Information Fusion for Unconstrained Iris Recognition

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Abstract

The majority of the iris recognition algorithms available in the literature were developed to operate on near infrared images. A desirable feature of iris recognition systems with reduced constraints such as potential operability on commonly available hardware is to work with images acquired under visible wavelength. Unlike in near infrared images, in colour iris images the pigment melanin present in the iris tissue causes the appearance of reflections, which are one of the major noise factors present in colour iris images. In this paper we present an iris recognition system which is able to cope with noisy colour iris images by employing score level fusion between different channels of the iris image. The robustness of the proposed approach is tested on three colour iris images datasets, ranging from images captured with professional cameras in both constrained environment and less cooperative scenario, and finally to iris images acquired with a mobile phone.

Keywords: *unconstrained iris recognition, visible spectrum iris images, information fusion*

1. Introduction

Due to the reliability and high accuracy shown by the iris recognition systems deployed worldwide, the iris has become a popular biometric trait over the last two decades. Most of the deployed iris recognition systems rely on the pioneering approach proposed by Daugman [2] but the scenarios where these systems could be employed are limited mainly because of the necessary near infrared illumination. This type of illumination introduces a distance related constraint because for the eye region to be properly illuminated the user has to stand very close to the acquisition device. Therefore, a desirable feature of an iris recognition system is to work efficiently with colour RGB iris images. This property is an essential one for less constrained iris recognition, since it will automatically allow the user to be recognized at a larger distance compared to the case when near infrared illumination is used.

Over the last few years, research in iris recognition has refocused more on unconstrained environment operation and implicitly on how the accuracy of these types of systems are affected when noisy colour images are used. To encourage the work of researchers in the direction of non-cooperative iris recognition, a competition was created for noisy colour images: Noisy Iris Challenge Evaluation (NICE). It took place in 2 parts: part1 assessed only the segmentation of a subset of UBIRISv2 [3] and part 2 the classification algorithms were assessed on the same images. The test images have not been made public for the objectiveness of the competition. The winning algorithm for segmentation is depicted in [4] and for part 2 the algorithms will be published soon.

A number of papers deal with iris images operating on colour images. A work on an Iris Recognition system processing colour iris images may be found in [5], where the image database was UPOL [6]. This database has very good quality colour iris images of 64 users and the obtained identification rate was 100%. RGB iris images were converted to Hue Saturation Intensity (HSI) colour space and the features used are the histograms of the HSI space. For each channel, a correlation coefficient was computed between the histograms of the testing and enrolled images. The fusion of the three results was done at the decision level by majority voting. To deal with non-cooperative Iris Recognition, in [7], after segmentation, the unwrapped iris image is divided into six regions and on those regions 2D Gabor Wavelet [2] feature extraction techniques are applied. Consequently six distinct biometric signatures are obtained. For each region, a dissimilarity threshold was set for features extracted from that region. The Equal Error Rate (EER) obtained for colour iris images from UBIRIS v1 database was 2.38%.

Another step towards non-ideal iris recognition is made in [8], where features from four different regions of the unwrapped iris image from UBIRISv1 database are extracted using Daubechies wavelet transform. The main contribution of this work consists in a novel feature selection method for dimensionality reduction of the features. Four feature selection methods are applied, i.e. k-Nearest Neighbor, Support Vector Machines, Entropy based algorithm and T-statistics and after that, Genetic Algorithms are employed to select the best features. To use the information available in the iris texture under both NIR and visible light illumination, Hosseini et all [1] fused features from iris images of the same eye captured under the two illumination conditions. Shape based analysis was used to extract binary features from RGB images after the unwrapped irises were enhanced with a Tikhonov filter. For the UBIRIS version 1 database [9], the obtained classification accuracy was around 95% but using the same feature extraction method on CASIA version 1 database [10], the classification accuracy was under 70%. Therefore, the shape analysis proposed in this work to extract the features cannot be applied on NIR iris images. This is explained by the fact that the eumelanin present in the iris pigment epithelium does not emit light when stimulated by NIR wavelengths.

