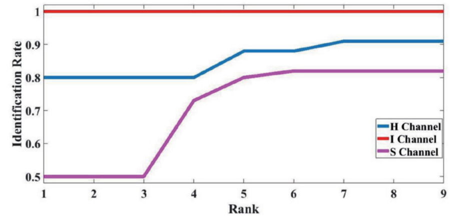
# Statistical approach based iris recognition using local binary pattern




## Enfoque estadístico para el reconocimiento del iris usando patrones binarios locales

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**DOI: http://dx.doi.org/10.6036/7997** | Recibido: 14/03/2016 • Aceptado: 29/03/2016

## RESUMEN

- Entre las características biométricas utilizadas para el reconocimiento de la identidad, el iris ha demostrado ser el más fiable en términos de carácter distintivo suficiente, lo que tiene implicaciones directas e importancia para mejorar el rendimiento y la seguridad del proceso de verificación de seguridad a través del cual se decide si a cualquier instancia se le debe otorgar permiso para acceder a lugares o fuentes de información reservados.
En este trabajo se aborda el principal desafío que implica el reconocimiento del iris, cuya complejidad computacional es relativamente alta, habiendo permanecido sin resolver hasta ahora, al menos, en lo que respecta a la literatura existente.
La mejora obtenida por la metodología propuesta se origina tomando ventaja de los patrones binarios locales para procesar cada segmento de la imagen original, habiendo experimentado la ecualización de antemano, así como aplicar funciones de distribución de probabilidad separadamente a cada capa de los valores de pıxel, mientras que estar representado con respecto a los canales de color de intensidad de saturación de color mutuamente independientes.
Además, la distancia Kullback-Leibler entre los vectores obtenidos a través de la concatenación de los vectores de características se toma en cuenta como criterio de clasificación, lo que ha llevado a una tasa de reconocimiento sobresaliente de 98,44 por ciento cuando se probó en la base de datos UPOL, con 192 imágenes de iris.
- **Palabras Clave:** Biometría, Distribuciones estadísticas, Análisis de imágenes en color, Reconocimiento de iris, Patrones binarios locales, Función de densidad de probabilidad.

## ABSTRACT

Among biometric features utilized for identity recognition purposes, iris has proven to be the most reliable one in terms of sufficient distinctiveness, which has direct implications and importance towards improving the performance and safety of the security verification process through which it is decided whether any instance at hand should be granted permission to access preserved locations or sources of information. This paper deals with the main challenge involved in iris recognition, which lies in its comparatively high computational complexity, having remained unresolved heretofore, at least, as far as the existing literature is concerned. The enhancement brought about by the proposed methodology originates from taking advantage of local binary patterns for processing each segment of the original image, having undergone equalization in advance, as well as applying probability distribution functions separately to every layer of the pixel values, whereas being represented with respect to mutually-independent hue-saturation-intensity color channels. Besides, the Kullback-Leibler Distance between the vectors obtained through concatenation of the feature vectors is taken into account as the classification criterion, which has led to an outstanding recognition rate of 98.44 percent when tested on the UPOL database, with 192 iris images.

**Key Words:** Biometric, Statistical distributions, Image color analysis, Iris recognition, Local binary pattern, Probability density function.

## 1. INTRODUCTION

Biometric recognition is a well-studied approach to the problem of security verification, which is demanded for ensuring the disallowance of unauthorized access to preserved or private resources of data or material [1-5]. Nevertheless, the issue of whether to consider biometric feature as a criterion, as well as how to evaluate it, is still being questioned and examined [6-10].

One of the rare biometric characteristics that is not only instance-specific, i.e. could be uniquely associated with the samples input to a classifier whereas being trained, but also differs significantly and sufficiently from a person to all others, is the iris pattern. More clearly, the combinations of the iris feature of different human beings, even if highly similar to each other in other terms, would always be uncorrelated enough to qualify as solid metrics for distinguishing them, which has been accepted as a well-established notion by the image processing research community for decades [11].

Thus iris recognition, to the existing knowledge and experience reported in the literature [12], has never failed to provide a reliably critical evaluation of the biometrics required for identity recognition or verification. From biological point of view, the latter virtue may be attributed to the earlier scientific finding that iris properties do not propagate through inheritance, at least in the same manner as other biometric specifications do [13].

