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A ROBUST IRIS SEGMENTATION METHOD USING DEEP NEURAL NETWORKS

[1]K A S S MOUNIKA, [2]Dr. A M PRASAD
[1]M. Tech Student, [2]Professor, Department of ECE
[1]Department of ECE,
[1]University College of Engineering, JNTUK, Kakinada, Andhra Pradesh,
[2]University College of Engineering, JNTUK, Kakinada, Andhra Pradesh

Abstract: Iris recognition is one of the key processes in verifying a person's identity. To get the accurate information about the identity of the person through it, iris segmentation plays a major role. With the increase in deep learning, researches on automatic iris segmentation schemes are increasing day-by-day. In this paper, an automatic iris segmentation scheme is proposed using the SEGNET model. This model is trained and tested on CASIA-Iris-Interval v4.0 dataset from [10] and segmentation results are obtained. The accuracy and errors are obtained by calculating 3 different parameters namely F1 score, Nice1 and Nice2 scores respectively. By using this method, it is observed that this model gives the results with better accuracy of 99.6% and the minimum Nice1 and Nice2 scores such as 0.6% and 0.3% respectively. As this model consists of number of training parameters, it is considered to be better and feasible model when compared to other Convolutional Neural Network (CNN) models such as U-Net.

IndexTerms - **Iris Recognition, Iris Segmentation, Deep Learning, Convolutional Neural Networks, U-Net, SEGNET**

I. INTRODUCTION

Biometrics is defined as "the science of measuring physical characteristics of individuals and it performs automatic identification of a person based on his/her physiological characteristics". The most common features to be measured are face, fingerprints, handwriting, iris, retinal, voice(speech). We apply these techniques in our day – to – day activities such as attendance system in schools, colleges and other work places, as an authentication for Government Ids etc.

The advantages of biometric identification are:

1. It is stable and convenient to use.
2. It cannot be forged easily.
3. It is easier to integrate computer with security, monitoring and management systems.

The different types of biometric identification techniques include Fingerprint Identification, Face recognition, Voice(speech) recognition, Iris recognition, Handwriting Identification etc.

Iris recognition is the most commonly used method among all the methods. It is an automated method which uses pattern recognition techniques on iris images of individual. Iris is the part of the eye which is present around the pupil of the eye. It contains unique and complex patterns which can be seen form some distance and is helpful in distinguishing one person from another.

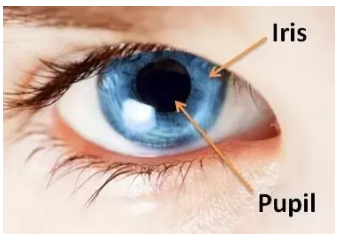


Figure 1: eye image representing iris and pupil regions

The advantages of Iris recognition technique are:

1. It is Unique from One person to another.
2. It is stable.
3. It is more convenient, safe and efficient than other methods.

Any iris recognition system mostly involves five basic steps. They are - iris image acquisition, pre-processing, iris segmentation, iris feature extraction and iris matching verification or identification. With the introduction of deep learning, the process to segment the iris region is simplified as there is no need for localization of iris region.

Among these steps iris segmentation is the most critical and important step in the complete process. It is used to separate the iris pattern from other parts of eye such as pupil, retina etc. Based on the accuracy of the iris segmentation, the accuracy of the whole iris recognition process depends. So, it is very important step in the whole process.

In this paper, an automatic iris segmentation scheme is proposed based on SEGNET and it is trained and tested using the popular Iris dataset and ground truth images.

II. RELATED WORKS:

In this section, different methods which are used for iris segmentation are mentioned.

A. Conventional Methods:

Iris segmentation is to accurately locate the iris region in the iris image. In the early time, iris segmentation was based on the concept that the pupil and the iris edge in an iris image are approximately circular.

Bowyer et al. [1] researched about different methods used for recognizing the iris biometrics. Daugman and John [2] used the calculus operator as the circular edge detector and segmented the iris by fitting the circular boundary of pupil and iris.

