Gabor Analytic Iris Texture Binary Encoder

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Abstract. The present paper proposes a new method for generating binary iris codes using *Hilbert Transform*. The *strong analytic signal* associated with the chromatic iris sequence is used to recover the phase information which it contains. A meaningful synthetic example is given in order to illustrate the iris binary code extraction. The reasons for canceling the discovery of the radial iris features and for choosing to encode iris features only in the angular direction are also explained here. *Gabor Analytic Iris Texture Binary Encoder* is introduced to prove that accurate recognition of similar iris images can be achieved comparing the binary iris codes that the encoder will generate for the similar circular iris rings (segments) previously extracted through *Circular Fuzzy Iris Segmentation* procedure. A new approach to iris recognition based on *Circular Fuzzy Iris Segmentation* and *Gabor Analytic Iris Texture Binary Encoder* is proposed and tested here. Experimentally results obtained using the *Bath University Iris Database* are also presented.

Key words: iris segmentation, iris recognition, Hilbert Transform, strong analytic signal, Circular Fuzzy Iris Segmentation, Gabor Analytic Iris Texture Binary Encoder, Bath University Iris Database

1 Introduction

The strong analytic signal was introduced by Gabor [4] for extracting phase information content from a finite, discrete signal given in time domain i.e. for recovering both the carrier wave and the message modulated on it from the given signal. Since the considered signals are discrete, the name ”analytic” is not a direct reference to a connection with the notion of analytic functions but is yet justified through the fact that each of these signals could be viewed as being obtained by sampling some continuous, finite, periodic (hence analytic) signal.

The form of a strong analytic signal is:

$$y = x + j * H(x)\,, \tag{1}$$

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where $H(x)$ is the Hilbert Transform of the finite, discrete signal x given in time domain, and j is the complex unit.

The *analytic image* [5] is the 2-dimensional version of the strong analytic signal (heaving the same form as mentioned above where x is an image instead) and can be used for iris recognition as in [9]. Inspired and motivated by this work, the currently proposed Gabor Analytic Iris Texture Binary Encoder is a simpler and more robust approach to iris binary code extraction based on the discovery of phase information available in the iris texture.

The main reason for working with the one-dimensional strong analytic signal instead of using the analytic image is that the critical information which decides the similarity or non-similarity between two iris rings is mainly stored as chromatic variation in the angular direction. On the other hand, accurate iris movement equations should be available in order to trace and to match chromatic variations along radial direction. Until knowing such motion laws, the chromatic variation along the radial direction will be, without any doubt, an important source of disagreement between those circular iris rings (segments) representing the same iris in different pupil dilatations. The essence of such a disagreement is that it is not "reconcilable" through an elastic deformation. As a practical example one can consider an iris image in which pupil dilatation is sufficiently strong to cause the iris area closest to the pupil to "disappear" or to change dramatically.

A question related to the use of analytic signals in iris recognition is whether the uniqueness of the iris is encoded in the carrier wave or in the carried message or in both of them? This paper confirms a partial answer to this question: the uniqueness of the iris is encoded sufficiently strong in the wave carrier component (i.e. in the phase information) of the analytic signal associated with the chromatic variation along the angular direction.

2 Hilbert Transform and the strong analytic signals. Basic properties

For a continuous time-domain signal $f(t)$, its Hilbert Transform is defined as follows:

$$\hat{f}(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{f(\tau)}{t-\tau}\, d\tau\,, \tag{2}$$

when the integral exists.

A strong analytic signal is the complex continuous time-domain signal $f(t)$ having the following property:

$$\hat{f}(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{f(\tau)}{t-\tau}\, d\tau = -jf(t)\,. \tag{3}$$

If the strong analytic signal $f(t)$ is separated into its real and imaginary parts:

$$f(t) = g(t) + jh(t)\,, \tag{4}$$

then:

$$\hat{f}(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{g(\tau)}{t-\tau}\, d\tau + j\frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{h(\tau)}{t-\tau}\, d\tau = h(t) - jg(t)\,, \tag{5}$$

and therefore:

$$\hat{g}(t) + j\hat{h}(t) = h(t) - jg(t)\,, \tag{6}$$

hence:

$$\hat{g}(t) = h(t)\;;\hat{h}(t) = -g(t)\,, \tag{7}$$

i.e.:

$$\widehat{Re(f(t))} = Im(f(t))\,. \tag{8}$$

As a consequence, any signal $y = x + j * H(x)$ is a strong analytic signal (Gabor analytic signal associated with x).

