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SUPPORT VALUE BASED FUSION MATCHING USING IRIS AND SCLERA FEATURES FOR PERSON AUTHENTICATION IN UNCONSTRAINED ENVIRONMENT

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Abstract

Existing iris recognition system provides accurate and reliable results based on Near Infrared Images when images are captured under constrained environment with user cooperation from fixed distance. But the performance of iris recognition system degrades for color eye images acquired under visible wavelength without user cooperation due to noise occurrence such as blur eye images, eyelash, occlusion and reflection. This paper present the multimodal eye biometric system based on support value based fusion for iris, sclera and pupil features depending on their match score value. Support value for iris, sclera and pupil is calculated using the log Gabor features, Y-shaped features and color histogram features. The robustness of proposed eye biometric system is tested on UBIRIS.V2 database for noisy eye images taken under unconstrained environment in visible wavelength. The propose algorithm significantly improve the accuracy of person authentication by reducing the time for segmentation and recognition.

Keywords: Match score, Multimodal, Support value based fusion, Unconstrained environment, Visible wavelength.

1. Introduction

Biometric technology for person authentication is based on person's physical and biological traits such as face, fingerprint, iris, retina, voice, signature, etc. [1]. Iris provides highest accuracy rate as compared to all other biometric trait because of unique texture pattern available in it which does not change throughout lifespan of person and commonly not affected by incidence [2, 3]. Most of the iris biometric systems used for authentication are based on images captured using near infrared wavelength (700-900 nm) with user cooperation which limits the performance of system with additional hardware setup cost. To avoid use of near infrared (NIR) camera and build user friendly authentication system, images can be acquired using visible spectrum camera which are easily available on mobile devices such as mobile phone, laptop, webcam, etc. in uncontrolled environment. However, there are some challenges in implementing iris recognition system due to acquisition of eye images in certain conditions such as without user cooperation, variable lighting conditions, long distance, eye movement, reflection, occlusion, etc. [4]. Detecting iris-pupil, iris-sclera boundaries and extracting accurate features from iris becomes difficult in such scenario which affects the performance of iris segmentation and recognition.

To overcome these challenges multimodal biometric system [5] is solution over traditional unimodal iris recognition system where more than one biometric modalities are combined together with iris such as ocular biometric (sclera, pupil retina, cornea), periocular biometric (eyelash, eyelid, skin) and non ocular biometric (fingerprint, face, ear, etc.) to get better performance of eye biometric system in unconstrained environment.

In this paper, iris features are combined with sclera as well as pupil features to develop multimodal eye biometric system for non-ideal iris images in unconstrained environment under visible wavelength. Iris provides unique texture feature information whereas sclera has prominent blood vessel structure. Combining iris, sclera and pupil features together provides more accurate results because of multiple and different features set can compensate by each other in haziness. For example, it is difficult to get complete iris ring and texture information for off-angle, partially closed eyes, dark iris images, etc. In such noisy condition sclera features could provide fault tolerance because sclera features are extracted in different way for same image at the same time. Sclera recognition is an emerging technology for biometric identification because of its unique vein structure which does not change with age [6].

We present entropy based Convolution Neural Network (E-CNN) segmentation algorithm depends on estimated color, texture and brightness contour features entropy values to select quality features. We also propose multi algorithmic feature extraction to extract color and texture features from iris and pupil in addition with y-shaped sclera features to retrieve maximum prominent features from image. Support value will be calculated based on all extracted features. To reduce computational complexity a novel Support Value Based Fusion (SVBF) Matching algorithm is proposed which improve the performance of recognition.

Motivation

Performance of existing eye biometric system degrades for color eye images acquired in non-ideal condition. Moreover, increased number of features from different modalities may cause extra burden of computational and time complexity while implementing multimodal eye biometric system which slow down system performance.

Contribution

We propose the efficient segmentation, feature extraction and optimal feature fusion algorithm for unconstrained eye images to improve the accuracy of segmentation as well as recognition by reducing time required for segmentation by proposing following algorithms.

