MULTIPLE CLASSIFIER BASED IRIS RECOGNITION SYSTEM

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Abstract: This paper devoted to an iris recognition system (IRS) designed using 2D-Discrete Cosine Transform (DCT) features and Self Organizing Map (SOM) and Radial Basis Function (RBF) which are an Artificial Neural Network (ANN) used as classifier. DCT is used for feature extraction to capture essential details. SOM and RBF are applied for classification with different functional paradigms. With respect to computational time, RBF network is better than SOM. In case of success rate, SOM is more suitable than RBF for Iris recognize classification.

Keywords: Iris, Biometrics, 2D-DCT, Image preprocessing, Self Organizing Maps Neural Networks, Radial Basis Function, Feature Extraction.

I. INTRODUCTION

The distinctiveness associated with the iris of the eye makes an Iris Recognition System (IRS) an important element of a biometric identification mechanism. Figures 1 and 2 show the eye and the iris respectively. The constituents are also shown. The iris of the eye is different for each person. Hence, an IRS based biometric verification system is found to be more effective than conventional approaches [1]. Iris based verification systems have already received attention of researchers all around the world. Some of the relevant literatures are [2], [3]. Here, we propose an IRS designed for biometric verification applications. The IRS is used to establish the identity of specific persons. The developed method for the IRS is configured using 2D-Discrete Cosine Transform (DCT) coefficients used as features, Self Organizing Map (SOM) and Radial basis Function (RBF) which are Artificial Neural Network (ANN)’s designed to serve the purpose of classification after training. Here, 2D- DCT processing is used for feature extraction; RBF and SOM ANN are applied for classification. The system thus developed proves to be effective with a range of inputs. Experimental results show that the proposed system is robust and proves to be suitable for application in verification stages.

The rest of the paper is organized as follows: Section II provides the background principles related to the working of the proposed model. All experimental results and related discussion is provided in Section III. The paper is concluded by summing up the work in Section IV.

In this paper, we compare between Radial Basis Function (RBF) and Self Organizing Map (SOM) for IRS classification. The system is based on the use of DCT coefficients to capture distinctive features from the iris image. These features are then applied to RBF and SOM for classification. A block diagram of the RBF based system is shown in Fig. 3 and a block diagram of the SOM based system is shown in Fig. 4.
The iris images used in this study are obtained from the Sri Sankardeva Nethralaya, Guwahati, Assam, India [4] numbering 60 iris images for 5 persons. For each person, 6 iris images are captured for the left eye and another 6 images for the right eye giving a total of 12 images for each person. The original size of each image is 1200×1600 pixels, with 256 grey levels per pixel.

Figure 3: Block diagram of the RBF based system

Figure 4: Block diagram of the SOM based system

Figure 5: The iris Images

The work presented here is based on the iris images of the right eye only. Figure 5 shows 6 samples iris images for a person's right eye. The left and right irises for a given person are different from each other. The images are next passed through pre-processing.

After pre-processing of image samples, DCT is taken. The DCT of an N×N image, f(x, y) is defined as

\[
f(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \cos \left( \frac{(2x+1)u\pi}{2N} \right) \cos \left( \frac{(2y+1)v\pi}{2N} \right)
\]

The inverse transform is defined by:

\[
f(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} c(u) c(v) \cos \left( \frac{(2x+1)u\pi}{2N} \right) \cos \left( \frac{(2y+1)v\pi}{2N} \right)
\]

where,

\[
c(u) = c(v) = \frac{1}{\sqrt{N}} \text{ for } u, v = 0
\]

\[
c(u) = c(v) = \frac{2}{N} \text{ for } u, v \neq 0
\]

The DCT has been used in many practical applications, especially in signal compression. The strong capability of the DCT to compress energy makes the DCT a good candidate for pattern recognition applications. Coupled with classification techniques such as Vector Quantization (VQ) [5] and ANN, the DCT can constitute an integral part of a successful pattern recognition system. The DCT decomposes a signal into its elementary frequency components. When applied to an M x N image/matrix, the 2D-DCT compresses all the energy/information of the image and concentrates it in a few coefficients located in the upper-left corner of the resulting real-valued M x N DCT / frequency matrix. This is shown in Fig.5 which shows an iris...
image (c) and its DCT transform (d). The transformed image has zero or low-level pixel values except at the top left corner where the intensities are very high. These low-frequency, high intensity coefficients, are therefore, the most important coefficients in the frequency matrix and carry most of the information about the original image.

