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Periocular Gender Classification using Global ICA Features for Poor Quality Images

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Abstract

In recent years, the research over emerging trends of biometric has grabbed a lot of attention. Periocular biometric is one such field. Researchers have made attempts to extract computationally intensive local features from high quality periocular images. In contrast, this paper proposes a novel approach of extracting global features from periocular region of poor quality grayscale images for gender classification. Global gender features are extracted using independent component analysis and are evaluated using conventional neural network techniques, and further their performance is compared. All relevant experiments are held on periocular region cropped from FERET face database. The results exhibit promising classification accuracy establishing the fact that the approach can work in fusion with existing facial gender classification systems to help in improving its accuracy.

Keywords: Periocular biometric, Gender Classification, ICA, BPNN, RBFNN, PNN;

1. Introduction

Periocular refers to the region of face at immediate vicinity of the eye. Capturing an eye or face automatically captures the periocular image. This gives the facility of recognizing an individual using the periocular data along with iris data without extra storage or acquisition cost. Moreover periocular features can be used when an iris image does not contain subtle details, which mostly take place due to poor image quality. Periocular biometric also comes into play as a candidate for fusion with face image for better recognition accuracy. Periocular biometric is an emerging trend which got popularity from past one or two year. A review on related work is shown in table 1. Authors in [1] have discussed about classification on 251×251 high quality periocular images whereas the proposed work deals with low quality images.

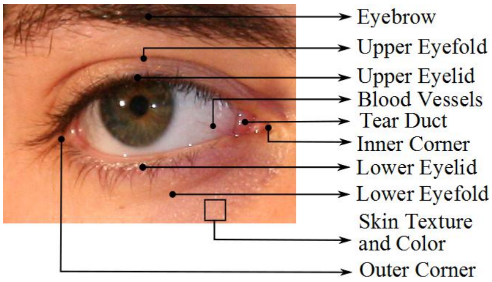

Fig. 1: Important features from a periocular image

2. Related Works

Periocular biometric is an emerging trend which got popularity from past one or two year. Research on periocular biometric is mainly divided into two categories, namely recognition and classification. The first category focus on identification of an individual while second includes the extraction of various features in an attempt to classify an images based on gender, ethnicity or whether the periocular shows a left or right eye. A survey on classification through periocular images are shown in Table 1.

Table 1: Related work on classification through periocular biometric

Author	Classification type	Algorithm	Classifier	Database	Accuracy (%)
Abiantum et al.[2]	Left vs. right eye	Adaboost, Haar, Gabor features	LDA SVM	ICE	89.95%
Bhat et al.[3]	Left vs. right eye	ASM	SVM	ICE, LG	Left eye 91% Right eye 89%
Merkow et al. [4]	Gender	LBP	LDA, SVM, PCA	Downloaded from web	84.9%
Lyle et al.[1]	Gender and ethnicity	LBP	SVM	FRGC	Gender 93% Ethnic 91%

3. Proposed Approach

The major challenge in gender classification is two-fold: A. to find discriminating features (feature extraction), and B. to find an optimum hyperplane for classifying male and female classes. In this paper, a novel approach for gender classification using poor quality grayscale periocular images is proposed. A block diagram of the proposed approach is shown in Fig. 2. Information maximization approach of Independent Component Analysis (ICA) is used to extract global features from periocular images. For separating male and female classes, different classifiers are used and their performance is compared.

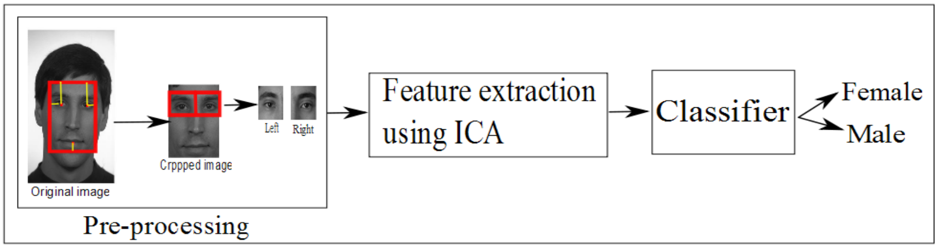

Fig. 2: Proposed model

The following subsections elaborate these issues:

3.1. Feature Extraction using ICA

Face image contains a lot of redundant information within itself. Hence, a technique is required to remove this spurious information. Independent Component Analysis (ICA) is one of such approach [5]. ICA is a computational method for separating a multivariate signal into additive subcomponents. It can be defined as: For the given set of input sample *x*, ICA finds a linear transforms $s = Wx$ such that the components, s is as independent as possible. Here, W is an unknown separating matrix and needs to be determined. There exist several algorithms for determining W like *Jade*, *Information Maximization (infomax)* and *Fast fixed point (fast)* ICA. The scheme proposed in the paper is based on the infomax ICA.

