is gaining traction in biometrics. Zhang [6] explored its ability on iris recognition, comparable recognition rate can be obtained to a conventional camera. In [13] [14], LFC were also adopted for the iris and face recognition, recognition results validated its outstanding ability on extended DoF and refocusing.

Novel imaging systems like synthetic aperture [2], integral imaging [9] can also capture light field in one snapshot. As those imaging systems can also capture images from different points of view, they all carry features of the multi-view vision system, like capable of seeing the occluded information. Methods to see through occlusion are well explored in those research areas. In [2], Vaish et al. used a focal-sweep process and some modified cost functions to estimate the depth of the occluded objects. For the reconstruction of occluded information, median color are used. In the integral imaging community, researchers [10] [11] [12] tried to remove occlusions and reconstruct occluded information by explicitly



(a) refocused on eyelash (b) refocused on iris

Fig. 3. Images refocused on different depth.

detect occlusion regions with stereo matching algorithm in sub-aperture images, and mask them off in the following computational process, so that the resultant images are occlusions free.

Compared to refocusing algorithm [7] in LFC which only involves translation and superposition, resorting to complicated stereo matching algorithm in integral imaging is very time consuming. This inefficiency motivates us to find better solutions to reconstruct occluded iris information with LFC. Although conventional cameras with a very large aperture are also capable of seeing through occlusions [8], they suffer from very small DoF and thus can't acquire clear iris images without strong restrictions. Another drawback of using conventional cameras lies in the fact that they can't capture enough information to facilitate the accurate reconstruction.

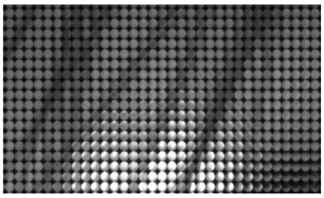
The rest of the paper is organized as follows: Section 3 gives the detailed description of the proposed method; Section 4 states the experiment setup and presents the experiment results; Section 5 concludes this paper with possible future research direction.

3 The Proposed Method for Eyelash Removal

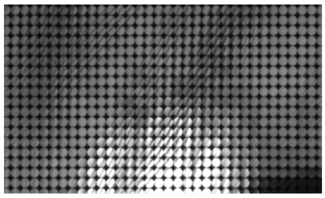
We've given some important information about LFC in previous sections, a detailed overview of the light field camera can be found in [14] [17]. Generally, we decode a raw light field image (which consists of macro pixels) shown in Fig.2(a) to 4D light field representation (which consists of sub-aperture images) [15] [16], as illustrated in Fig.2(b) for further implementation. Note that, these two kinds of image representations are significant to the understanding of our proposed methods and they can be easily converted to each other once we have properly calibrated the LFC camera [16]. To solve the eyelash occlusion problem, instead of operating on the 4D representation with a complicated stereo matching scheme, we seek methods to operate on the raw light field image, where we use novel statistics of the macro pixels to reconstruct the occluded regions.

3.1 A Different View of Refocus.

Based on the 4D representation and ray tracing diagram inside the camera, Ng [17] developed a digital refocusing algorithm after the picture is taken. This



(a) focus on eyelash



(b) focus on iris

Fig. 4. Comparison of raw light filed (LF) image focused on different depth. The cropped raw LF is taken from the rectangle in Fig. 3 of two raw LF image respectively.

algorithm can be formulated as follows:

$$E_{(\alpha F)}(x', y') =$$
$$\frac{1}{\alpha^2 F^2} \iint L_F{}^{(u,v)}(u(1 - \frac{1}{\alpha}) + \frac{x'}{\alpha}, v(1 - \frac{1}{\alpha}) + \frac{y'}{\alpha})dudv$$

where$E_{(\alpha F)}(x', y')$ is the refocused image; $L_F{}^{(u,v)}$ is a sub-aperture image at the coordinates of (u, v), and u indicates the row index, v indicates the column index; α denotes the ratio of the refocus depth to the current depth. The refocusing implementation is basically a shifting and adding process of the sub-aperture images(as previously mentioned, each sub-aperture image represents a picture taken under a specific viewpoint), and the amount of shifting determines the refocusing depth. This simple implementation benefits from the compact structure of the camera, which keep it from complicated stereo matching manipulation. If we see this process in the view of raw light field images, the refocusing process is simply taking the mean value of macro pixels after converting the shifted sub-aperture images to a raw light field image. In the refocused image, the mean value is adopted to represent pixels on each spot. This view inspires us to find alternative estimation other than the mean value to better reconstruct occluded regions.

