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Effective segmentation of sclera, iris and pupil in noisy eye images

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Abstract

In today's sensitive environment, for personal authentication, iris recognition is the most attentive technique among the various biometric technologies. One of the key steps in the iris recognition system is the accurate iris segmentation from its surrounding noises including pupil and sclera of a captured eye-image. In our proposed method, initially input image is preprocessed by using bilateral filtering. After the preprocessing of images contour based features such as, brightness, color and texture features are extracted. Then entropy is measured based on the extracted contour based features to effectively distinguishing the data in the images. Finally, the convolution neural network (CNN) is used for the effective sclera, iris and pupil parts segmentations based on the entropy measure. The proposed results are analyzed to demonstrate the better performance of the proposed segmentation method than the existing methods.

Keywords: *contour-based features, entropy measure, normalization, preprocessing, segmentation*

1. Introduction

Iris recognition emerging as one of the most preferred biometric technology modalities for automated personal identification [1-3]. It is a biometric recognition technology that utilizes pattern recognition techniques on the basis of iris high quality images [4, 5]. Since in comparison with other features, iris recognition is best biometric technologies [6]. Iris segmentation under visible spectrum (VIS) is still a very challenging problem. Non cooperative iris recognition refers to automatically recognize at a distance and dealing with several factors that deteriorate the quality of an image [7]. Many algorithms have been proposed for separating the iris region from the non-iris regions on images. One of the main approaches consists on boundary-based methods [8-11].

Moreover, segmentation of the sclera region helps to improve iris recognition accuracy under different lighting conditions and eye gazes [12]. After decades of research on iris recognition, the technology is now heading to improve recognition performance by combining other ocular (retina, cornea, sclera, pupil, periocular) or non-ocular (face, fingerprint, palm print etc.) modalities [13]. Although the accuracies of the visible spectrum, iris recognition systems are not comparable to those operating in the near infrared spectrum [14], the visible spectrum iris imaging has the advantage of permitting the integration of additional sources of information, such as eye color or sclera vasculature [15].

A method for sclera segmentation based on Fuzzy logic is proposed by [16, 17]. SVM and feature selection techniques [18], Circular Hough Transform and K-Means algorithm [19] Reverse bio-wavelet transform [20] for iris recognition. The highest difficulty of human iris segmentation is that it is hard to discover the apparent feature values in the image and to keep their represent capability high in a proficient manner [21]. Also, difficulty in sclera segmentation arises from the inclusion of eyelids and eyelashes in the sclera region and the noticeable effect of lighting conditions. The performance of iris, sclera and recognition systems highly depends on the segmentation process which is a challenging problem.

The main contributions of this paper are as follows: 1) contour Based Features are extracted for the effective segmentation of pupil, iris and sclera; 2) entropy is measured to effectively distinguishing the data in the images; 3) the CNN based on the entropy measure is used for the effective sclera, iris and pupil parts segmentations.

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2. Related Work

Andrea F. Abate et al. [22] proposed a novel human iris recognition approach based on a multi-layer perceptron NN and particle swarm optimization (PSO) algorithms to train the network in order to increase generalization performance. A combination of these algorithms was used as a classifier. A PSO algorithm was applied to train the NN for data classification. Naglaa et al. [23] presented a coarse-to-fine algorithm for efficient Iris Localization and Recognition, while achieving an acceptable accuracy. The iris gray image was transformed to a binary image using an adaptive threshold obtained from analyzing the image intensity histogram. Finally, a refinement step was made using an integral-differential operator to get the final iris and pupil centers.

Mohammed A. M. Abdullah et al. [24] proposed a novel segmentation method for non-ideal iris images. Two algorithms were proposed for pupil segmentation in iris images, they were captured under visible and near infrared light. The proposed scheme was robust in finding the exact iris boundary and isolating the eyelids of the iris images. Alkassaret al. [25] presented the design of a robust sclera recognition system with high accuracy. They also proposed an efficient method for vessel enhancement, extraction, and binarization. In the feature extraction and matching process stages, they additionally developed an efficient method, that is, orientation, scale, illumination, and deformation invariant. Pattabhi Ramaiah and Ajay Kumar [26] have developed a domain adaptation framework to address the problem and introduced a new algorithm using Markov random fields (MRF) model to significantly improve cross-domain iris recognition.

