Iris Recognition for Biometric Identification and Verification

Suhas Kamath Ammembal, *Member*, *IEEE*

***Abstract*— The work done in this project mainly deals with the use of iris as an efficient biometric feature for identification and verification. It is based on images of the eye acquired wherein the region or spot of interest is iris. Some of the most widely used biometric features for identification purposes include fingerprints, iris, face, retina, voice, palm veins etc. Out of the many available biometric features in the human body, iris is considered one of the most stable and commonly used one. The main reason that iris is so commonly used is because of the stable nature of iris as a biometric. Some other reasons to use iris as a biometric include ease of use and accuracy. Biometrics make use of the uniqueness of some of the physical features and behaviors in human bodies to serve as digital identifiers that computers can interpret and store in database and utilize whenever necessary. Biometrics have a wide range of applications such as national ID, employee identification, law enforcement, banking and financial services, healthcare services etc.**

The project implements iris recognition in 7 phases which include iris localization, normalization, image enhancement, feature extraction, iris matching, performance evaluation and iris recognition.

I. Introduction

THE word biometric is derived from the two Greek words 'bio' which means life and 'metrics' which means to measure. The concept of using biometrics for identification dates to several centuries. Its presence is more known nowadays because of its automation. The automation of biometric identification is made possible only because of very high computing powers of today's machines and advancements in science. Face is the oldest biometric feature used for identification by people. People in the early civilizations used face as a biometric feature to distinguish. The proof of using handprints as a biometric were found in the paintings and murals in the Babylonian civilizations. These paintings were dated as old as 500 BC. Joao de Barros, a Spanish scholar in his writing on the Chinese civilization mentions the use of fingerprints and footprints by Chinese traders as a mark of identification. In the 17th century, Mayer was the first to declare friction ridge skin as a unique human feature. As time passed, by early 19th century the population had become large enough and a system was needed to identify individuals. The development of first robust system for indexing fingerprints is credited to Azizul Haque for Edward Henry. This system was developed in Bengal, India. In 1963, Dr Hughes published his paper on fingerprint automation. In 1986, a patent was awarded to Dr Leonard Flom and Aran Safir stating that iris could be used as a biometric feature. The year 1994 was a breakthrough year for the use of iris as a biometric. This year, Dr John Daughman announced the first iris recognition algorithm. The algorithm proposed by Dr John Daughman was modified in the subsequent years and today the algorithm stands as a robust one with lot of advancements coming in the last decade or so. Wilde, Dorairaj, and Chandramurthy followed the footsteps and the legacy of Dr John Daughman and worked on the betterment of the algorithm. It is because of their combined efforts that iris as a biometric is accepted in most parts of the world across many applications.

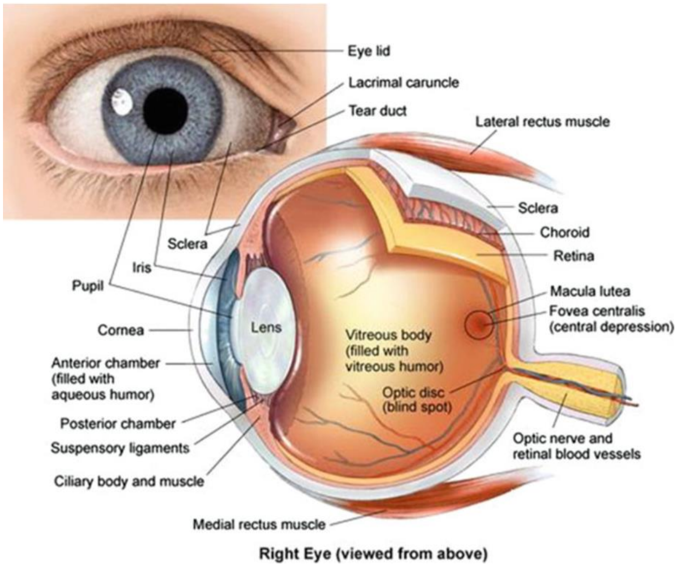

Fig 1.1 Structure of a human eye

Biometrics utilize some of the most unique features in the human body for identification and verification. As discussed earlier, iris is one of the most accurate and easily available biometric features in the human body. The iris is a muscular tissue in the eye responsible for controlling the diameter and size of the pupil. It controls the amount of light falling on the retina and defines the color of the eye. The iris is divided into two regions namely the pupillary zone and the ciliary zone. The pupillary zone is the inner region which shares the boundary with the pupil. The ciliary zone is the remaining portion of the iris that extends to its origin. The collarette is the region that separates the pupillary region from the ciliary region of the iris. As mentioned earlier the color of the eye is because of the pigments in the iris. These pigments are black, brown, blue, green or gray.