In contrast to the above approaches, the main contribution of this paper is to perform an analysis about which channels from the RBG and HSI colour spaces are more suitable to be fused in order to improve the system's overall accuracy. The theoretical analysis is validated by numerical results on three colour iris image datasets, ranging from non-noisy images from UPOL[6] dataset to images which include a controlled amount of noise from UBIRISv1 [9] dataset and finalizing with poor quality iris images acquired in-house with a mobile phone.

The remainder of this paper is organized as follows: in section 2 the analysis of which channels better reveal the iris texture is presented. In section 3 the proposed iris recognition methodology to fuse information from the most useful colour channels is described and in section 4 the experimental results are reported. Conclusions are given in section 5.

2. Information Theoretic Analysis of Iris Texture

There are a number of colour spaces available to represent digital images and their channels could potentially all be used to extract information from iris texture, but such an approach is not a practical one. The issue that appears is how to select the most discriminative few channels from various colour spaces and to find a fusion methodology to enhance the system's accuracy. A preliminary study was made in [11], where iris images acquired with a multispectral camera were saved in visible spectrum and near infrared spectrum simultaneously. The system's accuracy was assessed for each channel and it was found to be higher on the near infrared and Red channels, followed by the Red channel. On the Blue channel, the system performed poorly. As a reminder, the human eye is sensible to wavelengths from 390 nm to 750 nm, while the near infrared light ranges from 700 nm to 2000 nm. The research from [11] was extended in[12], where an analysis of different colour channels of iris images in various colour spaces was made. Between Red, Green, Blue and near infrared channels, a dynamic score level fusion was proposed to choose the best 2 channels for each unwrapped iris image in the matching process. The best 2 channels were selected based on a texture quality matrix consisting of 6 components: average intensity, average contrast, and smoothness across the image, skewness of the image histogram, uniformity and Shannon entropy. The reported system's performance did not improve when this quality matrix was used compared to the accuracies obtained by the red channel alone. The explanation of this result lies in the fact that techniques used to characterize iris texture overall using a single value will produce similar values for all the channels of the iris image, as reported in the following paragraphs.

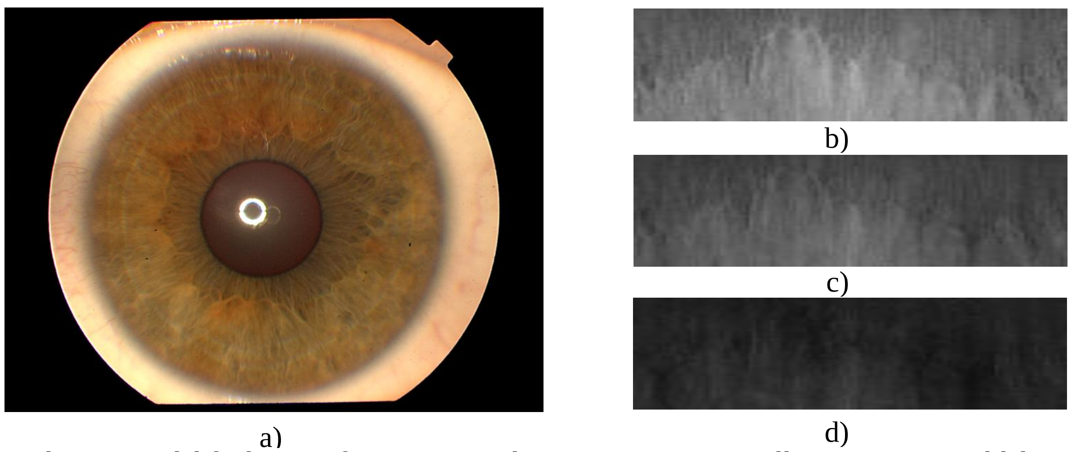


Figure 1: a) iris image from UPOL dataset; corresponding unwrapped iris image in b)red channel; c)green channel; d)blue channel