3. Research Method

This paper presents a proficient segmentation of iris, sclera, and pupil utilizing effective features and CNN clustering. Here, the CNN successfully clusters the data in images based on the similarity obtained by the entropy measure and subsequently results the sclera, iris and pupil segments separately. The processing flow of the proposed strategy is given in Figure 1.

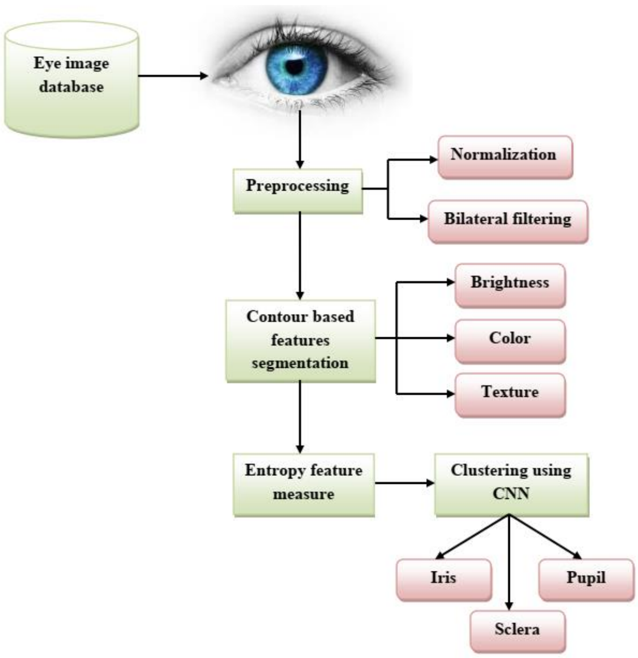


Figure 1. Processing flow of proposed method

3.1. Preprocessing

At first input image is taken from database and preprocessed by using normalization process and bilateral filtering to enhance the further processing. The pre-processing is described in following sections.

3.1.1. Normalization

Normalization achieves the linear transformation of the image to fit into a particular range. Here, Min-max normalization procedure is utilized for the standardization of image which linearly transforms the information. Min-Max normalization is done through the accompanying condition (1):

$$N' = \frac{\tilde{Y} - \tilde{Y}_{\min}}{\tilde{Y}_{\max} - \tilde{Y}_{\min}} \tag{1}$$

where, $\tilde{Y}_{\min}$ and $\tilde{Y}_{\max}$ are the minimum and maximum values in image $\tilde{Y}$, where N' is the normalized image.

3.1.2. Bilateral filtering

The bilateral filter takes a weighted sum of the pixels in a nearby neighborhood; the weights rely upon both the spatial distance and the intensity distance. Precisely, at a pixel location x, the output of a bilateral filter is computed as follows:

$$\hat{I}(x) = \frac{1}{C'} \sum_{y' \in N(x')} e^{\frac{-\|y'-x'\|^2}{2\sigma_d^2}} e^{\frac{-|I(y')-I(x')|^2}{2\sigma_r^2}} I(y') \tag{2}$$

where, σ_d and σ_r are parameters controlling the fall-off of weights in spatial and intensity domains, individually, $N(x')$ is a spatial neighborhood of pixel $I(x')$, and C' is the normalization constant. This Bilateral filter is mostly utilized for smoothing the image in the areas of low color variations that would improve segmentation.

3.2. Contour Based Features Segmentation

Contour features are metrics utilized to extract information about texture, color and brightness. This section depicts the brightness, color, and texture feature and how it is computed efficiently.

3.2.1. Texture feature

Computing this esteem is based on a simple comparison of text on distributions on either side of a pixel in respect to its overwhelming orientation. We can change over this to likelihood like esteem utilizing the function a stakes after

$$\tilde{P}_{texture} = 1 - \frac{1}{1 + \exp[-(X_{LR}^2 - \tau)/\beta]} \tag{3}$$

This esteem, which extends between 0 and 1, texture esteem is little if the distributions on the two sides are altogether different and huge otherwise and X_{LR}^2 is the maximal likelihood esteem. Generally, $\tilde{P}_{texture} = 1$ for situated energy maxima in texture and $\tilde{P}_{texture} = 0$ is for contours. $\tilde{P}_{texture}$ is defined to be 0 at pixels which are not situated energy maxima.

