QUALITY-BASED FUSION FOR MULTICHANNEL IRIS RECOGNITION

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ABSTRACT

We propose a quality-based fusion scheme for improving the recognition accuracy using color iris images characterized by three spectral channels - Red, Green and Blue. In the proposed method, quality scores are employed to select two channels of a color iris image which are fused at the image level using a Redundant Discrete Wavelet Transform (RDWT). The fused image is then used in a score-level fusion framework along with the remaining channel to improve recognition accuracy. Experimental results on a heterogenous color iris database demonstrate the efficacy of the technique when compared against other score-level and image-level fusion methods. The proposed method can potentially benefit the use of color iris images in conjunction with their NIR counterparts.

***Index Terms*—** Color iris recognition

1. INTRODUCTION

The human iris is a membrane composed of fibrovascular tissue or stroma that controls the amount of light reaching the retina. The complex textural pattern on the anterior surface of the iris serves as a biometric cue for recognizing individuals. Iris recognition systems typically use near-infrared (NIR) sensors to image this complex pattern. This is because NIR illumination can penetrate the surface of the iris thereby revealing the intricate textural details of even dark-colored irides. The color of the iris, as revealed in the visible spectra (i.e., Red, Green and Blue channels, or RGB), is not used by most recognition systems. However, more recent research [1] has demonstrated the benefits of incorporating both color and texture information for iris matching. As can be seen in Fig. 1, the individual color channels can reveal complementary information, especially in the case of light-colored irides, which can be exploited by iris recognition systems.

With the advancement in sensor technology, color iris images are relatively easy to capture and therefore databases such as UBIRIS (v1 and v2), MILES, and UPOL are available for research. Boyce et al. [1] first explored the feasibility of using different color channels in conjunction with the NIR band to improve recognition accuracy. On a small dataset, the results indicated that the multichannel information has the potential to further enhance the iris recognition performance. Thereafter, Krichen et al. [2], Sun et al. [3], and Burge and Monaco [4] showed the usefulness of multichannel color iris recognition.

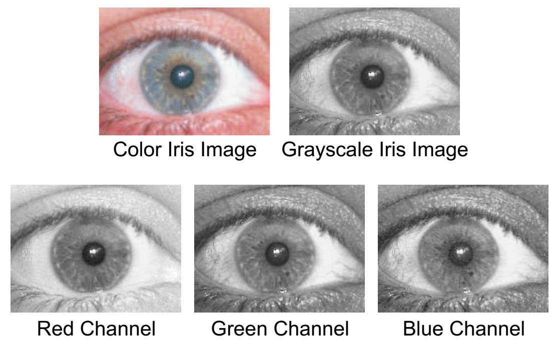

Fig. 1. A color iris image decomposed into three channels: Red (R), Green (G), Blue (B).

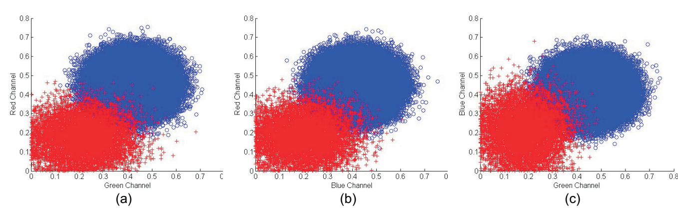

Fig. 2. Scatter plot of match scores between (a) red and green channels, (b) red and blue channels, and (3) green and blue channels. These scatter plots show that the match scores computed from different channels have limited correlation. Red points represent genuine scores and blue points represent impostor scores.

In this paper, we present a fusion algorithm that uses multichannel color iris information to enhance recognition accuracy. The motivation behind the approach is based on observing the pair-wise correlation of match scores between the red, green and blue channels. Using the approach by Vatsa et