- To provide efficient segmentation algorithm to meet the challenges of noisy eye images, we proposed E-CNN algorithm based on quality features by improving time required for segmentation and accuracy.
- To reduce the number of features by preserving important information in image during feature extraction process of multimodal eye biometric system, we proposed multi algorithmic texture, color and Y-shaped feature extraction from segmented iris, pupil and sclera region.
- To provide novel fusion algorithm for iris, sclera and pupil extracted features, we presents support value based fusion (SVBF) to improve recognition result.
- To analyse performance of proposed system, we evaluate performance of our methods on publicly available eye image dataset UBIRIS .V2.

In this paper, some of the existing methodology discussed in Section 2, proposed system describes in Section 3 followed by experimentation to evaluate performance of proposed methodology and results obtained for it in Section 4. Conclusion is presented in Section 5.

2. Related Work

Traditional iris biometric system is classified mainly into four stages: iris segmentation, feature extraction, matching template and recognition. Among all these, performance of recognition firmly depends on the accurate segmentation as it demarcates iris inner and outer boundary. From literature survey, Wildes [2] and Daugman [3] segmentation methods are common segmentation methods which are suitable for ideal scenario based on assumption that iris is circular object. But in non-ideal scenario performance of these algorithms degrade due to unable to localize whole circular iris ring. Proenca and Alexandre [7] present article to review iris segmentation methodology for non-ideal images in visible wavelength environment and proposed new segmentation algorithm for noisy eye images.

Zuo et al. [8] presented eclipse model for segmentation of unconstrained eye images based on shape and location information. Proenca [9] presented feed forward neural network for segmentation of relaxed on the move and distance images. It performed well for small training dataset also. Chen et al. [10] provided computationally efficient iris segmentation algorithm where approximate eye area selected to localized small target area using circular Hough transform (CHT) using different weights. Jeong et al. [11] proposed Adboost eye detection method with two circular edge detection to localize iris in non-ideal images. Accuracy of iris segmentation increased up to 98.7% for unconstrained eye images using k-mean with circular Hough transform [12] by reducing average segmentation time up to 1.49 sec. CHT and LHT methodology with canny edge detection algorithm is provided by Mahlouji and Noruzi [13] for unconstrained iris images. Least square ellipse fitting (LSEF) and geometric calibration (GC) methods for iris segmentation and Neu wave network for feature extraction presented by Moi et al. [14] specially for off angle iris image in which inner and outer boundaries are fitted iteratively to improve segmentation rate up to 99.83%. Alvarez-Betancourt and Garcia-Silvente [15] presented key points - based feature extraction using SIFT to attain better iris recognition performance for non-ideal real time images in visible wavelength. Acar [16] used KNN classification and local iris feature extraction using GLCM where for $k = 1$ provides recognition accuracy 85%. A robust automated iris segmentation using Histograms of Oriented Gradients descriptor and Support Vector Machine (HOG-SVM) presented by Radman et al. [17] to improve the verification rate more than 95% for images captured in non-constrained environment. Arsalan et al. [18] presented deep learning based two stage iris segmentation where CHT and CNN used in first and second stage respectively for segmentation to reduce the average segmentation rate. Furthermore, they presented Densely Connected Fully Convolutional Networks (IrisDenseNet) [19] to improve iris segmentation accuracy up to 98% for NIR images by avoiding pre and post processing. Bazrafkan et al. [20] presented end to end deep neural network to perform iris segmentation for the unconstrained eye images using fully convolution deep neural network (FCDNN) to improve the accuracy but due to the need of additional tunings computational and storage complexity increased.

