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A Robust Scheme for Iris Segmentation in Mobile Environment

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***Abstract*—With the advent of mobile ocular biometrics and ocular human-computer interactions (HCI), recent research has been focused on iris localization in the visible spectrum. Existing studies suggest that performance of the ocular HCI and biometric systems significantly degrades due to inaccurate iris segmentation, especially when operating in uncontrolled mobile environment which causes variations such as motion blur, specular reflection and illumination variation. This paper proposes a iris segmentation algorithm for visible spectrum which is based on the combination of K-means clustering and Daugman's integro-differential algorithm. Experimental investigation on the publicly available VISOB dataset prove the efficacy of the proposed approach. Experimental results show that iris segmentation increases 4 folds compared to Daugman's and 3.5 folds compared to Masek's methods. The proposed method also executes 5 times faster than Daugman's and 8 times faster than Masek's methods.**

***Index Terms*—Iris segmentation, Mobile biometrics, Visible Spectrum**

I. Introduction

With increasing functionality and services accessible via mobile phone, the industry has turned its focus on the integration of ocular human computer interface(HCI) and biometric technology into mobile phones, for instance for gaze based HCI or as a method of verifying the identity of a person accessing the services. The use of biometric techniques on mobile devices have been referred to as mobile biometrics which encompass the development of mobile devices to acquire biometric signals, and software algorithms for authentication [1].

According to Acuity Market Intelligence forecast[1], mobile biometric revenue is expected to surpass 33 billion dollars by 2020, not just for unlocking the device but to approve payments and as a part of multi-factor authentication services.

With advancements in computing and sensor technology, there is a sharp increase in the implementation of mobile biometrics in the handheld devices. Popular mobile biometrics modalities include fingerprints, face, Eyeprints, and iris. Recently, in 2016 MWC (Mobile World Congress), mastercard[2] introduced selfie authentication based on face biometrics, whereas VISA[3] payment system provides option to customers to choose one or more modalities among fingerprint, iris and face.

Among other mobile biometrics, face and Eyeprints have become especially popular. This is because these traits can be acquired using front facing color cameras already available in mobile devices. Iris is among the most popular and highly adopted biometric traits due to its accuracy, persistence and universality. Most of the existing studies on iris biometrics have reported the high performance when iris images were capturing using infrared imaging sensor or high quality DSLR cameras [2].

Reported studies suggest decrease in the recognition accuracy of iris biometrics can be attributed to iris segmentation error amogth other things - where iris is not appropriately localized, due to low quality eye images acquired in the uncontrolled mobile environment. The factors such as motion-blur, illumination variation, specular reflection, off-angle iris and occlusion by eyelids and eyelashes often attribute to low quality eye images. Further, pupil and iris boundary cannot be delineated for dark colored eye images in RGB due to high melanin content. Figure I shows example dark colored eye images with motion blurring and specular reflection acquired using front facing camera of iPhone 5. A good iris segmentation algorithm is required not only for better iris recognition accuracy, but also for proper segmentation of other ocular traits such as sclera and periocular regions [3], and gaze detection [4]. Accurate iris localization is useful in aligning both eyes on the same plane for face registration [5]. Thus, accurate RGB iris localization is of high importance in mobile applications.

The aim of this paper is to propose a robust and fast iris segmentation algorithm ideal for images acquired using RGB cameras in mobile environment. To this aim, we propose a novel iris segmentation technique which is based on the combination of intensity based region separation algorithm using K-means and Daugman's integro-differential algorithm [6].

[1]http://www.acuity-mi.com/GBMR_Report.php
[2]http://www.bbc.com/news/technology-35631456
[3]http://findbiometrics.com/mwc-2016-visa-isnt-picking-favorites-when-it-comes-to-biometrics-302255/

Fig. 1. Example eye images acquired using front facing camera of iPhone 5. The eye images show motion blurring, dark irises and illumination variation. The pupil and iris boundary cannot be distinguished for dark eyes.

