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Feature Level Fusion of Iris and Sclera using Entropy Based CNN Features to Improve the Performance of Biometric Authentication

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ABSTRACT

Today biometric system are commonly used for person authentication based on physical and behavioral biometric modalities like iris, face, finger prints, ear, sclera, DNA, voice, signature, etc. Instead of using standalone biometric system, multimodal biometric systems are secure and provide more accurate results for person identification and verification. This paper describes the multimodal eye biometric system where iris and sclera features are extracted using CNN based on entropy values to perform the accurate automatic segmentation. Feature level fusion is performed using color and texture characteristics of iris and pupil with Y-shaped sclera characteristics from eye image based on support value. Unconstrained color eye image database UBIRIS.v2 and MMU are used for experimentation and testing on MATLAB platform. The proposed eye biometric system outperform in case of segmentation and recognition accuracy. Segmentation accuracy 97.8% for iris, 98.1% for sclera and 99.4% for pupil is achieved for UBIRIS.v2 database. Recognition accuracy is 97.99% for unconstrained eye image UBIRIS.v2 and 93.33% for NIR image database MMU.

Key words: entropy value, Multimodal, support value, unimodal.

1. INTRODUCTION

Traditional human identification systems are based on password, PIN, cards, etc. which are not reliable because it can be forgotten, lost or stolen [1]. Therefore there is demand for more secure authentication system which uses unique and persistent characteristics of person that cannot be forgotten easily [2]. Biometric systems are classified as unimodal/standalone and multimodal biometric system. Unimodal biometric system uses single biometric modality such as iris, face, fingerprint, sclera, voice, signature etc. for person identification. Accuracy of unimodal biometric system is reduced because of the challenges such as noisy data, non universality, inter-intra class variation, spoofing attacks. These challenges are overcome by multimodal biometric system in which two or more different types of characteristics of either same biometric trait or features from different biometric trait are combined together to provide more accurate and reliable recognition results [3]-[5].

From literature among all the biometric iris provide the higher authentication accuracy. But success of iris recognition is depends upon the image acquisition and user cooperation. Performance of iris recognition degrades for color eye images acquired in non ideal case without user cooperation because of noisy, motion blur, off angle and illuminated images [6]. Multimodal eye biometric system can be provide solution to overcome these challenges in iris recognition by combining iris features with other eye biometric trait such as retina, sclera, conjunctival vasculature, cornea to improve recognition accuracy. Research in multimodal eye biometric such as ocular and peri-ocular biometric has been growing today due to ease of use in different nosy condition [7].

Proposed system represents the eye biometric system based on the content based image retrieval approach [30] for the fusion of iris, sclera and pupil features to improve the authentication for non ideal color eye images. Entropy values are estimated based on best quality features extracted from image such as color, brightness and texture to reduce the computational cost. These entropy values are used to classify iris, sclera and pupil region automatically using convolutional neural network (CNN) to get better the segmentation result and also reduce the segmentation error rate and time [8]. Multi-algorithmic feature extraction is applied to extract prominent features from segmented image which are combined together based on feature level fusion to calculate support value [9].

Table 1: Summary of ocular and periocular biometric fusion approach in eye biometric

Author	Multu-Biometric	Methodology	Type Of Fusion	Database	Result
Zhi Zhou et.al. [11]	Iris+Sclera	1-D Log-Gabor filter	Quality based Match score level	UBIRIS	FAR is 94.92% to 96.42%
Vikas Gottemukkula et.al.[12]	Iris + Conjunctival Vasculature	1-D Log-Gabor filter	weighted fusion with mach score	In-house database	EER of 2.83%
Chun-Wei Tan and Ajay Kumar [13]	Iris+ Periocular	random walker algorithm	Match score level fusion	UBIRIS.v2, FRGC and CASIA.v4	52.4% in rank-one recognition accuracy
Jibu Varghese K et.al. [14]	Iris+Sclera	Otsu's threshold method and Gabor filter	Individual Iris and sclrea recognition	In-house database	Accuracy=99.45%
C. Immaculate Mary [15]	Iris+Sclera	Least Mean Square(LMS) filtering	Interfusion of Iris and Sclera surface using Laplace	Q-FIRE	Accuracy=85%
Gil Santos et.al. [16]	Iris+ periocular	SIFT &GIST and 2D gabor wavelet	score level fusion	CSIP database	EER from 0.145% to 2.331%
Nassima Kihal et.al.[17]	iris and corneal shape	Zernike polynomial expansion,LDA and Gabour Filter	Match score level fusion	In-House database	EER equal to 0% and a FRR = 0% at 0.1% FAR
Mrunal Pathak, et.al. [18]	Iris+Sclera	GLCM,Gabor wavelet	Match score level fusion	UBIRIS V2	EER=2.31%
Nasir U. Ahmed et.al.[19]	Iris+ periocular	Multi-Block Transitional Local Binary Pattern	score level fusion	MICHE	EER =1.22%
Zi Wang et.al. [20]	eye region	mixed convolutional and residual network (MiCoReNet)	--	CASIA-Iris-IntervalV4 and the UBIRIS.v2	Accuracy for CASIA-Iris-IntervalV4= 99.08% and UBIRIS.v2=96.12%

