Off-angle Iris Recognition Using Bi-orthogonal Wavelet Network System

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Abstract

One important category of non-ideal conditions for iris recognition is off-angle iris images. Practically it is very difficult to get images captured with no offset. It then becomes necessary to deal with this off angle information in order to maintain robust performance. Bi-orthogonal wavelet based iris recognition system, previously designed at our lab, is modified and demonstrated to perform off-angle iris recognition. A bi-orthogonal wavelet network (BWN) is designed and trained for each class. The non-ideal factors are adjusted by repositioning the BWN. To test synthetic iris images are generated by using affine and geometric transforms of 0^o, 10^o *and* 20^o*experimentally collected images from* 101 *subjects. This approach is shown to perform better than a transformation based iris recognition approach. Iris images off-angle by up to* 42^o *are successfully recognized.*

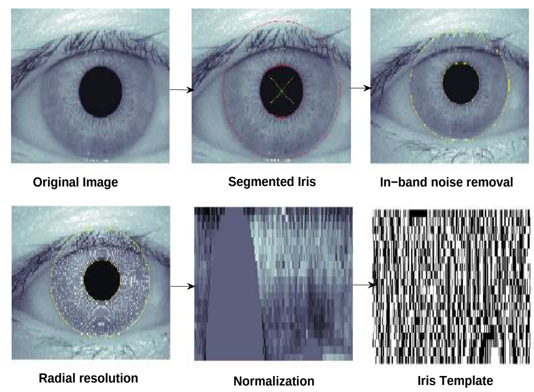

Figure 1. Bi-orthogonal wavelet based iris recognition.

1. Introduction and Background

Biometric identification is gaining popularity and acceptance in public as well as in private sectors. As technology and services have developed in the modern world, for many human transactions, faster, reliable and more secure personal identification is required. Iris recognition is considered to be highly accurate and reliable. Iris is unique, stable and easy to capture, and is classified as one of the better biometric identifiers [12, 15].

The unique epigenetic patterns of a human iris are used for personal identification. Image processing and signal processing techniques are employed to extract information from unique iris structure from a digitized image of an eye [5, 3, 10, 16]. This information is encoded to formulate a "biometric template", which is stored in a database. The purpose of the template formation is to mathematically encode the iris pattern and match it with other similar representations. Daugman developed an algorithm which most systems use commercially today [6, 5, 4]. This algorithm uses Gabor based encoding scheme. Others have used $1D$ wavelets [3], Harr wavelet [9], and laplacian of gaussian filters [15] to encode the iris information.

Bi-orthogonal wavelet based iris recognition is demonstrated in [2]. The designed system is shown capable of doing iris recognition under ideal conditions. The complete algorithm in snap shot is shown in Figure (1). Circular model based segmentation, in-band noise removal, normalization, followed by the bi-orthogonal wavelet based coding formulates the main framework of this algorithm. Match scores are calculated by the hamming distance. The wavelet based iris recognition was compared with method similar to the well known Daugman's system [6, 5]. The designed system shows comparable results and is capable of further improvements to deal with non-ideal cases of iris recognition.

The purpose of this research is to modify the bi-orthogonal wavelet method in order to perform iris recognition in non-ideal settings. This paper focuses on off-angle images. This paper presents two methods for non-ideal adaptation. The first uses a traditional approach of transforming the images using affine and projective transformations to match their angles before comparing. The second approach uses a bi-orthogonal wavelet network (BWN) to account for non-ideal conditions.

1.1. Effect of Angle on Iris Recognition

Before adapting the designed system to non-ideal conditions, it is essential to study the effect of non-ideal parameters on the system performance without any enhancements. This section discusses how the designed system reacts to off-angle iris images. The data needed to do the testing for off-angle cases was collected at the WVU(West Virginia University) Eye Institute. The available data is given in table (1),

No. of subjects	No. of classes	No. of images (0^o)	No. of images (10^o) and (20^o)
101	202	404(2 for each class)	202(1 for each class)

Table 1. Off angle data

For the first set of experiments, for each class, 0^o image is used for enrollment and recognition is performed for a second 0^o, 10^o, and 20^o images each. A total of $202 \times 400 = 80800$ inter-class and $202 \times 3 = 606$ intra-class combinations are exploited. Figure (2) gives the inter and intra class distributions. As seen, there is no separation between the two classes for $10^o$and 20^o images. The results indicate clearly that there is a need for improvement.

