Iris Segmentation using Machine Learning

Aashutosh Khandelwal
IIT2016514

Sourin Chakrabarti
IIT2016513

Harshit Agarwal
IIT2016108

Nistala Venkata Kameshwar Sharma
ISM2016005

May 10, 2019

Abstract

Iris segmentation is an important research topic that received significant attention from the research community over the years. Traditional iris segmentation techniques have typically been focused on hand-crafted procedures that, nonetheless, achieved remarkable segmentation performance even with images captured in difficult settings. With the success of deep learning models, researchers are increasingly looking towards convolutional neural networks (CNNs) to further improve on the accuracy of existing iris segmentation techniques and several CNN-based techniques have already been presented recently in the literature. We had initially used traditional methods for iris segmentation such as thresholding, Hough transform and Daugman transform. But due to unsatisfactory results, we moved to deep learning techniques for iris segmentation. In this paper, we have used U-Net architecture which is widely used in most areas of image segmentation.

1 Introduction

One crucial step in iris recognition systems is the segmentation of the iris region from the input image. This step has traditionally been solved using manually designed segmentation techniques and considerable performance has already been achieved on numerous datasets of variable quality. However, with the success of deep-learning models for other vision problems, researchers are increasingly looking into convolutional neural networks (CNNs) to further improve on the performance of existing iris segmentation techniques.

In this paper, we have used and studied the utility of U-Net, a deep convolutional neural network (CNN) commonly used for image translation tasks, for the problem of iris segmentation and compared with the several existing methods of iris segmentation such as Hough and Daugman Transforms and thresholding which fail to give competitive results.

Most of the commercial algorithms are based on linear search methods which make the identification process extremely slow and also raise the false acceptance rate beyond the acceptable range. The proposed iris recognition approach consists of an automatic segmentation system that is based on the deep learning algorithms and is able to localize the circular iris and pupil region, occluding eyelids and eyelashes and reflections.

2 Literature Review

Iris segmentation techniques represent an active topic of research within the research community. The interest in iris segmentation is fueled by iris recognition technology, where the detection of the region-of-interest (ROI) is the first (and of the most important) step is the overall processing pipeline. By segmenting the iris from the input image, irrelevant data that would otherwise interfere with the success of the recognition process is removed. Additionally, the segmentation step makes it possible to normalize the iris region and extract discriminative features from well aligned iris samples.

[YHLJ19] suggested the use of a well-designed Faster R-CNN with only six layers is built to locate and classify the eye. With the bounding box found by Faster R-CNN, the pupillary region is located using a Gaussian mixture model. Then, the circular boundary of the pupillary region is fit according to five key boundary points. A boundary point selection algorithm is used to find the boundary points of the limbus, and the circular boundary of the limbus is constructed using these boundary points.

[AF18] proposed using a convolution neural network for iris segmentation. Their network builds on the Mask R-CNN framework. Their approach segments faster than previous approaches including the Mask R-CNN network.

[EJK17] proposed the use of two domain adaptation methods to transfer the domains of source iris databases (for which segmentation labels are available) to those of the targets, generating adapted iris databases, which in turn, enable training of a Fully Convolutional Neural Network (FCN) for segmentation of iris in the target databases.

[VKG] used simple methods such as thresholding and canny edge detection for localization of the iris but could not achieve great results. As suggested by [VKG], existing approaches to iris segmentation include Daugman's integro-differential operator, active contour models and clustering algorithms as well as techniques exploiting gradient (edge) information, variants of the Hough transform and others

3 Proposed Methodology

3.1 Datasets used

Our main resource for training and testing our model will be the CASIA-IrisV4 and CASIA-IrisV1 dataset. CASIA-IrisV4 contains a total of 54,601 iris images from more than 1,800 genuine subjects and 1,000 virtual subjects. All iris images are 8 bit gray-level JPEG files, collected under near infrared illumination or synthesized. CASIA Iris Image Database Version 1.0 (CASIA-IrisV1) includes 756 iris images from 108 eyes. For each eye, 7 images are captured in two sessions with our self-developed device CASIA close-up iris camera. All images are stored as BMP format with resolution 320*280.