Infomax is a gradient based Infomax is a gradient based neural network and it maximizes information from input to the output network. The information maximization is achieved by maximizing the joint entropy of transformed vector where is a sigmoidal function. The joint entropy is given by $H(y) = -E[\ln f(y)]$ where $f(y)$ is multivariate joint density function of y calculated as $f(y) = \frac{f(x)}{|J_W|}$. $|J_W|$ denotes absolute of Jacobian matrix J_W defined as $J_W = \det\left[\frac{\partial y_i}{\partial x_i}\right]i$. On combining the above equations, $H(y)$ can be written as $H(y) = E[\ln|J_W|] + H(x)$. Maximization of $H(y)$ can be achieved by adapting W and can be achieved using only the first term.

3.2. Classification using ANN

An artificial neural network (ANN) is a mathematical model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation and can be used as a classifier for classifying gender from face images [6].

A. Back Propagation Neural Network (BPNN)

It is a feed forward neural network with back propagation algorithm. The input layer neurons contain face image values that constitutes inputs to the next layer neurons. There may be several such hidden layers. The final layer is the output layer where there are two nodes: one for male and another for female class. A single sweep forward through the network results in the assignment of a value to each output node, and the record is assigned to whichever class's node has the highest value. A back-propagation algorithm is applied to a feed forward multi-layer neural network. Here, the functional signals flows in forward direction and error signals propagate in backward direction. Sigmoidal activation function is chosen for hidden and output layer computational neurons.

B. Radial Basis Function Neural Network (RBFNN)

A radial basis function network is a variant of artificial neural network which uses radial basis function as an activation function. It consists of three layers: input layer, hidden layer and output layer. The input layer represents the input vector space and the output layer is represented as a pattern classes. Thus the whole architecture can be fixed only by determining the middle layer and the weights between the middle and the output layer. The input layer is fully connected with the middle layer. Each neuron in the hidden layer produces an activation based on the associated radial basis function. At last, each neuron in the output layer computes a linear combination of the activations of the hidden units.

The output $y : \Re^n \rightarrow \Re$ of the network is computed as $y_i = \sum_{i=1}^{N} \exp\left(-\frac{\|x - c_i\|}{2\sigma^2} \right)$ where N is the number of neurons in the hidden layer, c_i is the center of neuron *i*, and σ_i is the width of the neuron. These parameters are determined in a manner that optimizes the fit between the output and the data.

C. Probabilistic Neural Network (PNN)

PNN is a network formulation of probability density functions. It is defined as an implementation of Kernel Discriminant Analysis in which the operations are organized into multilayer feed forward neural network. It uses Bayes's rule for classification. The basic operation performed by PNN is an estimation of probability density function of feature vectors of each class from the provided training samples using Gaussian Kernel.

The PNN structure consist of neurons in four different layers as described below:

- Input layer: The number of nodes in input layer corresponds to the dimension of face image where each node consists of pixel values.
- Pattern layer: Each pattern node corresponds to one training example and it gives an estimation of probability density functions for the test image with respect to an individual train image. The PDF for each training node can be calculated as $\frac{1}{\sigma} W\left(\frac{x - x_k}{\sigma} \right)$ where, x is an unknown (test) sample and x_k is the k^{th} training sample, W is the weighting function and σ is the smoothing parameter.
- Summation layer: It represents the PDF for each class i.e. PDF for male and female class which is the average PDFs of male samples and same for PDF for female class also. Thus, summation layer consists of two nodes: First represents the PDF for male class and second node represents PDF for the female class. The estimated PDF becomes

$$g_i(x) = \frac{1}{n_i} \sum_{k=1}^{n_i} e^{-\frac{\|x - x_{ik}\|^2}{2\sigma^2}}$$

- Output layer: The output nodes are two input neurons which produces binary outputs. It uses the classification criteria as $g_i(X) > g_j(X), j \neq i$