Moreover, iris appearance of every individual comprises a complex combination of geometric arrangements, namely, pits, rings, furrows, and stripes [14], each of which is detailed enough to result in perceptible dissimilarities between samples. The uniqueness of iris patters has also been investigated in [4] and [5], both of which having concluded that it is at the same level as that of fingerprints. However, they assert that the iris is practically more feasible, as it leaves less chance of becoming entangled with illusions standing for untruthful matches between the instances under study.

As a prominent example from the list of the methods developed for the recognition of identity based on iris patterns, the Duagman's Algorithm could be mentioned [15-16], which deems the successfulness of a test regarding the statistical dependence of the iris phase structure, which has been encoded by means of a prescribed set of quadrate wavelets, the desired condition. Following up the aforementioned study, a device has been introduced in [17], which is responsible for capturing iris images from a distance. It is worth noticing that in order to obtain clearer images, the algorithm described in the latter reference processes and improves the original iris image through implementing super-resolution.

Among other tasks concerning recognition, numerous papers have concentrated on developing efficient approaches to extracting facial features. As an instance, [18] has suggested making use of Gabor filters, multi-channel filters or wavelets for performing the foregoing task. On the other hand, in [19], fusing global and local features has been proposed, where after normalizing the iris images, they are divided into local windows, according to which, the local features representing the fine texture are extracted.

According to [15], one of the major steps needed to be taken for the recognition purpose is detecting the location of the iris within the whole image, whose authenticity influences the performance, i.e. the recognition rate, considerably. For the latter goal, [20-21] denote one of the familiar strategies, namely, utilizing the Hough Transform. Last but not least, in the context of the methodology introduced in [22], minimum-variance investigation of the wavelet has been employed for the sake of recognizing the inner boundary of the iris, whereas a modified brightness-gradient technique handles distinguishing the outer one.

The algorithm presented in this paper, as the first stage, equalizes the input images, so that it could be ensured that undesired effects, such as the lightening conditions' variations, would not interfere with the physical interpretation of the mathematical information available to the recognition system.

Then the image is segmented, so that the details of each part could be examined separately, where a Local Binary Pattern (LBP) is applied, in order to closely study the slight nuances conveyed by the iris image, which is expected to lead to considerable enhancements in the overall performance.

As a major contribution of this paper, in spite of most recognition methods discussed in the literature, such as [23] and [24], instead of reviewing the full pixel information at once, each color channel included in the Hue-Saturation-Intensity (HSI) representation is dealt with individually, which, according to the experiments elaborated in the upcoming sections, results in more realistic analyses and higher recognition rates.

Besides, considering the aforementioned set of color channels, despite the case of RGB, brings about the advantage that their dependence on each other is avoided, and meaningful distinctions between the combinations of the values associated with the channels are exploited.

The Kullback-Leibler distance [25] is perhaps themost frequently used information-theoretic "distance"measure from a viewpoint of theory. If $P_0$, $P_1$ are two probability densities, the Kullback-Leibler distance is defined to be

$$D(\mathrm{p}_1 \| \mathrm{p}_0) = \int p_1(x) \log \frac{\mathrm{p}_1(x)}{\mathrm{p}_0(x)} dx$$

In order to substantiate the efficiency and applicability of the suggested iris-based recognition algorithm, it is applied to the UPOL database [26], which contains 64 instances, each corresponding to three sample images, where intact operation is demonstrated when taking the saturation channel into account for constructing the feature vectors. Also, the algorithm is tested on UBIRIS V1-1 database [27] and UBIRIS V1-2 database that composed of 1205 iris images of 241 subjects and 660 iris images of 132 iris object respectively, each subject corresponding to five sample images.

More detailed specifications and guidelines of the modules involved in the proposed recognition system are presented in the succeeding sections, as follows. The next section explains the preprocessing component, which equalizes and segments the iris image into different parts. Then the remaining elements, including the LBP and the creation of the feature vectors, being followed by classification, are clarified. Subsequently, the experimental results are illustrated and discussed.

## 2. IRIS LOCALIZATION AND PROCESSING OF IRIS IMAGES

In the context of the strategy proposed in this paper, the iris localization task is organized such that the area of interest is separated from the sclera and pupil, which is accomplished via detecting its inner and outer boundaries using the Hough Transform [15], [20], [28-29].