To show why texture analysis methods which yield a single value for the unwrapped image overall are not appropriate to be applied directly, let us consider the entropy of an unwrapped iris image from the UPOL database in the Red, Green and Blue channels. We chose images from the UPOL dataset to develop our analysis because they have almost no noise at all and we will be able to do a more objective characterization of the iris texture. In Figure 1, an image from UPOL dataset is shown together with the unwrapped images from RGB colour space.

The Shannon entropy E of a grayscale digital image is expressed by equation (1), where p(i) is the histogram count for the gray level i and n is the total number of bins. It is a statistical measure used to characterize the randomness of the texture. The larger the value of the entropy is, the more random information is available in the image texture.

$$E = -\sum_{i=1}^{n} p(i) * \log(p(i)) \tag{1}$$

The value of the entropy for the unwrapped iris image in the Red channel is 6.34, for the Green channel 5.85 and for the Blue channel 5.00. According to these values of the entropy the Red channel reveals the iris texture best, followed by the Green and Blue channels, but the difference between them is not a large one. It proves interesting to compute the entropy for all unwrapped iris images from UPOL database. The means and standard deviations of the entropy distributions for the Red, Green and Blue channels unwrapped images are presented in Table 1.

Table 1:Mean and standard deviation of the distributions of entropy on Red, Green and Blue channels of the unwrapped iris images from UPOL database.

Channel	Mean	Standard deviation
Red	5.96	0.43
Green	5.69	0.50
Blue	5.12	0.50

As we may observe, according to the entropy statistics, all the channels reveal a similar amount of discriminative information in the iris texture. This contradicts the experimental results obtained in [11], where the performance of the iris recognition system on the Blue channel was clearly worse than the performances obtained using the Red and Green channels. Therefore, the texture analysis methods similar to Shannon entropy, applied directly on the entire unwrapped iris image are not reliable techniques to decide on which channel the system's performance improves. We need a clearer separation between the quality measurements of the iris texture in different colour channels.

By visually observing Figure 1(a), we may conclude that the iris texture has a radial direction. The most prominent texture structures start from the pupil and head towards the sclera following mainly a straight direction. When the iris image is unwrapped, the radial trend of the texture will become a vertical one, as we see in Figure 1(b) and Figure 1(c). In the Blue channel of the unwrapped image (see Figure 1(d)), compared to Red and Green channels, most of the vertical patterns of the texture are not distinguishable.

a) b)

Figure 2: Red channel unwrapped iris image filtered with Sobel edge detector for a)horizontal edges; b)vertical edges.

For the investigation, we have filtered the unwrapped images in Red, Green and Blue channels with Sobel masks for edge detection in the vertical and horizontal directions. The result of applying Sobel edge detection on red channel unwrapped iris image for vertical and horizontal edge directions is shown in Figure 2.

By applying Sobel edge detection on the y axis, where y axis corresponds to 0^{o}, the vertical orientation of the texture structure is highlighted. The 2 Sobel masks Gx and Gy are given in (2):

$$G_x = \begin{array}{ccc} -1 & 0 & 1 \\ -2 & 0 & 2 \\ 1 & 0 & 1 \end{array}; \quad G_y = \begin{array}{ccc} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{array} \tag{2}$$

The direction of the edges is given by the gradient obtained from the 2 edge detectors. The distributions of the gradients converted in degrees from the Red, Green and Blue channels of the unwrapped iris image are shown in Figure 3.