If the object is in-focus, then pixels in each macro pixel represent the same object (as in Fig.4(a), the black line indicate in-focused eyelash), so the information is redundant; otherwise, the pixel in each macro pixel represent different objects (as in Fig.4(b), iris is in focus, eyelash pixels spread in many different macro pixels), thus taking the mean value will blur this area. Fig.3 illustrates the refocused images, which are obtained simply by taking the average of each macro pixel in Fig.4. Those two raw light field images can be obtained by translating the sub-aperture images and converting them back to a raw light field image. As we can easily convert between those two representations, we don't need to specify where the camera focus on when the picture is taken.

As we have mentioned above, macro pixels which corresponds to in-focus region have redundant information of the same object (the pixel values in one macro pixel should ideally be a Gaussian distribution if it captures the information of the same object), so the mean a good approximation of this region's

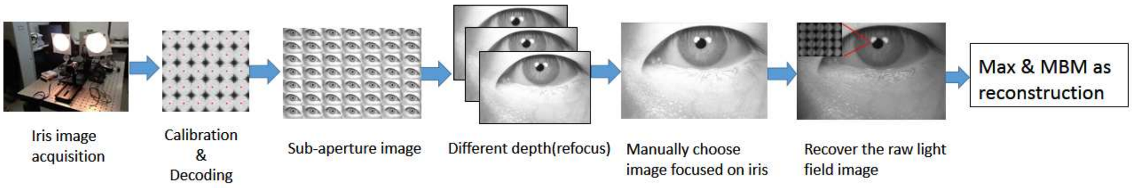


Fig. 5. Proposed eyelash removal method.

information. Benefiting from this redundancy, we may represent the refocused images with other statistics without degrading the image quality. Specifically, we can suppress the superimposition of the eyelash pixels in each macro pixel from the raw light field image focused on iris to increase the fidelity of the occluded region. Supposing now we have a raw light field image focused on iris, like the one in Fig.4(b). Then, the eyelash region's macro pixels contains both iris and eyelash information. So now, one question comes up, can we find a better statistics to represent iris information when it is occluded by eyelashes? Based on prior knowledge that the gray level of eyelash is darker than iris region, the max value of the macro pixels seems to be a good estimate. Although taking the max value is able to exclude eyelash pixels completely, it is less robust to outliers compared to the mean value, this indicates that the max value might not perform well for iris recognition purpose. To increase the robustness and exclude eyelash at the same time, we consider the mean of pixels bigger than the median value of the macro pixels. As the median value is a better estimate of the central tendency than the mean value when occlusions are less than 50%, it might suffice our demands. This statistics is denoted as MBM in this paper.

3.2 Block Diagram of Eyelash Removal.

Using some novel statistics, our proposed method is summarized in a block diagram in Fig.5. Firstly, we capture a NIR iris database with a specially designed microlens-based LFC. Note that we don't need to capture images strictly focused on iris, post refocus can help us do that. Then with preprocess like calibration and decoding [16], sub-aperture images are obtained to facilitate the refocus process to calculate images focused on different depth. From those refocused images we manually choose images focused on iris (auto-refocus methods can also be derived to determine the translation step before the refocus process, but we will defer this to future work, since discussion of this very complicated issue is out of the scope of this paper) and convert them back to raw light field images. Then we can use the proposed statistics of the macro pixels mentioned before (MAX and MBM) to reconstruct the occluded information. And finally the reconstructed images are eyelash free and can be used for iris recognition.

