Coarse Iris Classification Based on Box-Counting Method

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***Abstract*—This paper proposes a novel algorithm for the automatic coarse classification of iris images using a box-counting method to estimate the fractal dimensions of the iris. First, the iris image is segmented into sixteen blocks, eight belonging to an upper group and eight to a lower group. We then calculate the fractal dimension value of these image blocks and take the mean value of the fractal dimension as the upper and the lower group fractal dimensions. Finally all the iris images are classified into four categories in accordance with the upper and the lower group fractal dimensions. This classification method has been tested and evaluated on 872 iris cases, and the proportions of these categories in our database are 5.50%, 38.54%, 21.79% and 34.17%. The iris images are classified with the double threshold algorithm, which classifies iris images with an accuracy of 94.61%. When we allow for the border effect, the double threshold algorithm is 98.28% accurate.**

Keywords- Box counting; fractal dimension; iris image; coarse classification

I. INTRODUCTION

Biometrics is one of the most important and reliable methods for computer aided personal identification, having a wide range of applications, in government programs such as national ID cards, use in visas and visa processing, and in the war against terrorism, as well as having personal applications in areas such as logical and physical access control. The fingerprint is the most widely used biometric feature, but the most reliable feature is the iris and it is this that accounts for its use in identity management in government departments requiring high security.

The iris contains abundant textural information which is often extracted in current recognition methods. Daugman's method, based on phase analysis, encodes the iris texture pattern into a 256-byte iris code by using some 2-dimensional Gabor filters, and taking the Hamming distance [1] to match the iris code. Wildes [2], matches images using Laplacian pyramid multi-resolution algorithms and a Fisher classifier. This approach, however, has proven to be computationally expensive and is suitable only for verification. Boles et al, extract iris features using a one-dimensional wavelet transform [3], but this method has been tested only on a small database. Ma et al. construct a bank of spatial filters whose kernels are suitable for use in iris recognition. They have also developed a preliminary Gaussian-Hermite moments-based method which uses local intensity variations of the iris. They recently proposed an improved method based on characterizing key local variations [4].

Although these methods all obtain good recognition results, all iris authentication methods require the input iris image to be matched against a large number of iris images in a database. This is very time consuming, especially as the iris databases being used in identity recognition growing ever larger. To reduce both the search time and computational complexity, it would be desirable to be able to classify an iris image before matching, so that the input iris is matched only with the irises in its corresponding category. Like fingerprint classification, iris classification matches at a general level. As yet the subject of iris classification has received little attention in the literature.

This paper is intended to contribute to the establishment of meaningful quantitative indexes. One such index can be established by using box-counting analysis to estimate the fractal dimensions of iris images with or without self-similarity. This allows us to classify the iris image into four categories according to their texture and structure.

II. IRIS CLASSIFICATION COUNTING BOXES TO ESTIMATE THE FRACTAL DIMENSION OF THE IRIS

The concept of the fractal was first introduced by Mandelbrot, who used it as an indicator of surface roughness. The fractal dimension has been used in image classification to measure surface roughness where different natural scenes such as mountains, clouds, trees, and deserts generate different fractal dimensions. Of the wide variety of methods for estimating the fractal dimension that have so far been proposed, the box-counting method is one of the more used widely [5], as it can be computed automatically and can be applied to patterns with or without self-similarity.

In the box-counting method, an image measuring size $R \times R$ pixels is scaled down to $s \times s$, where $1 < s \le R/2$, and s is an integer. Then, $r = s / R$. The image is treated as a 3D space, where two dimensions define the coordinates (x, y) of the pixels and the third coordinate (z) defines their grayscale values. The (x, y) is partitioned into grids measuring $s \times s$. On each grid there is a column of boxes measuring $s \times s \times s$. If the minimum and the maximum grayscale levels in the $(i, j)^{th}$

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grid fall into, respectively, the k^{th} and l^{th} boxes, the contribution of n_r in the $(i,j)^{th}$ grid is defined as:

$$n_r(i,j) = l - k + 1 \tag{1}$$

In this method N_r is defined as the summation of the contributions from all the grids that are located in a window of the image:

$$N_r = \sum_{i,j} n_r(i,j) \tag{2}$$

If N_r is computed for different values of r, then the fractal dimension can be estimated as the slope of the line that best fits the points $(\log(1/r), \log N_r)$.