In summary, the two-fold contributions of this paper are as follows:

* Proposal of a novel iris segmentation scheme based on the combination of region separation using K-means and Daugman's integro-differential algorithm [6].

* Large-scale evaluation of the proposed iris segmentation scheme on the latest publicly available Visible Light Mobile Ocular Biometric Database (VISOB) dataset [7].

This paper is organized as follows: Section II reviews the state-of-the-art in iris segmentation in the visible spectrum. Section III described the proposed iris segmentation algorithm. Dataset, protocol and experimental results are discussed in section IV. Conclusions are drawn in section V.

II. Previous work on Iris segmentation in Visible Spectrum

This section reviews the existing iris segmentation techniques proposed for visible spectrum.

One of the classical iris segmentation algorithms is the one proposed by Daugman [6] which is based on an integro-differential operator. This technique searches for a circle in a given range of radii with highest gradient change. Integro-differential operator was used to search for highest gradient change between angles 0°to 45°, 315°to 360°and 135°to 225°, which helps to mitigate the effect of upper and lower eyelid occlusions. However, one of the limitations of this technique is that it searches the whole image, thus, there is a chance to find better gradient change at different local minima even outside the eye region.

In [8] Donida et al., reviewed the state-of-the-art methods for iris segmentation. Existing methods were divided into the following categories as: (i) Methods based on iris boundary approximation from two circumferences, (ii) Methods based on a-priori model, (iii) Methods based on the analysis of local characteristics, (iv) Methods based on active contours, and (v) Hybrid and incremental methods. Authors performed comparative analysis of the existing iris segmentation methods on the publicly available datasets such as UBIRIS, CASIA and ND-IRIS-0405.

Proenca in [9] proposed a novel iris segmentation method based on neural network in a pixel wise manner. Twenty features, based on mean and variance of hue, blue and red channels (within radii of $0, 3, 7$ pixels and pixel positions x & y), were extracted from the eye image to segment sclera region. Further, based on the segmented sclera region, a new set of features called "Proportion of sclera" are computed and fed to a neural network along with the mean and variance of saturation and blue color channels, and pixel position. Using the proposed method, author reported an error rate of $1.87 \pm 2.4 \times 10^{-3}\%$ on UBIRIS dataset, compared to $13.97 \pm 6.2 \times 10^{-3}\%$ when using integro differential algorithm proposed by Daugman [6].

In [10] Proenca et al., proposed an iris segmentation method based on fuzzy clustering where different clustering techniques were investigated to group different ocular regions. Then iris segmentation was performed using Canny edge detector and Hough circle transforms. Based on the visual inspection, authors reported correct iris segmentation accuracy of 97.6% on session 1 and 96.8% on session 2 of UBIRIS dataset.

Tan et al [11] also proposed a segmentation algorithm based on clustering using eight neighbor pixel connection and modified Daugman's integro- differential algorithm. Authors reported a correct segmentation accuracy of 100% and 99.4% on session 1 and session 2 of UBIRIS dataset, respectively.

III. Proposed algorithm on iris segmentation

Figure 2 shows the block diagram of the proposed iris segmentation algorithm. The proposed iris segmentation process can be divided in three parts (1) preprocessing, (2) iris clustering, and (3) iris detection. First specular reflection is removed, if any, and the image is enhanced using *Contrast Limited Adaptive Histogram Equalization* (CLAHE) [12]. Then, k-means clustering is applied to extract the region in which the iris is present. Finally, Daugman's integro-differential algorithm is used to find center and radius of the iris (x_c, y_c, r_c) and pupil (x_p, y_p, r_p). The proposed algorithm is explained in detail as follows:

A. Preprocessing

Image preprocessing is vital to accurate iris segmentation to mitigate the certain intra-class variations such as those caused by illumination variation. In this work, specular reflection and illumination variations caused by unconstrained lighting conditions and the relative position of mobile phone with face, were removed as a part of this processing step.