4. Experimental Evaluation

Smaller RGB images of the size 384×256 from FERET database [7] are taken for all experiments. Images are converted to gray scale, aligned and then conventional triangularization approach is applied to get rectangular face block of size 293×241. From these face blocks, periocular regions of size 74×88 are extracted by keeping pupil as center. The resulting images are of low quality as they are at gray scale with less resolution. The database is of size 200 consisting 50 faces from each gender with two periocular regions in all. The database also consists of face images of people wearing spectacles. The following subsections discuss the effect of applying different ANN approaches on periocular image based gender classification. Train dataset consists of 140 periocular regions and test dataset consists of 60 periocular regions. There are 139 coefficients corresponding to each face image. Coefficients optimization is a problem for a classifier because more number of coefficients may lead to over training where as less number of coefficients may lead to under training. Thus coefficient optimization is done for each classifier separately. The coefficients are varied in the range of 10, 20, ... , 140. Along with coefficients, classifiers parameters are also optimized which is described in the following subsection.

3.1 Feed forward back propagation neural network

The results obtained from BPFNN are shown in Fig. 3. Fig. 3(a) is the accuracy graph against number of independent components. The success rate of BPNN is 90% at the ICs 10 and 20. Thus the minimum number coefficients for training in the case of BPNN are 10. The convergence characteristics of BPNN at 10 ICs are shown in Fig. 3(b). Learning rate (η) and momentum (α) are the controlling parameters of the BPNN. These two parameters are varied in the range from 0-1 and corresponding results are recorded. The optimized η and α are found as 0.6 and 0.1 respectively.

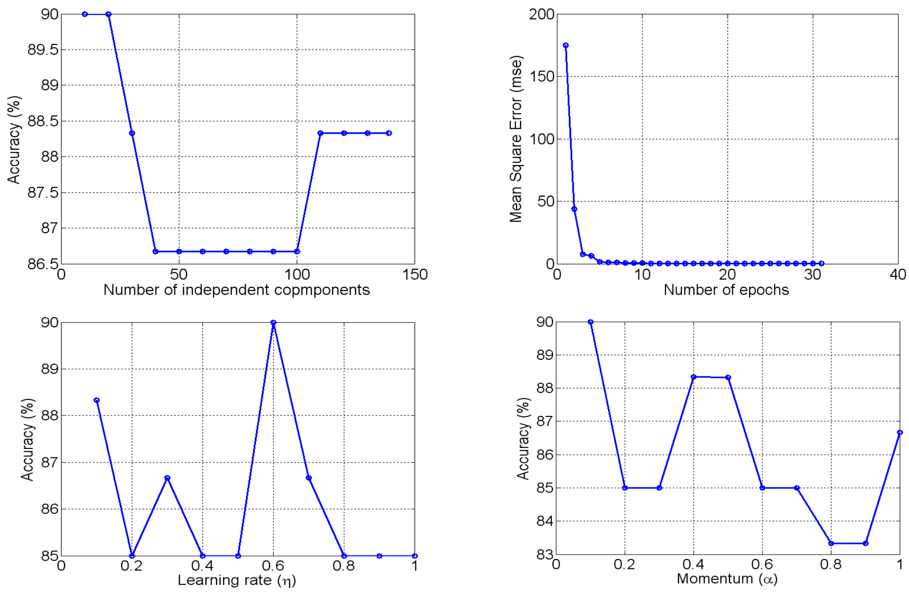

Fig. 4: Results obtained from BPNN: (a) Variation in accuracy for different number of independent components (top left), (b) Mean square error obtained from BPNN at 10 ICs (top right), (c) Variation in accuracy with the learning rate η (bottom left), (d) Nature of momentum (α) (bottom right).

3.2 Radial basis function neural network

The accuracy graph for RBFNN against number of independent components is plotted in Fig. 4(a). The maximum accuracy obtained from RBFNN is 90% at ICs 60 and 100. Thus the minimum number of coefficients required for training in the case of RBFNN is 60. The convergence characteristics of RBFNN at 60 ICs are shown in Fig. 4(b). RBFNN behaves differently with the spread of Radial Basis Function (RBF) and the number of RBFs, which are the learning parameters of RBFNN. The nature of spread and number of RBFs are shown in Fig. 4(c) and (d). The optimized value of spread is obtained as 0.8 and number of RBFs are 90.