The complete series of steps for calculating the fractal dimension are follows. First, the image is divided into regular meshes with a mesh size of r. We then count the number of square boxes that intersect with the image N_r. The number N_r is dependent on the choice of r. We next select several size values and count the corresponding number N_r. Following this, we plot the slope D formed by plotting $\log N_r$ against $\log(1/r)$. This indicates the degree of complexity, or the dimensions of the fractal. Finally, a straight line is fitted to the plotted points in the diagram using the least square method. In accordance with Mandelbrot's view, the linear regression equation used to estimate the fractal dimension is:

$$\log(N_r) = \log(K) + D\log(1/r) \tag{3}$$

where K is a constant and D denotes the dimensions of the fractal set.

III. IRIS CLASSIFICATION

A. *Image preprocessing*

An iris image has a unique and complex structure made up of numerous minute interlacing characteristics such as freckles, coronas, furrows, stripes, and crypts. Nonetheless, an iris also displays a variety of textures that it is possible to broadly classify. These textures can be represented numerically, as a calculation of the fractal dimension. The calculation of the fractal dimension begins with preprocessing the original image to localize and normalize the iris. A captured iris image is a 2-dimensional array $(M \times N)$. The gray level of a point (x, y) is described as $I(x, y)$. After localizing an iris, we detect the inner and outer boundaries. In an eye image, the iris may be partially concealed by the upper eyelid, the lower eyelid, or the eyelash. To exclude these influences, image preprocessing makes use of only the inner 3/4 of the lower half of an iris. As the size of an iris in a captured image always varies, the detected iris is normalized into a rectangular block using the following mapping:

$$I(x(r,\theta), y(r,\theta)) \to I(r,\theta) \tag{4}$$

where $x(r,\theta)$ and $y(r,\theta)$ are the linear combinations of a point in the inner boundary $(x_{Inner}(\theta), y_{Inner}(\theta))$ and a point in the outer boundary $(x_{Outer}(\theta), y_{Outer}(\theta))$ which are along the same radii:

$$\begin{cases} x(r,\theta) = (1-r)\cdot x_{Inner}(\theta) + r\cdot x_{Outer}(\theta) \\ y(r,\theta) = (1-r)\cdot y_{Inner}(\theta) + r\cdot y_{Outer}(\theta) \end{cases}, \quad r \in [0,1], \theta \in [0,\pi] \tag{5}$$

In our experiments, the preprocessed images were transformed into images measuring 256×64.

Because all iris images have a similar texture near the pupil, we do not use the upper part of the iris image when classifying an iris. Rather we make use only of the middle and lower part of the iris image. Preliminarily, we use the box-counting method to calculate the fractal dimension. To do this, we first divide a preprocessed iris image into sixteen regions. Eight regions are then drawn from the middle part of the iris image, as shown in Fig. 1. We call these the upper group. The remaining eight regions are drawn from the bottom part of iris image. These are referred to as the lower group. From these sixteen regions we obtain sixteen 32×32 image blocks. We then use the box-counting method to calculate the fractal dimensions of these image blocks. This produces sixteen fractal dimensions, FDi (i=1,2…16). The mean values of the fractal dimensions of the two groups are taken as the upper and lower group fractal dimensions, respectively.

$$FD_{upper} = \frac{\sum_{i=1}^{8} FD_i}{8}, \quad FD_{lower} = \frac{\sum_{i=9}^{16} FD_i}{8} \tag{6}$$

Once we have determined the values of the upper and the lower group fractal dimensions, we can classify the iris image using either the double threshold algorithm or the backpropagation algorithm.