The pixels belonging to specular reflection have high intensity level for all the three color channels i.e., red, green and blue. Specular reflections were removed by using thresholding based technique where pixel with intensity level greater than (> 235) are detected as specular reflection and then an inpainting algorithm [13] was used to fill in those regions

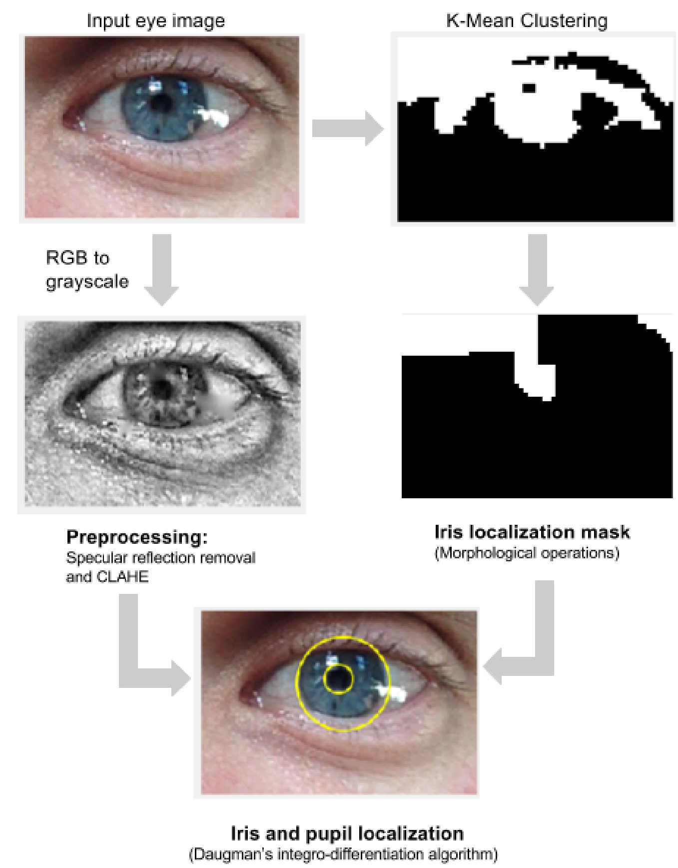
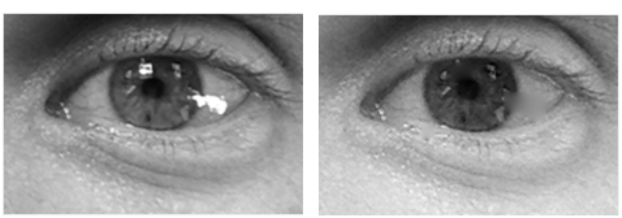


Fig. 2. Illustrates the block diagram of the proposed iris segmentation algorithm.



(a) (b)

Fig. 3. Shows the (a) original image converted to gray scale, and (b) results of specular reflections detection and inpainting algorithm.

for better segmentation. The results of this step are shown in Figure 3.

Illumination variations were removed using CLAHE. CLAHE is a popular histogram equalization technique which is used to prevent over-amplification (contrast limiting) of noise caused by Adaptive Histogram Equalization (AHE). AHE is an image enhancement method in which histogram equalization is performed over local neighborhoods of pixels. CLAHE also helps in enhancing the iris patters which in turn results in better recognition accuracy [12].

B. Iris Clustering Localization

Main disadvantage of Daugman's algorithm is that it may find better intensity change in other regions of and perform inaccurate segmentation especially for images taken in low lightning conditions as shown in Figure 4.

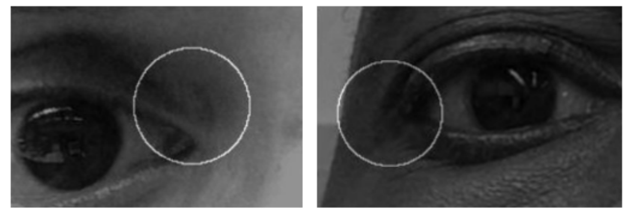


Fig. 4. Examples of error in iris segmentation using Daugman's method for images acquired in low lightning condition.