1.2. Problems in Segmentation

As the implemented segmentation methods use circular intensity comparisons, it is not effective when it comes to segmenting elliptical iris regions in the off-angle images. This can be seen in figure (3).

Segmentation forms the most important part of the process, since, if the non-ideal images are not segmented correctly, the information loss is irrecoverable. In this paper this problem is handled using repositioning of the bi-orthogonal wavelet network.

2. Iris Recognition Using Projective and Affine Transformation

Off-angle images are a major category of non-ideal iris images. In this section we explore use of affine and projective transformation to deal with non-ideal images. The section gives the techniques used to transform the iris images in order to: match the angles of an enrolled image and the image to be matched, reduce the artifacts produced due to the non-circular nature of iris region, and help equally distribute the radial resolution in all the quadrants.

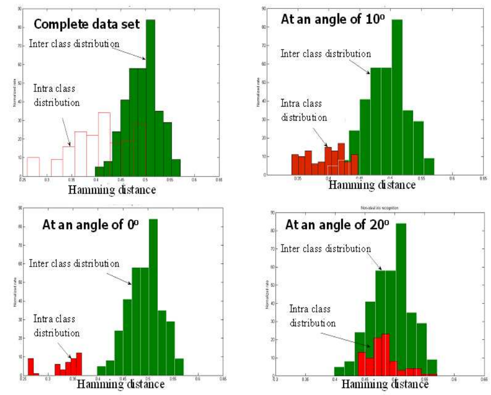

Figure 2. Off-angle inter and intra class distributions. Left top graph is for the complete data set.

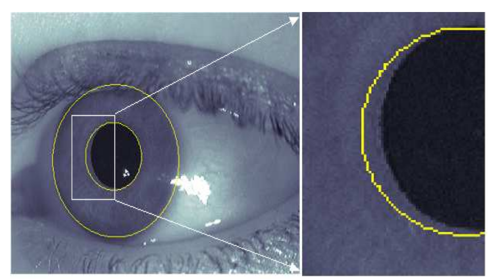

Figure 3. Segmentation problems with off angle images.

Spatial domain projective transforms are used to transform the off-angle images in order to match them up with on-angle images. To match the angles the methods assumes the angles are known. The transform used in this particular study is a combination of ‘affine’ and ‘projective’ transform. The ‘affine’ transform takes into account translations, while ‘projective’ transform maps the off-angle information using quadrilateral structure. Affine transforms are subsets of projective transforms.

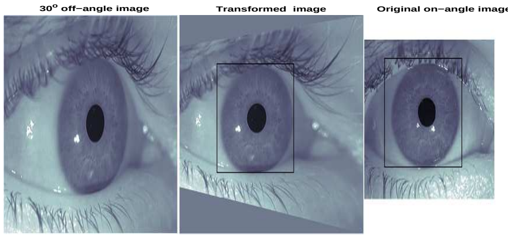

Figure 4. 20^o **off-angle image, transformed image and original on-axis image.**

Two combinations of transforming the images were carried out. Off-angle images were transformed to match on-angle representation or on-angle images were transformed to match off-angle images. The bi-orthogonal wavelet method described in [2] was used to perform iris recognition after transformation. In addition 'multiresolution features based energy thresholding' was performed, to select only the most significant of the coefficients.

Out of available 101 images, for each angle class, 40 images were used for training the separation threshold, and 61 were used for testing. It was found that transforming the on-angle images to match with the off-angle images produced better results. EER value of 0.038 was obtained. Results are summarized in table (2).

	Hamming	Distance
Distribution	Mean	Range
Intra class	0.39	0.12 - 0.44
Inter class	0.53	0.42 - 0.67

Table 2. Transform based iris classification performance for inter and intra class

While reasonable EER is achieved, more exploration is desired to further improve the classification. The transformation methodologies suffer with some serious drawbacks like blurring of the iris outer boundaries, thus experiencing an irrecoverable loss of information and eventually poorer classificaion. Also, this method requires a priori knowledge of the angle.