The calculation of the latter necessitates finding the global characteristics, which are used for connecting the discontinuous edge pixels that are supposed to constitute the aforementioned regions' outline. It is noteworthy that this task demands prior knowledge of the overall shape of the target.

In the next step, as stated before, the image is segmented into multiple components. This attitude provides an opportunity to study the image properties, aiming at making the most comprehensive inferences possible from the visual data.

Since throughout the database utilized for the purpose of this paper, namely, the UPOL database, the center of the iris rectangle is always approximately aligned with that of the iris itself, the result of the implementation of the Hough Transform, i.e. the iris pattern, according to the experiments conducted, will be noise-free. Moreover, the segmented iris image only contains the iris texture, but not the surrounding fragments, such as eyelid, pupil, sclera, and eyelash.

## 3. THE PROPOSED LBP-BASED IRIS RECOGNITION SYSTEM

The main recognition utility takes the preprocessed iris image, having gone through equalization, segmentation and iris localization, as the input, and evaluates it in terms of satisfactorily matching with, at least, one of the instances used to train the classifier.

The main elements of the foregoing process consist of finding the Probability Density Function (PDF) of each segment of the image, applying an LBP, constructing the feature vectors and classifying the image into the corresponding class on that basis, if any, which are explained in the following sections.

**a) PDF**

The PDF of an image is a mapping $\eta_j$, which outputs a value standing for the share of the pixel intensities confined within the $j^{th}$ mutually-exclusive interval, known as bin, spanning the whole range. Obviously, the length of each feature vector is equal to the size of the bin, which means that, assuming *N* as the total number of the pixels, taking the value 256 in case of a monochrome image, the following relationship holds:

$$N = \sum_{j=0}^{255} \eta_j . \tag{1}$$

Then the feature vector, *H*, is defined as follows:

$$H = \{p_0, p_1, \cdots, p_{255}\}, \qquad p_t = \frac{\eta_t}{N}, \quad t = 0, \cdots, 255. \tag{2}$$

**b) Color Channels Representations**

According to [29], PDF-based iris recognition could be performed in accordance with various color channels representations, such as HSI and YCbCr color spaces, in which the luminance and chrominance are separated from each other, whose inferences would be fused in the next phase, in order to guarantee that the most logical inference is made, i.e. the decision is based on the most reliable criterion extracted from the resources of data at the classifier's disposal.

Nevertheless, since highly correlated information might exist within different color channels, meaning that relatively great mutual entropy is visible among them, only a selection should take part in the decision-making process, which could be seen from Table 1, showing the mutual entropy between the channels of the HSI and YCbCr color spaces.

The high correlations between the pairs of color channels I-Y, I-Cb and I-Cr encourages the notion that, instead of using both color spaces at the same time, considering fusing the data stored on the channels of the HSI color space on its own would be enough to acquire an exhaustive resource of the knowledge demanded for achieving superior recognition rates.

| | H | S | I | Y | Cb | Cr |
|---|---|---|---|---|---|---|
| H | 100 | 26.49 | 9.36 | 5.28 | 9.29 | 16.13 |
| S | 26.49 | 100 | 25.97 | 32.91 | 52.51 | 65.58 |
| I | 9.36 | 25.97 | 100 | 99.05 | 98.32 | 93.39 |
| Y | 5.28 | 32.91 | 99.05 | 100 | 96.02 | 84.63 |
| Cb | 9.29 | 52.51 | 98.32 | 96.02 | 100 | 92.50 |
| Cr | 16.13 | 65.58 | 93.39 | 84.63 | 92.50 | 100 |

*Table 1: The correlations between the hsi and ycbcr color channels in percentage*

**c) LBP**

Aiming at deriving the slightest possible attributes of the preprocessed image, it undergoes further analysis through a separate module, where an LBP is applied to each segment, which describes the local spatial structure of the image [31]. In [32], it has been shown that LBP could be used for texture classification, as an effective discriminative measure.

By definition, for a pixel positioned at the point *(x,y)*, LBP indicates a sequential set of the binary comparison of its value with the eight neighbors. In other words, the LBP value assigned to each neighbor is either 0 or 1, if its value is smaller or greater than the pixel placed at the center of the mask, respectively. The decimal form of the resulting 8-bit word representing the LBP code can be expressed as follows:

$$LBP(x,y) = \sum_{n=0}^{7} 2^n s\left(i_n - i_{x,y}\right), \tag{3}$$

Where $i_{x,y}$ corresponds to the grey value of the center pixel, and $i_n$ denotes that of the $n^{th}$ neighboring one. Besides, the function *s(x)* is defined as follows:

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}. \tag{4}$$

The LBP operator remains unaffected by any monotonic grey-scale transformation which preserves the pixel intensity order in a local neighborhood. It is worth noticing that all the bits of the LBP code hold the same significance level, where two successive bit values may have different implications. The LBP code is also referred to as a kernel structure index.