From last decades, significant changes are made in traditional iris recognition system to improve iris biometric recognition performance by combining iris features with other ocular, periocular and non-ocular biometric modalities. Inter-fusion of sclera and iris surface features using Laplace Transform (IIST) with least mean square filtering method [21], quality based fusion [22], dual authentication system [23] based on iris and sclera features were used to improve the recognition rate for degraded noisy eye images. Inter ocular fusion of iris features by combining with 3-D corneal shape features [24] were used with to reduce equal error rate (EER). Fusion of the iris with conjunctival vasculature was performed based on weighted sum rule for small portion of ocular region to diminish EER up to 2.391% [25]. The multimodal ocular biometric system by combining iris, sclera and periocular modalities based on decision level strategy increased reliability and accuracy of person authentication in visible spectrum [22, 25]. The fusion of iris and sclera features based on iris and sclera descriptor values which were calculated after segmentation based on color distance map (CDM) using match score level fusion was used to improve the recognition performance [26].

In literature, we observed that several attempts have been made to improve the efficiency, accuracy and reliability of multimodal eye biometric system by combining iris features with sclera or another ocular biometric trait. Each of them has remarkable performance with some pitfall. Therefore, there is need to design multimodal eye biometric system with optimum utilization of biometric modalities to improve performance of recognition in unconstrained environment.

3. Proposed System

Individual unimodal iris and sclera recognition system performance degraded for color eye images due to noise introduced because of blur images, illumination effect, dark iris color, etc. To overcome these challenges, we propose the multimodal eye biometric system as shown in Fig. 1 for visible wavelength eye images acquired in unconstrained environment. Deep learning based effective segmentation algorithm is presented for iris, sclera and pupil by using the entropy based convolution neural network (E-CNN) based on brightness, color and texture features of biometric modalities. Proposed support value based fusion (SVBF) algorithm described in this paper is used to develop multimodal eye biometric system to improve recognition performance in terms of accuracy by reducing time required for segmentation as well as average segmentation error.

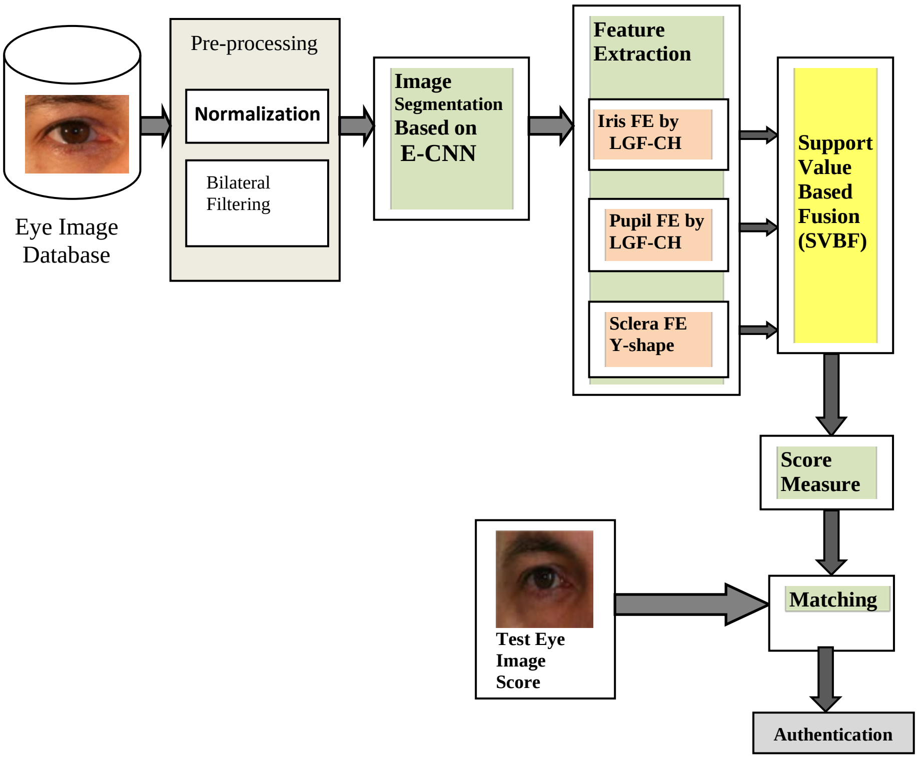


Fig. 1. Proposed multimodal Eye biometric system based on SVBF.