3.2.2. Brightness

A few objects in the image can be black or white. They are not salient in color but rather in brightness. It returns the intensity measure of brightness between a pixel and its neighbor through the whole image and, brightness is 0 for a constant image.

$$\hat{B} = \sum_{a,b} |a-b|^2 \, P(a,b) \tag{4}$$

In which, $\hat{B}$ is the brightness and $P(a,b)$ is the pixel at location (a,b).

3.2.3. Color feature

Color feature indicates the rate of occurrence of each color indexes in an image with dissimilar intensities. Color feature vector for a given image is segmented by the condition (5):

$$\hat{z} = \frac{1}{M}\sum_{j=1}^{M} z_i \tag{5}$$

where, M is the quantity of pixels within each block, z_i is the pixel intensity.

3.2.4. Entropy

Entropy (En) is utilized to describe the texture of of iris and non-iris like sclera and pupil the input image. Here the entropy is evaluated for the segmented contour based features. Entropy of the i^{th} super pixel E_y^i is computed by the condition (6) as:

$$E_y^i = \sum_{i=0}^{m-1}\sum_{j=0}^{m-1} P(i,j)(-\log_2(P(i,j))) \tag{6}$$

where i and j are the coefficients of co-occurrence matrix, $P(i,j)$ is the component in the co-occurrence matrix at the coordinates i, j and N is the dimension of the co-occurrence matrix.

3.3. Segmentation of Sclera, Iris and Pupil Regions using CNN Clustering

Convolutional neural networks are generally made by a set out of layers that can be gathered by their functionalities. The extracted entropy features set $f(E_y^i) = \{E_y^1, E_y^2, E_y^3, ...E_y^i\}$ are the input to the CNN classifier to segment the iris, sclera and pupil segments. The structure of Convolution neural network classifier is appeared in Figure 2.

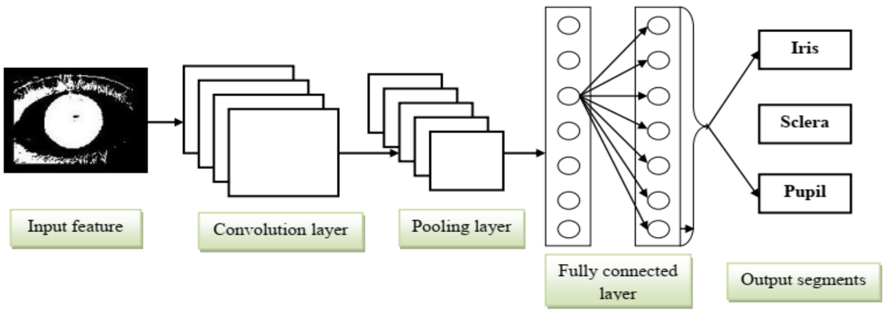


Figure 2. Structure of convolutional neural network

The concluding output decision of the CNN depends on the weights and biases. Consequently, these are updated with condition (7) and (8) correspondingly for each layer:

$$\Delta W_l = -\frac{x\lambda}{r}W_l - \frac{x}{n}\frac{\partial C}{\partial W_l} + m\Delta W_l(t) \tag{7}$$

$$\Delta B_l = -\frac{x}{n}\frac{\partial C}{\partial B_l} + m\Delta B_l(t) \tag{8}$$

where W, B, l, λ, x, n, m, t, C denotes the weight, bias, layer number, regularization parameter, learning rate, total number of training samples, momentum, updating step, cost function respectively. The CNN classifier consists of different types of layers as:

a) Convolutional layer: This layer performs the convolution on the input data with the kernel using (9):

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n} \tag{9}$$

here x, h, N, y denotes the input features, filter, number of elements in x, output respectively.

b) Pooling layer: The pooling layer reduces the dimension of output neurons.

c) Fully connected layer: This layer connects *every* neuron from the max-pooled layer to every one of the output neurons. The activation function used in this work is as follows:
Softmax: This function computes the probability distribution of the k output classes:

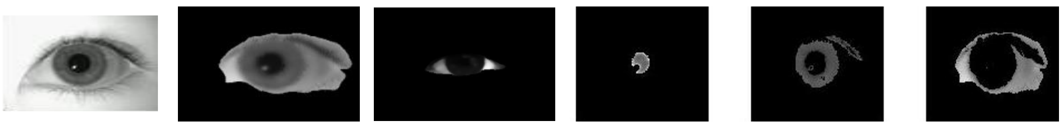
$$p_i = \frac{e^{x_i}}{\sum_1^k e^{x_i}} \tag{10}$$

here, the CNN clusters the data in images based on the entropy value and results the effective sclera, iris and pupil region segmentations.

