Analysis on Texture and Colour Based Features of Periocular For Low Resolution Colour Iris Images

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Abstract **– The low resolution iris images in non-cooperative environment has resultant in failure to determine the eye center, limbic and pupillary boundary of the iris segmentation. Hence, a combination with periocular area is suggested to improve the accuracy of the recognition system. However, the existing periocular features extraction methods to extract the texture features can be easily affected by a background complication and depends on image size and orientation. Although some of the existing studies have combined the texture and colour features to increase the accuracy of periocular recognition, still, the method of colour feature extraction is limited to spatial information and quantization effects. This paper presents the analysis of texture and colour based features of periocular for low resolution colour iris images. Two datasets: UBIRIS.v2 and UBIPr are used and the proposed method provides robust discriminative structure features and sufficient spatial information which has increased the discriminating power.**

Index Terms - Iris recognition; periocular recognition; low resolution; local binary pattern; color moment

I. INTRODUCTION

The eye images taken during image acquisition stage are expected to be captured using a sensor with high resolution [1]. Depending on the distance between the sensor and the subject, the performance of iris recognition in this environment is negatively impacted when the resolution of the images is low [2,3]. The resolution of the sensor and distance of the subject from the sensor are the two factors that determine the resolution of the captured eye images [1,4,5]. Besides, the resolution of the sensor is relies upon the zoom factor, resolution and view angle [4]. Although the first factor can be resolved using a high resolution sensor, it is still challenging to manage the distance of the subject from the sensor. An increase distance of the subject from the sensor causes a decrease in the size or pixel resolution of the captured eye images when using a fixed zoom-factor. This has reduced the textural quality of the iris and reduces the performance of the iris recognition system [2,3,15]. The selection of the periocular region as features for combination recognition provides better accuracy in the recognition system and the fusion in feature levels provides a better performance than the other fusion levels [7,8,16].

The challenges of texture and colour feature extraction in periocular are easily affected by a background complication, dependent on image size and orientation, limited to spatial information and the quantization effects. These have contributed to unable in selecting discriminative information of periocular. Hence, alternative methods of texture and colour features were proposed as those methods provide robust discriminative structure features in extracting spots, the line ends, edges and corners of texture, and capable of improving discriminating power of colour indexing as well as it provides better colour distribution for colour similarity. The rest of paper is presented as follows. The related works are presented in Section 2, followed by the proposed method is described in Section 3 and the experimental results are shown in Section 4. Finally, Section 5 provides conclusion and future work.

II. RELATED WORK

Bharadwaj et al. [9] proposed a global matcher (GIST) and circular local binary pattern (CLBP) to extract global and local features for periocular recognition. An eye image is preprocessed with Fourier transform and then, a spatial envelope is computed using set of Gabor filters which 4 scales × 8 orientations to produce 1,536 element of GIST descriptor. The CLBP is computed over the image and was divided into 64 sub-regions. For both method, matching is computed using chi-square distance (CSD) and to fuse both results, a sum of weighted min-max normalization was used. A result of GIST method has outperformed the CLBP method and a result of fusion methods has higher accuracy than the single methods. Miller et al. [10] used a uniform local binary pattern (ULBP) to extract the periocular features. The periocular region is cropped proportionally to the distance between the eyes and scaled to 100 × 160 pixels. Then, 7 × 4 grid of square region-of-interest (ROI) is defined, centered on the eye, and iris and sclera texture effects are eliminated overlapping an elliptical neutral mask to the image. Each region-of-interest's histogram is normalized and ULBP calculated using an 8-pixel neighborhood. As such neighborhood produces 59 different possible results in which 59-bin histograms are populated with the result count, and then merge to produce a single-dimension array as the final periocular features. City-block distance is used to measure the matching features. Park et al. [11] implemented a fusion of gradient orientation histogram and local binary pattern (LBP) to extract the global features of periocular while a scale invariant feature transform method is applied to extract the local features of periocular. A Euclidean distance (EUD) and CSD were used to measure the matching of global and local features, respectively.