Authentication is performed by matching support value match score with template stored value in database using Euclidean distance.

2. RELATED WORK

Recently eye biometric is explored to improve the biometric recognition results in non ideal scenario because of availability of prominent and stable features among each individual such as color and texture features presented in iris as well as sclera. Eye biometric can be categorized as ocular and periocular biometric system. Ocular biometric refers to combine biometric trait such as iris, sclera, pupil, retina, conjunctival vasculature features which are present inside the eye region whereas periocular refers to features from surrounding eye region [10]. In paper [11],[18], iris and sclera texture features are combined together using match score level fusion for good quality images only. Paper [12] describes multimodal biometric system based on match score level weighted fusion of iris and conjunctival vascular texture features. In paper [13] ,individual iris and sclera recognition is performed simultaneously using Otsu's threshold method and Gabor filter which is experimented only for frontal images. Iris and sclera surface feature's inter fusion is proposed in paper [14]-[15] using least mean square filtering method. Eye biometric system by combining iris and periocular features are described based on score level fusion for noisy eye images in paper [16]. [18]-[19] to reduce the equal error rate. In paper [16], eye biometric authentication is presented based on complete eye region using deep learning method.

3. PROPOSED EYE BIOMETRIC SYSTEM

This section elaborate on different phases of proposed multimodal eye biometric system such as image preprocessing, segmentation of iris ,sclera and pupil region using convolutional neural network(CNN}based on entropy values, multialgorithmic feature extraction, feature level fusion and matching.

3.1 Preprocessing

The objective of preprocessing is to enhance the input image by suppressing the unwanted distortion. At first stage, input image is taken from the database which is converted from

RGB image to gray image to minimize the computational complexity. Furthermore min-max normalization is used to perform linear transformation on input image to fit the data in specific range. Next, the non linear bilateral filtering is used for smoothing purpose by preserving edges.

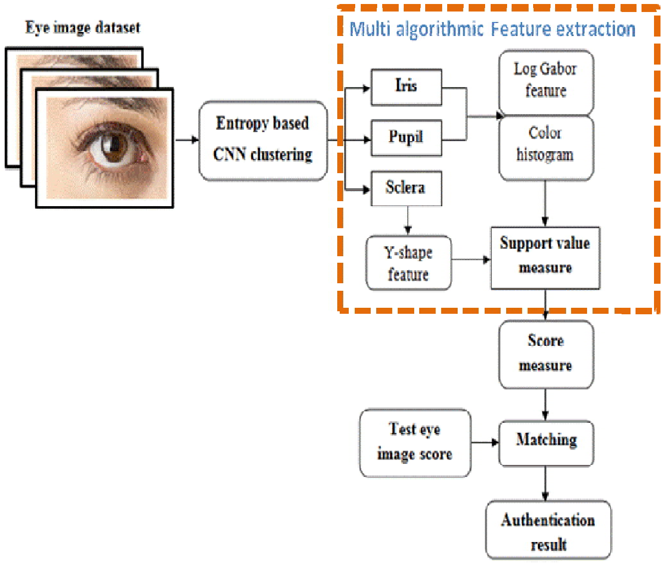


Figure 1: Proposed multimodal eye biometric system [21].

3.2 Entropy based CNN Segmentation

The purpose of segmentation in image processing is to identify the region of interest. Precise segmentation of image is necessary otherwise incorrect segmentation will results in poor performance of recognition [22]. In proposed system, entropy is derived from contour based color, texture and brightness features. Convolutional neural network is used to cluster iris, sclera and pupil region based on similarity obtained by entropy measures.

