Iris texture feature extraction with orthogonal polynomials

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Abstract- In this paper, a feature extraction technique with orthogonal polynomials based computational model to accurately extract local texture in iris images is presented. Initially, the normalized input iris image is subjected with the orthogonal polynomials model and the model coefficients are obtained. The model coefficients are subjected to statistical hypothesis testing with Hartley’s test so as to extract the signal components due to texture in the iris images and simultaneously separating out the noise components. These model coefficients due to the orthogonal polynomials model, are utilized to represent the iris texture patterns along with their zonal positions, as the locations of the micro texture present in the image analysis is considered to be significant. The texture primitives thus extracted are represented with a decimal number and used for feature extraction.

Keywords - Iris Biometrics, Orthogonal Polynomials, Hartley’s statistical test, Texture feature Extraction.

1 Introduction

Biometric systems allow identification of human persons based on physiological or behavioral characteristics, such as voice, handprint, iris or facial characteristics. Iris Recognition is considered to be a high-confidence biometric identification system due to its robustness and unobtrusiveness, as opposed to most of the currently deployed systems, and makes it a good candidate to replace most of the security systems around. The feature extraction is a crucial step in an iris recognition system since the extracted features should be significant, compact, and fast to compute. In order to provide accurate recognition of individuals, the most discriminating information present in an iris pattern must be extracted. Only the significant features of the iris must be encoded so that comparisons between templates can be made fast. For the iris feature extraction, effective extraction of feature information such as texture from each iris category that represents the inherent characteristics of the iris is essential.

From the viewpoint of feature extraction, it is observed that there are six main approaches for iris representation: phase-based methods [1], texture analysis [2-16], zero-crossing representation [17-20], intensity variation analysis [21-22], fractal dimension analysis [23] and neural network [24]. Daugman [1] has utilized the use of 2-D Gabor wavelets to extract phase structure information of the iris. The advantages of the Daugman’s approach are the speed of matching, easy handling of rotation and an interpretation of the matching as the result of a statistical test of independence. There are many categories of texture analysis methods that exist for identifying and manipulating the texture: Laplacian of Gaussian filters [2], Multi-channel Gabor filtering and the wavelet transform [3], Haar Wavelet transform [4], Multichannel Gabor filtering [5], Radial feature, circular feature, Fourier transform, and Circular-mellin filters [6], 1-D log polar Gabor wavelet [7], Multi-channel 2-D Gabor filter [8], Filter bank [9], Gabor filters and Wavelet maxima component [10], Laplacian of Gaussian (LoG) filters with many different scales [11], 1-D wavelet transform [12], Directional bi-orthogonal filters [13], spatial location of corner points [14], non-separable wavelet [15], and Daubchies wavelets [16]. The performance of an iris recognition system depends not only on the filter chosen, but also on the parameters of the filter. There are three categories of zero crossing representation such as One dimensional signal [17], discrete dyadic wavelet transform [18-19], and Discrete Cosine Transform (DCT) [20] that can be used to speed up the matching process. There are intensity variation analysis techniques such as Independent Component Analysis (ICA) [21], Dyadic wavelet [22] that can be used either as an alternative or supplement to wavelets for feature extraction. In [23], Chen and Yuan extracted unique iris features from iris images by using the fractal dimensions measure. The iris code representing the fractal dimension of the texture of an iris can then be used to recognize individuals. Liam et al. [24] have extracted the iris features with Self-Organization neural network.

Since the computational complexity of existing feature extraction methods is heavy and it could not be well suited to represent 2D singularities along edges or contours, a new iris feature extraction technique is presented in this paper. A low complexity integer orthogonal polynomials based framework is devised in this proposed work for feature extraction in iris images that represents the texture components.

2 Orthogonal Polynomials

In this section we describe the proposed orthogonal polynomials transform for analyzing the iris texture features. The orthogonal polynomials that have already been well established for iris localization [25] are extended in this proposed model to extract the iris local texture property. In the
previous study [25], edge detection has been discussed along the boundary extraction for localizing the iris boundary points.