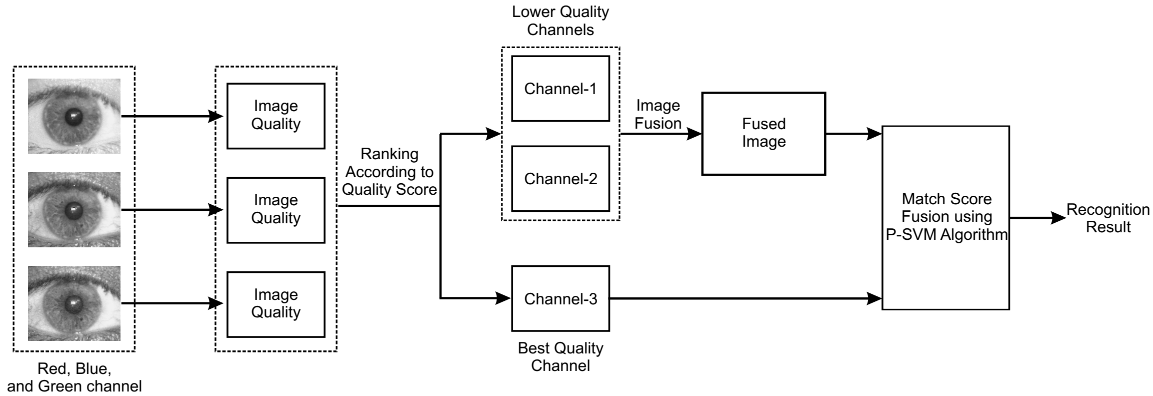

Fig. 3. Illustrating the steps involved in the proposed algorithm.

al. [5] for iris segmentation, feature extraction and matching, the scatter plots of match scores between red-green, red-blue, and green-blue channels show (Fig. 2) that the scores are not highly correlated. Further, when we compare the performance of individual color channels with the gray scale image (i.e., color iris images are converted into gray scale images), we observe that gray scale images provide better accuracy compared to individual channels (see Section 3). Since, we can view color-to-gray scale conversion as a simple image fusion technique, our analysis suggests that if we combine the multichannel information in a more systematic manner, the performance can be further improved. The proposed algorithm starts with computing the image quality of the probe color image based on the red, green and blue channels and ranks the individual channels based on quality. The two lowest quality channels are combined using the proposed image fusion algorithm and the resultant image is combined with the highest quality channel at the match score level. Fig. 3 illustrates the steps involved in the proposed algorithm.

2. FUSION OF MULTICHANNEL IRIS IMAGES

The proposed fusion algorithm that hierarchically performs image level fusion and match score level fusion is described in this section. The algorithm starts by segmenting iris images using the level set approach proposed by Vatsa et al. [5]. Segmented and unwrapped color iris images are then decomposed into red, green, and blue channels. A quality assessment algorithm [6] is used to compute the image quality scores of the three channels independently. Based on the quality scores, we select the two *lowest* quality channels and use Redundant Discrete Wavelet Transform (RDWT) based image fusion to combine them. In the context of multichannel iris recognition, RDWT is preferred over DWT because it provides resilience to noise and is shift invariant. We select the lowest quality channels since RDWT can be used to obtain useful information from these individual channels prior to fusing them. Thus, the noise component of these two channels are mitigated. Let I_{c1} and I_{c2} be the two channels. Three levels of RDWT decomposition is applied on both the channels to obtain the detail and approximation wavelet bands. Let I^a_{c1}, I^v_{c1}, I^d_{c1}, and I^h_{c1} be the RDWT subbands from I_{c1} channel. Similarly, let I^a_{c2}, I^v_{c2}, I^d_{c2}, and I^h_{c2} be the corresponding RDWT subbands from I_{c2} channel. For the four subbands, each subband is divided into blocks of size 3 x 3 and the entropy of each block is calculated using Equation 1.

$$e_i^{jk} = ln\sqrt{\left(\frac{\mu_i^{jk} - \sum_{x,y=1}^{3,3} I_i^{jk}(x,y)}{\sigma_i^{jk}}\right)^2 / m^2} \qquad (1)$$

where $j\ (= a, v, d, h)$ denotes the subbands, $m = 3$ (size of each block), k represents the block number, and $i\ (= c1, c2)$ is used to differentiate two channels I_{c1} and I_{c2}. μ_i^{jk} and σ_i^{jk} are the mean and standard deviation of the RDWT coefficients of the k^{th} block of j^{th} subband from i^{th} image respectively. Using the entropy values, the subbands for the fused image I^a_F, I^v_F, I^d_F, and I^h_F are computed using Equation 2. In this image fusion scheme, more weight is given to the highest entropy image and the fused image block I_F^{jk} is generated as:

$$I_F^{jk} = \begin{cases} \omega_1 I_{c1}^{jk} + \omega_2 I_{c2}^{jk}, & if \quad (e_{c1}^{jk}) > (e_{c2}^{jk}) \\ \omega_3 I_{c1}^{jk} + \omega_4 I_{c2}^{jk}, & otherwise \end{cases} \qquad (2)$$