The basic properties of the Hilbert Transform are the following:

1. Hilbert Transform of a time-domain signal $f(t)$ is another time-domain signal $\hat{f}(t)$.

2. Hilbert Transform of a real-valued signal $f(t)$ is also a real-valued signal $\hat{f}(t)$.

3. Hilbert Transform of an even function is odd and conversely.

4. Hilbert Transform of a constant function is null.

5. If H denotes the Hilbert Transform, then the inverse Hilbert Transform is $-H$:

$$\hat{\hat{f}}(t) = -f(t), i.e.: H^2 = -I\,. \tag{9}$$

6. Hilbert Transform commutes with temporal derivative:

$$\frac{d}{dt}\hat{f} = \widehat{\frac{d}{dt}f}\,. \tag{10}$$

7. Hilbert Transform is a convolution [6]:

$$\hat{f}(t) = \frac{1}{\pi t} \star f(t)\,, \tag{11}$$

$$F(H(f(\omega))) = -jsign(\omega)F(f(\omega))\,, \tag{12}$$

$$\hat{f}(t) = F^{-1}(-jsign(\omega)F(f(\omega)))\,, \tag{13}$$

where $\hat{f}$ and H denote Hilbert Transform and F is the Fourier Transform.

8. Hilbert Transform preserves the energy of the signal:

$$E_f = \int_{-\infty}^{\infty} |f(t)|^2\, dt = \int_{-\infty}^{\infty} |\hat{f}(t)|^2\, dt = E_{\hat{f}}\,. \tag{14}$$

9. Any signal with finite energy and its Hilbert Transform are orthogonal:

$$\langle f(t), \hat{f}(t)\rangle = \int_{-\infty}^{\infty} f(t)\hat{f}^{\star}(t)\, dt = \int_{-\infty}^{\infty} F(\omega)\hat{F}^{\star}(\omega)\, d\omega$$

$$= \int_{-\infty}^{\infty} F(\omega)[-jsign(\omega)F(\omega)]^{\star}\, d\omega = \int_{-\infty}^{\infty} j|F(\omega)|^2 sign(\omega)\, d\omega = 0$$

3 Recovering the phase information from Gabor analytic signal

In the iris recognition context, the most important property of the Hilbert Transform is that it preserves the signal energy. Hence f and $\hat{f}$ have the same energy but also

$$\frac{d}{dt}\hat{f},\ \widehat{\frac{d}{dt}f},\ \frac{d}{dt}f$$

share the same energy.

When f is assumed to be a line within the unwrapped iris, the meaning of the above fact is that the iris features in the angular direction is encoded with the same fidelity both in f and $\hat{f}$.

Now let us consider the real time-domain signal $f(t)$, its Hilbert Transform $\hat{f}(t)$ and the corresponding Gabor analytic signal:

$$z(t) = f(t) + j\hat{f}(t)\,, \tag{15}$$

expressed in polar form:

$$z(t) = A(t)e^{j\phi(t)}\,, \tag{16}$$

where:

$$A(t) = \sqrt{f^2(t) + \hat{f}^2(t)}\,, \tag{17}$$

is the instant amplitude and:

$$\phi(t) = arctan\left(\frac{\hat{f}(t)}{f(t)}\right), \tag{18}$$

is the instant phase. Instant phase can be used further to recover from the real time-domain signal $f(t)$ its carrier wave and its carried message.

4 A synthetic example on extracting the iris binary code

Let us consider that the signal $f(t)$ contains a carrier wave and a carried message:

$$f(t) = a(t)cos(\phi(t)), \tag{19}$$

where $\phi(t)$ is determined in the previous section.

As a synthetic example, let us consider the following Matlab code:

```
td = [0:0.1:4*pi+0.2];
f = 2*cos(td)+cos(pi/4+2* td);
gf = hilbert(f);%(Gabor analytic signal associated with f)
hf = imag(gf); %(Hilbert Transform of f)
```

Let **C** be the carrier wave within **f**, **M** - the carried message and **S** - the sign of the phase of the Gabor analytic signal **gf**. All of these signals are presented in figure 1.

