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Efficient Feature Fusion for Noise Iris in Unconstrained Environment

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***Abstract*—**This paper presents an efficient fusion algorithm for iris images to generate stable feature for recognition in unconstrained environment. Recently, iris recognition systems are focused on real scenarios in our daily life without the subject's cooperation. Under large variation in the environment, the objective of this paper is to combine information from multiple images of the same iris. The result of image fusion is a new image which is more stable for further iris recognition than each original noise iris image. A wavelet-based approach for multi-resolution image fusion is applied in the fusion process. The detection of the iris image is based on Adaboost algorithm and then local binary pattern (LBP) histogram is then applied to texture classification with the weighting scheme. Experiment showed that the generated features from the proposed fusion algorithm can improve the performance for verification system through iris recognition.

***Keywords*—**Image fusion, iris recognition, local binary pattern, wavelet.

I. Introduction

IRIS recognition is one of the most stable and reliable tool among biometric systems since it uses the unique and immutable patterns of human iris image. Also, iris recognition has the advantage that image acquisition can be easily achieved without direct user contact [1]-[3]. As a result, this topic has attracted many researchers to work on it. The state of the art iris recognition techniques were reviewed by authors [4]. However, constraints of the system are a major obstacle for the real applications of iris-based biometric systems, especially under variant environments.

Recent research interest in the field has focused on iris recognition in less constrained imaging conditions. Several factors make iris images non-ideal, such as at-a-distance imagery, on-the-move subjects, and high dynamic lighting variations. In such circumstances the iris image captured may be degraded due to off-axis imaging, image blurring, illumination variations, occlusion, specular highlights and noise [5]. Robust iris recognition in such degraded images becomes a grand challenge. Daugman [6] reported some advances including accurate iris boundaries localization with active contour and image registration through Fourier-based trigonometry, among others. Sun and Tan [7] presented a general framework for iris feature representation based on ordinal measure. Li and Ma [8] introduce a robust algorithm based on the random sample consensus for localization of non-circular iris boundaries and an image registration method based on the Lucas–Kanade algorithm.

Non-cooperative iris recognition has attracted much more attention since it greatly extends the iris recognition to real applications [9], [10]. For a non-cooperative iris recognition system, the iris images are often captured with more noisy artifacts. For example, they include blur, reflections, occlusions, oblique view-angles, etc., such that they are also called noise iris [11]. It makes non-cooperative iris recognition more challenge. The Noisy Iris Challenge Evaluation (NICE) competition [12] was concerned with methods that use the texture pattern of the iris as a means to recognize a person under non-cooperative conditions. In other words, NICE focused on performing iris biometrics on visible-light images. It attracted participation by many research groups from all over the world. Several top-performing algorithms [13] from NICE are considered, and suggestions are made for lessons that can be drawn from the results.

For iris image that are noised by image blurring, illumination variations, occlusion, specular highlights, most of the above recognition algorithm might be affected. Previously, weighted iris recognition was proposed for trying to solve these problems [14]. In the proposed iris recognition system, multi-iris images are first captured and then the features for recognition are generated by an efficient fusion algorithm. The objective of this paper is to combine information from multiple images of the same iris to overcome the difficulties under unconstraint environments. The result of image fusion is a new image which is more suitable for further iris recognition. A wavelet-based approach for multi-resolution image fusion is applied in the fusion process. The detection of the iris image is based on Adaboost algorithm and then local binary pattern (LBP) histogram is then applied to texture classification with the weight. Experiment showed that the proposed fusion algorithm provided more stable features for verification system through iris recognition.

II. Preprocessing Step

The first problem for iris detection occurs on classification between iris and non-iris regions due to the high local contrast. A coarse iris localization step may exclude the non-iris regions. In this section, the skin color classification is first described to separate iris and non-iris regions then illumination normalization steps are introduced. After these preprocessing, more stable features are obtained and they are used to be the input of the iris detection step.

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A. Skin Color Classification

Detecting pixels with the skin color provides reliable information for coarse classifying iris and non-iris regions. Researchers have discovered that skin colors regardless of different races tend to cluster closely in a compact region in 2D chromatic color space [24]. The following equation shows the transformation from RGB color space to YC_bC_r color space. The YC_bC_r model can have more stable chromatic information than original RGB one.

$$\left.\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ C_b &= B - Y \\ C_r &= R - Y \end{aligned}\right\} \quad (1)$$

Since the difference of color between skin and non-skin area is large, the simple formulas in the following equation can successfully detect non-skin region for the following iris detection.

$$\left.\begin{aligned} 80 <= C_b <= 125; \\ 136 <= C_r <= 177; \end{aligned}\right\} \quad (2)$$

B. Illumination Normalization

It is well known that each gray value in the image is very sensitive to the lighting variation. Considerably different images may be captured from the same object under different illuminations, especially for the proposed multi-iris recognition. Psychophysical experiments show that the human visual system is difficult to identify the images of the same object that are due to considerable changes in illumination [16]. For iris recognition system, it is also difficult to produce good detection and classification accuracy if image samples in the training and testing sets are taken from different lighting conditions. The general purpose of illumination normalization is to decrease lighting effect when the observed images are captured in different environment. A common idea is trying to adjust observed images to approximate the one captured under a standard lighting condition. Most of the past works tried to define the standard lighting condition in statistically and modify the observed images to match these statistic properties. In the proposed system, we extract the statistical histogram feature of standard lighting condition from the training images in the database. Each testing image will be adjusted based on the extracted histogram information of the standard lighting condition.

