Multimodal Biometric Personal Authentication Integrating Iris and Retina Images

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Summary. In this paper Iris and Retina features are combined for recognition in biometric system. In this multimodal biometric system two biometrics can be taken from the same acquisition process and image. Gabor transform to extract the features from Iris and Retina is used. Feature fusion is performed.

1 Introduction

Personal identification is crucially significant in a variety of applications. Conventional person's identification systems use keys, passwords, PIN numbers and other tokens as they are easy to use however they are insecure.

Using passwords as personal identification carries the risk as the user often forgets it or it can be a subject to fraud. Users encounter problems in terms of theft, loss, and reliance on the own (user's) memory. Biometric technology that uses human body information can decrease the risk because the biometric systems which recognise users based on their physiological and behavioural characteristics eliminate memorization and eliminate misplaced tokens.

Physiological biometrics (also known as static biometrics)are based on data derived from the measurement of a part of a person's anatomy. For example, fingerprints and iris patterns, as well as facial features, hand geometry and retinal blood vessels. Behavioural biometrics are based on data derived from measurement of an action performed by a person and, distinctively, incorporate time as a metric as the measured action. For example, voice (speaker verification).

All biometric systems work in a similar fashion:

1. The user submits a sample that is an identifiable, unprocessed image or recording of the physiological or behavioural biometric via an acquisition device,
2. This image and/or biometric is processed to extract information about distinctive features.

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Biometric systems have four main components [1]: sensor, feature extraction, biometric database, matching-score and decision-making modules (Fig. 1). The input subsystem consists of a special sensor needed to acquire the biometric signal. Invariant features are extracted from the signal for representation purposes in the feature extraction subsystem. During the enrolment process, a representation (called template) of the biometrics in terms of these features is stored in the system. The matching subsystem accepts query and reference templates and returns the degree of match or mismatch as a score, i.e., a similarity measure. A final decision step compares the score to a decision threshold to deem the comparison a match or non-match.

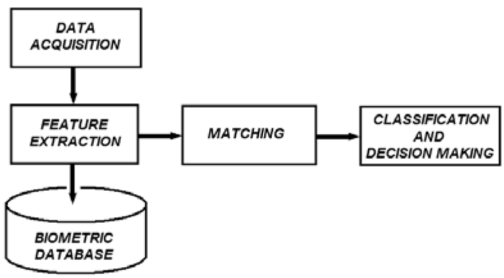


Fig. 1. Biometric system

The ideal biometric characteristics have five qualities:

1. Robust: Unchanging on an individual over time. "Robustness" is measured by the probability that a submitted sample will not match the enrolment image.
2. Distinctive: Showing great variation over the population. "Distinctiveness" is measured by the probability that a submitted sample will match the enrolment image of another user.
3. Available: The entire population should ideally have this measure in multiples. "Availability" is measured by the probability that a user will not be able to supply a readable measure to the system upon enrolment.
4. Accessible: Easy to image using electronic sensors. "Accessibility" can be quantified by the number of individuals that can be processed in a unit time, such as a minute or an hour.
5. Acceptable: People do not object to having this measurement taken on them. "Acceptability" is measured by polling the device users.

The problem of resolving the identity of a person can be categorized into two fundamentally distinct types of problems with different inherent complexities:

(i) verification (also called authentication) refers to the problem of confirming or denying person's claimed identity (Am I who I claim to be?)

(Fig. 2). It is required that a user claims an identity in order for a biometric comparison to be performed. Once the identity is claimed, the user provides biometric data, which is then compared against his or her enrolled biometric data. To claim an identity, the user may use a username, a given name, or an ID number. The answer returned to the system is a match or not a match.

and

(ii) identification (Who am I?) refers to the problem of establishing a subject's identity.They do not require that a user claims an identity before biometric comparisons take place. The user provides biometric data, which is compared to data from a number of users to find a match. The answer returned to the system is an identity.