Remarks[1]**:**

- The information contained in the carried message **M** is relatively poor when compared to the carrier wave **C**.;
- The local extrema of the carried message **M** are encoded anyway in the bipolar iris code **S**;
- The bipolar iris code **S** is syncronized with the monotony intervals of the carrier wave **C**;
- The jumps in the bipolar iris code are syncronized with the inflexion points of both the real and imaginary parts of the Gabor analytic signal;
- The real part and the imaginary part of the Gabor analytic signal are in fact orthogonal: $\langle f, \hat{f}\rangle = -1.5765e-014$;
- The real part and the imaginary part of the Gabor analytic signal are strongly uncorrelated: $corr2(f, \hat{f}) = -1.5965e-016$;
- The bipolar synthetic iris binary code **S** encodes the separation between the most correlated and the most uncorrelated parts of f and $\hat{f}$:

$$corr2(f(S == -1), hf(S == -1)) = -0.6509$$

.

[1] See the figure 1

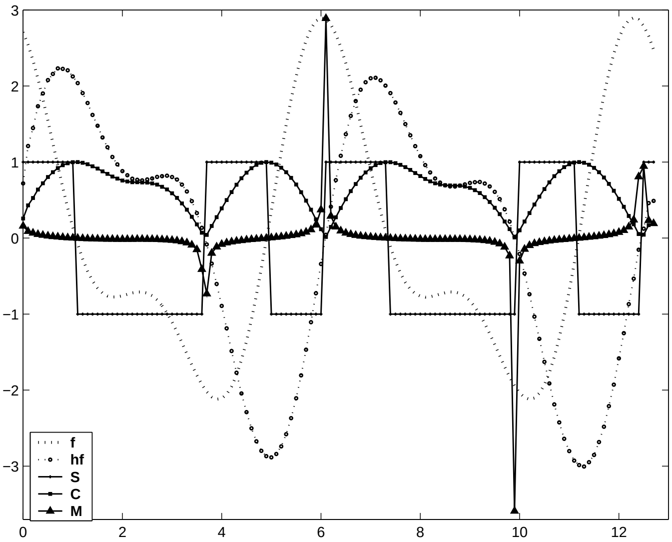

Fig. 1. f - original signal; hf - Hilbert Transform of f; S - bipolar iris code; C - carrier wave; M - carried message.

5 Encoding the real iris

The unwrapped iris is obtained by applying the Circular Fuzzy Iris Segmentation procedure [8]. Each line within the unwrapped iris is associated with a corresponding Gabor analytic signal. The bipolar iris code of that line is obtained as described in the previous section and it is binary encoded becoming a line in the binary iris code on which the iris recognition is based.

As a practical example, the iris codes extracted from two images within the Bath University Iris Database are presented in figure 2 (similar iris codes obtained for similar iris images: 0001-L-0001.j2c, 0001-L-0003.j2c). The Hamming similarity measure for the two iris codes in figure 2 is 0.7346.

Another example is given in the figure 3 in which three corresponding zones from two different images of the same iris are presented in some detail in order to illustrate the accuracy of both the segmentation and the recognition procedures.

It can be seen in the figure 3 that Circular Fuzzy Iris Segmentation is not the perfect segmentation procedure in terms of finding edges. This is why the circular iris ring is touching the sclera in the top-middle zones of each image. But most important, the segmentation procedure returns similar iris rings for similar eye images. Besides, even these zones are recognizable (as it can be seen in the corresponding zones of the binary iris codes). The Hamming similarity measure for the two iris codes shown in figure 3 is 0.7596.