3.1. Pre-processing

We used min-max normalization approach to fit the linear transformation of image into particular range. For smoothing the image bilateral filter is used after normalization in the area of low color variation so that we can improve the performance of image segmentation.

3.2. Proposed entropy based convolution neural network (E-CNN) segmentation

3.2.1. Entropy calculation

Contour feature is metric to extract the information about color, texture and brightness features with the help of function that predicts the posterior probability of boundary. Entropy provides the average information of images to measure degree of randomness to describe the texture of image [27].

Input:	RGB image from database
Output:	Entropy Feature map $f(E_y^i) = \{E_y^1, E_y^2, E_y^3, ...E_y^i\}$
1.	Select RGB image from database
2.	Convert RGB to gray image
3.	Pre-processing: i. Normalize image using min-max normalization ii. Perform edge smoothing using bilateral filter
4.	Contour Feature extraction: i. Compute color feature map based on color intensity ii. Compute brightness feature map iii. Compute texture feature map based on texon distribution
5.	Entropy feature Map: i. Define sub frames for contour image ii. Compute spectral sub energies iii. Compute spectral entropy

Algorithm 1: Steps for entropy value calculations [28].

We calculate the entropy for i^{th} pixel in image for segmented contour features to differentiate between iris and non iris part like sclera and pupil separately as follows:

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

where i and j are coefficient for component $P(i, j)$ in co-occurrence matrix of dimension N. Entropy is calculated for color, brightness and texture features which is input to CNN for segmentation of iris, sclera and pupil region separately as shown in Fig. 2.

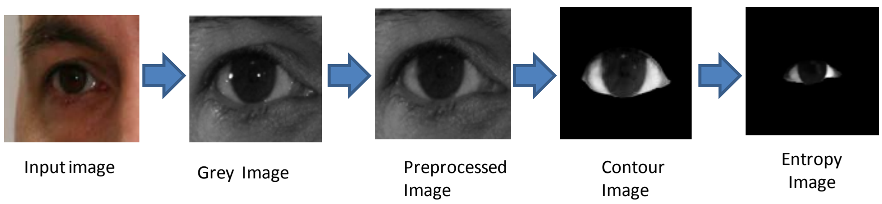


Fig. 2. Entropy based feature map for input image based on contour features.

3.2.2. E-CNN segmentation

In proposed system Entropy feature set are inputs to convolution neural network to identify iris, sclera and pupil region independently based on entropy value.

$$\text{Entropy feature set } f(E_y^i) = \{E_y^1, E_y^2, E_y^3, ...E_y^i\} \tag{2}$$

CNN is data driven automatically learning technique with layered architecture for optimal representation of features to improve the performance of segmentation and recognition provide [18]. We used CNN based architecture for classification of iris, sclera and pupil region as shown in Fig. 3. CNN architecture is comprised with mainly three layers: convolution layer, max pooling layer and fully connected layer followed by softmax function.

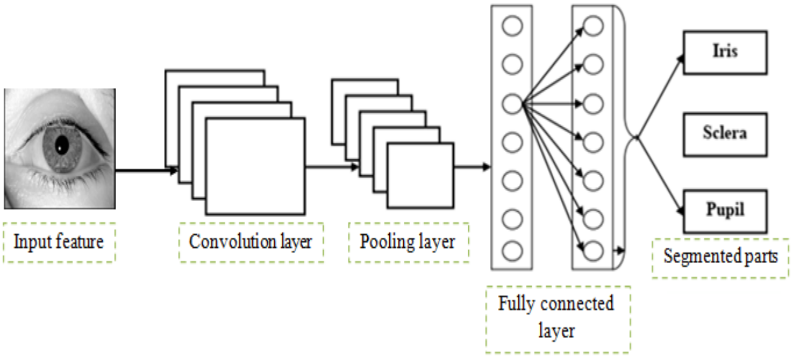


Fig. 3. The Structure of a CNN for Iris, Sclera and Pupil Segmentation [28].