4. Results and Analysis

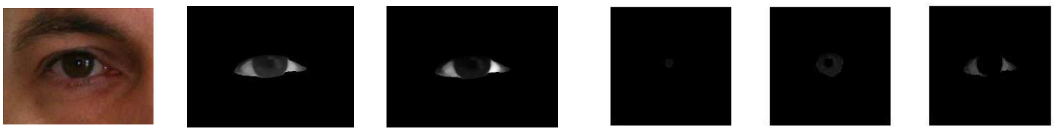
The proposed efficient segmentation of iris, sclera and pupil regions by utilizing entropy based CNN clustering is implemented in MATLAB. The freely accessible MMU database and UBIRIS.v2 database of eye images are utilized to assess proposed segmentations. In this section, the experimental results accomplished for the proposed technique are given.

Figure 3 and Figure 4 depicts the segmentation of iris, sclera and pupil for the number of input sample eye images taken from the MMU database and UBIRIS.v2 database respectively. The comparison Table 1, Table 2, and Table 3 illustrates that our proposed iris, sclera and pupil segmentation utilizing CNN is extensively better than the existing ANFIS and KNN. The comparison graph of segmentations regards of accuracy, sensitivity, PPV and specificity (FNR and FDR) of iris, sclera and pupil are shown in Figures 5-6, 7-8, 9-10 respectively.



(a) (b) (c) (d) (e) (f)

Figure 3. Segmentation of (a) Input image, (b) counter image, (c) entropy image, (d) pupil, (e) iris, and (f) sclera regions images taken from MMU database



(a) (b) (c) (d) (e) (f)

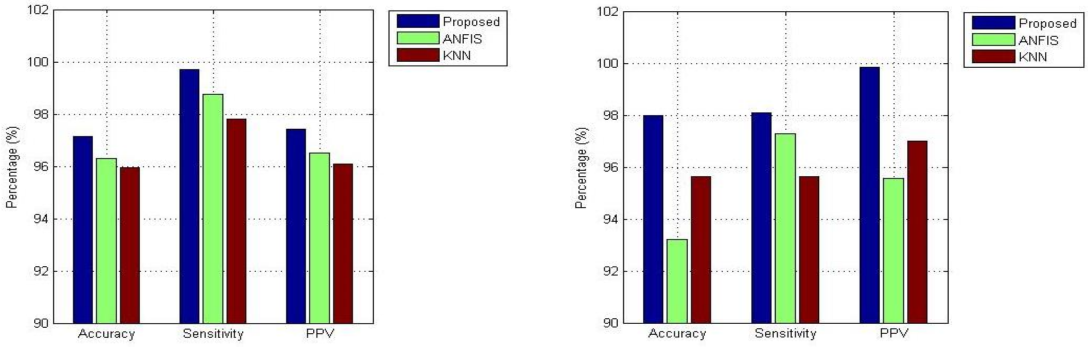
Figure 4. Segmentation of (a) input image, (b) counter image, (c) entropy image, (d) pupil, (e) iris, and (f) sclera regions images taken from UBIRIS.v2 database

4.1. Iris Segmentation

The comparison table of proposed iris segmentation with existing ANFIS, and KNN in regards to different execution measures is portrayed in Table 1.

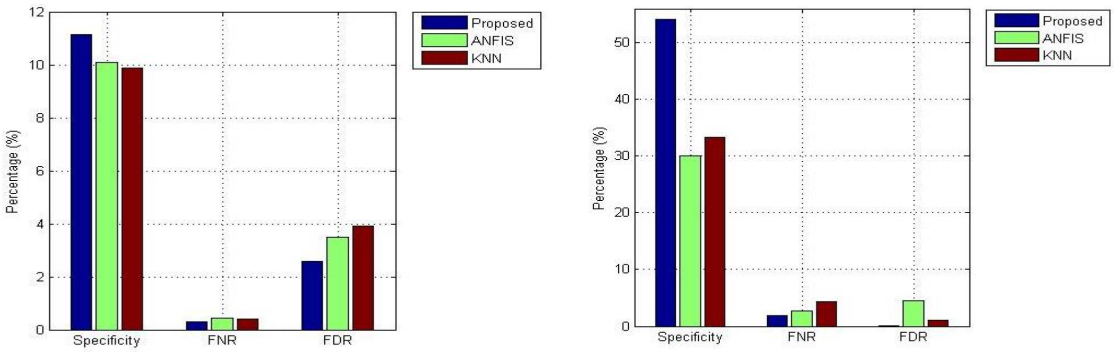
Table 1. Comparison Analysis of Proposed Method in Terms of Various Performance Measures