3.2 Dataset Preprocessing

In the pre-processing step, all the images need to be normalized and converted to 320x320 single channel gray scale image. Then, the ground truth values of all the images we fetched from the CC dataset (IRISSEG-CC Dataset). For the CC dataset the parameters define circles which give the iris boundaries and eyelid masks. Eyelashes occlusion is not included in the segmentation data.

3.3 Related Work

Initially we tried to localize the iris boundary using thresholding and canny edge detection. If the intensity of a pixel I(x, y) is greater than a threshold, it is marked as white, otherwise it is marked black. Thresholding produces a binary image. The image obtained was further processed using morphology techniques with openCV. On this preprocessed image, a Canny edge operator is applied to obtain a set of edge points. A voting procedure is employed to ascertain whether that edge point lies on a circular region or not. Finally, all the regions were classified using a binary classifier. Specular reflections in the eye can lead to incorrect detection of the pupil/iris boundary. Hence, all kinds of illumination was removed from the image. First, the image complement was analyzed. Areas of dark pixels surrounded by lighter pixels were replaced by the lighter pixels.

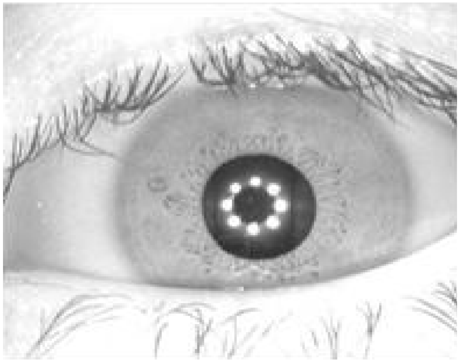

Figure 1: Original Iris Image.

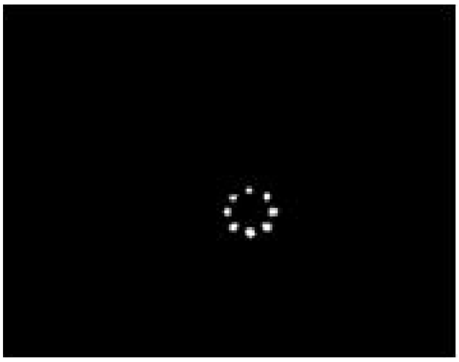

Figure 2: Binary Reflection Mask.

Next method used for segmentation was Hough transform. The general Hough transform can be used to detect geometric shapes that can be written in parametric form such as lines, circles, parabolas, and hyperbolas . The circular Hough transform can be used to detect the circles of a known radius in an image. As we don't know the definite radius of the pupil or iris, the transform must be computed for a range of radii. For each radius tested, the location and value of the maximum is stored. The radius with the highest peak indicates the most likely radius and center coordinate for the boundary. Another method used for our task was segmentation using Daugman's Integro Differential Operator (IDO) algorithm. Given a pre-processed image, the IDO an be used first to determine the iris's outer boundary. The operator searches over image domain for maximum in the blurred partial derivative with

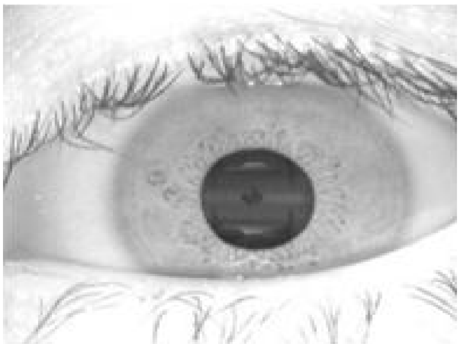

Figure 3: Image after reflection removal.

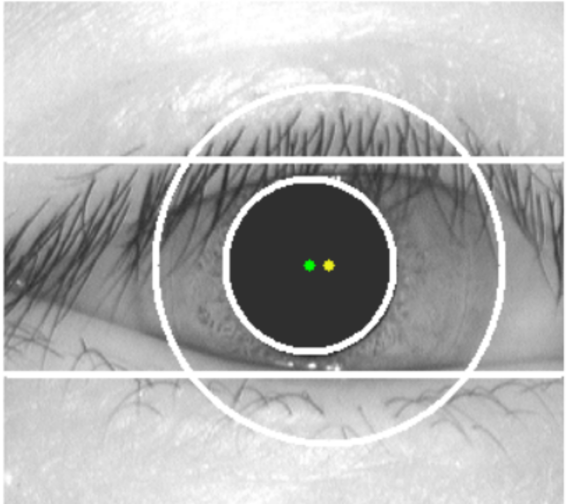

Figure 4: Iris segmentation using thresholding and canny edge detection. First, the iris and pupil boundary were detected and then the eyelid boundary was estimated.