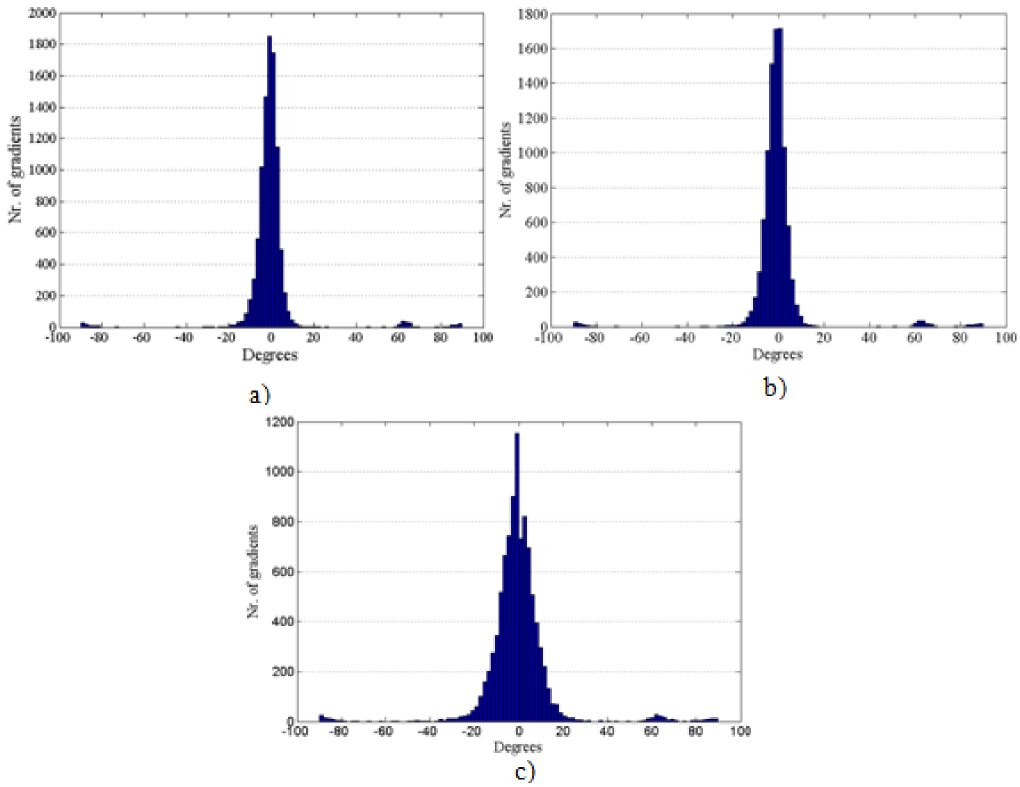


Figure 3: Distributions of gradients for a)Red channel; b)Green channel; c)Blue channel

In Figure 3 we may observe that the distribution of gradients of the Blue channel is significantly spread compared to the gradients of the Red and Green channels. The means of the three distributions are approximately 0, which is the main direction of the iris texture edges, but the Blue channel contains noisy orientations of the iris texture.

By taking the entropy of the gradient distributions, we are able to measure how much noisy directions of the iris texture are present in a particular channel. For narrow distributions of the gradients, the entropy will have a small value and for a wider spread distribution of the gradients, the entropy will increase. The Shannon entropies distribution means and standard deviations of the gradients for the Red, Green and Blue channels are presented in Table 2. In this table, the entropy values for Blue channels are clearly higher than those in the Red and Green channels. This approach could be used for other colour spaces to analyze which channels contain most discriminant information from the iris texture. In our experiments, we used RGB and HSI colour spaces. With a similar analysis, the intensity channel has shown to be appropriate to be used for recognition.