To overcome this problem, firstly, K-means clustering algorithm was used to localize the iris region. Crihalmeanu et al. [14] used K-means clustering algorithm to segment the sclera from the rest of the eye regions. However, in this work, instead of segmenting sclera region i.e., bright region of the eye, iris and eyebrow region were segmented which are the darkest part of the eye. K-means clustering is performed on the input RGB image transformed from three dimensional matrix $(m{\times}n{\times}3)$ to two dimensional matrix $(3{\times}mn)$. In this paper, $K = 2$ obtained better performance based on empirical evidence.

The darker region of all the three clusters was labeled as the region belonging to iris. Then morphological operation was used to fill holes in the clustered image caused due to noise.

C. Iris detection

For iris detection, Daugman's integro-differential algorithm was used to find iris boundaries from the localized map obtained from the clustering process described earlier. Daugman [6] assumed iris and pupil to be circular and proposed an integro-differential operator to find circles circumscribing iris and pupil.

$$\max_{(r,x_o,y_o)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{(r,x_o,y_o)} \frac{I(x,y)}{2\pi r} ds \right| \tag{1}$$

Equation-1 shows the integro-differential operator where $I(x, y)$ is the eye image and $G_\sigma(r)$ is the Gaussian kernel used for blurring the eye image. This operator does an exhaustive search on all pixels of $I(x, y)$ for highest gradient change for given radius r and the center (x_o, y_o). In this work, radius r in the range of $(25, 50)$ was used for iris detection and 10% to 80% of detected iris radius was used for pupil detection.

Daugman improvised the operator by searching for iris between angles 0° to 45°, 315° to 360°and 135° to 225° for avoiding the upper and lower eyelids.

In this paper, instead of performing exhaustive search for iris over all the pixels of image, Daugman's iris segmentation was applied only on the region containing the iris as obtained with K-means clustering discussed in section III-C. Due to this, the number of searches was significantly reduced and high gradient changes in other regions of eye image were ignored. The output of the operator is the center and radius of the iris (x_c, y_c, r_c) and the pupil (x_p, y_p, r_p).

IV. Dataset, protocol and results

VISOB (VISsible light mobile Ocular Biometric database) [7] consist of eye images from 550 healthy adult volunteers acquired using three different smartphones i.e., iPhone 5, Samsung Note 4 and Oppo. Each volunteer was required to pay two visits in the time lapse of $2-4$ weeks apart. At each visit, volunteers were asked to take selfie like captures using front facing cameras of the three different mobile devices in two different sessions that were about $10-15$ minutes apart. The volunteers used the mobile phone naturally within the distance of $8-12$ inches from the face. For each session, burst of images were captured in 4 different shots from three different mobile devices in three indoor settings for each subject. Under each lighting condition, each shot was repeated with and without glasses, if the volunteer was wearing prescription glasses. Each shot was also repeated while asking the volunteer to look straight at the cell phone screen or glance away to the left and right. The indoor conditions differ in lighting as follows: room lights on, room lights off (but dim ambient lighting still present), and finally under natural daylight setting. The collected database was preprocessed to crop and retain only the eye regions of the acquired images.

In this study, a subset of the whole dataset was chosen by randomly selecting 150 subjects from VISIT-I and 50 random subjects in VISIT-II. Note that VISIT-II also contain eye samples with glasses and off angle gaze. The accuracy of the proposed segmentation method was tested on 5400 eye samples randomly picked from 150 random subjects in VISIT-1 and 1800 eye samples are selected from 50 random subjects in VISIT-II set, for all the light conditions and mobile devices as shown in Table I.

Then, the proposed iris segmentation algorithm was tested and accuracy was determined using visual inspection similar to other iris segmentation studies proposed in [10], [11]. Comparative assessment of the proposed iris segmentation algorithm was done using publicly available Libor Masek method [15] and Daugman's method [16]. Experiments were performed on desktop PC with Intel core i7 860 processor running at $2.80GHz$ with $16GB$ of RAM. All the programs were written in Matlab 2015b.