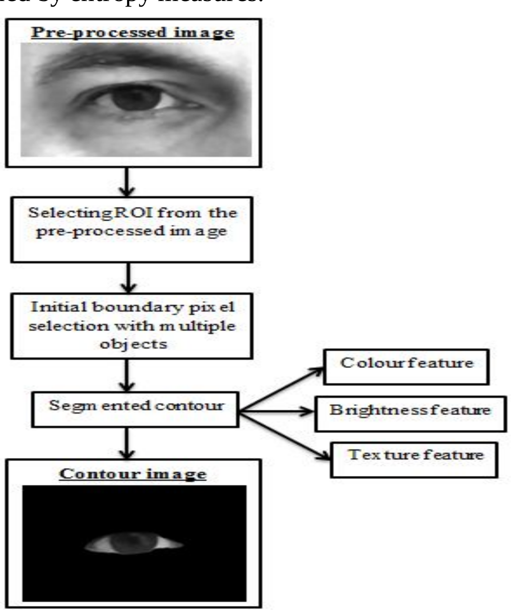


Figure 2: contour based feature extraction

Contour feature extraction

Contour represents characteristics of visual pattern available in image which are derived based on color, texture and brightness features. Therefore contours represent the subset of features which helps to perform segmentation accurately with less number of features [23]. The proposed contour based feature extraction is shown in figure 2.

Texture value of local region surrounding the pixel is estimated by comparing the texton distribution on either side of pixel relative to its dominant orientation. Value of texture lies between 0 and 1. The objects in image which are silent in color are may be black or white describe the characteristics of brightness. Brightness can be measured by comparing the intensity value of a pixel with its neighbor. For constant image, brightness value is zero. Color features are most widely used attribute to represent characteristics of image[24]. Color features are estimated based on occurrences of every color indexes in an image with dissimilar intensities.

Entropy Features Extraction

Entropy is a measurement of the degree of uncertainty that exists in a system. Shannon's entropy is an important measure for evaluating structures and patterns in the data which can be used to characterized texture in the image. The entropy is extracted for the effective segmentation of iris pupil and sclera regions. In proposed system this entropy values are calculated to distinguish iris, sclera and pupil region based on available texture in contour image [9],[23]. Entropy of the i^{th} super pixel E_y^i is computed using following the equation.

$$E_y^i = \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} P(i,j)(-\log_2(P(i,j))) \tag{1}$$

For N dimensional co-occurrences matrix, P(i,j) represent elements in matrix at coordinates (i,j)

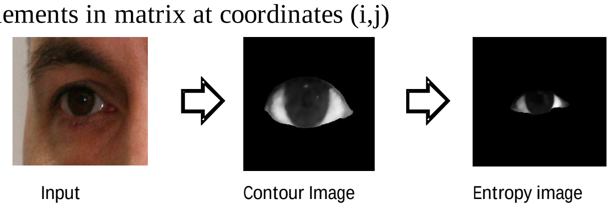


Figure 3: entropy image formation from contour image

Deep learning based image segmentation

We proposed deep learning based clustering approach to segment iris, sclera and pupil region by passing the entropy image through convolution neural network (CNN) which trends to extract global features available from image. CNN is one the variation of feed forward artificial neural network which is composed of with multiple hidden layers. Commonly CNN is composed of three basic layers: convolution layers, pooling layers and fully connected layers [25][31].

In convolution layers filters are applied on input image to generate the feature map. Each Convolutional layer consist of multiple series of filters known as kernel. In proposed system 5X5 filter size is used at each convolution layer to extract the local features which is referred as weight sharing. After convolution operation, a non linear activation function Rectified Linear Unit (ReLU) is applied to the output of convolution layer to accelerate the convergence of CNN. We proposed Cuckoo search method to update the value of weight and bios at each layer[29]. Next layer, pooling layer also known as down sampling layer is applied on output of convolution layer to reduce the dimensions and number of parameters of CNN. The Max-pooling layer is used to perform the local max operation over the input features using 2X2 filter size to reduce the parameters and obtain local invariant features. Fully connected layers takes output of last pooling layer as an input to flattened into a single vector of values, each representing a probability that a certain feature belongs to a either iris, sclera or pupil region after applying the softmax function [9],[23]. Detail structure of convolutional neural network used in proposed system is described by figure 4.