Table 2: Mean and standard deviation of the distributions of entropy of the gradient distributions from Red, Green and Blue channels from UPOL

Channel	Mean	Standard deviation
Red	6.59	1.49
Green	8.97	2.77
Blue	15.03	6.15

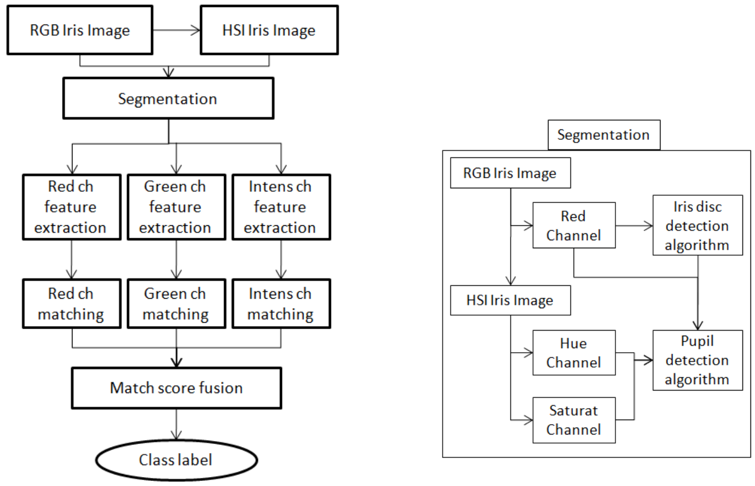


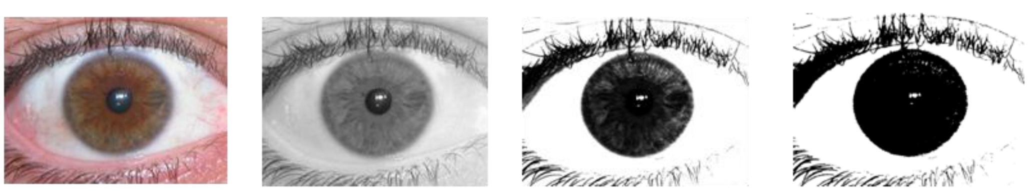
Figure 4: Block diagram of the proposed iris recognition system

3. Proposed Iris Recognition System

In the iris recognition system that was developed for colour iris images, the information is extracted and fused from the RGB and HSI colour spaces. From the RGB colour space the Red and Green channels are used and from HSI colour space the intensity channel is used. A block diagram of the system is presented in Figure 4.

3.1. Segmentation

The segmentation of the iris and pupil described in this section will be exemplified on colour images from UBIRISv1 dataset. The segmentation will be only briefly described because the main focus of the paper is on fusing information from various channels to improve iris recognition accuracy. In our segmentation methodology, we assumed that the iris and the pupil have approximately the shape of a circle.



a) b) c) d)

Figure 5: Iris image transformations: a) original RGB image from UBIRISv1 dataset; b)red channel image; c)image after contrast adjustment; d)binarized

For iris segmentation only the Red channel has been used, as the iris-sclera boundary is more distinguishable in this channel compared to other channels. To cope with illumination variations of the iris image, a dynamic contrast adjustment was made. The adjustment parameters depend on the average intensity of all pixels from the Red channel iris image. The image was then binarized using a threshold depending on the same average intensity of all pixels. The effects of these transformations are shown in

Figure 5. Now the iris is a black circular disc and clearly separated from the rest of the image and any circle detection method could easily detect the iris.

When detecting the pupil, specular reflections have been detected and removed using thresholding techniques and only the region from the red channel image that is inside the detected iris is used by the proposed segmentation algorithm. The average of the intensity of the remaining pixels from inside the iris was calculated after reflections are excluded. This average value was then used to dynamically adjust the parameters of a contrast adjustment operation. After this operation, the pupil region becomes clearly separated from the iris texture. Further, the pupil region was enhanced by using information from hue and saturation channels from HSI colour space. After all these steps, a simple circle detection method is able to correctly detect the pupil inside the iris. A detailed version of our segmentation methodology was submitted as a separate paper [14].