In the field of content-based image retrieval, features that could be extracted for image similarity are texture, color, shape, intensities and spatial information. However, according to Singh and Hemachandran [12], other than the texture features, the color features is the most widely used features in image retrieval because it is easier to extract, relatively robust to background complication and independent of image size and orientation. In the periocular recognition, most of the existing studies use only texture for periocular features except for Woodard et al. [13] which use a fusion of texture and color features. According to Woodard et al. [13], the fusion features of texture and color provide higher accuracy than single features while texture features give higher accuracy than color features.

III. The Proposed Method

A. Conversion to HSV Channel

The main principle of color feature extraction is the selection of a color space [12, 14]. Normally, a RGB color space has been used as the color space for the feature extraction. However, this color space is easily loss of features information and does not consistent to the corresponding perception of color similarity. Hence, the RGB color space is changed into another color space such as hue-saturation-value (HSV) which is also a nonlinear transformation of the RGB (see Figure 1). This color channel is believed could increase the discriminative properties in LBP. To extract the texture features, the eye images from the hue channel of HSV are used and to extract the color features, the eye images from all channels of HSV are utilized.

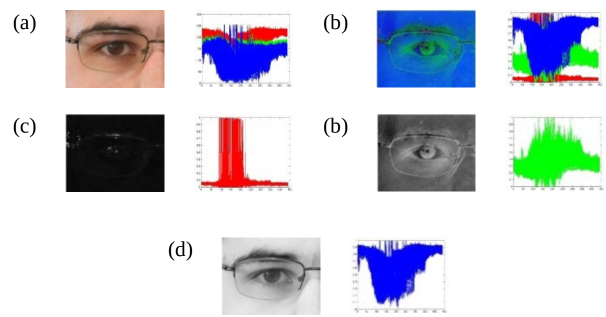

Fig. 1. An example output of preprocessing process. (a) Eye image in RGB channel; (b) Eye image in HSV channel; (c) Eye image in hue, £ channel; (d) Eye image in saturation, ω channel; (e) Eye image in value, þ channel.

B. Texture feature extraction using a rotation invariant uniform local binary pattern

The LBP method has several attributes that makes it popular to use because it provides a discriminative texture structure while adapting to monotonic lighting changes [9, 10]. Moreover, it is useful to extract spots, line ends, edges and corners of the periocular texture. The extension versions of the rotation-invariant and uniform in LBP are functioned to remove the rotation effect and reduce dimensionality, respectively. The method of RIULBP can be performed as follows:

Step 1: To extract the texture features, only the hue image is utilized. The process of texture feature extraction starts with partitioning the hue eye image into 25 × 25 sub-regions. Next, each pixel in the sub-regions is compared with its eight neighbours with radiuses of 1. Figure 2 presents example outputs for this step.

Step 2: The RIULBP is performed according to the formula below:

$$RIULBP_{P,R} = \begin{cases} \sum_{P=0}^{P-1} s(i_P - i_c) \; ; if \; U(LBP_{P,R}) \leq 2 \\ P+1 \; ; otherwise \end{cases} \quad (1)$$

where$(LBP_{P,R}) = \sum_{n=0}^{P-1} |s(i_P - i_c) - s(i_{P-1} - i_c)|$.

where i_c and i_P are respectively hue-level values of the central pixel and P is surrounding pixels in the circle neighbourhood with a radius, R and function $s(x)$ is defined as

$$s(x) = \begin{cases} 1, if\ x \geq 0 \\ 0, if\ x < 0 \end{cases} \quad (2)$$

The operator $RIULBP_{P,R}$ produces 2^P different output values, corresponding to 2^P different binary pattern formed by surrounding pixels.

Step 3: A binary number is obtained by concatenating all these binary values in a clockwise direction for each pixel, which starts from the one of its top-left neighbour. The decimal value of the generated binary number is then used for labelling the given pixel. The derived binary numbers are referred to be the RIULBP codes.

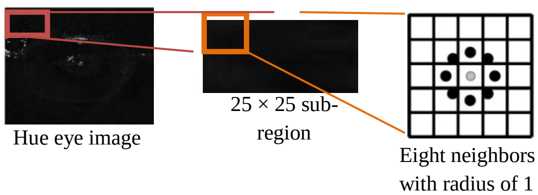

Fig. 2. Example outputs for step 1.

