ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

Gender Classification from Human Iris Texture

Aswathy .C, Dr .Shanavaz K.T, Deepa M.S

Department of Elecrtronics and Communication
College of Engineering Kallooppara

aswathycmohan@gmail.com

shanavazkt@yahoo.co.in

deepams2012@gmail.com

***Abstract*—Rather than finding the identity of a person, this paper deals with the analysis of iris texture to find soft biometric characteristics of a person that is gender. Gender classification system includes image acquisition, Segmentation, normalization, features extraction, and classification. Iris images are downloaded from Gender from iris(ND-GFI)database.Canny edge detection is used to detect the edges of the eye image. Hough Transform is used to separate the iris region from the eye image. Also to localize circular iris and pupil region of eye image, a circular Hough transform is used. Normalization technique convert the polar coordinated into Cartesian coordinates. These Normalized image is used for feature extraction. Feature extraction is performed by convolving the normalized iris region with Gabor filter. Finally for classification support vector machine isused.**

Key words: ND-GFI dataset, Segmentation, Canny edge detection, Circular Hough Transform.

I. INTRODUCTION

Gender clarification from the biometric sample is an active area of soft biometrics.Genarally face images is used for classification purpose.At the same time authentication based on iris pattern is one of the most trending authentication method. A number of authors have found that, by using iris pattern dissimilar from that used for authentication we can classify the gender. In this work the iris code that is used for authentication is given as an input for gender classification.

Currently, all commercial systems use iris code proposed by Daugman for identification. Thus code is already being formed in iris recognition systems and could be used for other purposes. Commercial iris recognition systems naturally do not take face fingerprint images, and so gender-from-iris is the only option for gender info in an iris recognition system. Our approach is the first to classify gender from the same iris- code used to identify people. If the gender is computed before a search for a match to an enrolled iris code, then the average search time can potentially be cut in half. In instances where the person is not recognized, it may be useful to know the gender and other information about people trying to gain entry.

There are a number of reasons why 'gender-from-iris' is an interesting and potentially useful problem.

One possible use arises in searching an enrolled database for a match. if the gender of the sample can be determined, then it can be used to order the search and reduce the average search time.
Another possible use arises in social settings where it may be useful to screen entry to some area based on gender, but without recording identity. Gender classification is also important for demographic information collection, marketing research, and real time electronic marketing. For example, displays at retail stores could offer products according to the person's gender. Another possible use is that in high-security scenarios, there may be value to knowing the gender of the persons who attempt entry but are not recognized as any of the enrolled persons. And, at a basic science level, it is of value to more fully understand what information about a person can be extracted from analysis of their iris texture.

Thomas et al.[9] were the first to explore gender-from- iris problem. They used a set of over 50,000 left-iris images, and performed several different experiments. They segmented the iris region, created a normalized iris image, and then created a log-Gabor filtered version of the normalized image. In addition to the log-Gabor texture features, they used seven geometric features of the pupil and iris. They developed a random subspace ensemble of decision trees to predict gender based on the iris texture and the geometric features, and reported accuracy close to 80% in certain circumstances.

Lagree et al and Bowyer [10] computed texture features separately for eight five-pixel horizontal bands, running from the pupil-iris boundary out to the iris-sclera boundary, and ten twenty-four-pixel vertical bands from a 40×240 image. The normalized image is not processed by the log-Gabor filters that are used to create the iris code that is

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

used for identity recognition purposes. Also, this work does not use any geometric features. Classifiers are developed to predict gender and ethnicity based on the texture features computed from the normalized iris image.

Bansal et al.[5] used a statistical feature extraction technique based on correlation between adjacent pixels, that was combined with a 2D wavelet tree based on feature extraction techniques to extract significant features from the iris image.This approach yielded an accuracy of 83.06% for gender classification. However, the database used in this experiment was small (300 images, and without person- disjoint training) compared to other studies. SVM based gender classification model that combines statistical features with 2-*D* DWT based features has been proposed and implemented in this work.