3.2. Normalization

No noise removal techniques were applied after the centers and radiuses of the pupil and iris have been detected. Noise detection, such as eyelash/eyelids removal is generally time consuming and reduces the chances of the system being implemented in a realistic scenario. To cope with eyelash and eyelids, we have considered in the normalization process only the sector defined between -45^{o} and +45^{o} of the vertical axis in the top half of the iris was disregarded as this was found empirically to be the most useful. In this way, the eyelids and eyelashes present in the majority of the iris images in the top half side are not present in the unwrapped image. No masks were created for the iris images. The rationale behind this approach is to try to eliminate the accuracy improvements brought by noise isolation and to observe how using features from various channels of different colour spaces is beneficial itself.

3.3. Feature Extraction

The classical 2D Gabor Wavelets have been employed in feature extraction. 2D Gabor filters are expressed as the product between a complex sinusoidal and they have the property to provide information about the spatial frequency content and orientation of the image texture. The parameters of the 2D Gabor filters have been determined using the methodology presented in [13].

The features are binary strings, and for each pixel of the unwrapped image, 2 bits are stored into the feature. Since no masking is used, the features are also extracted from noisy areas of the iris image. Features are extracted from the Red, Green and Intensity channels.

3.4. Matching

Hamming distance [2] is used as a basic matching score between two iris images. The issue of rotation is addressed by shifting one binary string 4 bits to the left and 4 to the right, and the minimum Hamming distance out of the 8 computations is stored.

As we may see from Figure 4, the scores are computed for Red, Green and Intensity channel separately when an image is presented to the system. After 3 scores are obtained for each channel, an average match score fusion is applied. After the fused score is computed, a threshold based decision is taken.

4. Experimental Results

In the experimental setup we show how the proposed methodology of combining the most useful channels from RGB and HSI colour spaces of the iris image is coping with different levels of quality of the images.

4.1. Datasets

The first dataset used in our experiments is UPOL [6]. This dataset contains colour RGB images acquired in a controlled environment using a professional camera. It has 64 users enrolled with 3 images for left and right eyes, totaling 384 iris images. The images are 768 by 576 pixels in raw format.

The second database used in our experiments is UBIRISv1 [9] and contains images acquired in a semi-controlled environment. This database consists of 1877 800x600 pixles, colour RGB images collected from 241 individuals in 2 sessions. The enrollment has been made using only the right eye with 5 images for each user. In the first session the images are captured by minimizing noise factors. In the second session the environment is one with reduced constraints and noise factors are present in the images, such as reflections, luminosity variations and poor focus. In the first session, all 241 users have been enrolled, resulting in a total of 1205 images, while in the second session, only 132 users out of the 241 are enrolled.

The third database used in the experiments was collected by the authors using a mobile phone equipped with 5 mega pixel photo camera. The motivation in collecting such a dataset is that there is no known publicly available iris dataset acquired with the standard camera of a mobile phone. This dataset is called KEnt Mobile Iris Database (KEMID) and consists of 240 RGB colour images captured from 30 individuals enrolled using both eyes with 4 images/eye. A justification for the inclusion of only 30 users is that, on a mobile phone which could be shared in a realistic scenario, it is unlikely to have more than 30 users and hence 30 represents a practical scenario. The images from this dataset contain strong noises and they are compressed using JPEG algorithm. The dimension of the images is 300 by 150 pixels and the iris diameter is around 100 pixels, which is lower than the minimum recommended diameter for iris recognition systems [2]. Several examples of images from this dataset are shown in Figure 6.