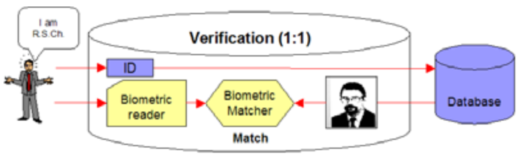


Fig. 2. Verification process

Unimodal biometric systems make use of a single biometric trait for user recognition. It is difficult to achieve very high recognition rates. A multimodal biometric system utilizes a number of different biometric templates like face, fingerprint, hand-geometry, and iris. Such system can achieve higher recognition accuracy than unimodal systems. However, a multimodal system will require longer verification time.

In this paper recognition methods are presented for authentication of a person on the basis of a feature vector derived from an iris and retina input images.

2 Iris and Retina Recognition

The iris and retina features are combined for recognition in biometric system. In this multimodal biometric system two biometrics can be taken from the same acquisition process. Invariant features are extracted from the signal for representation purposes in the feature extraction subsystem. During the enrolment process, representation (called template) of the biometrics in terms of these features is stored in the system. Feature fusion is performed. The matching subsystem accepts query and reference templates and returns the degree of match or mismatch as a score, i.e., a similarity measure. A final decision step compares the score to a decision threshold to deem the comparison a match or non-match.

Iris texture patterns are believed to be different for each person, and even for the two eyes of the same person. It is also claimed that for a given person,

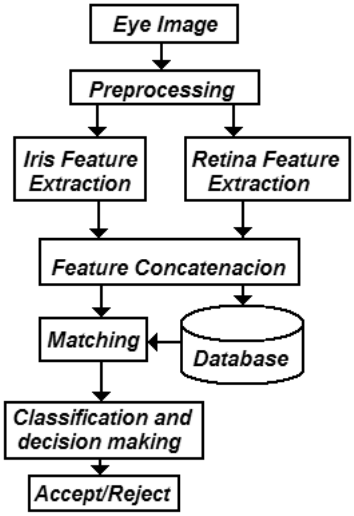


Fig. 3. The block diagram of the multimodal biometric system based on fusion of iris and retina features

the iris patterns change little after youth. The iris is the coloured portion of the eye that surrounds the pupil. Its combination of pits, striations, filaments, rings, dark spots and freckles are the very accurate means of biometric identification [6]. Its uniqueness is such that even the left and right eye of the same individual is very different.

Retina recognition technology captures and analyzes the patterns of blood vessels on the thin nerve on the back of the eyeball that processes light entering through the pupil. The retina biometric analyzes the layer of blood vessels located at the back of the eye. The blood vessels at the back of the eye have a unique pattern, from An eye to an eye and a person to a person. The retina, a layer of blood vessels located at the back of the eye, forms an identity card for the individual under investigation.

A major approach for iris and retina recognition today is to generate feature vectors corresponding to individual iris and retina images and to perform these matching based on some distance metrics [6, 11].

Random iris and retina patterns can be seen as texture, so many well-developed texture analysis methods can be adapted to recognize these images. Gabor filters are used to extract the iris and retina features. Additionally we used Haralick texture features for the iris template and some geometrical features for retinal templates.

The general functionality of the 2D Gabor filter family can be represented as a Gaussian function modulated by a complex sinusoidal signal [12] (Fig. 4).

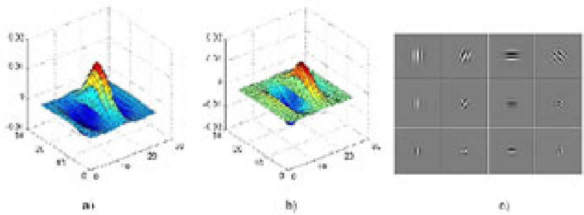


Fig. 4. Real (a) and imaginery (b) parts of Gabor wavelets and Gabor kernels with different orientations (c)

In our work we use a bank of filters built from these Gabor functions for texture feature extraction.

The two-dimensional Gabor filter is defined as

$$Gab(x, y, W, \theta, \sigma_x, \sigma_y) == \frac{1}{2\pi\sigma_x\sigma_y} e^{\left[-\frac{1}{2}\left(\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2\right) + jW(x\cos\theta + y\sin\theta)\right]} \quad (1)$$

where $j = \sqrt{-1}$ and σ_x and σ_y are the scaling parameters of the filter, W is the radial frequency of the sinusoid and $\theta \in [0, \pi]$ specifies the orientation of the Gabor filters.