Tapia et al. [3] explored using different implementations of Local Binary Patterns (LBP) from the normalized iris image masked for iris region occlusion. They found that Uniform LBP with concatenated histograms significantly improved accuracy of gender prediction relative to using the whole iris image. Although the results using

1,500 images were intended to be computed on the basis of a person disjoint training and testing division of the dataset, this was not actually achieved due to the dataset having multiple images for some subjects.

None of the previous gender-from-iris work has attempted to predict gender from the same binary iris code that is computed for recognizing/verifying identity. The various approaches have each computed their own different type of texture feature from the iris image or a Gabor-filtered version of this image.

II. Proposed System

Iris Image acquisition, segmentation, normalization, feature extraction and classification are the different stages in gender classification. The Architecture of gender classification is shown in Fig.1

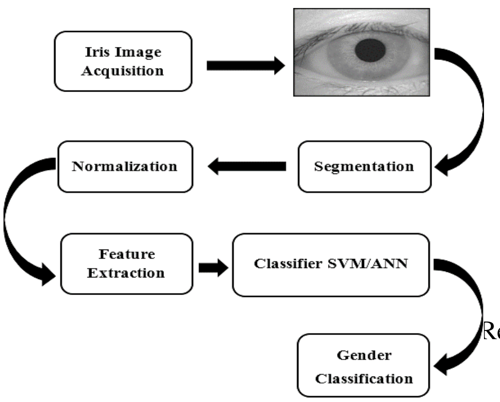


Fig.1 Block diagram

A. *FeatureExtraction*

The iris feature extraction process involves the following steps. First, the iris sensor acquires a near-infrared image of the eye. Then the iris region is segmented, after that it transformed into a fixed-size rectangular ’unwrapped’ iris image. This enables creating a fixed-size iris code that is simply compared to other codes.

Image acquisition

Infrared camera should be used for taking good quality images with high resolution and low illumination,. For the purposes of implementing and testing application Gender from iris (ND-GFI)database is used. The first task is to implement the functionality of loading images into the application from this database.

Gender from iris (ND-GFI) dataset

This is a set of images acquired using an LG 4000 sensor. It is divided into left and right images, and it includes the gender of each subject. In the basic part of the dataset there is one image per left and right iris of each of 750 males and 750 females, for 3000 total images.

Segmentation

In the second stage of this system the iris region is separated. The iris region viewed as two circles, sclera/iris boundary and pupil/iris boundary. The eyelashes and eyelids cover the upper and lower parts of the iris region. Also, specular reflections occur within the iris region degrading the iris pattern. Segmentation is the method used to separate and eliminate these artifacts as well as finding the circular iris region.

Canny edge detection

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1.Apply Gaussian filter to smooth the image in order to remove the noise

2.Find the intensity gradients of the image

3. Apply non-maximum suppression to get ridof spurious response to edge detection
4. Apply double threshold to determine potential edges
5. Track edges.

Circular Hough transform

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

The Circular Hough transform is generally used for determining the parameters of circular objects present in an image. Here the radius and center coordinates of the pupil and iris regions are finding with circular Hough transform.

In a two-dimensional space, a circle can be described by:

$$A^2+B^2-r^2=0 \qquad (1)$$

where (A,B) is the center of the circle, and r is the radius.

If a 2D point (x,y) is fixed, then the parameters can be found according to above equation.The parameter space would be three dimensional,(a,b,r).And all the parameters that satisfy (x, y) would lie on the surface of an inverted right- angled cone whose apex is at(x, y,0).Inthe3Dspace,thecircleparameters can be identified by the intersection of many conic surfaces that are defined by points on the 2D circle. This process can be divided into two stages.The first stage is fixing radius then find the optimal center of circles in a 2D parameter space. The second stage is to find the optimal radius in a one dimensional parameter space.