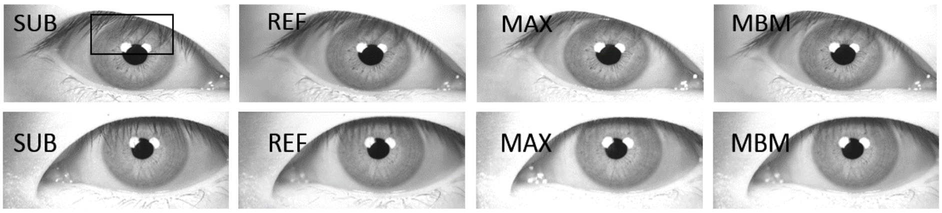


Fig. 6. Visual results of four sets of images. Each row of image come from the same eye, it is obvious our proposed method can remove the eyelashes with reconstructed iris information.

4 Experiments and Results

To verify the effectiveness of our proposed method, we capture a new NIR light-field iris database and experiment our method on this database. Using a specially designed microlens-based LFC, we capture NIR iris images of 21 subjects, 42 eyes with over half the images suffering from severe eyelash occlusions. As for the preprocess, calibration methods in [16] are implemented to identify the center of each microlen image and get the decoded 4D representation. Proposed method are implemented to get two sets of pictures, the max images (denoted as MAX) and images consisting of mean of pixels bigger than median (denoted as MBM). For comparison purpose, we also get refocus image focused on iris (denoted as REF), which is adopted in [6] [14] and the middle sub-aperture images (denoted as SUB), which can be seen as a picture taken by a hypothetical conventional camera.

We compare the visual effects of the four sets of images in Fig.6. Our proposed reconstructions have a significant increase in the fidelity of the occluded regions compared to sub-aperture and refocused image. The MAX image looks best as it is able to exclude most part of the eyelash pixels while the MBM image may still be affected when eyelash occlusion is more than 50%.

	SUB	REF	MAX	MBM
EER	9.02%	6.79%	6.1%	**5.76%**
DI	2.3035	2.6761	2.7543	**2.7557**

Table 1. Iris recognition results on four sets of images.

We evaluate our method on iris recognition task with comparison to other two sets of images. To emphasize the effectiveness of reconstruction of the occluded regions, we use only the upper half of iris images (as illustrated in the first image of Fig.6 with a black rectangle) for the test, as eyelashes only affect the upper half of iris regions most of the time. We implement the iris localization and segmentation process following the work of Li et al. [18]. Ordinal features introduced by Sun et al. [19] are adopted for the feature encoding procedure and

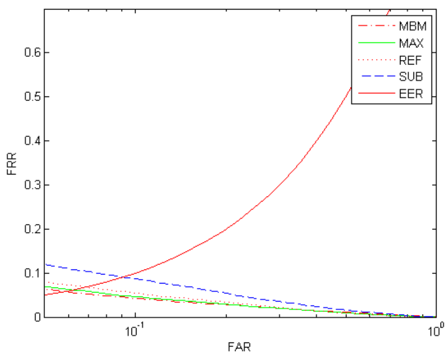


Fig. 7. Roc curve of the iris recognition test.

the hamming distance of two iris codes are calculated to measure the similarity. Table.1 illustrates the recognition results on these four sets of images. Our proposed two sets of images outperform the sub-aperture and refocus images in both Equal Error Rate (EER) and discriminative index, which are two major evaluation criterions for the iris recognition task . Fig.7 shows the ROC curve of the recognition test. Both visual and recognition results verify the proposed method's superiority over previous refocused image [6] [14] and conventional camera image in iris recognition task with sever eyelash occlusions.

5 Conclusion

To address the eyelash occlusion problem in iris recognition, we adopt a new yet powerful iris sensor for acquisition of iris image and propose a novel method to reconstruct iris information occluded by eyelashes. To the best of our knowledge, this the first time that the LFC is used for eyelash removal in iris recognition research. Compared to conventional eyelash removal methods, our proposed method can exploit more texture information of iris regions for accurate iris recognition; compared to previous works on biometrics with the LFC, we explore its ability to reconstruct occluded information and get better visual and recognition results. Our future works might include exploring glare reduction and auto-refocus using the light field camera for automatic and accurate iris recognition.

6 Acknowledgement

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