An extended variant of the original idea of LBP has been presented in [33], which applies the operator to a circular neighborhood of different radius size. The LBP, *R* notation has been employed for referring to P equally-spaced pixels on a circle of radius *R*.

Among major advantages of LBP, is its low computational complexity, which renders it suitable for various image processing applications, such as visual inspection [34], face recognition [35-36], motion detection [37], face detection [38] and image retrieval [39]. Besides, taking advantage of the low computational complexity of LBP in creating feature vectors is a substantial element in improving the affordability of the whole system to the existing real-world identity recognition processors.

d) Feature Vector Construction

In the settings associated with the technique proposed in this paper, similarly to that of [36], the feature vector corresponding to each segment of the preprocessed image, in fact, contains the cumulative histogram, $h_i$, of the LBP codes calculated at the pixels' locations, defined as follows:

$$h_i = \sum_{x,y} I\{f_1(x,y) = i\} \quad i = 0, \ldots, m \tag{5}$$

where $f_1(x,y)$ is a labeled image, *m* denotes the number of the different labels produced by the LBP operator, and the binary function *I* is expressed as follows:

$$I(A) = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases} \tag{6}$$

It is leading the histogram to contain information about the distribution of the local micropatterns, such as spots, edges, and flat areas, over the whole image. Retaining the spatial information is required for an efficient iris representation; hence the image is divided into regions $R_0, R_1, \ldots, R_{m-1}$.

The spatially enhanced histogram is defined as:

$$h_{i,j} = \sum_{x,y} I\{f_1(x,y) = i\} I\{(x,y) \in R_j\} \quad i = 0, \ldots, m, \tag{7}$$

in which, a description of the iris on three different levels of locality exists: The labels for the histogram contain information about the patterns at pixel level The labels are summed over a small region to produce information at regional level; And the regional histograms are concatenated to build a global description of the iris.

### e) Classification Metric

The classification component is devised such that the Kullback-Leibler Distance (KLD) is considered as a measure for evaluating the divergence between the PDFs, since it has proven stable and applicable for the purpose of identity recognition in numerous preceding studies [24], [30], [40].

As a relevant note, due to the fact that decreasing the number of the bins causes a loss of information delivered by the PDF patterns, which decreases the recognition rate, a compromise should be found between the foregoing quantity and the consequent computational cost. Fig. 1 shows a diagram of the proposed method.

have quoted the results of existing methods from the respective articles.

The qualitative strength of the method introduced and implemented in this paper, which directly affects the quantitative measure used to judge the proficiency, originates from employing the LBP, as it could be seen from Fig. 2, which makes it possible to rigorously study the features in accordance with the color information contained in each individual segment. More clearly, the binary patterns implemented on the segments, which have been equalized before, enhance the stability of the whole mechanism by means of closely examining the details.

The preceding concept may be more clearly understood by noticing the fact that all the data included in those segments, as per the practices under usage by other existing systems, would be treated cumulatively, which causes the dismissal of a chance to take advantage of the slight differences between each segment of an image and the one coinciding with it in others.

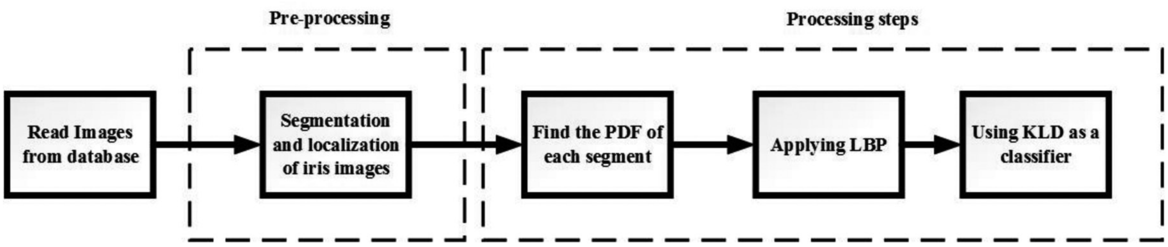


*Figure 1: block diagram of the proposed method*

## 4. THE EXPERIMENTAL RESULTS AND DISCUSSIONS

In the context of this paper, the proposed iris-based recognition methodology is implemented on a database of iris images, such that first, the PDF associated with each image is obtained. In order to do so, an LBP is applied to the image, where the HSI representation is chosen, due to the fact that the information conveyed by the illuminance color channel correlates considerably with that of the YCbCr color channels.