Visual inspection was performed by a trained human inspector labeling eye images as correctly segmented if none to very few pixels are mis-segmented, or wrong segmentation otherwise, using a graphical user interface (GUI). Figure 5 shows example of iris segmentation, obtained using the proposed method, deemed as correct or incorrect based on visual inspection.

Figure 6 shows the GUI interface for performing visual inspection for all the iris segmentation methods mentioned above. The trained human inspector selects one of the three options (iris, iris and pupil, or segmentation error) for each eye sample based on if only iris is properly segmented, both iris and pupil are properly segmented, or both iris and pupil are inaccurately segmented.

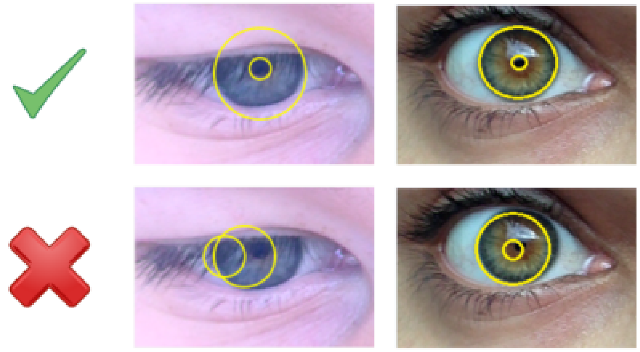


Fig. 5. Shows example of iris segmentation deemed as correct or incorrect using the visual inspection.

Following visual inspection and labelling of the segmented iris images, two performance metrics were computed: Rate of limbic and pupil boundary detection $(RLPD)$ and rate of outer iris boundary (limbic boundary) correct detection (RLD). High $RLPD$ is ideal for iris recognition applications where iris needs to be correctly segmented (iris and pupil boundaries need to be correctly localized). Algorithms with high RLD may be used for iris detection applications where only iris outer (limbic) boundary needs to be accurately segmented, but pupil boundary may not need be localized. For instance, in gaze detection [4], usually the localization of iris outer boundary is required to detect visual focus. Same is truefor segmenting other ocular regions such as sclera and periocular region where the localized iris outer boundary aids in better segmentation [3].

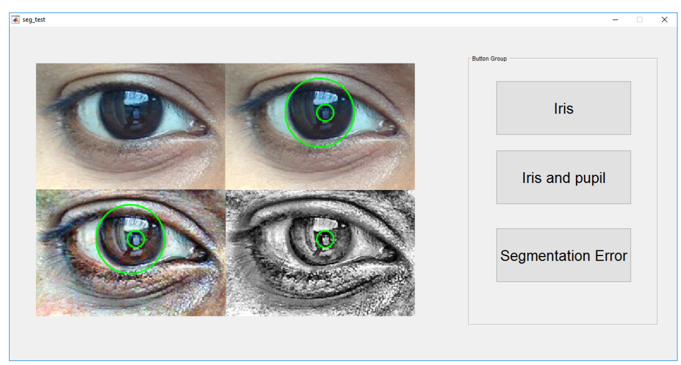


Fig. 6. GUI used to evaluate iris segmentation algorithms based on visual inspection.

Table II shows the RLPD and RLD for three methods tested in this paper. The results are obtained on a subset of VISOB dataset (see Table I). Compared to Daugman integro-differential method and our proposed method, Masek method gave better results in RLD (limbic boundary detection). On an average, Masek's method performed only 2.6% higher than the