Database	Methods	Accuracy	Sensitivity	Specificity	PPV	FNR	FDR
	Proposed	97.145	99.694	11.130	97.426	0.305	2.573
MMU	ANFIS	96.306	99.761	10.081	96.514	0.238	3.485
	KNN	95.931	99.798	9.880	96.100	0.201	3.899
	Proposed	97.996	98.101	54.171	99.837	1.898	0.162
UBIRIS.v2	ANFIS	93.203	97.295	29.977	95.550	2.704	4.449
	KNN	95.634	95.640	33.333	96.993	4.359	1.006



(a) (b)

Figure 5. Comparison graph of iris segmentation in terms of accuracy, sensitivity and PPV for (a) MMU database (b) UBIRIS.v2 database



(a) (b)

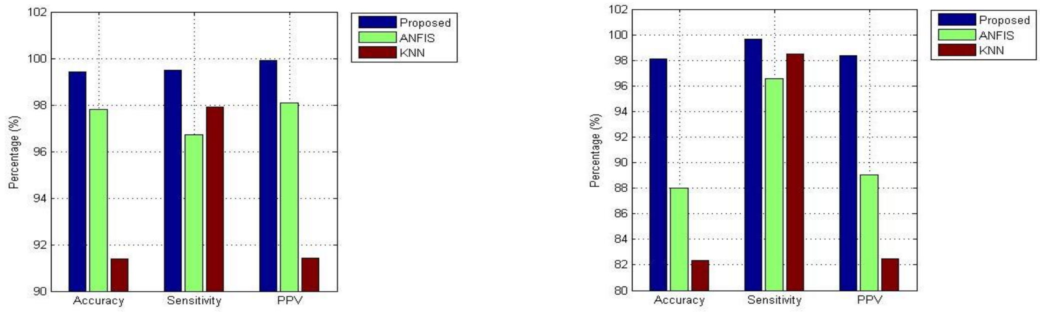
Figure 6. Comparison graph for iris segmentation in terms of specificity, FNR and FDR for (a) MMU database (b) UBIRIS.v2 database

4.2. Sclera Segmentation

The comparison table of proposed sclera segmentation with existing ANFIS, and KNN in regards to different execution measures is portrayed in Table 2.

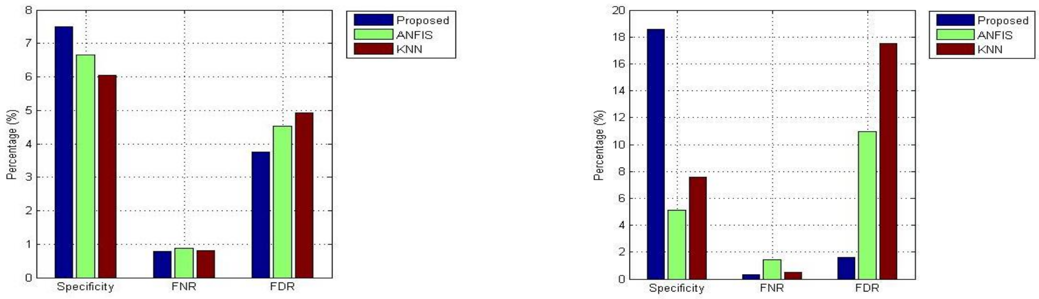
Table 2. Comparison Analysis of Proposed Technique in Terms of Different Performance Measures

Database	Methods	Accuracy	Sensitivity	Specificity	PPV	FNR	FDR
	Proposed	95.538	99.210	7.504	96.257	0.789	3.742
MMU	ANFIS	96.640	99.125	7.652	97.464	0.874	2.535
	KNN	95.344	99.183	6.652	96.085	0.816	3.914
	Proposed	98.080	99.663	18.571	98.377	0.336	1.622
UBIRIS.v2	ANFIS	88.002	96.588	5.119	89.052	1.411	10.947
	KNN	82.363	98.486	7.583	82.460	0.513	17.539