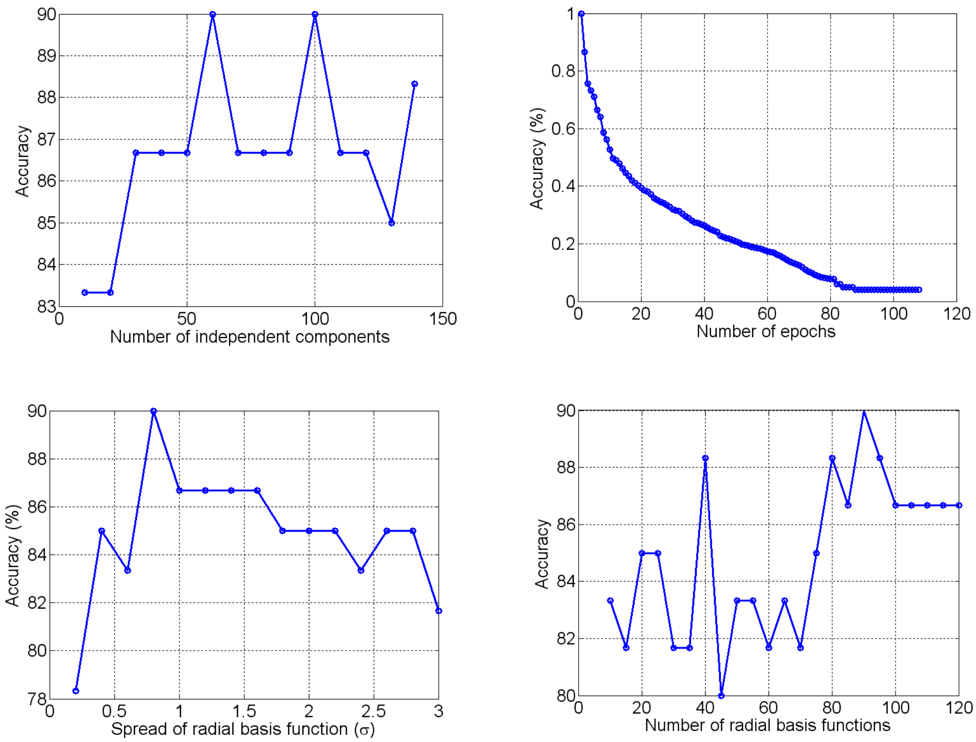

Fig. 4: Results obtained from RBFNN: (a) Variation in accuracy for different number of independent components (top left), (b) Mean square error obtained from RBFNN (top right), (c) Variation in accuracy with the spread of radial basis function (bottom left), (d) Nature of number of radial basis functions (bottom right).

3.3 Probabilistic neural network

. Fig. 4 shows the variation in accuracy of PNN with σ and experiment is also carried out for optimizing the number of independent components. The maximum accuracy obtained from PNN is 85% at ICs = 20, 40, 60, 70, 90, 100 and 130. Thus PNN needs only 20 coefficients to decide that whether a given face image is of male or female. Sigma (σ) is the smoothing parameter for PNN. The nature of PNN at 20 ICs are shown in Fig. 5. The optimized value of σ is found as 0.55.

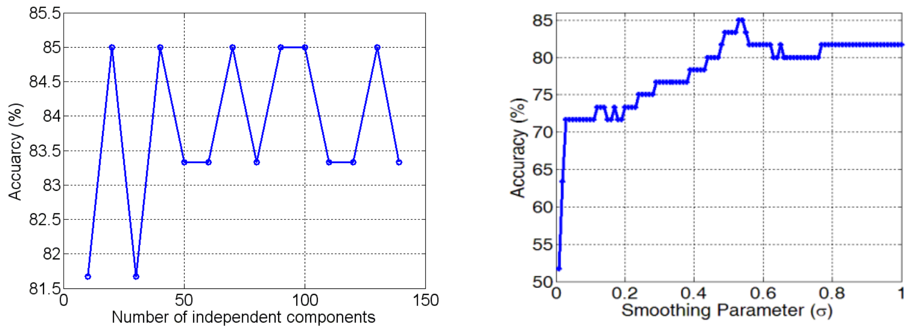

Fig. 5: Results obtained from PNN: (a) Variation in accuracy achieved for different number of independent components (left), (b) Variation in accuracy with smoothing parameter σ at ICs = 20 (right).

4. Conclusions and Future Work

Authors have proposed a method for gender classification using periocular image as a biometric trait in this paper. The significance of the research lies in the fact that periocular biometric is a part of face and hence needs no extra storage. Rather classification is done only using approximately 25% data of whole face image and a high accuracy is obtained. Various classifiers have been used to evaluate the global gender features extracted from ICA. However obtained performance of BPNN and RBFNN are same. Though the experiments are done on low quality images, the accuracy obtained is satisfactory. Further improvement of accuracy can be achieved for high quality images.

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