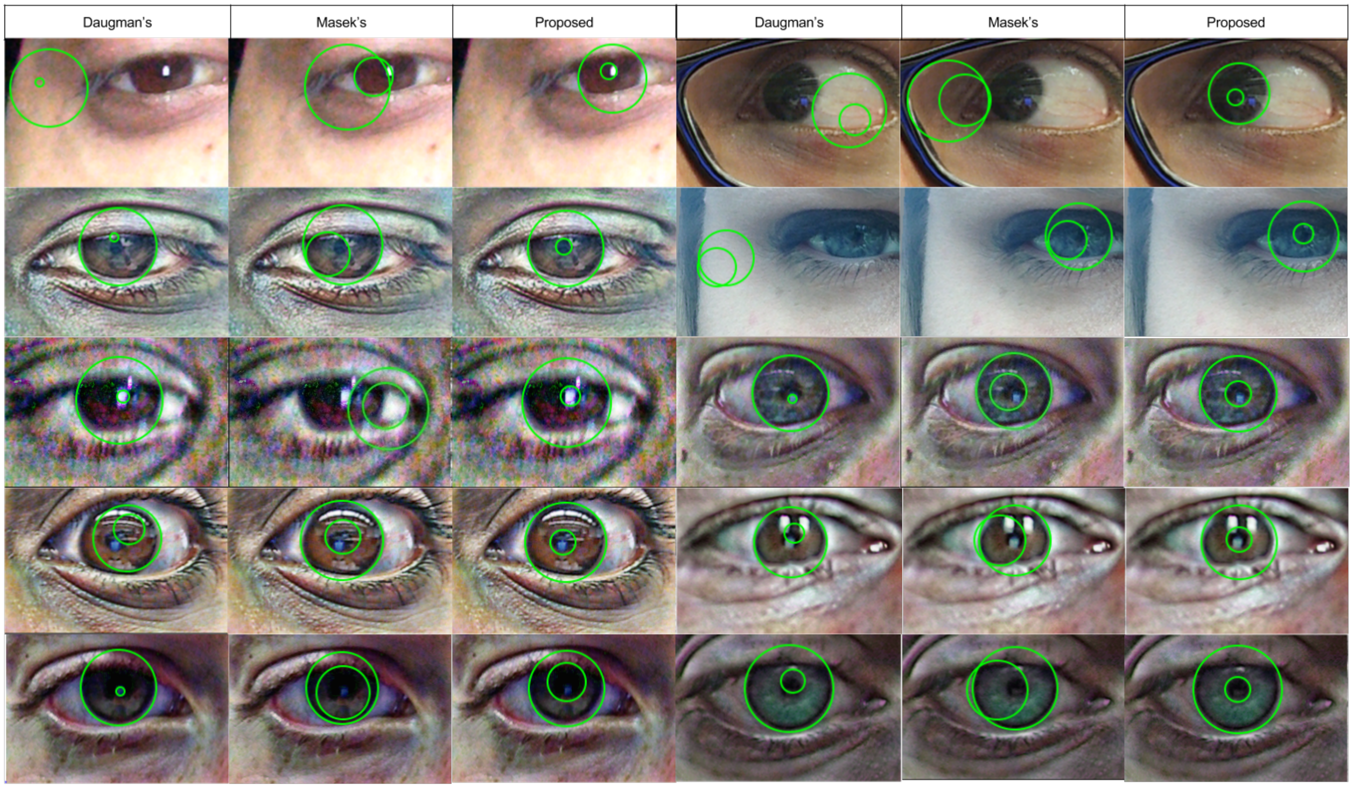


Fig. 7. Comparison of proposed iris segmentation algorithm with Daugman's [6] and Masek's [15] algorithms for eight randomly selected subjects.