In this section the orthogonal polynomials model for analyzing the structure of an eye image is presented. In order to investigate the structure of iris from an eye image, a linear 2-D image formation system is considered around a cartesian coordinate separable, blurring, point spread operator in which the image results in the superposition of the point source of impulse weighted by the value of the object \( f \). Expressing the object function \( f \) in terms of derivatives of the image function \( I \) relative to its cartesian coordinates is very useful for analyzing the image. The point spread function \( M(x, y) \) can be considered to be real valued function defined for \((x, y) \in X \times Y\), where \( X \) and \( Y \) are ordered subsets of real values. In case of gray-level image of size \((n \times m)\) where \( X \) (rows) consists of a finite set, which for convenience can be labeled as \(\{0, 1, \ldots, n-1\}\), the function \( M(x, y) \) reduces to a sequence of functions.

\[
M(i, t) = u_i(t), \quad i, t = 0, 1, \ldots, n-1
\]

The linear two dimensional transformations can be defined by the point spread operator \( M(x, y)(M(i, t) = u_i(t)) \) as shown in equation (2).

\[
\beta(\zeta, \eta) = e^{-\int_{\zeta}^{\eta} M(\zeta') M(\eta') I(\zeta, \eta') d\zeta d\eta}
\]

(2)

Considering both \( X \) and \( Y \) to be a finite set of values \(\{0, 1, \ldots, n-1\}\), equation (2) can be written in matrix notation as follows

\[
|\beta| = (|\rho| \otimes |\rho|)^t
\]

(3)

where \( \otimes \) is the outer product, \( |\beta| \) are \( n^2 \) matrices arranged in the dictionary sequence, \( I \) is the image, \( |\beta| \) are the coefficients of transformation and \( |M| \) is

\[
|M| = \begin{bmatrix}
    u_0(t_0) & u_1(t_0) & \cdots & u_{n-1}(t_0) \\
    u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\
    \vdots & \vdots & \ddots & \vdots \\
    u_0(t_{n-1}) & u_1(t_{n-1}) & \cdots & u_{n-1}(t_{n-1}) 
\end{bmatrix}
\]

(4)

The set of orthogonal polynomials \( u_0(t), u_1(t), \ldots, u_{n-1}(t) \) of degrees \(\{0, 1, 2, \ldots, n-1\}\), respectively are considered. The generating formula for the polynomials is as follows

\[
u_{i+1}(t) = (t - \mu)\nu_i(t) - b_i(n)\nu_{i-1}(t) \quad \text{for} \quad i \geq 1,
\]

(5)

where

\[
u_0(t) = t - \mu, \quad \text{and} \quad \nu_0(t) = 1,
\]

\[
b_i(n) = \frac{\langle u_i, u_i \rangle}{\langle u_{i-1}, u_{i-1} \rangle} = \frac{\sum_{t=0}^{n-1} u_i^2(t)}{\sum_{t=0}^{n-1} u_{i-1}^2(t)}
\]

and

\[
\mu = \frac{1}{n} \sum_{i=1}^{n} t_i
\]

Considering the range of values of \( t \) to be \( t_i = i, \ i = 1, 2, 3, \ldots, n \), we get

\[
b_i(n) = \frac{\mu^2(n^2 - 1)}{4(d^2 - 1)},
\]

\[
\mu = \frac{1}{n} \sum_{i=1}^{n} t_i = \frac{n+1}{2}
\]

Next, point spread operator \( |M| \) of different sizes are constructed from the above orthogonal polynomials as follows

\[
|M| = \begin{bmatrix}
    u_0(t_0) & u_1(t_0) & \cdots & u_{n-1}(t_0) \\
    u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\
    \vdots & \vdots & \ddots & \vdots \\
    u_0(t_{n-1}) & u_1(t_{n-1}) & \cdots & u_{n-1}(t_{n-1}) 
\end{bmatrix}
\]

(6)

for \( n \geq 2 \) and \( t_i = i \).

For convenience of point spread operations, the elements of \( |M| \) are scaled to make them integers.

These point spread operators are then utilized to characterize texture primitives in an iris image region.

3 Framework for iris texture characterization based on Orthogonal Polynomials

In this work, a framework based on modeling the iris image for textureness is proposed. The texture information is modeled as feature descriptors and the resulting feature descriptors are used for discrimination as representative of the iris image. The feature descriptor constitutes the components of numerical characterization sequence. The proposed discriminative feature extraction approach is a direct and significant technique that varies from the conventional approaches and provides a comprehensive basis for the entire system design.