Convolution Layer is core layer which concerned with the learn weight grids known as filters. Input images from UBIRIS.V2 database is normalized to 256x256x3. At each convolution layer input is taken into 16x16 patch sizes with 5x5 filter sizes. Entropy based normalization is performed using Z-score normalization. Output of past layer is convolved with multiple filter masks which are known as learned kernels.

Pooling Layer is nonlinear down sampling layer to optimize the output neurons to reduce computational power and over fitting. Max-pooling is commonly used method. We uses 2x2 filter size in max pooling whereas 3x1 filters sized used at fully connected layer. Weight and bias values varies at each layer. Fully connected Layer has full connection with its previous layer by connecting all its neuron with each neuron from its previous layer.

3.3. Feature extraction

Eye images are rich in color and texture features for Iris, Sclera and Pupil. Therefore, feature extraction in proposed multimodal eye biometric system is based on multi-algorithmic features extraction to utilize the maximum color and texture feature from iris and pupil color images where we are combining Color Histogram algorithm with Log Gabor Filter. Color histogram is used to extract the color features of iris and pupil and Log Gabor Filter is used to extract the texture features. For sclera, we are extracting the Y-shape features which are stable during eye movement [29].

3.3.1. Iris and pupil feature extraction

Color Histogram: It extract the features to represent frequency occurrence of RGB channels into three histograms to estimate the probability distribution of color pixels in image [30].

$$\mathrm{H}[\mathrm{R},\mathrm{G},\mathrm{B}] = \mathrm{Probability}\ (\mathrm{R},\mathrm{G},\mathrm{B}) \quad (3)$$

In proposed system RGB feature for color eye image (I') are described by using color histogram as below;

$$D'_{CH}(I') = \sum_{K=1}^{N} \sqrt{\sum_{i=1}^{N} \left\{ \tilde{H}_Q^K[i] - \tilde{H}_i^K[i] \right\}^2} \tag{4}$$

where $\tilde{H}_Q^K$ and $\tilde{H}_i^K$ are color histograms for K region from color block $\tilde{H}_Q^K[i]$ and $\tilde{H}_i^K[i]$ among N blocks.

Log-Gabor Filter: Log Gabor filter extract the textural information from image [31]. Frequency response for log Gabor filter where filter bandwidth (σ) and centre frequency (f_c) is derived as;

$$\tilde{G}(f) = \exp\left(\frac{-(\log(f/f_c))^2}{2(\log(\sigma/f_c))^2} \right) \tag{5}$$

3.3.2. Sclera feature extraction

Blood vessel patterns available in sclera are the unique feature to identify person. Sclera comprises with several layers of veins and patterns of the vein varies due to the changes occurs in blood vessels pattern because of motion of these layers [29]. Among all these Y-shape often observed as stable feature during formation and deformation of blood vessel patterns. Corner response *R'* is defined by points:

$$R' = \det(B) - kT_r^{\,2}(B') \tag{6}$$

where T_r is matrix trace, k is constant and B is image structure matrix based on image derivatives where I_y and I_z are the partial derivatives in y and z individually calculated as:

$$B' = \begin{bmatrix} I_y^2 & I_y I_z \\ I_y I_z & I_z^2 \end{bmatrix} \tag{7}$$

3.4. Support value based fusion (SVBF) matching

To detect person authentication SVBF match process is presented. Support value is estimated from the extracted features for iris, sclera and pupil region. It is derived as;

$$\tilde{S}_{value} = (G'(f) + R' + D'_{LCH}(I')) \Big/ G'(f) * R' * D'_{LCH}(I') \tag{8}$$

where, $G'(f)$ is the log Gabor feature, R' is the sclera Y-shaped feature, $D'_{LCH}(I')$ is the color histogram feature. For each biometric trait score value is calculated based on the support value, minimum and the maximum weight assigned in CNN for all features.