2.1 Iris Recognition

The initial stage deals with iris segmentation. This consists of Localized iris inner (pupillary) and outer (scleric) borders. Robust representations for iris recognition must be invariant to changes in the size, position and orientation of the patterns. To each pixel of the iris, a pair of real coordinates (r, θ), where r is on the unit interval $[0, 1]$ and θ is an angle in $[0, 2\pi]$.

Because most of the irises are affected by upper and lower eyelids, the iris is divided into two rectangular (Fig. 5a) or two angular sectors (Fig. 5b) having the same size. The blocks of interest (ROI) should be isolated from the normalized iris image.

Two sectors with Fig. 5 are transformed into a normalized rectangular blocks each of size 32×128 to achieve size independent iris recognition.
We uses in our iris recognition systems features based on Gabor functions analysis and texture features based on the Haralick's approach.

Gabor filtered output of the image is obtained by the convolution of the image with Gabor functions.Given an image $F(x, y)$, we filter this image with $Gab(x, y, W, \theta, \sigma_x, \sigma_y)$

$$G(x, y) == \sum_k \sum_l F(x - k, y - l) * Gab(x, y, W, \theta, \sigma_x, \sigma_y) \quad (2)$$

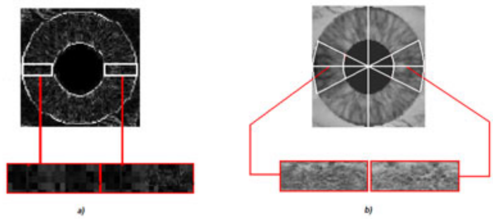


Fig. 5. The iris ROI

The magnitudes of the Gabor filters responses are represented by three moments

$$\mu(x,y) = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y} G(x,y) \tag{3}$$

$$std(x,y) == \sqrt{\sum_{x=1}^{X}\sum_{y=1}^{Y} \left(|G(x,y)| - \mu(x,y)\right)^2} \tag{4}$$

$$Skew = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y} \left(\frac{G(x,y) - \mu(x,y)}{std(x,y)}\right)^3 \tag{5}$$

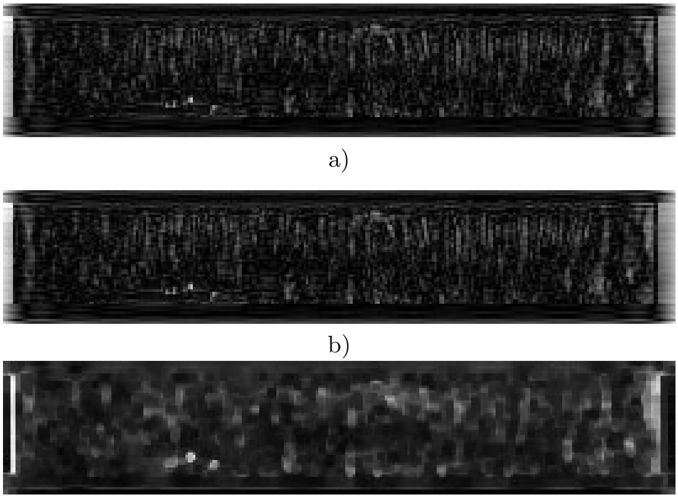
The feature vector is constructed using $\mu(x,y)$, $std(x,y)$ and $Skew$ as feature components.

Gabor filters worked as local bandpass filters and each filter is fully determined by choosing the four parameters $\{\theta, W, \sigma_x, \sigma_y\}$. Assuming that N filters are needed in an application, $4N$ parameters need to be optimized. The orientation parameter θ should satisfy $\theta \in [0, \pi)$. W is the radial frequency of the Gabor filter and is application dependent. σ_x and σ_y are the effective sizes of the Gaussian functions and are within the range $[\sigma_{min}, \sigma_{max}]$.