3. Wavelet - Neural Network system

In this section a novel approach is described which uses bi-orthogonal wavelet network (BWN). A discrete iris template representation by linear combination of $2D$ bi-orthogonal wavelet functions, i.e. bi-orthogonal wavelet network (BWN), is discussed. This method is based on wavelet networks developed theoretically in [8, 11]. The weights and wavelet parameters like scale, orientation, and number of retained coefficients is determined optimally.

This recognition is insensitive to the homogeneous noise and deformations. From the very basic nature of the processes itself, it can be seen that BWN combines template-based and feature-based approaches. Using this method, an effective iris recognition method is achieved that is robust to various noise sources.

The complete method for wavelet network based iris recognition is given in figure (6). This method consists of several steps. First, segmentation and noise removal was performed as in [2]. After transforming the iris information from x, y to r, θ domain, the wavelet template is created. Wavelet coefficients represent the model of iris features. 'Multiresolution based thresholding' is used to retain the most significant coefficients. As the number increases the presentation becomes more general, but more coefficients make the network more complicated. With an enrollment image, a wavelet network is created for the 0^o enrollment image and images at multiple other angles. The significant coefficients and a set of weights for each angle represents the iris template. For an authentication image the process is repeated, where the optimal wavelet template is created and then compared to the template stored for the various angles. The minimum Euclidean Distance (ED) determines the match score. The next section describes the method in detail.

3.1. Wavelet Network

Inspired by wavelet decomposition and neural networks, wavelet networks can replace a feedforward NN. The wavelet decomposition allows decomposition of any function $f(x) \in L^2(R^n)$ using the filter family, obtained by dilating and translating a single mother wavelet $\psi : R^2 \rightarrow R$. Traditional wavelet implementation is chosen over a lifting scheme in order to do sub-band oriented analysis from here on. Function $f(x)$ may be expressed as linear combination of wavelets, where wavelet weights are estimated by the decomposition process. The number of wavelet coefficients and parameters are optimized by the learning process. The method which follows is multiresolution features based energy thresholding [7, 18, 17, 1]. The architecture of the wavelet network is shown in figure (5).

Mathematically it can be expressed as,

$$f^{'}(x) = \sum_{i=1}^{M} W_i \psi_{\overrightarrow{n_i}}(x) + \overline{f} \tag{1}$$

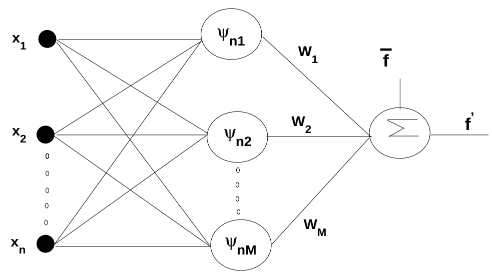

Figure 5. Wavelet Network

where $W_i \in R$, ψ_{ni} is a wavelet function and n_i is the parameter vector e.g. dilation, orientation, position.

For this application, the iris template is represented by a wavelet network where the mother wavelet is a $5/3$ bi-orthogonal tap. For an iris image f an energy (error) function is specified which is minimized by the means of learning process that respects the desired wavelet network parameters [14, 1, 17].

$$E = \min_{\overrightarrow{n_i}, w_i, \forall_i} \| f - (\sum w_i \psi_{\overrightarrow{n_i}} + \overline{f}) \|_2^2 \quad (2)$$

Gradient descent method is used for minimizing error, but the method may get stuck in local minima, and hence initial parameters are selected carefully.

As seen from figure (5), two optimized vectors $\psi = \{\psi_{n1}, \psi_{n2}, ...\psi_{nM}\}$ and $w = \{w_1, w_2, ..., w_M\}$ constitute an optimized BWN. The reconstruction formula is as given in equation (1).

A pyramidal scheme is used to optimize BWN and gets distributed at every layer. First, 4×4 coarse wavelets are equidistantly positioned in the iris region. These form the first pyramid layer. They are roughly initialized and optimized with respect to the energy function. The result is BWN_{16} representing image I'_{16}.