If the radius is fixed, then the parameter space would be reduced to 2D (the position of the circle center). For each point (x, y) on the original circle, it can define a circle centered at (x, y) with radius R.The intersection point of all such circles in the parameter space would be corresponding to the center point of the original circle.

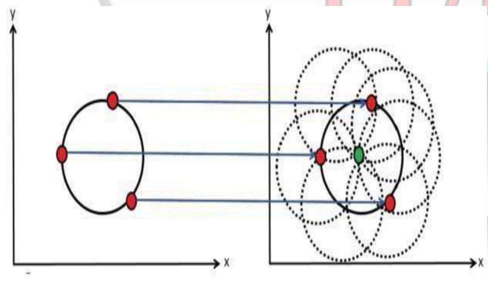


Fig 2: Circular Hough transform

Normalization

Once the iris region is successfully segmented from an eye image, the next stage is to transform the iris region so that it has fixed dimensions in order to allow comparisons. The dimensional inconsistencies between eye images are mainly due to the stretching of the iris caused by pupildilation from varying levels of illumination.Other sources of inconsistency include, varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket.

The homogenous rubber sheet model devised by Daugman remaps each point within the iris region to a pair of polar coordinates (*r*,θ) where *r* is on the interval [0,1] and θ is angle [0,2π].

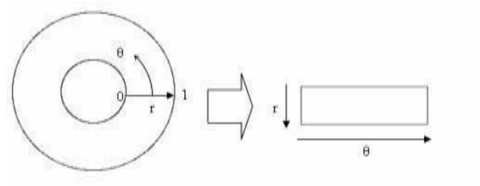


Fig 3 : Normalized iris

B. *Feature Coding*

The 2D normalized pattern is broken up into a number of 1D signals, and then these 1D signals are convolved with 1D Gabor filters with the following parameters:the wavelength(in pixels) of the log Gabor filter was 18 pixels and the ratio (σ/ $f0$) of the log Gabor filter was 0.5, where σ denotes bandwidth and $f0$ denotes the central frequency.The output of the Gabor filters is transformed into the binary iris code by quantizing the phase information into four levels, representing the four quadrants in the complex plane.

C. *Classification*

The dataset is divided into train-set and test-set in the ratio of 7:3, i.e. 70% data of the whole dataset is used for training our classifier, rest 30% is used for the testing process. The data from the train-set is used to create a classification model with a linear multiclass SVM.The same model is used to predict the unknown class labels of the test-set.

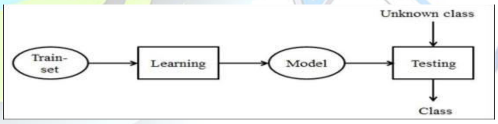
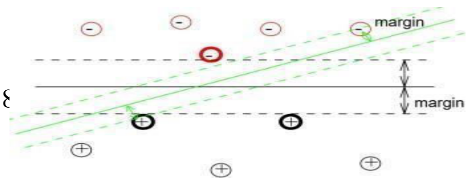


Fig 4:Classification approach

Support vector machines

An SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Svm can be used for both classification and regression challenges.



ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

Fig 5:Hyperplane selection in SVM

III. RESULTS AND DISCUSSION

The database ND-GFI is used to test the proposed method. It consists of equal number of male and female images.

The performance of the algorithm in classification is quantified using the following definitions: True positive (TP):Male is classified as male, False negative (FN): Male is classified as female, False positive (FP):Female classified as male, True negative (TN): Female is detected as female

Total 100 images were tested, out of which 50were male images 50 were female images Out of the 50 male and female images, 42 classified correctly as male and 40 as female respectively.

The accuracy, precision and recall for proposed method are defined as below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Two characteristics *precision* and *recall* are used to evaluate the performance of the proposed scheme. *Precision* is the probability that the detected regions are relevant. *Recall* is the probability that the relevant regions are detected. In general, a higher *precision* and a higher *recall* indicate superior performance.