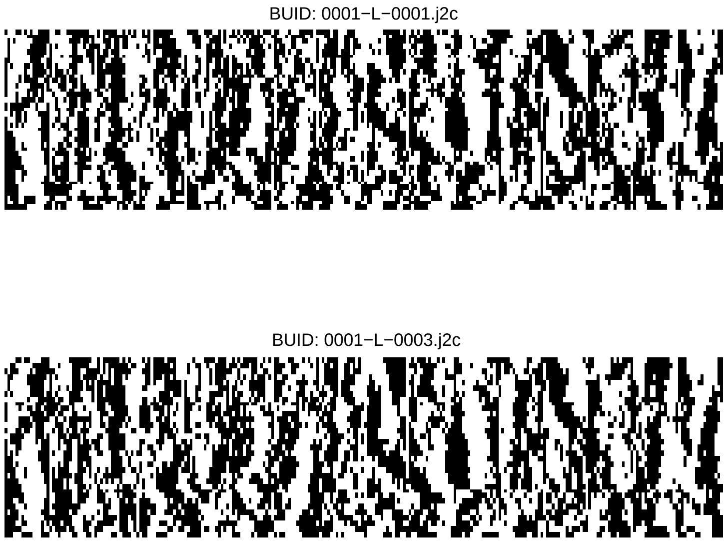

Fig. 2. Two similar iris codes obtained for two similar iris images.

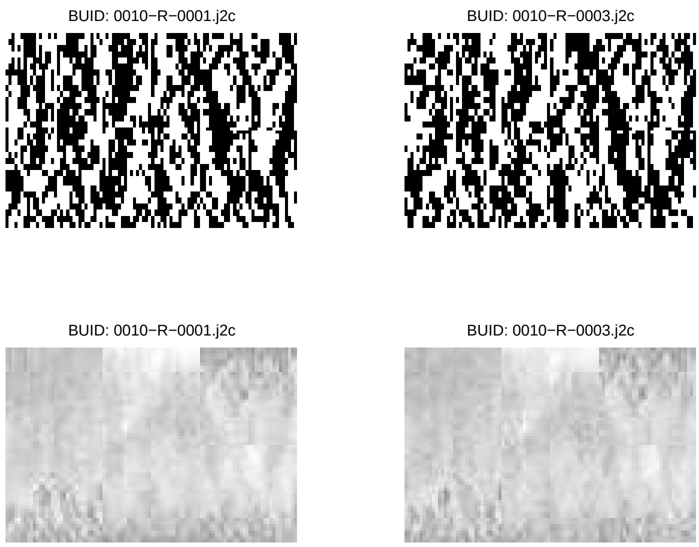

Fig. 3. Two iris codes in some detail.

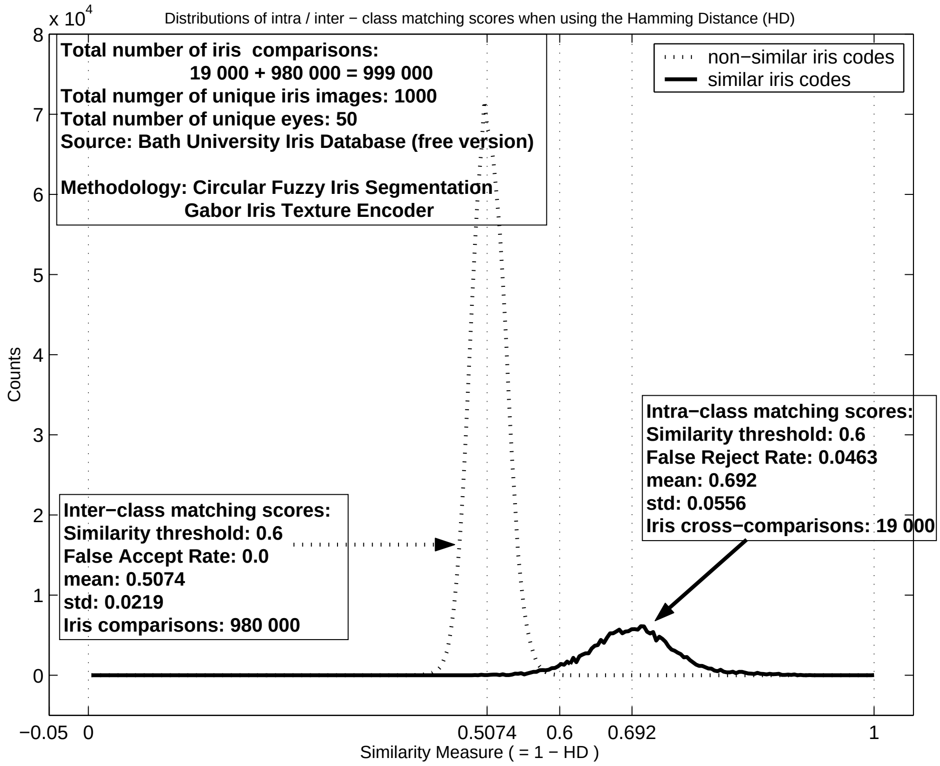

Fig. 4. Distributions of intra / inter - class matching scores when using Hamming Distance.