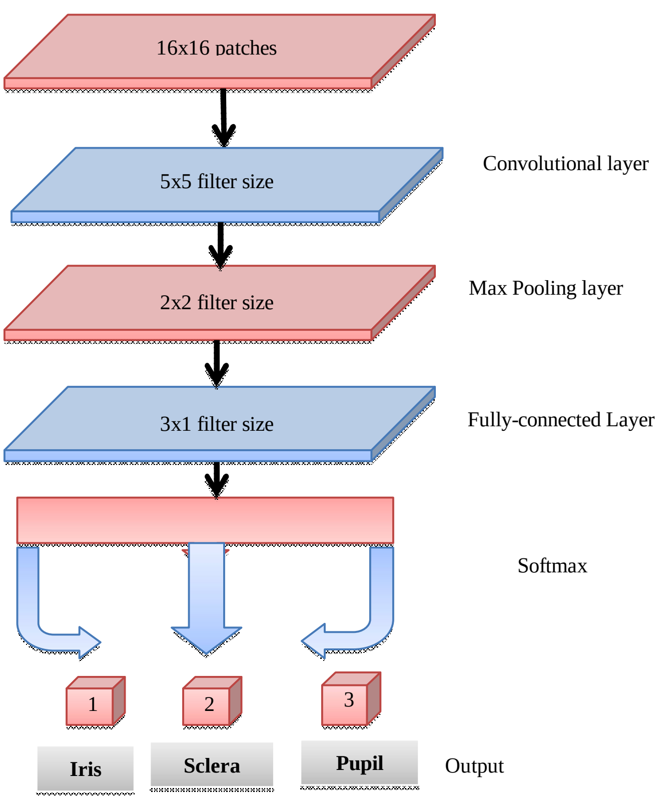


Figure 4: Structure of Convolution Neural Network

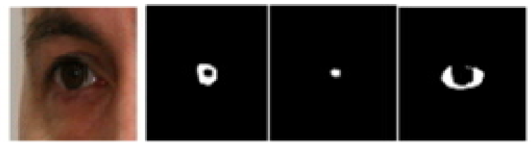


Figure 4: segmentation of iris, pupil and sclera

3.3 Feature extraction

In eye biometric system color, texture and shape are the prominent and reliable features for iris, sclera and pupil which can be used generate the feature vector for correct authentication. In proposed system we extract the color and texture information from segmented iris and pupil region which is combined with the Y-shaped features extracted from sclera. Color histogram algorithm is used extract the color features where as log Gabor filter is used to extract the texture features. Sclera of human eye is compromised with different layers [26] which form the stable blood vessel pattern which is unique for every person. These blood vessels forms Y shaped branches which are stable used to calculate sclera descriptor value. In proposed system to find out Y-shape features (S_{shape}), we look for nearest set of neighbors in all line segments at regular distance and classify the angles between these neighbors to derive structure [27].

3.4 Feature level fusion

We proposed the feature level fusion of feature extracted from iris , sclera and pupil biometric trait. These features are taken together to calculate joint feature vector known as support value [9].

$$\tilde{S}_{value} = \frac{(G'(f) + R' + D'_{LCH}(I'))}{G'(f) * R' * D'_{LCH}(I')} \tag{2}$$

Where, $G'(f)$ is the log Gabor feature, R' is the sclera Y-shaped feature, $D'_{LCH}(I')$ is the color histogram feature. The score measure dependent on the support value, minimum and the maximum value of all features is portrayed as,

$$S' = \tilde{S}_{value} + W_{\max} + W_{\min} \tag{3}$$

$$W_{\max} = \max\{all\ \ features\} \tag{4}$$

$$W_{\min} = \min\{all\ \ features\} \tag{5}$$

3.5 Matching

We use the Euclidean distance method to compare the support match score value of test data with estimated values stored in trained enrollment database. Euclidean distance is applied for pixel wise comparison of images. If the calculated distance is lesser than threshold value then data classified as recognized otherwise it is rejected.

4. RESULT AND DISCUSSION

The proposed eye biometric system is implemented on working platform MATLAB. Experimentations are performed on freely available research database MMU and UBIRIS.v2. MMU database contains the 450 images acquired with the help of dedicated semi automated camera (LG Iris Access) from distance 7-25cm. For unconstrained or relaxed color eye images we used UBIRIS.v2 database which contains 11102 images acquired at different session from distance 4- 8 meters with the help of Canon EOS 5D. It represent 14 different type of noise such as motion blur, off angle, poorly focused, obstruction of eye lashes glass, hair, etc. 300 and 2000 images from MMU and UBIRIS.v2 are used respectively for training and testing purposes in ratio 80:10.