TABLE I
PERFORMANCE OF SVM CLASSIFIER

Total test images =100			
		True	False
Female (50)	Left(25)	F=21	M=4
	Right(25)	F=19	M=6
Male (50)	Left(25)	M=20	F=5
	Right(25)	M=22	F=3

Table I shows the experimental results of the proposed method using SVM.

The performance of the algorithm in classification is quantified using the following definitions: True positive (TP): negative (FN): False positive (FP):True negative (TN):

TABLE II.
PERFORMANCE COMPARISON USING SVM AND ANN CLASSIFIER

Classifier	Performance (%)		
	Accuracy	Precision	Recall
SVM	82	83.33	80
ANN	78	80.4	75

From Table II, it can be observed that SVM classifier determines better classification result than ANN classifier. It can be easily observed that the recall of the SVM classifier is much better than that of the ANN classifier.

IV. CONCLUSION

It is very challenging to classify gender from iris. In this, a nove lgender classification algorithm is proposed. The circular hough transform algorithm is used to segment the iris region. Then normalization is performed. Gabor filter is applied to each normalized image for coding the significant features. Lastly, classification using support vector machine and the artificial neural networks is performed. The proposed method is evaluated on a number of original and images. Experimental results showed that the method is quite attractive with an accuracy of 82% and with a smallest false negative rate, which means the proposed scheme is good at classification.

The number of images used for the work is small as compared to the total number of images in database. So more number of images can be used for processing. The computation time can be further reduced by using any feature selection methods such as mutual information.Similar to gender the ethnicity of people can also be found, also any other classification approach can be used other than support vector machine.

ACKNOWLEDGMENTS

We would like to thank the principal Dr. Deepa J, College of Engineering, Kallooppara, for her valuable support. Our special thanks to Dr Shanavaz K T, the HOD of ECE and coordinators for their support and assistance.

REFERENCES

[1] Juan E. Tapia, Claudio A. Perez "*Gender Classification from the Same Iris Code Used for Recognition*" ieee

transactions on information forensics and security, vol. 11, no. 8, August2016

[2] JohnDaugman*" Information Theory and the IrisCode*" ieee transactions on information forensics and security, vol.11, no. 2, february2016

[3] Juan E. Tapia, Claudio A. Perez "Gender Classification Based on Fusion of Different Spatial Scale Features Selected by Mutual Information From Histogram of LBP, Intensity, and Shape" ieee transactions on information forensics and security, vol. 8, no. 3, march2013

[4] Pablo A. Estévez, Michel Tesmer, Claudio A. Perez, and Jacek M. Zurada, "Normalized Mutual Information Feature Selection" ieee transactions on neural networks, vol. 20, no. 2, february2009

[5] Bansal, R. Agarwal, and R. K. Sharma, "SVM based gender classifi- cation using iris images," FourthInternational Conference on Computational Intelligence and Communication Networks (CICN),, pp. 425–429, Nov 2012.

[6] Giteh.r., mahenderc.n. "*iris code generation andrecognition"*International Journal of Machine Intelligence 2011

[7] Debnath Bhattacharyya, Poulami Das "*IRIS Texture Analysis and Feature Extraction for Biometric Pattern Recognition"* International Journal of Database Theory andApplication

[8] AalaaAlbadarneh, IsraaAlbadarneh "*Iris Recognition System for Secure Authentication Based on Texture and Shape Features"* 2015 IEEE Jordan ConferenceonAppliedElectricalEngineeringandComputingTechnologies

[9]Thomas, N. Chawla, K. Bowyer, and P. Flynn, "*Learning to predict gender from iris images*," in First IEEE International Conference on Biometrics: Theory, Applications, and Systems, BTAS 2007., pp. 1–5, Sept 2007.

[10] S. Lagree and K. Bowyer, "Predicting ethnicity and gender from iris texture," in IEEE International Conference on Technologies for Homeland Security(HST),,pp.440–445,Nov2011.

[11] John Daugman, "*How Iris Recognition Works"* IEEE transactions on circuits and systems for video technology vol. 14, no. 1, february2004.