C. Colour feature extraction using a colour moment

The method of colour moment is able to overcome the limitation of the quantization effect of the colour histogram method and is very effective for the colour image-based analysis. The common feature vectors of colour moment are first moment (mean), second moment (standard deviation) and third moment (skewness). The method of colour moment is conducted as follows:

Step 1: Partitions the HSV eye image into three equal non-overlapping horizontal regions to improve the discriminating power of colour indexing techniques. The size of the region of each region is 100 × 400.

Step 2: For each non-overlapping horizontal region, the colour moments feature vectors from each colour channel is extracted using Step 2.1 until Step 2.3.

Step 2.1: Estimate mean of colour moment, $E_{r,c}$.

$$E_{r,c} = \sum_{j=1}^{N} \frac{1}{N} P_{cj} \quad (3)$$

Step 2.2: Calculate standard deviation of colour moment, $\sigma_{r,c}$.

$$\sigma_{r,c} = \sqrt{\left(\frac{1}{N}\left(\sum_{j=1}^{N}\left(P_{cj} - E_{r,c}\right)\right)^2\right)} \quad (4)$$

Step 2.3: Compute skewness of colour moment, $s_{r,c}$.

$$s_{r,c} = \sqrt[3]{\left(\frac{1}{N}\left(\sum_{j=1}^{N}\left(P_{cj} - E_{r,c}\right)\right)^2\right)} \quad (5)$$

where N is the total image pixel, j is the image pixel, c is the colour channel, r is the region and P_{cj} is the value of the c^{th} color channel at the j^{th} image pixel.

Step 3: The colour moments feature vectors store the 27 floating point numbers in the index of the image.

D. Periocular template matching

Different methods of periocular templates matching are required in order to compute the matching score for the different periocular features. To measure the texture template scores, a method of chi-square distance, χ^2 (Bharadwaj et al., 2010) is used as follows:

$$\chi^2(B, D) = \sum_{m,n} \frac{\left(B_{m,n} - D_{m,n}\right)^2}{B_{m,n} + D_{m,n}}, \quad (6)$$

where B and D are the two texture features to be matched while m and n correspond to the m^{th} bin of histogram belonging to n^{th} local region. To measure the similarity of color features, a EUD is applied as follows:

$$EUD = \sqrt{\sum_{k=1}^{27}\left(f'(k) - f(k)\right)^2}, \quad (7)$$

where k represent the floating point numbers, and f' and f represent the feature vector of the query and database images. The matching scores of texture and color features are then normalized using a method of MMN (Prajapati and Bodade, 2017). The MMN is carried out as follows:

$$f_{P-Q}(S) = \frac{S - P\{S_t\}}{Q\{S_t\} - P\{S_t\}}, \quad (8)$$

where S_t represents the comparison scores for each different systems, t=1,2,…,N are the score sets, and $P\{S_t\}$ and $Q\{S_t\}$ are the minimum and maximum values of the raw scores. The MMN transforms all the scores into a standard interval [0, 1] while maintaining the original distribution.

IV. Result And Discussion

This section evaluates the proposed and existing methods for the periocular recognition. Table 1 presents the results of periocular recognition accuracy of the proposed and existing methods for UBIRIS.v2 and UBIPr datasets in accordance to different distances. For the UBIRIS.v2 dataset, as the levels of distance increased, the accuracy of the periocular recognition is increased. This is because the largest distances had a larger area of periocular compared to the shortest distances. Hence, more discriminative features of periocular were extracted. The use of colour feature for the periocular recognition has overcome the limitation of texture feature for the eye images that were taken at different distances and contained high level of noises.

Therefore, methods that extracted two features achieved a maximum accuracy of 90.0% compared to the methods that only extracted one feature and only obtained a maximum accuracy of 70.1%.