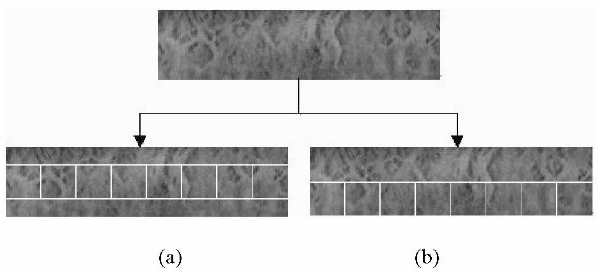
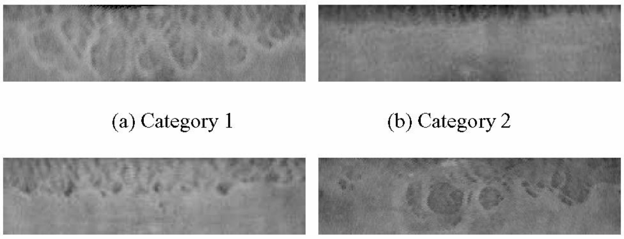


Fig. 1 Image segmentation. (a) upper group image blocks. (b) lower group image blocks

B. Classifying an iris using the double threshold algorithm

The values of the upper and lower group fractal dimensions can be used to classify the iris into the following four categories, according to their texture.



(a) Category 1 (b) Category 2

(c) Category 3 (d) Category 4

Fig. 2. Examples of each iris category after processing

Category 1 (net structure): The iris image appears loose and fibrous. The fibers are open and coarse, and there are large gaps in the tissue. The values of both the upper and lower group fractal dimensions are less than the first threshold E_I.

$$\{(FD_{upper}, FD_{lower}) \mid FD_{upper} < E_I \;\&\; FD_{lower} < E_I\} \quad (7)$$

Fig. 2 (a) shows a Category 1 iris.

Category 2 (silky structure): The iris image appears silky. It displays few fibers and little surface topography. The Autonomic Nerve Wreath (also known as the Ruff and Collarette) is usually located less than one-third the distance from the pupil to the iris border. The values of the upper and lower group fractal dimensions are more than the second threshold E_{II}.

$$\{(FD_{upper}, FD_{lower}) \mid FD_{upper} > E_{II} \;\&\; FD_{lower} > E_{II}\} \quad (8)$$

Fig. 2 (b) shows a Category 2 iris.

Category 3 (linen structure): The iris image appears to have a texture between those of Category 1 and Category 2. The Autonomic Nerve Wreath usually appears one-third to halfway between the pupil and the iris border, and the surface of ciliary zone is flat. (The Autonomic Nerve Wreath divides the iris into two zones, an inner pupillary zone, and an outer ciliary zone.) The value of lower group fractal dimension is more than the second threshold E_{II} and the value of upper group fractal dimension is less than the second threshold E_{II}.

$$\{(FD_{upper}, FD_{lower}) \mid FD_{upper} < E_{II} \;\&\; FD_{lower} > E_{II}\} \quad (9)$$

Fig. 2 (c) shows a Category 3 iris.

Category 4 (hessian structure): The iris image appears to have a similar texture to Category 3 but with a few gaps (Lacunae) in the ciliary zone. When the upper and lower group fractal dimension values of an iris fail to satisfy the rules of Categories 1, 2, or 3, they are classified into Category 4. Fig. 2 (d) shows a Category 4 iris.

Fig. 2 shows the range of possible textures. Categories 3 and 4 are both in a range between Categories 1 and 2. Category 3 is more like Category 2 and Category 4 is more like Category 1. Table 1 shows the fractal dimension values of the four categories of the images in Fig. 2.

Because the value of a fractal dimension is continuous, when classifying we must take into account the border effect. For the value near the threshold, we can't simply classify the image into one category. Therefore, the nearby categories should be considered at one time. The complementary rules for classifying the image are as follows：

Rule1. If $\{(FD_{upper}, FD_{lower}) \mid FD_{upper} \le E_I \;\&\; (E_I - \Delta E \le FD_{lower} \le E_I + \Delta E)\}$ or $\{(FD_{upper}, FD_{lower}) \mid (E_I - \Delta E \le FD_{upper} \le E_I + \Delta E) \;\&\; FD_{lower} \le E_I\}$,the image belongs to Category 1 or Category 4, so Category 1 and Category 4 should be matched. Here ΔE is a small value.