Here, $\omega_1, \omega_2, \omega_3$, and ω_4 are defined as,

$$\omega_1 = \frac{2e_{c1}^{jk} + e_{c2}^{jk}}{e_{c1}^{jk} + e_{c2}^{jk}}, \quad \omega_2 = \frac{e_{c2}^{jk}}{e_{c1}^{jk} + e_{c2}^{jk}} \qquad (3)$$
$$\omega_3 = \frac{e_{c1}^{jk}}{e_{c1}^{jk} + e_{c2}^{jk}}, \quad \omega_4 = \frac{e_{c1}^{jk} + 2e_{c2}^{jk}}{e_{c1}^{jk} + e_{c2}^{jk}}$$

Finally, using Equation 4 the inverse RDWT is applied on the fused subbands to generate the fused iris image, I_F. Fig.

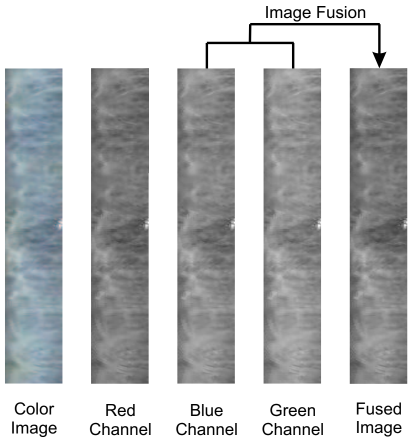

Fig. 4. Example illustrating the result of the proposed image fusion algorithm.

4 shows an example where the blue and green channels of an iris image are fused.

$$I_F = IRDWT(I_F^a, I_F^v, I_F^d, I_F^h) \quad (4)$$

In the next step, we individually extract and match iris features of the best quality channel and the fused image using the approach by Vatsa et al. [5]. Once the scores pertaining to good quality channel and fused image are obtained, we perform match score fusion using probabilistic support vector machine fusion (P-SVM) [7]. In this score fusion scheme, the likelihood ratio test statistic is integrated in a SVM framework. The score fusion can be denoted as

$$M_{fused} = PSVM(M_{c3}, M_F), \quad (5)$$

where M_{c3} represents the match score obtained by matching the channel image with the highest quality, M_F represents the match score obtained by matching the RDWT-fused image, M_{fused} is the fused match score and $PSVM$ denotes P-SVM fusion.

3. EXPERIMENTAL RESULTS

The proposed algorithm is evaluated using a a heterogenous color iris database. Description of the database and experimental protocol is explained in Section 3.1. Further, the product of likelihood ratio (PLR) based match score fusion [8] (i.e. fusion of match scores obtained from individual channels) and simple color-to-gray scale conversion (i.e. image fusion) are used for performance comparison.

3.1. Database

To evaluate the performance on a large number of iris classes, we combined multiple color iris databases. WVU multispectral iris database [1] contains multispectral iris images (RGB channels + NIR image) pertaining to 25 eyes with 5 images per eye. From this database, we used only the RGB channels and excluded the NIR component. Next, we used the UPOL color iris database that contains 384 images pertaining to 128 eyes (i.e. 3 images per eye). Miles iris database[1] is a high resolution color iris database. From this database we chose over 600 color images pertaining to 250 eyes. Finally, we combined color iris images from the UBIRIS v1 and UBIRIS v2 databases [9], [10]. Total number of images in the combined database is over 14,000 pertaining to 1,166 distinct eyes. From these images, 4200 images pertaining to 350 subjects ($\tilde{3}0\%$ of complete images) are used for training and the remaining non-overlapping distinct eye classes are used as testing or gallery-probe set. This train-test partitioning is performed 10 times for cross validation. The experiments are performed for both verification (1:1 matching) and identification (1:N matching) scenarios. For verification, Receiver Operating Characteristics (ROC) curves are generated by computing the genuine accept rates (GAR) over the cross validation trials at different false accept rate (FAR). For identification, Cumulative Match Characteristic (CMC) plots are computed for identification accuracies ranging from rank 1 to 10.