Two methods are followed to extract features from these low-frequency DCT coefficients. The first method is a square-windowing method that extracts the $L \times L = L^2$ lowest-frequency coefficients in the upper left corner of the DCT matrix, as shown in Fig. 7. This windowing method makes use of the fact that the DCT pushes most of the energy/information of the signal in the dc component and the lower frequency components. The dc coefficient (first harmonic) contains the highest value or most of the energy. The second harmonic has the second highest value and so on.

To illustrate the scanning scheme of the square window, let $a_{mn}$ designate the coefficient in the DCT matrix located in the $m^{th}$ row and $n^{th}$ column. Then a 1×1 window, generates the vector $W_{1,1} = [a_{11}]$. Similarly, a 2×2 window generates the vector $W_{2,2} = [a_{11} \ a_{12} \ a_{21} \ a_{22}]$ and a 3×3 window produces the vector $W_{3,3} = [a_{11} \ a_{12} \ a_{13} \ a_{21} \ a_{22} \ a_{23} \ a_{31} \ a_{32} \ a_{33}]$. This is shown in Figure 6.

The second or alternative method is a zig-zag method, as depicted in Fig. 8. Here, the coefficients are more selectively scanned, depending on their magnitudes. To classify the DCT feature vectors obtained from the DCT coefficients, we apply the SOM which is a subtype of ANN. The SOM is trained using unsupervised learning to produce low dimensional representation of the training samples while preserving the topological properties of the input space. Thus, SOMs are suitable for obtaining reasonable forms which enable visualizing low-dimensional views of high-dimensional data, akin to multidimensional scaling.

The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a one or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion. SOMs learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. They provide a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimensionality reduction and invariance to minor changes in the image sample [6], [7].

Self-organizing maps are a single layer feed forward network where the output syntaxes are arranged in low dimensional (usually 2D or 3D) grid. Each input is connected to all output neurons. Attached to every neuron there is a weight vector with the same dimensionality as the input vectors. The number of input dimensions is usually a lot higher than the output grid dimension.

Again we employ the RBF which is a type of ANN. Typically a RBF network, there are three layers: one input, one hidden and one output layer. The hidden layer uses the Gaussian transfer function instead of the sigmoid function. In RBF networks, one major advantage is that if the number of input variables is not too high, the learning is much faster than other types of networks [7].

### III. EXPERIMENTAL RESULTS AND DISCUSSION

The selection of feature set is critical for the work. The feature set must be of optimal length so that the decision given by the work is satisfactory.

Here, we investigate the optimum number of DCT coefficients for feature extraction which is used with the SOM classifier. The SOM in the optimal structure is configured for classification. The number of DCT coefficients retained for the SOM based classification stage is critical for proper recognition. This is obvious from certain results derived. Figure 9 shows the error rate as a function of the number of DCT coefficients used. It is clear from Figure 9 that as the number of DCT coefficients/features increases, the error rate decreases. We found that with 100 DCT coefficients, the error rate is minimum so we take that...
many number of coefficients for use with the SOM and RBF.

![Figure 9: Percentage error rate Vs number of coefficients.](image)

<table>
<thead>
<tr>
<th>Input image</th>
<th>Original image size (KB)</th>
<th>Compressed Image size (KB)</th>
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<tbody>
<tr>
<td>Image 1</td>
<td>74.5</td>
<td>5.6</td>
</tr>
<tr>
<td>Image 2</td>
<td>47.5</td>
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<tr>
<td>Image 3</td>
<td>73.5</td>
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<tr>
<td>Image 10</td>
<td>69.5</td>
<td>5.9</td>
</tr>
</tbody>
</table>

Table 1: Image Compression using 2D-DCT

The SOM and RBF thus have an input layer of 100 neurons. The DCT method also provides image compression. Table 1 shows that using DCT samples images are compressed between 88 - 92% [8],[9] which helps in reducing correlation between the coefficients and thereby provide the best feature set. Table 2 shows the results generated by varying the number of epochs computational time of RBF is less than SOM. Table 3 shows network accuracy of SOM is higher than RBF.

<table>
<thead>
<tr>
<th>Number of epochs</th>
<th>Computational time of RBF (sec)</th>
<th>Computational time of SOM (sec)</th>
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<td>25</td>
<td>4.35</td>
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<td>3000</td>
<td>1014.45</td>
<td>1158.5</td>
</tr>
</tbody>
</table>

Table 2: Comparison of number of epochs vs. computational time of RBF and SOM

IV. CONCLUSION

In this study, comparison of RBF and SOM network for iris recognize classification with DCT coefficients. Computational time point of view RBF network is better over SOM network and In the success rate consideration SOM network is more suitable than RBF network for Iris recognize classification.

REFERENCES