![Figure 1: Proposed orthogonal polynomials based feature extraction technique](image)

The proposed orthogonal polynomials based iris texture feature extraction technique is presented in Figure 1, wherein we design two schemes to:
i. Analyze orthogonal polynomial coefficients to extract the texture region.
ii. Design a texture descriptor to represent the texture present in the iris region.

3.1 Texture Characterization

Consider an \((n \times n)\) iris image region from the eye \(I(x, y)\), where \(x\) and \(y\) are two spatial coordinates:

\[
I(x, y) = g(x, y) + \eta(x, y)
\]

In equation (7), \(g(x, y)\) accounts for the spatial variation owing to texture and \(\eta(x, y)\) is the spatial variation owing to additive noise. In order to measure the spatial variations owing to texture and noise separately, \(I(x, y)\) is represented as shown in equation (8), that follows in terms of a set of uncorrelated basis spatial variations.

\[
[I^*_i] = \sum_{j=0}^{n-1} \sum_{j=0}^{n-1} \beta_{ij} [O^*_i]
\]

where \([I^*_i]\) is \((n \times n)\) gray level image matrix, \([O^*_i]\) accounts for the spatial, model variation and \(\beta_{ij}\) is \((i, j)\)th coefficient of variation. \(\beta_{ij}\) is basically the effect of the variation accounted for by \([O^*_i]\) over the image region \(I(x, y)\). \([O^*_i]\) is selected in such a manner that effects \(\beta_{ij}\) orthogonal to each other. Using the statistical design of experiments paradigm, we consider \(I(x, y)\) to be the yields of the experiment with two factors \(x\) and \(y\) each at \(n\) different levels. Two types of spatial variations are considered. In one, spatial coordinate at a time is varying when the other remains constant. In the other, both the spatial coordinates vary jointly. The orthogonal effects due to the former kind of variation are called main effects, whereas the orthogonal effects due to the latter are called interaction effects. It has been observed experimentally that the spatial variation that causes the interaction effects are owing to micro texture present in the image region \([I^*_i]\). The other spatial variations are owing to noise present in \([I^*_i]\). Hence, the texture is characterized by the interaction effects. This is because, in presence of micro texture the two factors \(x\) and \(y\) do not operate independently rather the effect of one is dependent on different levels of the other. For computing orthogonal effects, the set of orthogonal polynomials has been used. \([O^*_i]\) are \((n \times n)\) polynomial basis operators and \(\beta_{ij}\) are orthogonal effects due to spatial variations of gray levels present in the image region \([I^*_i]\). The spatial variations are modeled by the polynomial basis operators \([O^*_i]\). Various micro textured regions can then be characterized by estimating the orthogonal effects and their mean squares. The proposed methodology for texture detection is as follows:

Let the image under analysis be of size \((image\ width \times image\ height)\) and \([M]\) be the polynomial operator size of \(3 \times 3\) and \([I]\) be a small region of size \(3 \times 3\) extracted from the iris image. The orthogonal effects \(\beta_{ij}\) are computed as

\[
[\beta] = ([M]e^t[M]e^t)[(M][I][M][I])^t
\]

and the mean square variances, \([Z^2]\) corresponding to the orthogonal effects \(\beta_{ij}\) are computed as

\[
[Z^2] = ([M]e^t[M])^t([M][I][M][I])^t
\]

The value \(Z_o = (Z^2)^{1/2}\) is described as the mean squared amplitude response of the operator \([O^*_i]\). The set \(A = \{Z_{i1}, Z_{i2}, Z_{i3}, Z_{i4}\}\) are the set of variances due to the main effects and the set \(B = \{Z_{ij}, Z_{ji}, Z_{ij}, Z_{ji}\}\) are the set of variances due to the interaction effects. In this study, the presence of texture is characterized by proposing the Hartley’s test among variances.

Based on the above computational model with orthogonal polynomials, a statistical test is proposed in the next subsection for separating out the texture features from the unwanted noise components.

3.1.1 A statistical procedure for separation of responses towards noise from the response towards signal (textures)

In the proposed orthogonal polynomials model, let \(\psi_e\) be the set of estimated variances corresponding to the mean squared amplitude responses towards signal and \(\psi_o\) be the set of estimated variances corresponding to the mean squared amplitude responses towards noise. The mean squared error variances are computed as the sum of those estimated variances in \(\psi_e\), which are basically estimates of the same noise variance \(\eta_o^2\). In order to ensure that a set of \(\chi^2\) variates with known degrees of freedom are basically the estimates of the same noise variance, the following statistical procedure is used in this work.