$$S' = \tilde{S}_{value} + W_{\max} + W_{\min} \tag{9}$$

$$W_{\max} = \max\{all \;\; features\} \tag{10}$$

$$W_{\min} = \min\{all \;\; features\} \tag{11}$$

Input: Image from training dataset
Output: Final Support value based score for matching

```
1. read input image from the dataset
        Inp_img = imresize(imread(['.\trainingdata\' flist(i).name]),[256,256])
2.segmentation using cnn
    [pup,iris,sce] = cnnsegment_train(inp_img,i);
3.feature extraction
    [hp, hi, gp, gi, c, w1, w2] = featureextraction_train(pup,iris,sce);
    where,
    hp - histogram of pupil; hi - histogram of iris ;gp - gabor of pupil;
    gi - gabor of iris; c - count of y-shape
4.calculate support value(sv)
    sv = (hp + hi + gp + gi + c) / (hp * hi * gp * gi * c);
5.calculate score value
    score = sv + w_max + w_min;
    w_max = hp_max + hi_max + gp_max + gi_max;
    w_min = hp_min + hi_min + gp_min + gi_min;
score_val(i,1) = score;
```

Algorithm 2: Pseudo code to calculate Support value based fusion score.

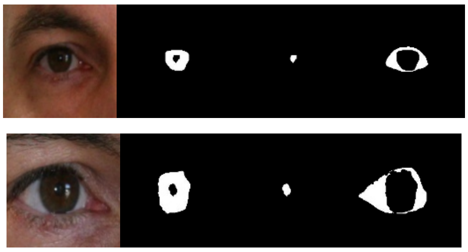
Euclidean distance is used to determine the matching score between training and testing images based on final support value based fusion (SVBF) score estimated for training and testing data. If the calculated value for distance is lesser than threshold value then recognition result is Accepted else Fail authentication.

$$\tilde{E}_D = \sqrt{\sum_{j=1}^{N} \left(S_{training} - S_{testing}\right)^2} \qquad (12)$$

4. Experiments and Results

Proposed multi biometric system for person authentication is implemented on MATLAB 2018 platform. We used UBIRIS.V2 database for experimentation and evaluating the performance of proposed multimodal eye biometric system based on fusion of iris, sclera and pupil modalities. UBIRIS.V2 is freely available database comprises 11102 images, 522 iris for 261 users acquired in unconstrained environment under visible wavelength from distance 4m to 8m in two sessions [32]. For experimentation we select 3,450 (for each user 5 frontal, 5 off-angle (left), off-angle (right) images for 115 volunteers for training purpose. 1035 images are used for testing. Figure 4 shows the segmentation of iris, sclera and pupil for color eye image in unconstrained environment for proposed entropy based CNN segmentation algorithm.

Performance of proposed E-CNN segmentation algorithm for iris, sclera and pupil segmentation is checked and compare with existing segmentation algorithm Adaptive neuro fuzzy inference system (ANFIS) and K-Nearest Neighbours (K-NN) techniques in terms of accuracy, positive predictive value, false negative rate and false discovery rate [33]. From Table 1 it can be observed that proposed system provides good results as compared to current state-of-art. We achieve the best accuracy results for segmentation of iris, sclera and pupil. It is also observed that there is considerable reduction in FNR and FDR during classification of iris, sclera and pupil region.



(a) Input image (b) Iris (c) Pupil (d) Sclera

Fig. 4. Segmentation of iris, pupil and sclera for the images from UBIRIS.V2.

Proposed segmentation algorithm for unconstrained color eye images improve the performance of accuracy as well as segmentation time with respect to other available methods [34-36] as shown in Tables 1 and 2.

Table 1. Comparison of iris, sclera and pupil segmentation accuracy using E-CNN with ANFIS and KNN for images from UBIRIS.V2 database.

Performance Metric (%)	Methods	UBIRIS.V2 Database		
		Iris	Sclera	Pupil
Accuracy	Proposed (E-CNN)	97.8	98.1	99.4
	ANFIS	93.2	88.0	97.8
	KNN	95.6	82.4	91.4
Positive Predictive Value (PPV)	Proposed (E-CNN)	99.8	98.4	99.9
	ANFIS	95.6	89.1	98.0
	KNN	96.9	82.4	91.4
False Negative Rate (FNR)	Proposed (E-CNN)	1.8	0.3	0.5
	ANFIS	2.7	1.4	0.8
	KNN	4.3	0.5	0.7
False Discovery Rate (FDR)	Proposed (E-CNN)	0.1	1.6	0.1
	ANFIS	4.4	10.9	1.9
	KNN	1.0	17.5	8.5

Table 2. Performance comparisons in terms of average computation times with different segmentation methods.

