

Iris Code Construction for Human Identification

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Abstract : The variation of the directional properties of an image is used to extract the iris code for human identification. In order to conserve the original information while minimizing the effect of noise, scale-space filtering is applied. Resulting binary codes have been tested on a set of 272 iris images obtained from 18 persons.

INTRODUCTION

The pattern of the human iris differs from person to person, even between monocular twins. Because irises react with such sensitivity to light, causing the size and shape to change continuously, counterfeiting based on iris patterns is extremely difficult. However, the iris pattern is so highly detailed that it is also difficult to identify.

In 1991, Daugman 1 introduced the iris identification technique by transforming the 244 degree-of-freedom iris features into a 256-byte binary code, dramatically reducing identification errors to 1/800,000,000. Because the extracted code consists of 1's and 0's, the identification process can be easily performed by a simple XOR operation. Several other iris recognition algorithms have been proposed using isotropic band-pass decomposition 2 and multi-channel Gabor filtering 3. Recently, an approach was presented that used zero-crossings of the wavelet transformations at various resolution levels [4,7-9]. This approach extracts 2D analog features and uses dissimilarity functions for identification. A modified Haralick's co-occurrence method with multilayer perceptron is also introduced for extraction and classification of the irises [10,11]. However, most iris identification methods, except [1,5,6], use gray scale iris code vectors, thus suffer from the computational cost of physical implementation.

This study features an extraction method using scale-space filtering with resulting binary iris codes that can be used directly with a system of rapid and automatic identification.

PREPROCESSING

The initial stage begins with locating the center of the iris and determining the radius of the pupil, in order to separate the iris image. Because the pupil is simple in

shape, the efficiency of the estimation depends on computational speed coordinates image transformed rather than accuracy. Fig 1(a) depicts an eye image in the Cartesian coordinates, and Fig. 1(b) the corresponding polar

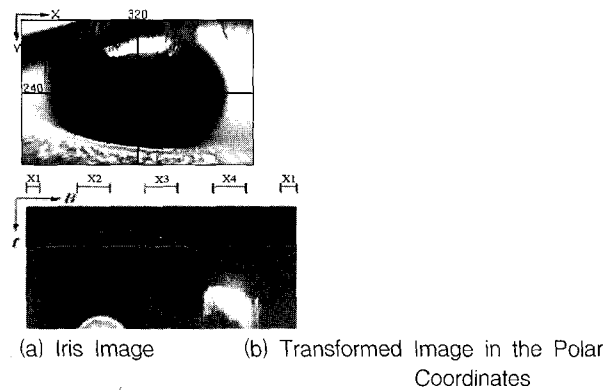


Fig.1. Iris Image

Letting $r(\theta)$ represent the curve describing the iris/pupil boundary, the circumference of the pupil equals the area of the rectangular figure shown in Fig. 1(b). To determine the center and radius of the pupil, one must move the origin successively, in such a manner that $r(\theta)$ becomes a straight line, so as the pupil's image will become rectangular, accordingly. The brief algorithm for calculating the center and radius of the pupil is as follows: Let $f(r, \theta)$ be the iris image in the polar coordinates system and $f_{avg}(\theta)$ denote the average image values for with respect to r . Note that pixels belonging to an iris are smaller than $f_{avg}(\theta)$, and the darkest pixel is usually found inside the iris. We must first estimate a rough boundary, followed by the determination of a second, more precise boundary. The rough boundary is the group of image points where $\partial f(r, \theta) / \partial r$ is maximized in the region whose $f(r, \theta)$ is smaller than $f_{avg}(\theta)$. The same process is then performed an additional time inside the established rough boundary. The points of the maximum derivative are the boundary $r(\theta)$. The centroid of the

pupil (x0, y0) is estimated by using the inner pupil/iris boundary;

$$(x_0, y_0) = ((X_0 - X_2)/2, (X_1 - X_3)/2) \tag{1}$$

where X_i 's denotes the average values of a portion of the pupil/iris boundary. As shown in Fig. 1(b), they are separated by 90 degrees. The radius of the pupil is computed as the mean of X_i 's. The radius of the outer boundary is estimated in a similar manner. The process is repeated until X_0 and X_1 converge with X_2 and X_3 , respectively. That is, the boundary becomes a straight line in the polar coordinates.