For example, if R is the observed image and h is the histogram feature of standard lighting condition we get, the modification strategy [17] we used is to transform the statistic histogram of region R to the histogram h so that the transformed result has similar statistic histogram to h. The transform t is the one to one function T which can be expressed as:

$$T = G^{-1} \circ H, \quad (3)$$

where G is the empirical cdf of h and H is the empirical cdf of region R if we treat the intensity histogram at the region R as probability density function. Each pixel in the region R is normalized by using the transfer function T. Let R_t be the normalized region, then

$$R_t(x, y) = T(R(x.y)) = G^{-1} \circ H(R(x, y)), \quad (4)$$

Ideally, R_t will have similar histogram distribution to the one under standard lighting condition has.

C. Iris Detection and Boundary Extraction

For the fine detection of the iris, the AdaBoost [18] can automatically select some weak classifiers from the weak classifier space. It constructs a strong classifier through the weighted integration of selected weak classifiers to detect the target. Some authors proposed modified versions of AdaBoost just like [19], and [20]. They were used extensively on face detection [21], [22]. Iris has very fine textures compared with the other area of the eye image such that the AdaBoost has the ability to detect the iris and extract the exact boundary between iris and non-iris region.

The proposed iris detection method applied the Adaboost algorithm of [18]. The method brings together new algorithms to construct a framework for robust and extremely rapid visual detection. This system achieves high frame rates working only with the information present in a single grey scale image. This is very useful to detect iris image under unconstrained environment in the proposed system. An integral image generated by only simple operations allows for very fast feature evaluation.

The second step is a simple and efficient classifier that is built by selecting a small number of important features from a huge set of potential features using AdaBoost. Within any image sub-window the total number of Haar-like features is very large, far larger than the number of pixels. In order to ensure fast classification, the learning process must exclude a large majority of the available features, and focus on a small set of critical features. As a result each stage of the boosting process, which selects a new weak classifier, can be viewed as a feature selection process. AdaBoost provides an effective learning algorithm and strong bounds on generalization performance.

III. Wavelet-Based Image Fusion Scheme

The representation or transformation of an image requires that the image can be reconstructed without any information lost. Features generated from iris images need more precise information for further fusion. Many researches showed that multi-resolution transforms, e.g., wavelet transform, are powerful technique for image fusion [25]. The discrete wavelet transform of each of the two or more images is first computed. Then, fuse the wavelet coefficients using the fusion rule in the wavelet transform domain. Specifically, the wavelet coefficients are fused using different combining rule for low frequency band and high frequency band respectively. Finally, the fused image is formed by using inverse wavelet transform.

The schematic diagram for wavelet based multi-resolution image fusion is shown in Fig. 1.

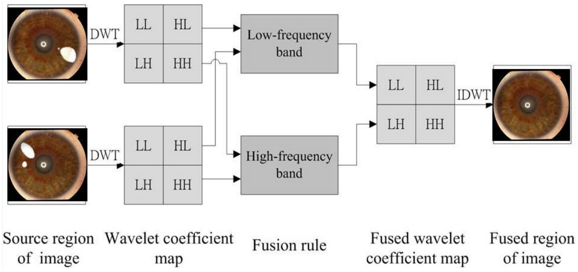

Fig. 1 Wavelet fusion scheme

Here, H and L represent the high-pass and low-pass filter respectively. In this way, subimages (LL, LH, HL and HH) can be obtained to represent the average and different information in horizontal, vertical and diagonal directions of the input image.

The perception of fused wavelet coefficients is of important for the fused result. The different feature information at the different levels of wavelet decomposition of image, therefore we need dividing the information represent high frequency band and low frequency band. Since wavelet coefficients with high frequency having large absolute values contain the information about the salient features of images such as edges and lines, we try to select the maximum of the corresponding high frequency wavelet coefficients. Then, wavelet coefficients with low frequency contain the information about the profile features of images, and it is possibly to have local reversed contrast of the images. So considering the correlation information between wavelet at low frequency of images, general method of fuse has using wavelet energy maximum, average and weight value of the regions. In this paper, we adapted maximum and average for high frequency and low frequency wavelet coefficients, respectively. They are shown in the following equations.

$$W_{xx} = \max\left[|W_{xx}^{A}(M,N)|, |W_{xx}^{B}(M,N)| \right] \tag{5}$$

$$W_{LL\_average} = \frac{\left[W_{LL}^{A}(M,N) + W_{LL}^{B}(M,N)\right]}{2} \tag{6}$$

IV. Iris Recognition Based On Wighted Scheme

After the feature fusion, the local binary patterns (LBP) are adopted to represent texture patterns of iris images. The LBP played as a simple yet very efficient texture operator and became a popular approach in various applications of texture analysis [23]. LBP is defined for each pixel by comparing its 3×3 neighborhood pixels with the center pixel value, and considering the result as a binary bit string.