The structure and pattern of the iris generally remains stable and consistent throughout the human life span. This is the reason why iris is the preferred biometric feature used for identification and verification. Biometric recognition systems illuminate the iris with infrared radiations to extract the unique patterns. The scanners then filter out the unnecessary obstructions like the eyelids, eyelashes and specular reflections. The filtered image finally contains only iris as the region of interest. After filtering and obtaining the iris, the bit pattern that encodes the iris is analyzed and extracted. The bit pattern extracted is digitized and stored in the database. According to a study at the Carnegie Mellon University, iris recognition systems collect about 240 to 250 features and the combination of them is unique to each human eye. The process of iris recognition can be divided into 4 major parts which include iris segmentation, iris normalization, feature extraction and iris matching.

II. Literature Survey

I have spent substantial amount of time in learning the requirements and importance of biometric features in identification and verification of individuals. In the last 30 years many papers regarding iris recognition have been published by various researchers and scholars. Among the many papers published over the years, I have surveyed 10 papers which provided me the base to start my project.

Daugman, who is considered the father of iris recognition systems, presented his idea in 1993 for the first time. His idea forms the basis for most systems developed since then. In 1997, Wilde tried a different approach and used circular Hough transforms for image segmentation. This method though more complex proved to be more efficient than its predecessor. In 2004, Daugman suggested an improvement to his earlier work. This new model considered the noise disturbances present in the captured eye images. The new Daugman model was successfully able to identify eye occlusions. In 2005, Dorairaj developed an algorithm to process off-angle eye images using the PCA encoding technique. In 2009, Chandramurthy proposed an efficient technique to identify fake images using Wavelet Packet transforms followed by radial basis kernel function of SVM classifiers. In 2010, Hussain proposed a technique to extract features from the rectangular iris codes in the Eigen space domains. In 2011, Farouk proposed a system based on circular Hough transform and Gabor wavelets to decompose the texture information. The proposed system used elastic graph matching to determine the similarity and dissimilarity between any two iris codes. Over the last decade, more researchers have focused on better image acquisitions, data preparation. image segmentation and classification.

III. Project Implementation

As mentioned earlier this project can be split into 4 major stages. The implementation of each of the four stages is done in python. The project uses CASIA and multimedia university (MMU1) data sets for training the model. The data set consists of grayscale images of the eye of random people from different parts of the world.

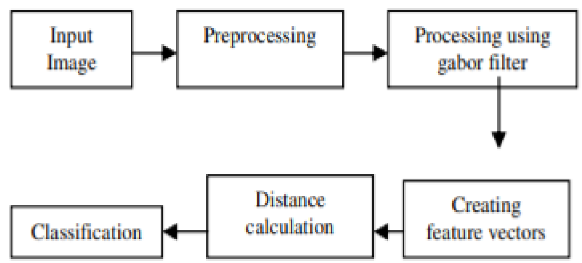

Fig 2.1 Flow chart depicting the procedure undertaken in the project

The dataset includes sample images from different genders and age groups. It is very important to have a diverse data set as most of the exceptions can be handled. The model is trained with over 400 images and then tested with the test set.

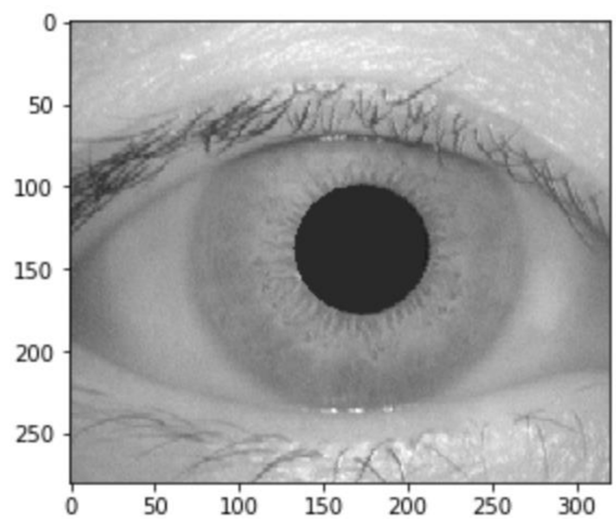

Fig 2.2 Grayscale image of the eye from CASIA

Fig 2.2 shows the grayscale image of the eye from the CASIA eye image dataset. The dark region is the pupil and surrounding it is the iris with 240 features.