The iris features information is extracted based on the Haralick's approach [13]. The co-occurrence matrixes $P_{\delta,\theta}(x,y)$ are bi-dimensional representations showing the spatial occurrence organization of the gray levels

Table 1. Mean and standard deviation Gabor phase iris image

Iris image	$\mu(x,y)$	$std(x,y$
$\theta = 0$	223,93	33,86
$\theta = 45$	223,84	33,75
$\theta = 90$	224,02	34,38
$\theta = 135$	225,35	32,40
$\theta = 45$ blob	215.18	27,33



a)

b)

c)

Fig. 6. Gabor transform of iris image: (a) power; (b) phase, and blob detection results for Gabor phase image (c)

in an image. They represent a bi-dimensional histogram of the gray levels, where fixed spatial relation separates couples of pixels, defining the direction and distance (δ, θ) from a referenced pixel to its neighbour.

The features are:

1. Second Angular Moment

$$SAM = \sum_{x=1}^{k} \sum_{y=1}^{l} [P_{\delta,\theta}(x,y)]^2 \tag{6}$$

2. Contrast

$$Con = \sum_{x=1}^{K} \sum_{y=1}^{l} (x-y)^2 P_{\delta,\theta}(x,y) \tag{7}$$

3. Correlation

$$Corr = \frac{\sum_{x=1}^{k} \sum_{y=1}^{l} [xyP_{\delta,\theta}(x,y)] - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{8}$$

4. Inverse Differential moment

$$IDM = \sum_{x=1}^{k} \sum_{y=1}^{l} \frac{P_{\delta,\theta}(x,y)}{1+(x-y)^2} \tag{9}$$

5. Entropy

$$E = -\sum_{x=1}^{k}\sum_{y=1}^{l} P_{\delta,\theta}(x,y)\log P_{\delta,\theta}(x,y) \tag{10}$$

2.2 Retina Recognition

To represent retinal characteristic we using luminance component (Y) from YC_bC_r (YIQ) color space (Fig 7).

We used Gabor filters with different scales and orientation to detect blood vessels in image of the retina.

The normalized retinal image (Y components) are divided into blocks (Fig. 8). The size of each block in our application is $k \times l \quad (k = l = 20)$. Each block (Fig. 9) is filtered with equation (2).

The magnitudes of the Gabor filters responses are calculated using eqs. (6) - (10).

Finally, a feature vector is constructed for each block using these components.

Table 2. Texture parameters iris image

Left ROI Iris Image		
Parameter	θ	$\delta = 1$
ASM	0 and 180	0.012
	90 and 270	0.009
Con	0 and 180	911.819
	90	1413.594
	270	2891.061
Corr	0 and 180	3.182E-4
	90	2.791E-4
	270	1.729E-4
IDM	0 and 180	0.262
	90 and 270	0.161
E	0 and 180	7.302
	90	7.791
	270	7.664

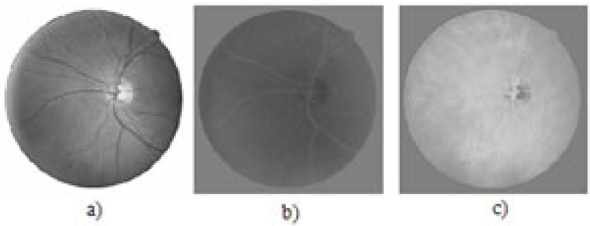


Fig. 7. Retina image in YC_bC_r color space: a) Y component and components C_b (b), C_r (c) respectively.

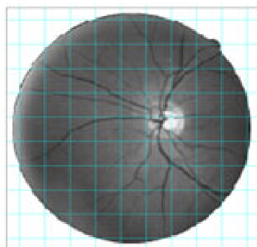


Fig. 8. Original block retinal images (Y component)