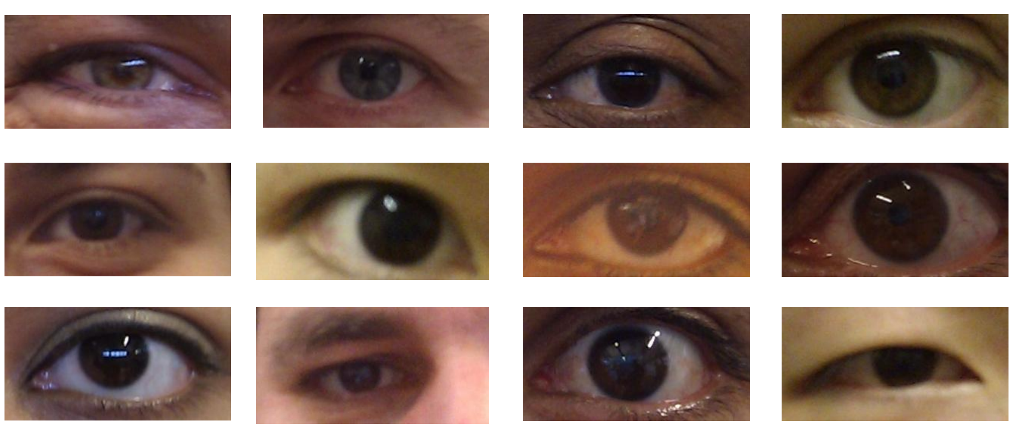


Figure 6: iris images from KEnt Mobile Iris Database (KEMID)

4.2. Results

To validate the analysis developed in section 2, the Hamming distance distributions have been created for all the channels of RGB and HSI colour spaces of UBIRISv1 dataset, session 1, and their corresponding means and standard deviations (in brackets) are presented in Table 3.

Table 3: Hamming distance distributions for UBIRISv1 Session 1 dataset

Channel / HD for	Red	Green	Blue	Hue	Saturation	Intensity
Authentics	0.199 (0.065)	0.233 (0.075)	0.361 (0.067)	0.433 (0.038)	0.378 (0.053)	0.249 (0.065)
Impostors	0.411 (0.037)	0.415 (0.034)	0.429 (0.028)	0.459 (0.024)	0.439 (0.027)	0.414 (0.033)

The best channels in terms of the separation between the authentic-impostor Hamming distance distributions are the Red, Green and Intensity channels, as shown in Table 3.

The Red channel yields the largest separation between authentic-impostor distributions, but we would like to know in how many cases the system would perform better on other channels than the Red channel. In authentic distributions, the lower the Hamming distance is the better and in impostor distribution, the higher the Hamming distance the better. By taking the Hamming distances for the same images in all channels in authentic distributions, we observed that in a number of cases, the Hamming distances from other channels was smaller than the Hamming distance obtained on Red channel. Further, in impostor distributions, in a number of cases, the Hamming distances from other channels are larger than those obtained using the Red channel. In Table 4 the percentages of the cases when the Hamming distances on Red channel are not so relevant than Hamming distances obtained using other channels are reported. These percentages are not a quantitative indication of how the system's performance will improve if the respective channel is used in those cases though. They are only bringing another argument in the analysis of which channels to use in order to improve the system's accuracy.

Table 4: Percentages of cases when the Hamming distance obtained on other channels are more relevant than the Hamming distance obtained using the Red channel of UBIRISv1

Scenario	Authentics	Impostors
HDs from Intensity Channel < HDs from Red Channel	9.12 %	46.55 %
HDs from Green Channel < HDs from Red Channel	24.14 %	45.48 %
HDs from Blue Channel < HDs from Red Channel	1.82 %	34.91 %
HDs from Saturation Channel < HDs from Red Channel	1.99 %	27.92 %
HDs from Hue Channel < HDs from Red Channel	0.82 %	13.51 %

On experiments ran on UBIRISv1 dataset, 4 images were kept in the training database and 1 was used for testing. For UPOL dataset, 2 images are enrolled and one is used for testing and in KEMID dataset 3 images are used as training and one is used for testing.

We will first present the experimental results for the score level fusion approach between Red, Green and Intensity channels. The Receiving Operator Characteristic (ROC) curves for the three datasets are shown in Figure 7, when the average between Hamming distances of the three channels was used as score fusion.

A comparison on the Equal Error Rate (EER) obtained using the proposed approach and the EER obtained using individual channels is presented in Table 5.