A. *Iris Segmentation*

The first stage is the iris segmentation. In this stage, the main task is to isolate the iris from the acquired image of the eye. The input to this stage of the algorithm is a grayscale image of an eye from the dataset. Image localization is done to remove out the obstructions such as eyelids, eyelashes, dust, specular discrepancies etc. The output image finally comprises of the iris only.

Image localization is performed using a bilateral filter that removes various noises from the image using the image blurring technique. The next step is to estimate the approximate center of the pupil. The estimated pupil center is used to binarize the 160 X 160 co-ordinate space around it. After this, we find the dark region in the co-ordinate space derived from the previous step. The dark region gives us the accurate pupil center. The resultant image now is masked from all possible distractions and obstructions due to external factors. The next step involves performing the Canny edge detection on the resultant image from the previous step. The Canny edge detection helps us to get some edges along the boundary of the pupil. The next step is applying the Hough transform to the Canny edged image. We apply the Hough transform in order to detect all the circles in the image. The Hough circle whose center is the closest to the pupil center is finalized. The outer boundary of the circle is drawn by adding a constant (between 50 and 55) to the radius of the Hough circle derived from the previous step.

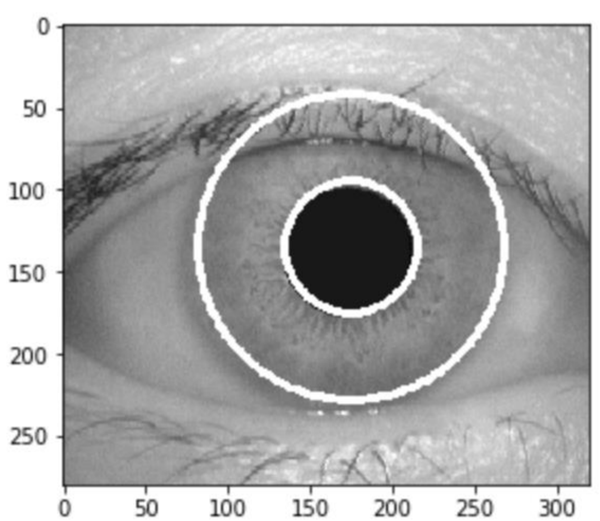

Fig 2.3 Grayscale image of the eye after iris localization

The Fig 2.3 shows the grayscale image of the eye after first stage of iris localization. The 'boundary' list in the project stores all the images with the inner and outer circular boundaries drawn on the images, the 'center' list in the project stores the center of the circles stored in the 'boundary list.

B. *Image Normalization*

Image normalization is a technique in which the cartesian co-ordinates are converted into polar co-ordinates using the image registration technique. This process in scientific terms is known as iris unwrapping. The iris normalization stage of the algorithm accounts for variations in sizes of the pupil and illumination of the original image. In this project we first sequentially load the boundary list and create an empty list to dedicate space to store all the normalized images. To convert polar co-ordinates from their cartesian form, we need to concentrate only on the region of the image between the boundaries.

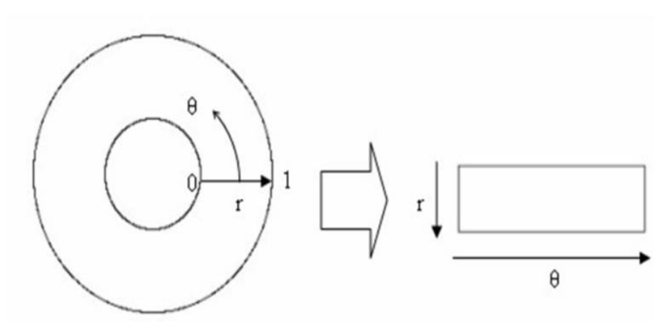

Fig 2.4 Diagram to show polar to cartesian conversion

We then define an iterative loop over an equally spaced interval to convert cartesian to polar co-ordinates. We use the simple formula x = rcosΘ and y=rsinΘ where x and y are cartesian co-ordinates and r is the radius of the circle and Θ is the angle subtended at the center by the arc. After this, we resize the image to a 64 X 512 pixel resolution.