Given a pixel $f(x,y)$ in the image, an LBP code is computed by comparing it with its neighbours:

$$LBP(x,y) = \sum_{p=0}^{P-1} s(f(x,y) - f_p(x,y))2^p, \tag{7}$$

where $s(z)$ is the thresholding function

$$s(z) = \begin{cases} 1, & \geq 0 \\ 0, & < 0 \end{cases} \tag{8}$$

Here P represents the number of sampling points, i.e., 8 surrounding points. After the LBP pattern of each pixel is identified, a histogram of the image with size $I \times J$ is built to represent the texture image:

$$H(k) = \sum_{i=0}^{I}\sum_{j=0}^{J} w(i,j) g(LBP(i,j),k), k \in [0,K], \tag{9}$$

where $g(x,y)$ is the thresholding function:

$$g(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \tag{10}$$

After LBP, we followed the setup of [23] for nonparametric texture classification. The LL distance is suited for histogram type features. For histogram type features, we used the log-likelihood statistic, assigning a sample to the class of model minimizing the LL distance

$$LL(h^S, h^M) = -\sum_{b=1}^{B} h^S(b) \log h^M(b), \tag{11}$$

where $h^S(b)$ and $h^M(b)$ denote the bin b of sample and model histograms, respectively. Gaussian weighting functions used in the weighting scheme is based on the distance from the border to the center of the iris since most noise or error detection happened on the outer border.

V. Experimentation Results

For simulating the variant environment, an online testing system was built as the experimental platform, including a notebook with a 3rd generation Intel® Core i7 processors and Windows 7 Professional.

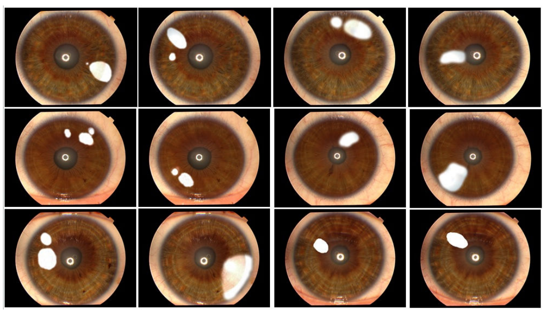

Fig. 2 Twelve examples of the noise iris images in the experimentation

In the experiment, it contains two types of images for testing the performance of the proposed method. The first one applied the existing data set of iris images [15]. Secondly, the built-in webcam captured the iris image online. 50 individuals are enrolled in the training and testing database and 40 images are captured for each person under different conditions. Some images from [15] are shown in Fig. 2. Fig. 3 shows six examples of fused image from the original noise iris images in Fig. 2. Totally, the online test under different lighting conditions is performed 1000 times. The average accuracy of verifications for the online test is about 90.5%. Comparison of the average results between fusion and non-fusion algorithm is listed in the following table.

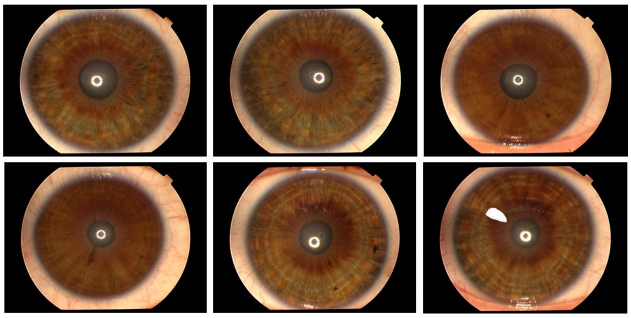

Fig. 3 The examples of fused image from the original noise iris images in Fig. 2

TABLE I
RMSE OF THE FUSED IMAGES

Testing set	Fusion applied	No fusion applied
Blur	90.3	63.7
Reflection	93.2	71.8
Occlusion	88	62.1

VI. CONCLUSIONS

This paper presents an efficient fusion algorithm for iris images to generate stable feature for recognition in unconstrained environment. Recently, iris recognition systems are focused on real scenarios in our daily life without the subject's cooperation. Under large variation in the environment, the objective of this paper is to combine information from multiple images of the same iris. The result of image fusion is a new image which is more stable for further iris recognition than just one noise iris image. A wavelet-based approach for multi-resolution image fusion is applied in the fusion process to generate features. The detection of the iris image is based on Adaboost algorithm and then local binary pattern (LBP) histogram is then applied to texture classification with the weighting scheme. Experiment showed that the generated features from the proposed fusion algorithm can improve the performance for verification system through iris recognition.

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