Afterward, the image undergoes segmentation and equalization, which is followed by dividing it into different sub-images. Next, the PDFs associated with each color channel are found. More clearly, each sub-image resulted from dividing the original image on the basis of the separate color channels will lead to different sets of PDFs. Then all the PDFs corresponding to each color channel are concatenated into a single vector, which will be used as the criterion for the classification procedure, which, as aforementioned, is performed by means of the KLD algorithm, at the next stage.

For the sake of verifying and demonstrating the applicability and superiority of the foregoing technique, i.e. statistical-approach-based iris recognition, a selection of the existing methods from the lists of conventional and state-of-the-art algorithms reported in the literature, which deal with the recognition task, have been implemented on the same database, in the same settings, along with the one suggested in this paper, so that the performance achieved could be fairly compared, both qualitatively and quantitatively.

The strategies utilized for the above goal consist of a classical PCA-based iris recognition system and the most recent instances, such as Majority Voting (MV) [23], Feature Vector Fusion (FVF) [15], Ahamed et al. [45], Umer et al. [46] and Harjoko et al. [47], which to the authors' knowledge, are considered the most prominent practices suggested in the literature heretofore. Note that we

Besides, it is noteworthy that equalizing the images, as an initial task within the recognition scheme, assures that sudden, undesired changes in the irrelevant circumstances, such as lightening, would not be allowed to mislead the mathematical interpretation whereas introducing random changes into the input data.

The quantitative comparison is based on the common index recognition rate, where the percentage of the ratio between the number of the instances recognized correctly by the algorithm and the total number of the cases under experimentation is taken into account as the efficiency measure. In other words, each class consists of the samples taken from the same instance whereas training the classifier, and the competitiveness of the criterion considered for classification is evaluated on the basis of its capability of assigning the input test sample to the authentic class of the training class, i.e. recognizing the associated identity properly.

Tables 2-4 show the recognition rate achieved through the utilization of each of the H, S and I color channels for recognition, along with that of the aforementioned solutions presented in the literature, namely, PCA, MV and FVF, which clearly proves the outstanding competence of the statistical-based iris recognition process introduced in this paper. Table 5 shows the recognition rate achieved through the utilization of each of the H, S and I color channels with a leave-one-out classification strategy for the UBiris1-1 and UBiris1-2 databases respectively. In all experiments, we found a recognition rate for all possible situation for training and testing set as shown in Tables 2-4, for example there are 5 images per subject, the recognition rate is founded when different number of images of each subject are considered in the training set and the rest as a testing set. As it shows in Tables 3-4 for the UBiris database, system is trained with 4 images per subject for the first row of the table then with 3 images per subject for the second row. Fig. 2 shows a CMC curve of all three channels of H, S and I on UBiris1-2 database.

| Training set | H | S | I | PCA | MV [23] | FVF [15] | Ahamed et al. [45] | Umer et al. [46] | Harjoko et al. [47] |
|---|---|---|---|---|---|---|---|---|---|
| 2 | 87.5 | 100 | 95 | 70 | 96.88 | 98.44 | 97.80 | 100 | 82.90 |
| 1 | 86 | 100 | 93.5 | 60 | 89.84 | 92.19 | ---- | ---- | ---- |

*Table 2: Recognition rate percentages obtained through considering three different color channels, h, s and i, compared with that of the pca, mv and fvf techniques*

| Training set | H | S | I | Umer et al. [46] |
|---|---|---|---|---|
| 4 | 100 | 80 | 100 | 97.51 |
| 3 | 75 | 70 | 100 | ---- |
| 2 | 70 | 57 | 77 | ---- |
| 1 | 53 | 43 | 75 | ---- |