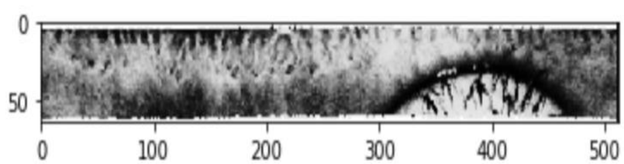

Fig 2.5 Enhanced and Normalized 64 X 512 grayscale image

The next step involves image enhancement using the histogram equalizer to increase the contrast ratio and thus provide us with a better-quality image before feature extraction.

C. Feature Extraction

The third stage of the algorithm is the feature extraction. In this project, the feature extraction is done using 2D Gabor filters. A large number of banks of Gabor filters are applied on the normalized images by varying the orientation angles and the frequencies of the filters. In our project, we use the in-built 2D Gabor filter function provided by the Scikit. The results obtained after applying each of the Gabor filters are evaluated and compared. The 2D Gabor filter is given by:

$$G(x, y; \theta, f) = \exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\delta_x^2} + \frac{y'^2}{\delta_y^2}\right]\right\}\cos(2\pi f x')$$

$$x' = x\cos\theta + y\sin\theta$$

$$y' = y\cos\theta - x\sin\theta$$

In the Gabor filter equation above, δx and δy represent the spatial size of the filter, θ represents the orientation angle, f represents the frequency of the filter.

Fig 2.6 Real and Imaginary parts of the feature vectors

When an input image is convolved with a bank of Gabor filters, the output obtained is an equal number of real and imaginary feature vectors. The bank of Gabor filters is applied to all the images in the dataset. In this project we use the Scikit function 'gabor' to apply the Gabor filter on the normalized image. We then use the scikit function 'spatial' to create an 8 X 8 block which runs over the normalized image to extract features.

D. Iris Matching

In this project, we use hamming distance as the classifier to compare the extracted iris features in the previous step. The resultant feature vectors obtained from the Gabor filters are converted to a binary form and compared using the Hamming distance. The hamming distance is given by:

$$HD = \frac{1}{N}\sum_{j=1}^{N} X_j (XOR) Y_j$$

Here, X and Y are the binary form of the feature vectors obtained from the previous stage. The hamming distance is calculated by taking the exclusive OR between X and Y for all the bits and dividing by the number of bits N. In the model we match our training and testing feature vectors. Here, we use the in-built 'hamming' function from Scikit to calculate the hamming distance. We match the feature vectors from the test image against each one of the training set images. We calculate the L1, L2 and cosine distances for every test image against all the images from the training set. The minimum of the 3 values is taken as the matched index and stored in the list. If the match distance for the image is correct, we add the image to the 'match' list, otherwise we add it to the 'no-match' list. In this stage, we also calculate the Receiver operating Characteristic (ROC) curve and evaluate the accuracy for the model. The accuracy of the model is given by the ratio of correctly identified images to the total number of test images.

IV. Experiment and Results

This section contains the experiments done and the results obtained from those experiments.

The experiment mainly involves the following steps:

1. Reading all the images and running iris localization algorithm on them.
2. Run normalization and image enhancement algorithms on the localized images.
3. Run the feature extraction algorithm on the normalized and enhanced images obtained from the previous step.
4. The above steps are performed on both training as well as the test data.
5. Run the iris matching algorithm on the feature vectors and evaluate the performance.
6. Calculate the ROC and evaluate the accuracy for the algorithm.
7. Plot the ROC curve for FMR vs FNMR with threshold increasing constantly.

The results were recorded for the experiments done. One of results was to obtain the relation between accuracy or correct recognition results and feature vector dimension. Other results included determining the ROC curve and measuring false positive and false negative results for the algorithm. The false positives are termed as FMR and FNMR is considered as false negative.

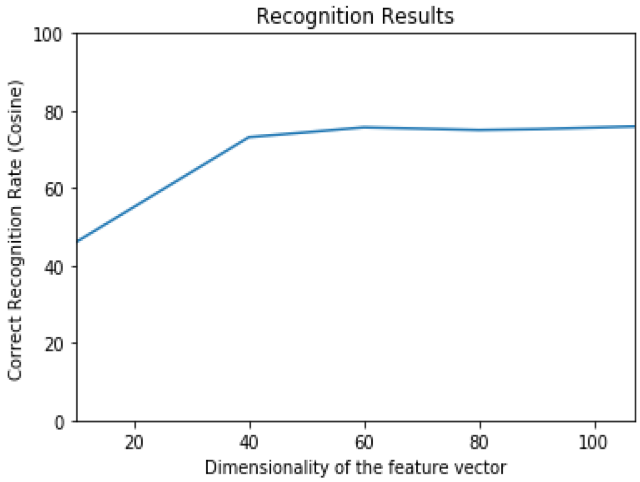

Fig 2.7 Recognition results using features of different dimensions

Fig 2.7 shows the graph obtained for recognition results against feature vector dimensions. The graph suggests that the accuracy or the recognition rate increased linearly up to 40 dimensions. The recognition rate then remained constant at about 75 percent even when the experiments were extended to 100-dimension feature vectors.