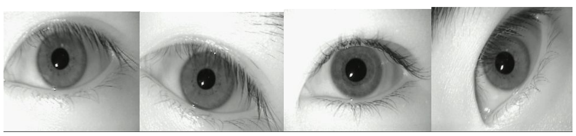


Figure 5: sample images for MMU database

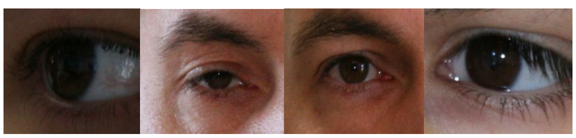


Figure 6: sample images for UBIRIS.v2 database

Performance of segmentation is analyzed for proposed entropy feature based deep learning segmentation method using CNN. From contour image generated based on the color, texture and brightness features, we calculate the entropy value which minimize the feature set by avoiding the redundant and poor quality features. This helps to reduce the computational complexity as well as time required for segmentation.

Table 2: Entropy values for MMU database images

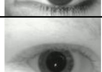
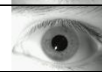
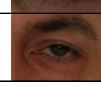
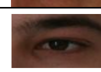
Labeled images	Entropy value	Classification Accuracy
	10.84560658	88.74
	12.91781241	100
	13.18990281	100
	13.36857564	94
	13.72492633	98.3
	13.84040755	100
	13.87388653	100
	11.03423424	92.4
	11.3308829	100
	11.4825514	95.9

Table 3: Entropy values for UBIRIS.v2 Database images

Labeled images	Entropy value	Classification accuracy
	10.84951952	94.3
	12.00494672	100
	14.08889121	100
	14.22193309	100
	13.4799699	100
	13.41671058	100
	13.56116364	100
	11.16364744	99
	10.93134463	98.64
	11.32630209	100

From table 2 and table 3, we observed that if the entropy value is increased then classification accuracy for iris, sclera and pupil region using CNN is also improved for MMU and UBIRIS.v2 database images We able to achieve classification accuracy up to 100% for image entropy values lies between 13-14. If we compare the images from MMU and UBIRIS.v2 database, Entropy value for gray images are less as compared to entropy values estimated for color eye images due to availability of less number of color and texture feature in input eye images.

Accuracy of iris, sclera and pupil segmentation is enhanced by using proposed segmentation algorithm for images taken for UBIRIS.v2 database as compared to MMU database images prominent large number of visible colour and texture features. Performance comparison of segmentation results for MMU and UBIRIS.v2 database is given in table 4.

Table 4: Performance of segmentation of iris, sclera and pupil region based MMU and UBIRIS.v2 database [9]

Biometric Trait	Database	Accuracy	Positive Predictive value (PPR)	False Negative Rate (FNR)	False Detection Rate (FDR)
Iris	MMU	97.15	97.43	0.31	2.57
	UBIRIS.v2	97.99	99.84	1.89	0.16
Sclera	MMU	95.54	96.26	0.79	3.74
	UBIRIS.v2	98.08	98.38	0.34	1.62
Pupil	MMU	98.28	98.31	0.04	1.69
	UBIRIS.v2	99.42	91.42	0.70	8.58

It is difficult to extract the Y-count sclera feature for gray or black and white images as compared to color images because of their appearance. Therefore from table 5 and table 6, we can say that value of sclera Y-count features decreases for gray images compared to color images. This results in performance of recognition accuracy. Recognition accuracy of eye biometric system is increases if the value of sclera Y count is good.