(a) (b)

Figure 7. Comparison graph for sclera segmentation in terms of accuracy, sensitivity and PPV for (a) MMU database (b) UBIRIS.v2 database



(a) (b)

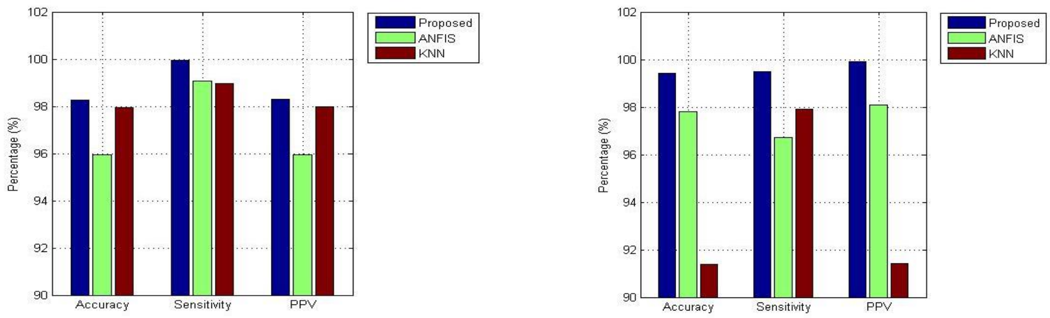
Figure 8. Comparison graph for sclera segmentation in terms of specificity, FNR and FDR for (a) MMU database (b) UBIRIS.v2 database

4.3. Pupil Segmentation

The comparison table of proposed pupil segmentation with existing ANFIS, and KNN in regards to of different execution measures is portrayed in Table 3.

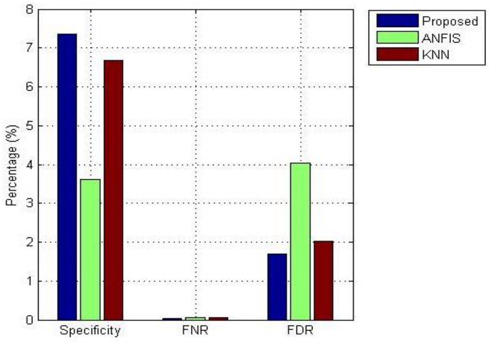
Table 3. Comparison Analysis of Proposed Method in Terms of Different Performance Measures

Database	Methods	Accuracy	Sensitivity	Specificity	PPV	FNR	FDR
	Proposed	98.275	99.957	7.363	98.314	0.042	1.685
MMU	ANFIS	95.942	99.974	3.605	95.960	0.0259	4.039
	KNN	97.947	99.968	6.676	97.974	0.0317	2.025
	Proposed	99.423	99.495	33.913	99.926	0.504	0.073
UBIRIS.v2	ANFIS	97.821	96.728	18.887	98.072	0.871	1.927
	KNN	91.389	97.899	6.779	91.420	0.700	8.579

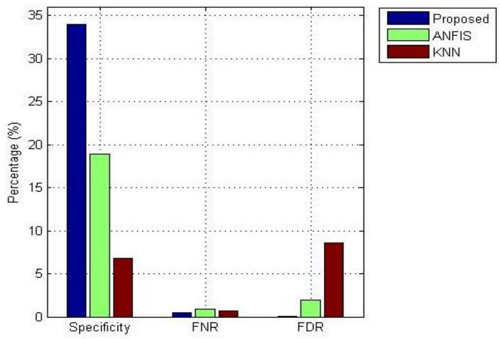


(a) (b)

Figure 9. Comparison graph for pupil segmentation in terms of accuracy, sensitivity and PPV for (a) MMU database (b) UBIRIS.v2 database



(a)



(b)

Figure 10. Comparison graph for pupil segmentation in terms of specificity, FNR and FDR for (a) MMU database (b) UBIRIS.v2 database

5. Conclusion

In this paper we have presented a proficient segmentation of iris, sclera and pupil regions from the eye images individually utilizing entropy based CNN clustering. The performance of iris, sclera and segmentation is highly depends on the segmentation process. Here, CNN effectively segments the iris, sclera regions based on the entropy measures. The experimental outcomes exhibit that our proposed classification out performs the existing KNN and ANFIS methods in regards of performance measures such as, accuracy, sensitivity, specificity, PPV, NPV, FPR, FNR, FDR, F-measure and MCC.

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