He et al. [3] built Adaboost-cascade iris detectors and an elastic model named 'pulling and pushing method' to segment the iris.

The above two methods are the conventional methods for iris segmentation.

These methods have drawbacks such as:

i. They require high-quality iris images, and need a clear and regular shape of iris boundaries.
ii. For the non-ideal iris images, there are some noises such as blur, glasses occlusion, and so on.

B. Iris Segmentation Using CNN:

With the increase in deep learning theory, researches are being conducted to segment iris using deep learning techniques. CNN is a typical network structure in deep learning. CNN can be used to segment the iris image, which reduces the procedures of iris feature extraction and feature selection to further improve the segmentation accuracy.

Liu et al. [4] proposed Hierarchical Convolutional Neural Network (HCNN) and Multi-scale Fully Convolution Network (MFCN) to deal with noisy iris images acquired in long distance and in motion. Yang et al. [5] proposed a network model combining FCN with dilated convolution to segment iris. Bazrafkan et al. [6] proposed an end-to-end convolutional neural network for low-quality iris image segmentation with good results. Lozej et al. [7] implemented end-to-end iris segmentation using U-Net model.

Hofbauer et al. [8] worked on implementing and obtaining the ground truth images for a set of images in different datasets such as Casia-4i, IIT Delhi, ND-IRIS-0405, UBIRIS.v2. Wei Zang et al. [9] implemented an iris segmentation scheme based on improved U-Net. In this paper, four different networks are implemented by combining U-Net with Dilated Convolutions namely Part Dilated Convolution U-Net 1 (PD U-Net1), Part Dilated Convolution U-Net 2 (PD U-Net2), Part Dilated Convolution U-Net 3 (PD U-Net3) and a Fully Dilated Convolution U-Net (FD U-Net). Among the four networks FD U-Net is considered as better network.

III. MODEL AND ARCHITECTURE:

In this section, the architecture of SEGNET model is studied and its advantages are discussed.

A. SEGNET MODEL:

SEGNET is a deep fully convolutional neural network model used for Pixel-Wise Semantic Segmentation. This consists of an Encoder-Decoder type architecture where the encoder part extracts the feature maps by doing Down-Sampling operation and the Decoder part is used for up-sampling of the outputs obtained in the corresponding encoder layers. Unlike other networks, in SEGNET, the pooling indices are transferred from encoder to decoder and through up-sampling, the feature maps are processed. The architecture of the SEGNET is shown below.

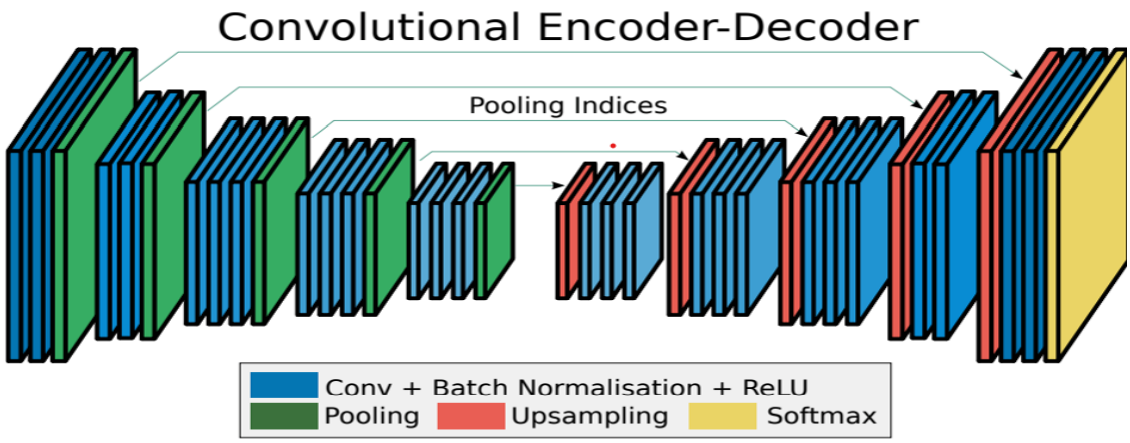


Figure 2: architecture of SEGNET

From the above architecture, we can observe that when the input image is given, by doing successive convolutions and pooling operations the image size is reduced and the feature maps are obtained. The convolution layers are activated by the ReLU activation function and the Batch Normalization layer divides the images into mini batches to obtain the accurate outputs. Later, the pooling indices of each layer obtained in the encoder are transferred to the corresponding layers in the decoder and the up-sampling operation is done to increase the features in the image. The illustration of up-sampling operation is shown below.