We first compute the divergence among variance, in order to separate out the response from the responses towards noise, without any corrective factor as required in the Bartlett criteria [26]. It is observed that even using the corrective factor the \(D^1\) approximation is not altogether satisfactorily if some of the degrees of freedom, \(v_j\) are 1, 2 or 3. Hence in this work, Hartley’s approximation [27] has been adopted as it is more convenient and accurate. The \(D\) criterion for computing the divergence among variances is given by
where \( V_i \) are the set of variances, \( U_i \) are the degrees of freedom, \( D \) is the total degree of freedom, and \( \overline{V}_{av} \) is the average variance. The divergence values for various significance levels with different degrees of freedom are given by Hartley [27] and a portion of the table is shown in Table 1. It is also proved in [27] that the approximation is sufficiently accurate to allow the degrees of freedom \( \nu \) to drop to 2 and the approximation is still fair if some of the degrees of freedom are as small as 1. In this case, it is noted that a member passing the statistical test implies that it has significant contribution towards micro textures present in the iris image under analysis.

Table 1: Significant divergence (\( D \)) among variances for different degrees of freedom \( k \)

<table>
<thead>
<tr>
<th>Degree of Freedom in denominator</th>
<th>5%</th>
<th>10%</th>
<th>20%</th>
<th>25%</th>
<th>50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>18.51</td>
<td>8.53</td>
<td>3.56</td>
<td>2.59</td>
<td>0.667</td>
</tr>
<tr>
<td>3</td>
<td>10.13</td>
<td>5.54</td>
<td>2.68</td>
<td>2.02</td>
<td>0.585</td>
</tr>
<tr>
<td>4</td>
<td>7.71</td>
<td>4.54</td>
<td>2.35</td>
<td>1.8</td>
<td>0.548</td>
</tr>
</tbody>
</table>

In this case, since each estimated variance is a \( \chi^2 \) \( \sigma^2 \) variate with one degree of freedom, \( U_1 = U_2 = \ldots = U_k = 1 \). If the computed value \( D \) is greater than the tabulated value then the divergence among the variances is significant i.e., they are not estimating the same noise variance. Those estimated variances in \( \psi_e \) for which the computed \( D \) value is not significant are called noise variances.

Finally, the mean square error variance \( \overline{\eta}_0^2 \) is computed as the sum of the estimated noise variances divided by their total degrees of freedom. After computing the error variance \( \overline{\eta}_0^2 \) the significance of the set \( \psi_e \) of estimated variances corresponding to the mean squared amplitude responses towards signal may be measured to select only the significant responses towards signal. Since \( \frac{Z_{ij}^2}{\overline{\eta}_0^2} \) is distributed as the \( F \) distribution [28] with 1 and \( m \) degrees of freedom, where \( m \) be the number of \( Z_{ij}^2 \) taken from \( \psi_e \) to compute the error variance \( \overline{\eta}_0^2 \), the \( F \)-test is conducted with each \( Z_{ij}^2 \in \psi_e \) at the desired level of significance to determine whether this can be accounted for the signal compared to the noise present.

Table 2: \( F \) Distribution values, assuming the numerator has one degree of freedom

<table>
<thead>
<tr>
<th>Values of ( k )</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>5% points</td>
<td>5.99</td>
<td>7.81</td>
<td>9.49</td>
<td>11.07</td>
<td>12.59</td>
</tr>
<tr>
<td>10% points</td>
<td>4.61</td>
<td>6.25</td>
<td>7.78</td>
<td>9.24</td>
<td>10.65</td>
</tr>
<tr>
<td>20% points</td>
<td>3.22</td>
<td>4.64</td>
<td>5.99</td>
<td>7.29</td>
<td>8.56</td>
</tr>
</tbody>
</table>

Actually, the \( F \)-test is conducted to determine whether the null hypothesis that \( Z_{ij}^2 \in \psi_e \) is the estimate of the same error variance \( \frac{\overline{\eta}_0^2}{\overline{\eta}_0^2} \) is unacceptable. The hypothesis is unacceptable if the tabulated value at the desired significance in the \( F \)-distribution table is less than the value computed for \( \frac{Z_{ij}^2}{\overline{\eta}_0^2} \). The portion of the \( F \)-distribution table which has relevance to this work is shown in Table 2.