For identification scenario, in Figure 8 is shown how the proposed fusion approach improves the system's accuracy.

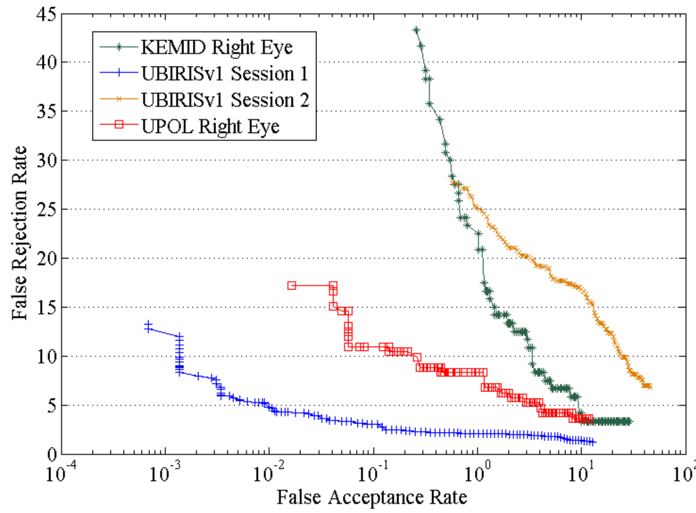


Figure 7: ROC curves for the proposed match score fusion approach

Table 5: EER obtained using individual channels and proposed match score fusion

Dataset	Red	Green	Intensity	Fusion
UBIRISv1 Session 1	6.08 %	2.82 %	4.83 %	1.99 %
UPOL Right eye	4.68 %	5.20 %	4.70 %	3.16 %
UPOL Left eye	4.25 %	3.12 %	3.64 %	3.64 %
KEMID Right eye	8.33 %	8.33 %	7.64 %	6.43 %
KEMID Left eye	10.17 %	10.4 %	7.50 %	7.50 %

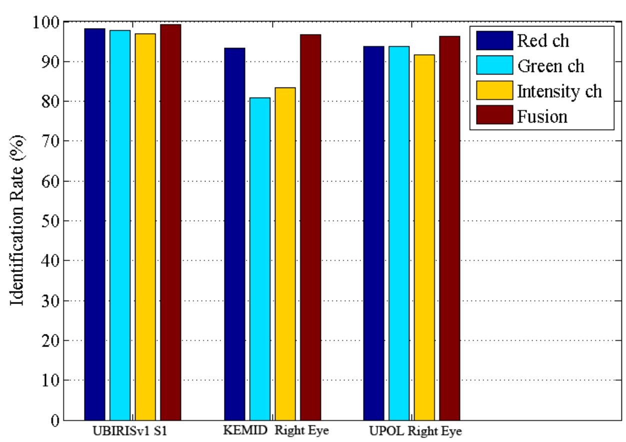


Figure 8: Identification rate using individual channels and fusion

To compare our results with other reported results in the literature, we considered the identification scenario for UBIRISv1 dataset. We chosen the identification scenario for comparison because we could not find any other reported results for identification apart from the results reported in [1]. The comparison of the obtained accuracies is made in Table 6.

Table 6: Comparison of identification accuracies for UBIRISv1 dataset

Method	Session 1	Session 2
Hosseini et al [1]	95.08 %	91.37 %
Proposed channel fusion	99.25 %	91.96 %

5. Conclusions

In iris recognition systems designed to work in a less constrained environment, the ability of the system to work with colour iris images has a significant importance because in a common realistic scenario near infrared illumination is not available. In the present paper we show how to determine which channels from RGB and HSI colour spaces reveal useful information from the iris texture by the means of an information theoretical analysis. Also, we propose an iris recognition system which uses score level fusion to combine information from the channels that were selected during the analysis. The experimental results show that the proposed approach is significantly improving the system's accuracy.

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