The difference between the original image and its reconstruction $D = I - I'_{16}$, which is approximated by 12×12 finer wavelets is calculated. These form the second layer of pyramid. Both layers merged together define BWN_{160} and the reconstructed image I'_{160}. Therefore, the iris template is described by the 160 wavelet coefficients. Thus, proceeding from coarser wavelets to finer ones, the process is stopped when number of coefficients reaches a pre-defined M value, where $M = 160$ in this implementation. The initial orientations are random and initial dilations are constant in each layer. Their values are obtained from respective distances with the neighboring wavelet [14].

3.2. Weights calculations

Unlike other parameters, wavelet network weights are not calculated using gradient descent method. Instead, a direct method to calculate the weights is used [13]. The approach is based on the principles of biorthogonality and dual wavelets. Let's say we have $\psi = \{\psi_i\}$ for decomposition and $\psi' = \{\psi'_i\}$ for reconstruction. ψ and ψ' are bi-orthogonal as for all i, j if they satisfy,

$$< \psi_i, \psi'_i >= \delta_{i,j} \quad (3)$$

where, $\delta_{i,j}$ is a dirac function and $< \psi, \psi' >$ indicate the inner product. The wavelet ψ' is called dual of ψ if,

$$\psi'_{\overrightarrow{n_i}} = \sum_{j=1}^{N} (\Psi_{i,j})^{-1} \psi_{\overrightarrow{n_i}} \quad (4)$$

where,

$$\Psi_{i,j} =< \psi'_{\overrightarrow{n_i}}, \psi_{\overrightarrow{n_i}} > \quad (5)$$

Using duality of wavelets and orthogonality, weights are directly calculated as,

$$w_i =< \psi'_{\overrightarrow{n_i}}, f > \quad (6)$$

The combination of wavelet coefficients and weights from the template. This template is stored for each desired angle, as in figure (6).

3.3. Repositioning of BWN

For authentication, the process is repeated, the wavelet transform calculated and multiresolution feature based energy thresholding performed. Repositioning is performed for each angle of the template to account for non-ideal conditions and allow the best possible match between the stored and unknown template. Once repositioned, euclidian distance (ED) is calculated for each angle and the minimum ED becomes the match score.

The BWN repositioning consists of determination of correct parameters if the iris undergoes any transformations. As shown in figure (5), BWN is described by two vectors $\psi = \{\psi_{n1}, \psi_{n2}, ...\psi_{nM}\}$ and $w = \{w_1, w_2, ..., w_M\}$. Biorthogonal superwavelet is defined as a linear combination of ψ_{ni} such that,

$$\Psi_n(x) = \sum_i w_i \psi_{\overrightarrow{n_i}} (P_1 P_2 (x - P_3) + P_3 + P_4) \quad (7)$$

where vector n of parameters of the superwavelet Ψ_n determines the dilation matrix S, the rotation matrix R, the translation vector T, and the vector C that contains the coordinates of the iris center.

$$P_1 = \begin{pmatrix} P_{1x} & 0 \\ 0 & P_{1y} \end{pmatrix} \quad (8)$$

$$P_2 = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \tag{9}$$

$$P_4 = (p_{4x}, p_{4y}) \tag{10}$$

$$p_3 = (p_{3x}, p_{3y}) \tag{11}$$

For the new presentation, superwavelet parameters are optimized using the energy function as before. In order to include the correction factor for affine transforms along with translation, dilation and rotation, P_1 parameter is modified as,

$$P_1' = \begin{pmatrix} P_{1x} & 0 \\ P_{1xy} & P_{1y} \end{pmatrix} \tag{12}$$

The energy function has to be minimized in order to find the optimal parameters.

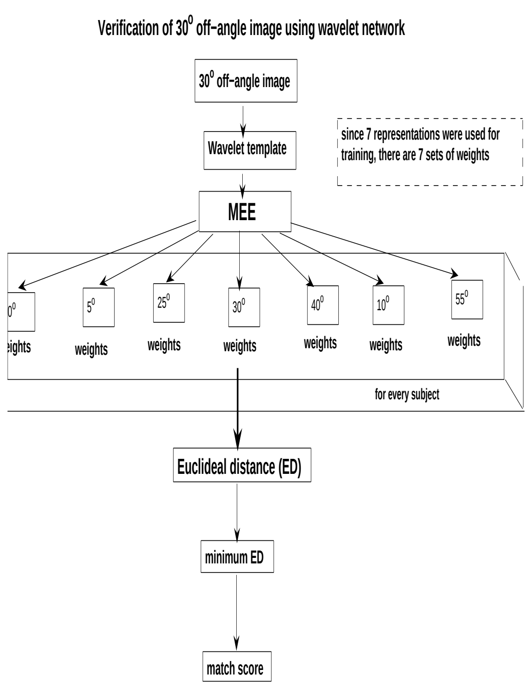

Figure 6. Wavelet network based iris recognition. 8 bits are used for coefficients and 1 for weights. To maintain template size the representation length is fixed to 160. Thus 1440 bits are getting encoded per angle.