TABLE I
SAMPLES SELECTED FROM VISOB DATASET FOR TESTING THE ACCURACY OF THE PROPOSED IRIS SEGMENTATION METHOD

Visit #	Subejcts	No. of eye pairs (L+R)	No. of mobile phones	No. of light condtions	Total No. of samples
VISIT-I	150	2	3	3	150*4*3*3 = 5400
VISIT-II	50	2	3	3	50*4*3*3 = 1800

TABLE II
IRIS SEGMENTATION RESULTS FOR VISIT-I AND VISIT-II OF VISOB DATASET

	Visit-I (5400 samples)		Visit-II (1800 samples)	
Methods	RLPD(%)	RLD(%)	RLPD(%)	RLD(%)
Masek [15]	11.2	**94.3**	8.7	**93.1**
Daugman [6]	10.04	89.9	6.94	86.6
Proposed	**34.3**	91.52	**33.6**	90.7

proposed method and 5.5% higher than Daugman's algorithm. However, RLPD (limbic and pupil boundary detection) of the proposed method increased 3.5 fold compare to the Masek method and 4 folds compared to Daugman's algorithm.

TABLE III
ACCURACY OF IRIS SEGMENTATION ALGORITHM ON DIFFERENT LIGHTING CONDITIONS. IN VISIT-I, THERE ARE 1800 SAMPLES FOR DIFFERENT LIGHTING CONDITION AND FOR VISIT-II, THERE ARE 600 SAMPLES FOR DIFFERENT LIGHTING CONDITION.

	VISIT-I			VISIT-II		
	Daugmanś Method [6]					
	Daylight	Dimlight	Office	Daylight	Dimlight	Office
RLPD(%)	18.7	1.17	10.22	11.67	0.17	9
RLD(%)	91.39	85.94	92.44	91.5	78.5	89.83
	Masek Method [15]					
	Daylight	Dimlight	Office	Daylight	Dimlight	Office
RLPD(%)	6.67	15.89	11.11	5.33	11.17	9.67
RLD(%)	95.11	92	94.22	94.33	92.67	92.33
	Proposed Method					
	Daylight	Dimlight	Office	Daylight	Dimlight	Office
RLPD(%)	41.5	21.72	39.6	39.33	27.33	34.16
RLD(%)	94.28	88.06	92.22	90.67	89.83	91.67

Even though the RLD of our proposed method is 2.6% lower than Masek method, this small increase in success rate with Masek's method is achieved at high computational cost. Table IV shows the average time taken by all the methods in segmenting the iris and pupil boundaries. The proposed method is the fastest with 8-fold reduction in the execution time compared to Masek and 5 folds faster compared to Daugman's algorithm.

TABLE IV
EXECUTION TIME COMPARISON OF PROPOSED ALGORITHM WITH MASEK'S AND DAUGMAN'S ALGORITHMS

Method	Masek [15]	Daugman [6]	Proposed
time(sec)	2.36	3.6	**0.46**

For in-depth analysis of each segmentation method, RLPD and RLD were estimated separately for each one of the three lighting conditions available in VISOB dataset i.e., office light, dim ligh, and daylight. From Table III, in general, both RLPD and RLD, are low for dimlight compared to daylight and office light for all the methods. As can be seen, Daugman's method performance is impacted the most in dimlight condition, this is because Daugman's method is detecting specular reflections as pupil which is a drawback for Daugman's segmentation method in unconstrained visible lighting. For Visit-II, Daugman's method was able to segment iris and pupil of only a single eye sample (0.17%) whereas the proposed method was able to segment more than 27% of the eye samples. Another difference that can be deduced from Table III is in daylight and office light conditions with significant specular reflections on the eyes, Masek's method (edge detection based method) fails to detect pupil boundary, whereas Daugman's and our proposed methods (both being intensity based methods) performed better. In contrast, Masek's method obtained better performance in dimlight conditions.

V. CONCLUSION

In this paper, we proposed an RGB iris segmentation scheme based on the combination of K-means clustering and Daugman's integro-differential algorithm. First, K-means clustering is applied to extract the region in which the iris is present. Then, Daugman's integro-differential algorithm is used to find center and radius of the iris. Comparative analysis with Daugman's and Masek's algorithm suggest that the proposed algorithm can obtain higher iris segmentation accuracy (RLPD) for varying illumination conditions and involves less execution time. As a part of future work, comparative analysis will be done with other existing iris segmentation algorithms proposed for the visible spectrum.

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