Next, a 16x16 window is applied to $f(r, \theta)$ at 8 pixel intervals, deleting uncertain regions, which lead to false identification. These regions correspond, in general, to corrupted areas by artifacts or specular reflection and have particularly low standard deviations.

FEATURE EXTRACTION

The variation of the directional properties of brightness of the image is used to describe iris features. The derivative of grey level is investigated as to whether it is continuously increasing (concave-down) or decreasing (concave-up). Only the direction of concavity, not the magnitude, is considered. This is easily checked, since the direction inverts at the zero-crossing of second derivatives. Value 1 is set to the pixel with positive second derivatives and 0 to the negative. This approach has the advantage of dealing with various colors or the brightness of the eye plably. Since the derivatives are very noise-sensitive, consistent iris feature extractions are difficult. In order to conserve the maximum original signal while minimizing the effect of noise, scale-space filtering techniques are applied.

Let one-dimensional iris signature, $f(\theta)$, denote the gray values on a virtual concentric circle of an arbitrary radius. The concavity of $f(\theta)$ is investigated in the scale-space domain. Let $F(\theta, \sigma)$ be the result of the scale space filtering of $f(\theta)$ at the scale σ . $I(\theta, \sigma)$ is defined as the two-dimensional feature pattern in the scale space. $I(\theta, \sigma)$ takes 1 or 0 for positive or negative value of $F(\theta, \sigma)$. Only the sign information is used for feature extractions. The magnitude, or amplitude information is not very discriminating, as it is depends on extraneous factors such as contrast, illumination and camera gain. To conserve detailed information and dilute the effect of noise, $I(\theta, \sigma)$ at all scales is added in a dyadic manner and transformed into a one-dimensional feature code, $I(\theta)$. It is set as 1 or 0 to the positive and negative, respectively. Fig. 2(a) and (b) show a sample iris signature $f(\theta)$ and

result $I(\theta, \sigma)$ after scale-space filtering, respectively, and Fig. 2(c) shows the resulting iris pattern code $I(\theta)$.

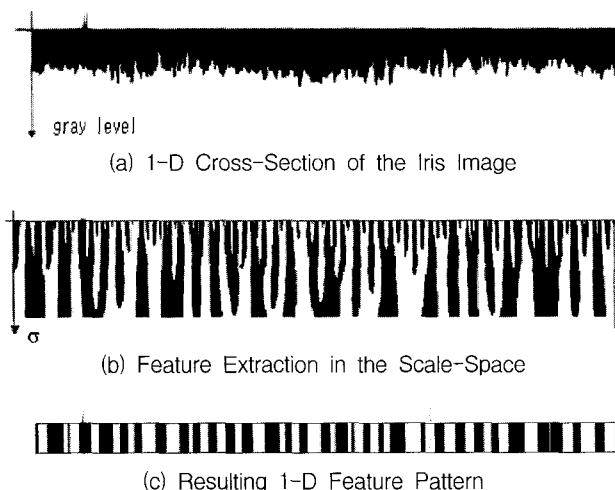


Fig. 2. An Example of Feature Extraction\

RESULTS

Experiments were performed on a photographic database of eye images using a Windows 2000-based computer. Some images were rejected manually before the experiments because of excessive eyelid or poor focus. The outer diameter of the iris is greater than 60 pixels. 178 sheets of 640x480 gray scale images are chosen from a group of 18 people. Total of 3,172 tests are made with 1,586 pairs of different images of same irises and 1,586 pairs of different irises. On average, 2.75 iterations are needed to locate the iris with a margin of error of less than 2 pixels. Once the iris is located with its established radius, regions that may contain 'possible noise' are removed at an average rate of .11 seconds. Scale-space filtering is finally applied to the resulting images and iris patterns are extracted.