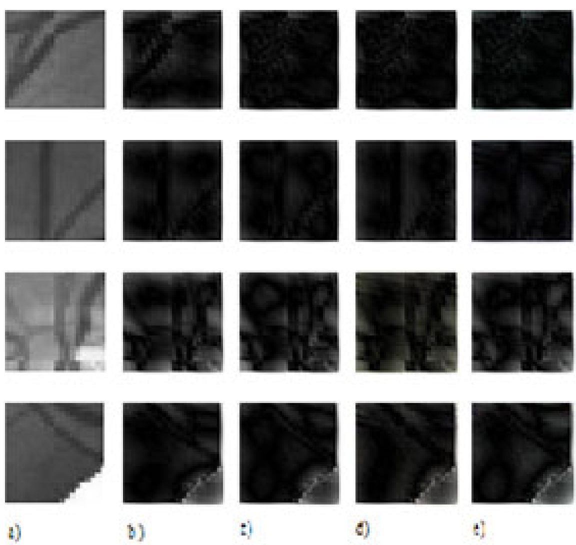


Fig. 9. Original block retina image (a) and real part of $Gab(x; y; \theta_i)$ for $\theta = 0$ (b), $\theta = 45$ (c), $\theta = 90$ (d), $\theta = 135$ (e)

Table 3. Mean, standard deviation and skewnes Gabor power some block (Fig. 9) retina image

Parameters	Retinal image 1		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	25.971	33.468	3.712
$\theta = 45$	15.867	26.176	4.614
$\theta = 90$	15.900	26.901	4.525
$\theta = 135$	15.466	25.409	4.591
Parameters	Retinal image 2		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	23.204	34.360	4.402
$\theta = 45$	18.494	32.176	4.655
$\theta = 90$	22.769	34.375	4.366
$\theta = 135$	16.307	27.644	4.781

3 Conclusion

A new method has been presented for iris and retina recognition based on Gabor and textural features. This paper analyses the details of the proposed method. Experimental results have demonstrated that this approach is promising to improve iris and retina recognition for person authentication.

References

1. Goh, K.G., Lee, M.L., Hsu, W., Wang, H.: ADRIS: An Automatic Diabetic Retinal Image Screening System. In: Medical Data Mining and Knowledge Discovery, Springer, Heidelberg (2000)
2. Hsu, W., Pallawala, P.M.D.S., Lee, M.L., Kah-Guan, A.E.: The Role of Domain Knowledge in the Detection of Retinal Hard Exudates. In: IEEE Computer Vision and Pattern Recognition, Hawaii (December 2001)
3. Li, H., Chutatape, O.: Automated feature extraction in color retinal images by a model based approach. IEEE Trans. Biomed. Eng. 51, 246–254 (2004)
4. Salem, N.M., Nandi, A.K.: Novel and adaptive contribution of the red channel in pre-processing of colour fundus images. Journal of the Franklin Institute, 243–256 (2007)
5. Kirbas, C., Quek, K.: Vessel extraction techniques and algorithm: a survey. In: Proceedings of the 3rd IEEE Symposium on BioInformatics and BioEngineering, BIBE 2003 (2003)
6. Chang, S., Shim, D.: Sub-pixel Retinal Vessel Tracking and Measurement Using Modified Canny Edge Detection Method. Journal of Imaging Science and Technology (March-April 2008)
7. Chanwimaluang, T., Fan, G.: An efficient algorithm for extraction of anatomical structures in retinal images. In: Proc. IEEE International Conference on Image Processing, pp. 1093–1096 (2003)

8. Farzin, H., Abrishami-Moghaddam, H., Moin, M.S.: A novel retinal identification system. EURASIP Journal on Advances in Signal Processing 2008, Article ID 280635 (2008)
9. Choras, R.S.: Image Feature Extraction Techniques and Their Applications for CBIR and Biometrics Systems. International Journal of Biology and Biomedical Engineering 1(1), 6–16 (2007)
10. Choras, R.S.: Iris Recognition. In: Kurzynski, M., Wozniak, M. (eds.) Computer Recognition Systems 3. AISC, vol. 57, pp. 637–644. Springer, Heidelberg (2009)
11. Choras, R.S.: Iris-based person identification using Gabor wavelets and moments. In: Proceedings 2009 International Conference on Biometrics and Kansei Engineering ICBAKE 2009, pp. 55–59. CPS IEEE Computer Society, Los Alamitos (2009)
12. Gabor, D.: Theory of communication. J. Inst. Elect. Eng. 93, 429–459 (1946)
13. Haralick, R.M.: Statistical and structural approaches to texture. IEEE Transaction on Systems, Man and Cybernetics 67, 786–804 (1979)