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Recognition results using Different Similarity Measures :

Similarity Measure                       L1
CRR for Original Feature Set        60.8796
CRR for Reduced Feature Set (107)   66.2037
Name: 0, dtype: object

Similarity Measure                       L2
CRR for Original Feature Set        54.3981
CRR for Reduced Feature Set (107)   73.6111
Name: 1, dtype: object

Similarity Measure                  Cosine Distance
CRR for Original Feature Set                54.3981
CRR for Reduced Feature Set (107)           75.9259
Name: 2, dtype: object
```

Fig 2.8 Recognition results using different similarity measures

Fig 2.8 shows the recognition results using different similarity measures. In our model, we use 3 distances L1, L2 and cosine distances to classify the iris during the iris matching process. The recognition results for the 107-feature set is about 75 percent. Considering the complexity of the algorithm, the recognition results are pretty good.

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ROC Measures :

Threshold    0.400000
FMR          0.021739
FNMR         0.700000
Name: 0, dtype: float64

Threshold    0.500000
FMR          0.037634
FNMR         0.605691
Name: 1, dtype: float64

Threshold    0.600000
FMR          0.130303
FNMR         0.401961
Name: 2, dtype: float64
```

Fig 2.9 ROC measures for different thresholds

Fig 2. shows the ROC measures calculated for various thresholds of 0.4, 0.5 and 0.6. Here, False Match Rate (FMR) is given by the ratio of number of images in the ‘match’ list correctly recognized to the total number of images in the match list. FMR is also known as the false positive ratio. False Non-Match Rate (FNMR) is given by the ratio of number of images in the ‘no match’ list to the total number of images in the ‘no match list’. From the results obtained, we can infer that the FMR increases and the FNMR decreases as the threshold is increased.

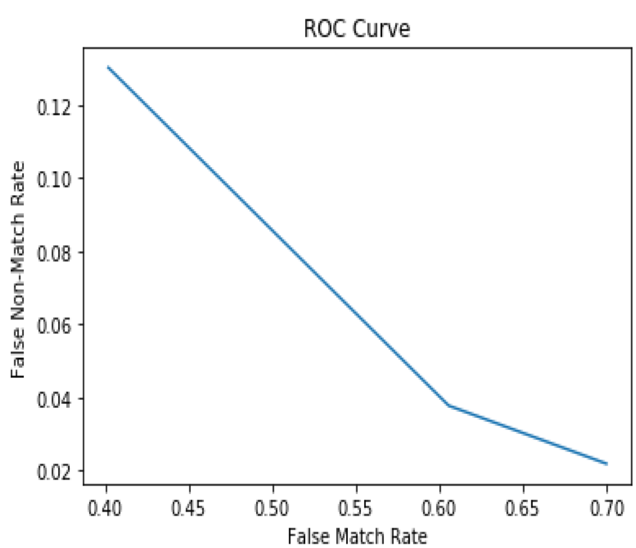

Fig 2.10 ROC curve

Fig 2.10 shows the ROC curve for False Non-Match rate against the False Match Rate. As the threshold is increased, the FNMR decreases and FMR increases.

V. Conclusion

The use of iris as a biometric identifier is quite successful as of today. Though the algorithms used are very complex and need thorough understanding of the subject, the extreme computing powers of present generation computers make the implementation possible. The iris a stable tissue, though there have been cases where the structure of the iris is subject to mutation. This raises small doubts in the brains of the researchers developing algorithms for using iris as a biometric feature in identification and verification. However, as our experimental results for the algorithm suggest, we have a very accurate model with slightly more than 75 percent accuracy for human iris recognition. The accuracy of the model can be improved by using more complex image pre-processing algorithms involving Fourier transforms. The accuracy of the system can be increased at least by 5 to 10 percent by using better image pre-processing techniques. Orientation of the image and its illumination also effect the accuracy of the model.

Acknowledgment

I would like to thank professor Dapeng Wu for giving me an opportunity to work on this interesting project. There was a huge learning curve for me in this project and completing it would not have been possible without the guidance of Dr John Daughman's papers and other references.

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