Table 1. Periocular recognition accuracy of the proposed and existing methods for UBIRIS.v2 and UBIPr datasets in accordance to different distances

Dataset	Distance (metres)	Methods				
		Bharadwaj *et al.* [9]	Miller *et al.* [10]	Park *et al.* [11]	Woodard *et al.* [13]	**This Study**
UBIRIS.v2	4	50.3	45.1	53.8	67.3	**71.5**
	5	53.5	47.2	57.3	70.1	**78.7**
	6	60.2	53.1	61.9	73.1	**81.3**
	7	61.5	57.6	62.5	75.5	**87.3**
	8	63.7	58.7	64.3	77.3	**90.0**
	Overall	61.9	50.7	62.1	73.6	**89.2**
UBIPr	4	65.1	54.7	67.9	74.1	**85.7**
	5	67.9	57.3	68.1	76.4	**95.7**
	6	63.5	56.5	65.7	73.5	**93.5**
	7	69.3	59.5	69.3	77.2	**96.2**
	8	62.7	52.7	63.2	71.1	**83.5**
	Overall	65.7	55.3	68.7	74.7	**93.1**

Considering the methods that only extracted one feature, the utilization of global and local information applied in the Bharadwaj et al. [9] and Park et al. [11] methods have obtained more accuracy than the Miller et al. [10] method with a minimum accuracy of 50.3% and 53.8%, respectively. This is because the Miller et al. [10] method only uses local information to extract the periocular features.

Considering the methods that extracted two features, the proposed method has outperformed the Woodard et al. [13] method. This is because the colour method of Woodard et al. [13] depends on the distributions of histogram bin and extracts insufficient spatial information during the process of colour feature extraction which leads to a low discriminating power. Besides, the eye images that were captured at different distances had different distributions of histogram bins. Hence, the colour method of Woodard et al. [13] was incapable of achieving the similarity match between the query and data images due to large differences in the two distributions of histogram bins. Besides, the proposed method has achieved the highest accuracy of periocular recognition with 71.5% accuracy at a distance of four metres, 78.7% accuracy at a distance of five metres, 81.3% accuracy at a distance of six metres, 87.3% accuracy at a distance of seven metres, 90.0% accuracy at a distance of eight metres and 89.2% accuracy at all distance.

For the UBIPr dataset, the distance of seven metres obtained the best performance due to its sufficient information of the periocular recognition. At the distance of eight metres, the eye images had the smallest scale compared to the other distances. Thus, the accuracy of recognition at this distance achieved the lowest accuracy due to less information of discriminative features being extracted. Although the shortest distance, four metres, had the largest scale of images, it does not obtain the highest accuracy of periocular recognition. This is due to the presence of detailed information in the high resolution of the eye images. The accuracy of periocular recognition for the eye images at the distances of five and six metres are also low because of the presence of detailed information in the high resolution of the eye images.

Moreover, the methods that extracted two features achieved a minimum accuracy of 71.1% compared to the methods that extracted only one feature which only obtained a maximum accuracy of 72.1%. Considering the method that extracted two features, the proposed method has achieved the highest accuracy with a maximum accuracy of 96.2%. This is because the Woodard et al. [13] method was incapable of achieving the similarity match between the query and data images due to large differences in the two distributions of histogram bin.

V. CONCLUSION

In this work, a rotation invariant uniform local binary pattern method was proposed to extract the texture features and a colour moment method was proposed to extract the colour features. The rotation invariant uniform local binary pattern method was able to reduce the effects of the rotation and dimensionality while being very robust to extract texture features such as spots, line ends, edges and corners. Furthermore, the use of a hue-saturation-value channel has provided a better stability of colour distribution for the colour similarity. In addition, the partitioning process of eye images into equal non-overlapping horizontal during the process of colour feature extraction has stored sufficient spatial information which has increased the discriminating power. Besides, the characteristics of the colour moment method that extracted local information such as mean, standard deviation and skewness in the eye images has provided a better colour distribution for the colour similarity between the query and data images. The proposed method has increased the accuracy of periocular recognition. Finally, the combination of iris and periocular recognition systems has increased the accuracy of recognition compared to the single recognition in identifying a person.

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