The iris parts are XOR-ed to each other, to compare the degree of mismatches. Fig. 3 illustrates the result of two different iris patterns run through XOR operation. To prevent non-iris artifacts from influencing iris comparisons, AND operation is also applied like other methods [1]. The XOR operation detects disagreement between any corresponding pair of bits, while the AND operation ensures that the compared bits are both deemed to have been uncorrupted by specular reflections and other noise. The norms of the resultant XOR-ed bit patterns and of the AND-ed mask vectors are then measured in order to compute a fractional Hamming Distance, HD:

$$HD = \frac{\| (codeA \oplus codeB) \cap (maskA \cap maskB) \|}{\| maskA \cap maskB \|} \tag{2}$$

Hamming Distance is the similarity measure which is the fraction of bits in two codes that disagree. The performance of a biometric identification scheme is

characterized by the graph superimposing the two fundamental histograms of similarity that the test generates: one when comparing biometric measurements from the same, and the other when comparing measurements from different persons. Because this determines whether any two templates are deemed to be same or different, the two fundamental distributions should ideally be well separated, as any overlap between them causes decision errors [5,6].



(a) Same Person



(b) Different Person

Fig. 3. XOR-ed Image of Two Iris Codes

Fig. 4 illustrates the distribution of the Hamming distance obtained from the test group. The two distributions on the graph show the results when different images of the same and the different eyes are compared.

Iris patterns belonging to the same person can be matched at an average of 85.08%, with a variance of 3.63%. On the other hand, bit patterns extracted from different people match with an average of only 58.79% and a variance of 1.55%. This is slightly higher than 50%, the probability of matching two uncorrelated binary patterns. Because the size and shapes of irises constantly change, such a result is inevitable. Note that no overlapping regions go unobserved, as shown in Fig. 3. That is, persons can be clearly discriminated from others.

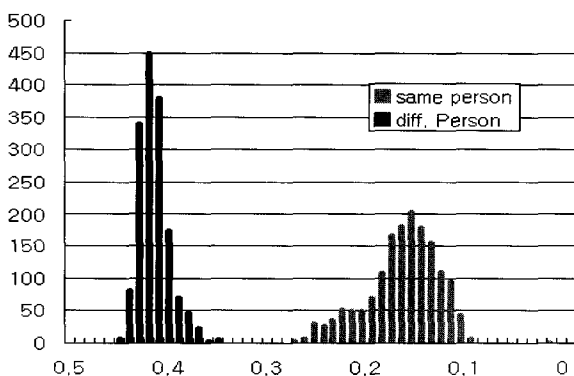


Fig. 4. % Distribution of the Hamming Distance

The decidability index d measures how well separated the two distributions are [5,6]. This is defined as the separation between the means of the two distributions, divided by the square-root of their average variance:

$$d = \frac{|m_1 - m_2|}{\sqrt{(\sigma_1^2 + \sigma_2^2)/2}} \quad (3)$$

where m_i and σ_i^2 represent the mean and variance of the distributions, respectively. The measured decidability is $d = 9.087$, which is higher than that of other measurements, biometric or inferred, from their corresponding dual distribution plots showing similar and different pattern comparisons.

This proposed approach is effective. If a larger group is tested, the shape and distribution of Hamming distances become sharper, and thus more separable.

CONCLUSION

In our paper we suggested a new approach which use scale-space filtering to extract unique features from an iris image. The algorithm uses the direction of concavity of image data. This approach can overcome the misidentification problems caused by variation of color and brightness among people with different illumination conditions. The scale-space filtering technique is presented to overcome the problem that the second derivatives are very sensitive to noise. Iris codes are obtained on the virtual circles centered at the centroid of the pupil.

Resulting iris code can be used to develop a system for rapid and automatic identification of persons, with high reliability and confidence levels. Simulation results is very similar to that of Daugman's work [1,5,6] which use Gabor filtering. Considering that the commercial iris identification system take several images (7 images for [5]) and keep only the best value, the proposed approach provides one of the effective methods of iris pattern code extractions.

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