Having described the statistical design of experiments for low level feature extraction process, the next task is to propose a texture representation based on this model and the same is presented in the next section.

### 3.2 Texture representation

With respect to the presence of texture in the image under analysis, the micro texture regions are represented properly to obtain a better local texture descriptor. A small region \((3 \times 3)\) is considered as a sample for performing the test. All the samples drawn from the image under analysis are included for the test as per the procedure stated in Section 3. The mean square error variance (\( msv \)) is computed as follows

\[
msv = \frac{\sum_{ij} Z_{ij}^2}{|V|}
\]

where \(|V|\) is the cardinality of the set \( V \). Each of the variances in \( \{A + B - V\} \) is divided by the mean square error variance (\( msv \)) for computing the Signal-to-Noise Ratio. The strength of this signal compared to the noise present is measured by conducting the \( F \)-ratio test [29]. The fact that a member passing the test implies that it has significant contribution towards micro texture formation. If the contribution towards the presence of texture is not significant, it shall be assumed that the region may be noise or smooth. In case of significant contribution, the pixel in the original texture image whose zonal position corresponds to the zonal position of the variance term corresponding to the interaction effect is represented as 1; otherwise, it is represented as 0. The positions corresponding to the variance terms in \( V \) which are used for computing \( msv \) are represented as 0s. Then, the outcome of this test for measuring significance towards the micro texture is encoded as a binary string. The equivalent decimal number is obtained next in order to characterise the micro texture. The numerical characterization sequence is used as feature vector for further processing in iris recognition.

### 4 Experimental Results

The proposed feature extraction method for iris recognition has been experimented with all the 756 samples from standard CASIA V1.0 iris database [29]. Sample test images of size \((340 \times 280)\) with pixel values in the range \((0–255)\) are presented in Figure 2. In order to compensate the deformations
in iris texture, the iris region is unwrapped to a rectangular normalization block with a fixed size of \((360 \times 45)\), and is presented in Figure 3 for the original image shown in Figure 2. The normalized iris image is divided into \((n \times n)\) blocks of overlapping regions and the orthogonal polynomials based transformation is applied to extract the transformed coefficients \(\beta_j\) as described in Section 2. The variance \(Z^2\) is computed from the transformed coefficients and the sets such as main effects (Set A), interaction effects (Set B) are obtained as described in Section 3.1. To test whether a given region belongs to a textured region, the Hartley’s criteria are applied for testing the homogeneity among variances as described in Section 3.1.1. If all the mean square variances in \(B\) corresponding to all the interaction effects estimate the same variance, then one variance at a time is eliminated and the remaining variances are considered to check whether they are not estimating the same variances. In the worst case, at least two variances must be present so that they do not estimate the same variance. Otherwise, it is concluded that the region under consideration is not a textured region. That is, if the image region \([I]\) is tested for texture, that is \(B\) to be more divergent and set \(A\) to be more convergent. Then, the image region \([I]\) under consideration may be concluded to be a textured region.

Figure: 2: Original sample test images considered for feature extraction

\[ \begin{array}{c}
\text{(a)} \\
\text{(b)} \\
\text{(c)} \\
\text{(d)} \\
\end{array} \]

Figure: 3: Rectangular normalization of the sample test images shown in Figure 2

Once, texture regions are identified, The F-ratio test is applied as described in Section 3.2. The outcome of the F-ratio test for measuring significance towards the micro texture is encoded as a binary string. The equivalent decimal number is obtained next in order to characterise the micro texture. The numerical characterization sequence is used as feature vector for further processing in iris recognition. The sample result of texture representation for the test image shown in Figure 2 is presented in Figure 4.