4. Results

The complete method for wavelet network based iris recognition is given in figure (6). There are 101 subjects collected at WVU Eye Institute. Each subject has 20 representations generated from the 0^o on-angle image. These 20 representations are synthetically generated at angles 0^o, 5^o, 10^o, 15^o, 20^o, 25^o, 30^o, 35^o, 40^o, 42^o, 44^o, 45^o, 46^o, 48^o, 50^o, 52^o, 54^o, 55^o, 58^o, 60^o. Out of available 20 representations (for each off-angle variation), 7 were randomly selected and used for training/learning and 13 were used for testing. In addition, two experimentally collected images at 10^o and 20^o were used for testing. The simulations are performed using $MATLAB7.0$.

	Euclidean	Distance
Distribution	Mean	Range
Intra class	7.93	3.1 - 17.2
Inter class	71.31	24.2 - 100

Table 3. Iris classification performance of the BWN for inter and intra class (only up to 42^o)

Up to 42^o angle offset all the templates were recognized correctly, without a single failure. As shown in Table (3), there was complete separation of inter and intra class for both synthetic and experimental images.

To further probe into the method, a synthetic data base of iris images with up to 50^o translational variations was developed. Training of these images is simpler as the transformation parameters are already known. All the templates give perfect match for all the possible variations up to 42^o. A sudden drop in the system performance, defined by correct classification sets, was observed for iris images off-angle by more than 42^o.

Results showing capability of the system to perform recognition is demonstrated in figure (7). Figure also shows the system limitation. The system fails to perform well for iris images off-angle by more than 42^o. This may be because of insufficient data left in the image after being off-angle by angle as big as or more than 42^o.

5. Discussion and Conclusion

A robust BWN based method is designed to perform non-ideal iris recognition. The designed system is tested for experimentally collected data as well as synthetically generated data. The essential property of wavelet representation, the ability to generalize the iris template using the optimum of wavelet coefficients, remain valid and the wavelet

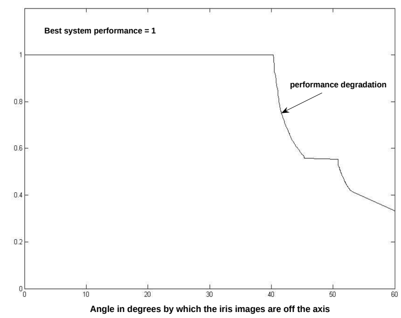

Figure 7. Performance of the designed system degrades when images are off-angle by more than 42^o.

presentation using the NN architecture worked well for different individuals.

A bank of neural networks is designed, each with its own specific set of weights, specialized for each angle with a resolution of 5^o. Since only 0^o, 10^o, 20^o images were available, synthetic images were generated by projective and affine transformations from 0^o image. Seven images at different angles were used to generate euclidian score for the stored template. It is unknown what this minimum number needed to achieve robust performance. Seven was sufficient for this small data set. The size of the template is directly dependent on the number of angles represented. One wavelet representation is 160 coefficients, with 8 bits for each wavelet coefficient plus one for the weights, resulting in 1440 bits. For seven angles, that totals $10,080$ bits, comparable to Daugman's algorithm which uses 9600 bits. Further exploration is needed to determine size versus performance characteristics.

The system recognizes all the classes efficiently. This method has the advantage that advance knowledge of the angles is not needed, unlike simpler transformation methods. In addition, this methods may also be useful in accounting for other non-ideal conditions, like noise, rotation, and other angular positions.

One potential drawback is the computational complexity of the method which will need to be studied.

Acknowledgements: The work was funded by the NSF Center For Identification Technology Research (CITeR).

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