3.2. Experimental Analysis

Fig. 5 illustrates the performance of the proposed method along with the performance of individual channels, color-to-gray scale converted iris images, and PLR match score fusion. The key results and analysis of our experiments are summarized below.

- In general, red channel results in better performance compared to the other channels. This could be because the red channel shows high reflectance property and is very close to the NIR wavelength. It was also observed that the blue channel shows the least accuracy (as observed also by Boyce et al. [1]).

- Conversion from color to gray scale (simple image fusion) improves the recognition performance. Similarly, PLR match score fusion scheme shows better performance compared to individual channels. These results substantiate our hypothesis that combining multichannel iris information can improve performance.

- The proposed hybrid fusion algorithm utilizes both image level fusion and match score fusion, thereby improving the performance significantly. t-test statistic suggests that at 95% confidence interval, the proposed fusion algorithm is significantly different than the PLR fusion and color-to-gray scale conversion. On combining the match scores of the fused image with that of the best quality channel, the verification accuracy at 0.01%

[1] http://www.milesresearch.com/

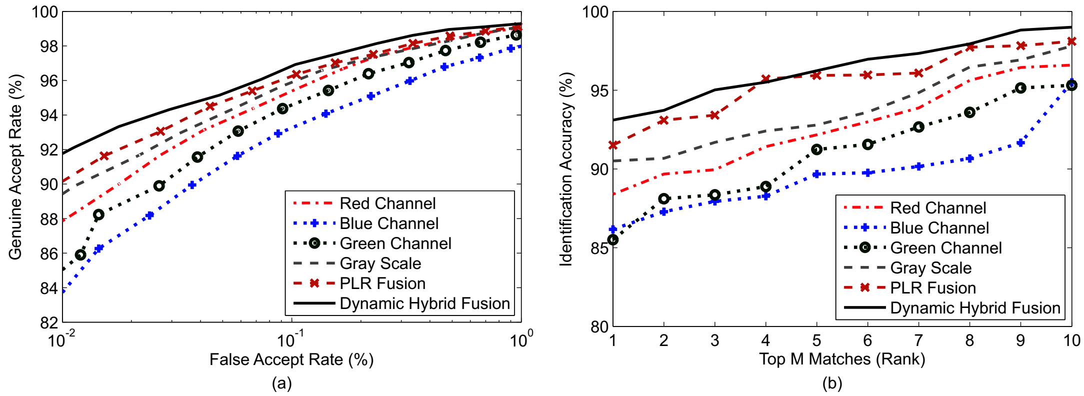

Fig. 5. Experimental results: (a) ROC plots and (b) CMC plots.

FAR is 91.9% and rank-10 identification accuracy is 99.0%.

- Best accuracy with the proposed fusion is lower than state-of-the-art results on other datatsets. This is because UBIRIS v1 and v2 databases contain several non-ideal images that reduce the performance significantly.

- On a 2 GHz Pentium Duo Core processor with 4 GB RAM under C programming environment, the proposed hybrid fusion algorithm require around 1 second for segmentation, feature extraction, fusion and decision making. For identification, it require less than 2 seconds to find Rank-10 matches. This computational time requirement is comparable to PLR match score fusion and slightly higher than color-to-gray scale conversion. Therefore, we can assert that the time requirement of the proposed approach is reasonable.

4. SUMMARY

A method to exploit the multiple spectral channels of an iris image has been proposed. The fusion method consolidates information at the image-level as well as the score-level in a hierarchical fashio. RDWT is used to fuse information at the image level by extracting the useful components of those channels with the lowest quality. The resultant fused image is then used in a score-level fusion scheme along with the channel exhibiting the highest quality. The proposed method is observed to result in better performance than other score-level and image-level fusion methods. We are currently exploring methods to effectively match color iris images with their NIR counterparts.

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