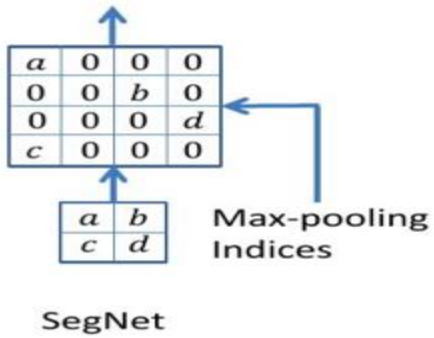


Figure 3 : up sampling of the outputs obtained in encoder

Finally, the softmax activation function is used to predict the output and the Pixel Classification layer is used to classify the pixels in the image and obtain the desired output.

B. ADVANTAGES OF USING SEGNET:

The advantages of using this model are:

1. The number of trainable parameters in this network is less compared to other networks.
2. SEGNET consumes less memory than U-Net as only Pooling indices are transferred from encoder to decoder.
3. The segmentation accuracy of SEGNET is more.
4. The time taken to train the model is reduced.

IV. DATASET AND EXPERIMENT:

In this section, the dataset used in this paper for iris segmentation is discussed and the different methods to evaluate the performance of the output are verified.

A. DATASET USED:

The network given above is trained and tested on CASIA-IRIS-Interval V4.0 dataset. This dataset is the subset of CASIA IRIS-v4 dataset. It consists of about 2000 images and the mostly all the images in the dataset taken in the indoor environment with a close-range infrared iris camera. The ground truth images (masks) used in the project are obtained from [9]. Generally, the size of the images used in the dataset is 320 x 280.

B. EVALUATION CRITERA:

After retrieving the iris region from the image, 4 parameters are calculated by comparing the obtained imaged with its corresponding mask. They are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). All these values are shown in fig4.

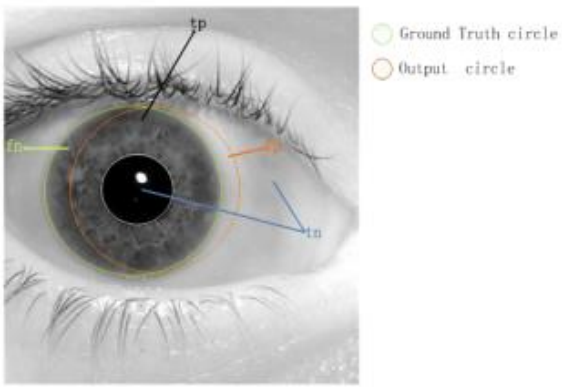


Figure 4.: eye image representing different parameters

From the fig 4 we can understand that TP indicates the number of iris image pixels which are segmented correctly, TN indicates number of non-iris pixels which are not recognized in the output image, FP indicates the number of iris image pixels which are recognized incorrectly and FN indicates the number of unrecognized iris image pixels.

After the above four parameters are obtained, the performance of the network is evaluated by using the nice1 and nice2 scores for obtaining the error scores and the accuracy of the network is obtained by using the F1 scores. The Nice1 score which used for obtaining the error rate is calculated by "the ratio of inconsistent pixels in the resulting image to all the pixels in the image". It is mathematically calculated by using the formula,

$$Nice1 = \frac{1}{N \times m \times n} \sum_{k=1}^{N} \sum_{i,j \in (m,n)} G(i,j) \oplus O(i,j) \qquad \text{---------- (1)}$$

Here N represents the number of images, (m, n) represents the spatial resolution of the image, G (i, j) represents the ground truth image pixels and O (i, j) represents the predicted output image pixels.