6 Conclusions and Experimentally results

The figures (4, 5) show all statistic data collected when running the proposed iris recognition procedure on Bath University Iris Database. The database contains 1000 images taken for 50 unique eyes.

Figure 4 presents the statistic data obtained when using the regular Hamming Distance. For the data in figure 5, a custom modified Hamming-Correlation distance was used. As a consequence the distance between the mean of the two classes of scores increases. But this better separation comes at a greater computational cost. Since the False Reject Rate remains nearly unchanged (the False Accept Rate is zero in both cases), modifying the similarity measure proves to be just an exercise.

The most important thing regarding these results is the fact that they come to confirm the quality of the segmentation and recognition procedures: Circular Fuzzy Iris Segmentation and Gabor Analytic Texture Encoder. The False Reject

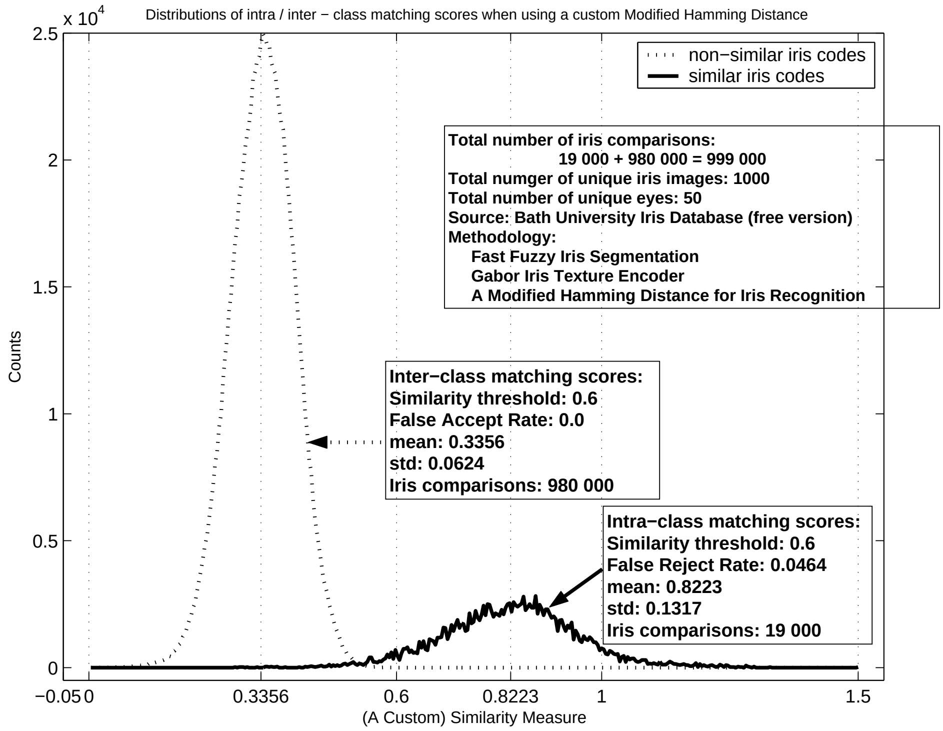

Fig. 5. Distributions of intra / inter - class matching scores when using a custom Modified Hamming Distance.

Rate (5%) proves that the accumulated effects of segmentation and recognition errors are very small indeed.

The quality of the segmentation was evaluated also by running two limbic boundary detectors complementary to each other. A segmentation result was considered credible if it was confirmed by both detectors with a maximal error of 8 pixels. Very few exceptions occurred. This proves that the false matching rate is caused mainly by noise, rotated iris, very dilated/contracted pupil. There are two different images of the same iris having the Hamming similarity measure exactly 1 (0008-R-0005.j2c, 0008-R-0001.j2c).

At last, but not the least, the results presented in the figures (4, 5) prove the efficiency of the newly iris recognition approach proposed in this paper. Further developments of the proposed approach are under way and the results will be reported in the near future.

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