Table 5: Feature and Support values for MMU Database images

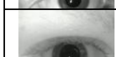
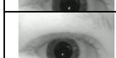
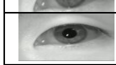
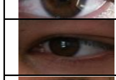
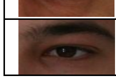
Labeled images	Feature values					Support value	Classification Accuracy	Recognition Accuracy
	Iris		pupil		Sclera Y-count			
	himax	gimax	hpmax	gpmax				
	64464	2.95E-14	65264	2.63E-14	20	1.45E+24	88.74	89
	64161	3.00E-14	65341	2.34E-14	67	1.74E+23	100	100
	64146	1.91E-14	65120	3.15E-14	127	2.12E+22	100	100
	63827	2.46E-14	65087	2.80E-14	230	3.75E+22	94	94
	64040	2.28E-14	63912	3.50E-14	253	5.49E+23	98.3	97.6
	64096	2.76E-14	61656	2.71E-14	271	4.17E+22	100	100
	63883	2.66E-14	62769	3.27E-14	358	6.70E+21	100	100
	64140	2.80E-14	65450	2.94E-14	60	2.62E+23	92.4	91.7
	64160	3.24E-14	65358	3.39E-14	87	3.02E+22	100	100
	64501	2.54E-14	65466	2.31E-14	97	3.61E+22	95.9	96.1

Table 6: Feature and Support values for UBIRIS.v2 Database images

Labeled images	Feature values					Support value	Classification Accuracy	Recognition Accuracy
	Iris		pupil		Sclera Y- count			
	himax	gimax	hpmax	gpmax				
	65244	2.53E-14	63621	2.58E-14	75	1.90E+23	94.33	97.6
	64884	2.40E-14	59448	3.41E-14	165	1.75E+23	100	100
	64900	2.33E-14	58528	4.16E-14	237	2.02E+22	100	100
	64981	2.13E-14	58502	4.30E-14	310	1.60E+23	100	100
	64706	2.30E-14	55567	2.70E-14	314	2.19E+23	100	100
	63859	2.52E-14	56732	3.07E-14	425	3.46E+22	100	100
	64245	3.27E-14	56682	3.78E-14	428	1.41E+22	100	100
	65198	2.74E-14	63567	3.31E-14	111	3.42E+22	99	99
	65257	2.38E-14	63139	2.90E-14	116	7.33E+22	98.64	99.2
	65155	1.79E-14	63773	3.26E-14	118	1.26E+23	100	100

From table 7, we can say that the eye biometric system recognition performance is improved for the feature level fusion as compared to score level fusion because of availability of large number of features [29-30] for feature vector generation which is used for matching with template stored in trained database.

reducing time required for segmentation up to 0.9sec for noisy color eye images.

Table 7: Performance analysis for eye biometric recognition system based on level of fusion

Author	Modality Fusion	Fusion Technique	Database	Result (EER %)
Zhou et al.	Iris and sclera	Score level fusion	UBIRIS V1	2.73% - 3.06%
Gottemukkula et al.	Iris and sclera	Weighted score fusion	In House (Constrained Images)	2.39%
Zhou et al.	Iris and sclera	Score level fusion	IUPUI green-wavelength database	0.63%
Jibu Varghese K. et.al.	Iris and Sclera	No Fusion Simultaneous	In House database only high quality images used	Accuracy -99.4%
C. Immaculate Mary	Iris and sclera	Inter-Fusion using Laplace Transform	Quality—Face/Iris Research Ensemble	Accuracy=85%
Nassima Kihal et. al	Iris and corneal shape	Match score	In-house (Constrained	0.09%
Abhijit Das et. al	Iris, sclera and peri-ocular	Decision level	Multi angle sclera database(MASD)	Iris+sclera=> Accuracy=91.78 Iris+sclera+periocular=> Accuracy=96.53%
M.K.Pathak et.al	**Iris, sclera and pupil**	**Feature level fusion**	**MMU and UBIRIS.v2**	**Accuracy for MMU =93.33% UBIRIS.v2=97.99%**

From table 7, we can say that the eye biometric system recognition performance is improved for the feature level fusion as compared to score level fusion because of availability of large number of features [29,30] for feature vector generation which is used for matching with template stored in trained database.

5. CONCLUSION

Present standalone biometric systems are not 100% reliable, they also suffer from spoofing attacks due to lack of invariant representation and noisy input. Therefore multiple biometric cues are combined together to achieve better performance of biometric authentication. Proposed eye biometric system combines the prominent features of iris, sclera and pupil to improve the accuracy of recognition for the images acquired in unconstrained or relaxed environment. Entropy based feature selection proves that it reduces time required for segmentation because of selection of optimal set of feature selection. Classification accuracy is increases with increase in entropy values for input image. From results proposed system also represent that for greater count of Y-sclera features, accuracy of eye biometric system also improved. Overall multimodal eye biometric system recognition performance with respect to accuracy, PPV, GAR, etc. is improved by

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