The Nice2 score is also used to find out the error rate of the obtained output. It is obtained by the average of the False Positive Rate (FPR) and False Negative Rate (FNR). FPR is calculated by the formula below:

$$FPR = \frac{FP}{FP+TN} \qquad \text{---------- (2)}$$

FNR is calculated by using the formula below:

$$FNR = \frac{FN}{FN+TP} \qquad \text{----------(3)}$$

The Nice 2 score is calculated by using the formula:

$$Nice2 = \frac{1}{2} \times (FPR + FNR) \qquad \text{---------- (4)}$$

The F1 score is calculated for finding the segmentation accuracy of the output. It is defined as "harmonic average of the precision and recall values". It is calculated by using the formula:

$$F1 = \frac{2TP}{2TP+FP+FN} \qquad \text{---------- (5)}$$

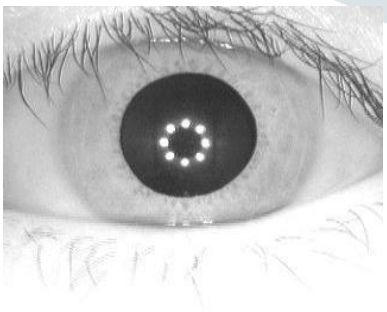
It can also be calculated by

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \qquad \text{---------- (6)}$$

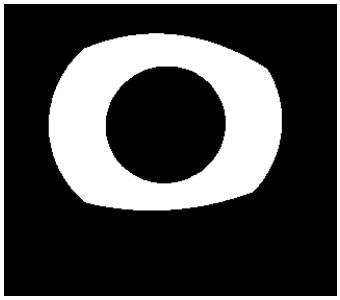
If the F1 value is high, it indicates that the output obtained through network is more accurate.

V. Results:

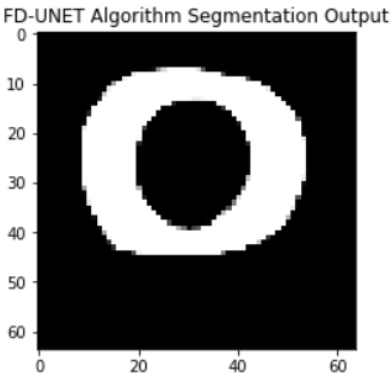
Figure below shows the segmentation output of the image using different architectures.



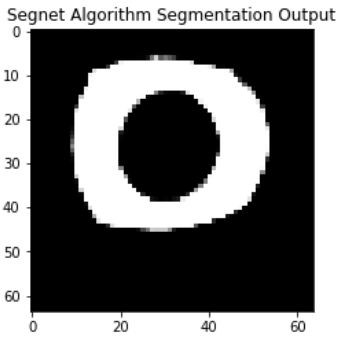
(a)



(b)



(c)



(d)

Figure 5: outputs obtained using (a) Input Image (b) Ground truth Image (c) FD U-Net output (d) SEGNET Output

The F1 accuracy and Error scores are found using the equations above and the results are compared with the results obtained in [9] and the results shown in table below.

Table 1: comparison table for different algorithms

Sl. No	Algorithm Name	Nice1	Nice2	F1 %
1	U Net	0.055534	0.028155	97.10
2	PD1-U Net	0.040637	0.020449	97.91
3	PD2- U Net	0.019739	0.009923	98.99
4	FD-U Net	0.010007	0.005027	99.49
5	SEGNET (Proposed)	0.006961	0.003486	99.65

VI. CONCLUSION:

In this paper, U-Net, PD U-Net1, PD U-Net2 and FD U-Net are studied and executed as given in [9] using the CASIA Iris dataset. Among those networks, FD U-Net is considered as the better network. To get more accurate results, the SEGNET model is implemented as an enhancement and the results obtained through this network are compared with above mentioned networks. From the comparison, SEGNET is the more accurate network in segmenting the iris region.

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