During experimentation, the time taken to extract the texture features with the proposed technique is also obtained. The system used for this purpose is Intel (R) Core (TM) i7 CPU 965@3.20GHz system with 4.00GB RAM. The time consumed for the proposed feature extraction for each image is noted and is averaged for all the 756 CASIA iris images. The proposed technique takes an average of 32ms for texture feature extraction with a feature vector of 1800. This time consumption for feature extraction and the feature vector size of the proposed feature extraction technique are presented in Table 3. The performance of the proposed texture feature extraction is analyzed by comparing with other existing techniques. In this proposed work, four existing schemes viz. Daugman’s method [1], Ma’s method [22], Monro’s method [20] and Vatsa’s method [7] are considered. The Daugman’s method [1] uses 2-D Gabor wavelets and results with a feature vector of dimension 2048. The time taken by this method for feature extraction is found to be 334ms. These results are also incorporated in Table 3. In the case of Ma’s method [22], they constructed 1-Dimensional intensity signal and used particular class of wavelet with vector of position sequence of local sharp variations points as features and results with a feature vector of dimension 660. The time taken by this method for feature extraction is found to be 260ms. These results are also incorporated in Table 3. Monro [20] adopted DCT coefficient weighting factor in choosing the most discriminating bits and result with a feature vector of dimension 300. The time taken by this method for feature extraction is found to be 30ms. These results are also incorporated in Table 3. Vatsa [7] used a typical Daugman-style iris code as a texture features and Euler code as topological features and results with a feature vector of dimension 1684 (1680 textural features and 4 topological features). The time taken by this method for feature extraction is found to be 253ms. These results are also incorporated in Table 3.

\[ \begin{array}{c}
4 12 3 4 36 4 3 4 7 2 4 7 12 4 7 8 16 4 14 219 4 11 3 4 \\
8 4 44 36 5 36 44 12 76 36 255 3 36 12 4 36 12 36 72 \\
219 36 32 72 36 12 36 14 36 1 36 8 36 32 8 36 12 \\
36 5 36 44 36 16 36 12 72 36 12 5 36 8 5 36 32 12 36 \\
12 36 72 12 ................................... \\
\end{array} \]

\[ \begin{array}{c}
36 4 3 100 36 44 4 3 32 4 64 12 4 8 4 16 8 4 72 19 1 \\
4 13 64 8 3 44 4 5 36 12 1 76 1 255 3 36 13 24 36 12 \\
36 72 219 1 36 72 5 36 12 36 13 4 72 5 25 8 1 72 9 36 \\
12 72 5 9 44 36 16 36 5 72 36 8 5 36 13 5 13 36 12 36 \\
12 144 72 4 .................................. \\
\end{array} \]
It is evident from Table 3, that the proposed orthogonal polynomials based feature extraction approach requires least amount of computations among all approaches except Monro’s method. It is also evident from Table 3, that the feature vector size of proposed orthogonal polynomials based feature extraction is comparable with Daugman’s method and Vatsa’s method except Ma’s method and Monro’s method.

Table 3: Time taken for feature extraction with the proposed technique and feature vector size comparison with existing techniques

<table>
<thead>
<tr>
<th>Method</th>
<th>Computation time (ms) for Feature Extraction</th>
<th>Feature vector size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed System</td>
<td>32</td>
<td>1800</td>
</tr>
<tr>
<td>Daugman [1]</td>
<td>334</td>
<td>2048</td>
</tr>
<tr>
<td>Ma [24]</td>
<td>260</td>
<td>660</td>
</tr>
<tr>
<td>Monro [22]</td>
<td>30</td>
<td>300</td>
</tr>
<tr>
<td>Vatsa [9]</td>
<td>253</td>
<td>1684</td>
</tr>
</tbody>
</table>

It can be ascertained from Table 3 that the performance improvement, due to the usage of orthogonal polynomials based feature vector, is significant. Hence, it is concluded that extracting the feature in the orthogonal polynomials domain is superior to extracting it in the original image domain. This method avoids that the features extracted from typically noisy regions can corrupt the biometric signature. It is concluded that the proposed iris feature extraction makes iris recognition system more robust than the various feature extraction methods.

5 Conclusion

The orthogonal polynomials based iris feature extraction framework that has been proposed in Section 3 is implemented successfully for detection of textures in 2-D monochrome normalized iris images. The local image regions are represented by the proposed set of orthogonal polynomials and the spatial variation has been measured in terms of orthogonal effects. The orthogonal effects are divided into two subsets, namely, main and interaction effects. The interaction effects where both the spatial coordinates are varying jointly are due to the presence of texture. The main effects where the spatial coordinates are varying independently are due to the presence of Gaussian noise and can be considered as an estimate of the noise variance. The detected micro texture is then represented locally by measuring and combining the significance of the orthogonal effects. The local texture descriptor is computed for normalized iris image and stored as feature vector for further processing. Future work will include feature selection and iris classification strategy.

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