Rule2. If $\{(FD_{upper}, FD_{lower}) \mid (E_{II} - \Delta E \le FD_{upper} \le E_{II} + \Delta E) \;\&\; E_{II} \le FD_{lower}\}$ or $\{(FD_{upper}, FD_{lower}) \mid E_{II} \le FD_{upper} \;\&\; (E_{II} - \Delta E \le FD_{lower} \le E_{II} + \Delta E)\}$, the image belongs to Category 2 or Category 3, so Category 2 and Category 3 should be matched.

Rule3. If $\{(FD_{upper}, FD_{lower}) \mid FD_{upper} < E_{II} - \Delta E \;\&\; (E_{II} - \Delta E < FD_{lower} < E_{II} + \Delta E)\}$ the image belongs to Category 3 or Category 4, so Category 3 and Category 4 should be matched.

IV. EXPERIMENTAL RESULTS

Extensive experiments on a large image database were carried out to evaluate the effectiveness and accuracy of the proposed methods. An iris image is correctly classified when the label of its category is the same as that of the iris. When there is no such match, the iris has been misclassified. The following subsections detail the experiments and their results.

Our iris classification algorithm was tested on a database containing 872 iris images captured from 218 persons having both left and right eyes. There are two images of each eye. The images measure 758×568 with eight bits per pixel and the irises have been labeled manually. In this database, 48 samples belong in Category 1, 336 belong in Category 2, 190 belong in Category 3 and 298 belong in Category 4.

After selecting the values for E_I and E_{II}, we carried out experiments on these two thresholds to classify the iris. Of the 872 irises in the database, 47 samples were misclassified: 6 in Category 1, 5 in Category 2, 20 in Category 3 and 16 in Category 4. This is a classification accuracy of approximately 94.61%. It shows that many misclassified irises are to be found in neighboring categories.

TABLE 1 IRIS CLASSIFICATION WITH $E_I = 2.2100$ AND $E_{II} = 2.2500$

	Category 1	Category 2	Category3	Category4
FD_{upper}	2.1780	2.2648	2.1925	2.2011
FD_{lower}	2.2009	2.2610	2.2556	2.2324

TABLE 2 CLASSIFICATION ACCURACY OF THE DOUBLE THRESHOLD ALGORITHM WITH AND WITHOUT BORDER EFFECT

Total Samples	Correctly Classified Samples	Misclassified Samples	Classification Accuracy %
Without border effect	825	47	94.61
Consider border effect	857	15	**98.28**

To reduce the influence of the border effect on classification accuracy, we have added three iris classification rules. If an iris satisfies one of the rules, it is simultaneously matched in two neighboring categories. As can be seen in Table 2, applying these rules, and with $\Delta E = 0.0050$, the classification was 98.28% accurate. Clearly, this is a great improvement on the method which did not take into account the border effect.

The results reveal three conditions for misclassification: 1) The texture will be blurry and the calculation of the fractal dimension will quite unlike its true value if the image resolution is lower than a certain value. 2) The calculation of the fractal dimension will be affected if parts of the iris image are obscured by the eyelids. 3) It can be difficult to detect textures if an iris image is very dark, it can be difficult to detect textures.

V. CONCLUSION

As the demand for information security increases, so does the attention that is paid to biometrics-based, automated personal identification. Among the biometrics approaches, iris recognition is known for its high reliability, but as databases grow ever larger, an approach needed that can reduce matching times. Iris classification can contribute to that. As the first attempt to classify iris images, this paper presents a novel iris classification algorithm based on the box-counting method of fractal dimension. The approach uses the fractal dimension of the iris image to classify the iris image into four categories according to texture. The classification method has been tested and evaluated on 872 iris cases. After taking the border effect into account, the best result was obtained using the double threshold algorithm, which was 98.28% accurate.

In the future, we will modify the image preprocessing method to reduce the influence of light and eyelids. There is also much work to be done on the selection of classification methods. We will also try other approaches to the improvement of classification accuracy, such as neural networks, fuzzy logic, and genetic algorithms.

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