Approach	Computation Time (Seconds)
Fast iris segmentation algorithm	1.09
Geodesic active contours	6.2
Balloon active contour	2.2
Hough transform and active contour	5.8
Proposed Method	0.9

We illustrate and compare the result of proposed SVBF matching algorithm with existing ANN, KNN, SVM, and CNN classification algorithm for matching [35] with respect to the different performance metrics such as accuracy, false acceptance rate (FAR) and false rejection rate (FRR), etc.

From Table 3, we observe that proposed entropy based convolution neural network outperform classification algorithm provides the better results as compare to state of the art system by increasing the recognition accuracy up to 98%.

Table 3. Comparison of proposed E-CNN classification results with other methodology.

Year	Author	Classification Technique	Database	Result
2015	Satyanarayana and Rajan [37]	ANN	CASIA	Efficiency rate=94%
2011	Rashad et al. [38]	LVQ+ANN	CASIA, MMU	Recognition rate=99.87%
2012	Zhang and Guan [39]	KNN	CASIA	Recognition rate =99%
2013	Kulkarni et al. [40]	FUZZY KNN (FKNN) & KNN	CASIA Iris V3	Accuracy=88.50%
2016	Sachdeva and Kaur [41]	FUZZY SVM	IITD	Accuracy=99.14%
2017	Radman et al. [17]	SVM-HOG	NICE-II ICHE	Segmentation error rate -1.6%
2018	Arsalan et al. [19]	Densely onnected fully convolutional network (IrisDenseNet)	UBIRIS .V2, MICHE, CASIA v4, IIT D dataset	Accuracy up to 98%
2018	Bazrafkan, et al. [20]	Fully convolution deep neural n/w (FCDNN)	Bath80, CASIA, UBIRIS, MobBio	Accuracy up to 94% to 97.84%
2018	Proença and João [35]	CNN and sparse linear regression	CASIA-IrisV4 and UBIRIS.V2	0.99 rank-1 average accuracy in the CASIA-IrisV4- and over 0.88 in UBIRIS.v2
2019	**Proposed Method**	**Entropy based CNN(E-CNN)**	**UBIRIS .V2**	**Accuracy=97.99%, PPR=99.84% , Avg. Segmentation Error rate=0.16%**

We compare the average segmentation error rate of our proposed entropy based CNN segmentation algorithm with existing methodology from literature as shown Table 4. It is observed that proposed algorithm outperform by reducing segmentation error rate up to 0.6%.

Table 4. Comparison of proposed segmentation method with state of the art iris segmentation method with respect to error rate.

Method	Segmentation Error Rate (%)
Proenca and João [35]	3.8
Tan et al. [42]	3.5
Tan and Kumar [43]	2.8
Tan and Kumar [44]	1.8
Radman et al. [17]	1.6
Proposed method	**0.6**

5. Conclusion and Feature Work

Performance of iris and sclera recognition is highly dependent on the segmentation procedure. In this paper we presented an efficient entropy based convolution neural network (E-CNN) algorithm for iris, sclera and pupil segmentation which improve the accuracy and also reduces time required for segmentation up to 0.9 seconds by reducing feature dimensionality. As color and texture are prominent features in color eye images, we introduce multi algorithmic feature extraction based on color histogram and log Gabor filter for iris and Y-shape features of sclera to enhance the performance. A novel support value based fusion (SVBF) matching algorithm have been developed which increases the accuracy of multimodal eye biometric system for person identification. However, more experimentation is needed to check the performance of proposed system on images acquired in different conditions. In future we will be combine periocular features to improve performance of recognition and will check the performance of proposed algorithm for real time applications.

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