*Table 3: Recognition rate percentages obtained through considering three different color channels, h, s and i, for the first 100 images of UBiris1-1 database*

| Training set | H | S | I |
|---|---|---|---|
| 4 | 80 | 50 | 100 |
| 3 | 65 | 40 | 85 |
| 2 | 57.5 | 34 | 84 |
| 1 | 54 | 30 | 80 |

*Table 4: Recognition rate percentages obtained through considering three different color channels, h, s and i, for the UBiris1-2 database*

| UBiris1 database | | | UBiris1-2 database | | |
|---|---|---|---|---|---|
| H | S | I | H | S | I |
| 92 | 74 | 92 | 76 | 45 | 100 |

*Table 5: Recognition rate percentages obtained through considering three different color channels, h, s and i, with a leave-one-out classification strategy*

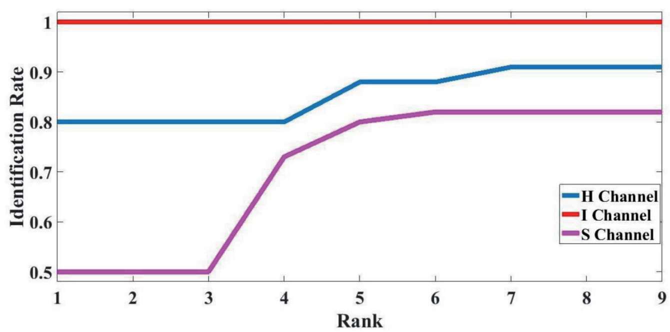


*Figure 2: CMC curve for UBiris1-2 database on all three channels*

Among others, one of the important conclusions derived from the foregoing table is that the recognition rate accomplished via training the classifier on the basis of the saturation color channel is 100 percent in case of both of the training procedures, meaning that the latter could be deemed robust enough to provide a foundation for flawless operation in terms of identity recognition.

Moreover, even though the performances achieved via other color channels, i.e. hue and intensity, are not as sound as that of the saturation color channel, they are still great enough to be fairly compared with the recognition rates associated with the state-of-the-art approaches MV and FVF, where the performance of the classical PCA-based system is strongly outperformed by the suggested algorithm.

The aforesaid excellence of the proposed technique, especially when using the saturation color channel information, could be attributed to the aggregated effect of introducing a set of innovative modifications made to the recognition system, which basically lie in a bunch of certain notions, being briefly discussed in what follows.

First, the fact that the H, S and I color channels are distinguished from each other, and the analysis is applied to each of them separately, plays a paramount role in improving the sensitivity of the feature vectors to the variations of the properties from a training class to the others. More clearly, since the information provided by the R, G and B color channels is not as distinctive as the data brought by H, S and I channels, the studies conducted based on the RGB representation of the colors do not typically result in satisfactory recognition rates [23][44]. In other words, compared to HSI, the RGB information normally bears higher proneness to mixed and biased data consistently appearing in all the images prepared whereas creating a database, which, effectively, is not the case of the HSI representation.

Secondly, the data fusion module helps boost the recognition performance by combining the decisions obtained via different making process. In the foregoing settings, even if one of the criteria fails to spot the original class, still the knowledge accumulated in the aforementioned step-by-step algorithm ensures that others would prevent opting for wrong choices on the classes, being successfully demonstrated by the numerical values shown in Table 2, standing for the unimpaired recognition achieved whereas considering the saturation color channel for constructing the feature vectors.

## 5. CONCLUSION

This paper introduced and verified the efficiency of an innovative statistical-based iris identity recognition system, which, has its own advantages, improves the computational cost, and increases the resulting recognition rate, simultaneously. The classification criterion was based on the fusion of the Kullback-Leibler Distances between the feature vectors constructed upon concatenating the cumulative histograms of the local binary pattern codes corresponding to different segments of the iris images having passed through a preprocessing module, being responsible for equalization, as well as the detection of the iris boundaries against the surrounding parts of the eye, namely, sclera and pupil. The main contribution arose from performing analysis on each of the mutually-independent color channel separately, rather than dealing with all of them at once. The results of the implementation of the proposed method, when compared with that of the existing state-of-the-art techniques, being applied to the same database, i.e. the UPOL, demonstrated its unrivaled performance, with a flawless functionality whereas depending solely on the saturation color channel.

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## ACKNOWLEDGMENT

This research is supported by the Estonian Research Council Grant PUT (PUT638).