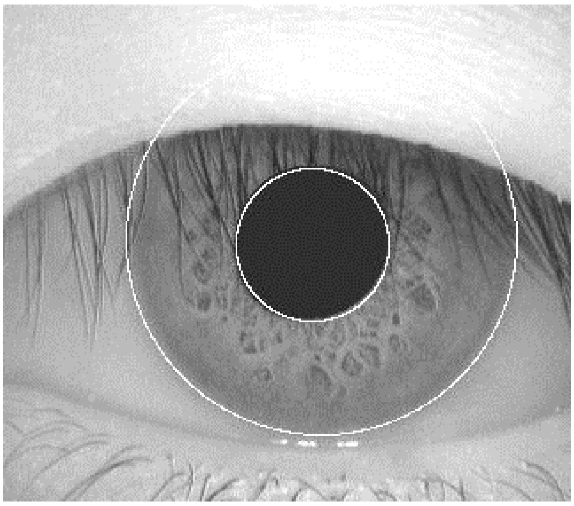

Figure 5: Iris segmentation using Hough Transform.

respect to increasing radius of the normalized contour integral of along a circular arc of some radius and center coordinate. obtained in Figure 1.

3.4 Deep Learning Architecture

The U-Net model represents a popular CNN architecture for solving biomedical problems and other image translation tasks. The main advantage of this model is it's ability to learn relatively accurate models from (very) small datasets, which is a common problem for data-scarce computer-vision tasks, including iris segmentation. U-Net uses an encoder-decoder architecture. The architecture is divided into corresponding encoder and decoder convolutional layers. The left side of the model is the encoder path and the right side is the decoder path. The encoder follows a typical CNN architecture, as popularized by the VGG network consisting of two 3×3 convolutional layers followed by a ReLu activation layer with max pooling. Each down-sampling step of the encoder doubles the amount of feature channels

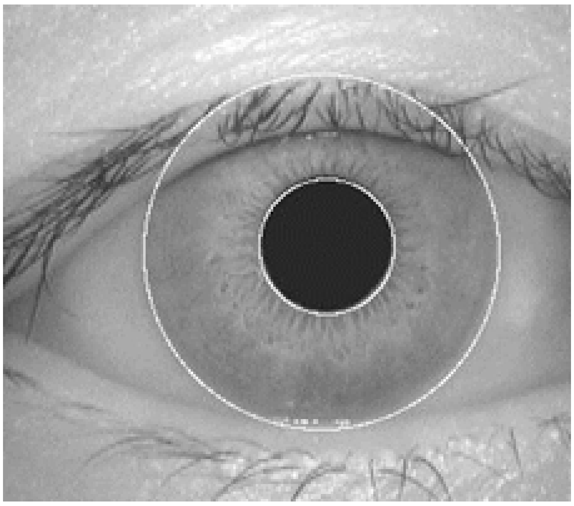

Figure 6: Iris segmentation using Daugman's Integro Differential Operator.

and decreases the image resolution by half. The decoder part than up-samples the feature maps of the lower layer while also concatenating and cropping the output of the encoder part of the same depth. This process ensure that information is propagated from the encoder to the decoder at all scales and no information is lost during the down-sampling operations in the encoder. The final layer of the network is a 1×1 convolutional layer that mixes the output channels of the preceding layer and produces the segmentation maps (one per class - iris vs. non-iris) that represent the output of the U-Net model (Note that for binary segmentation problems the masks are complements of each other).

3.5 Training details

The model was first trained on the Casia V1 dataset which contains iris images without specular reflections. Then, the model was trained with images from the Casia V4 dataset. The ground truth values were obtained from the IRISSEG-CC Dataset. All models are trained using the Adam optimizer with a learning rate of $10-4$ and zero decay. During training no augmentations are used. The models were implemented in python using Keras high-level neural network API with Tensorflow as its backend.

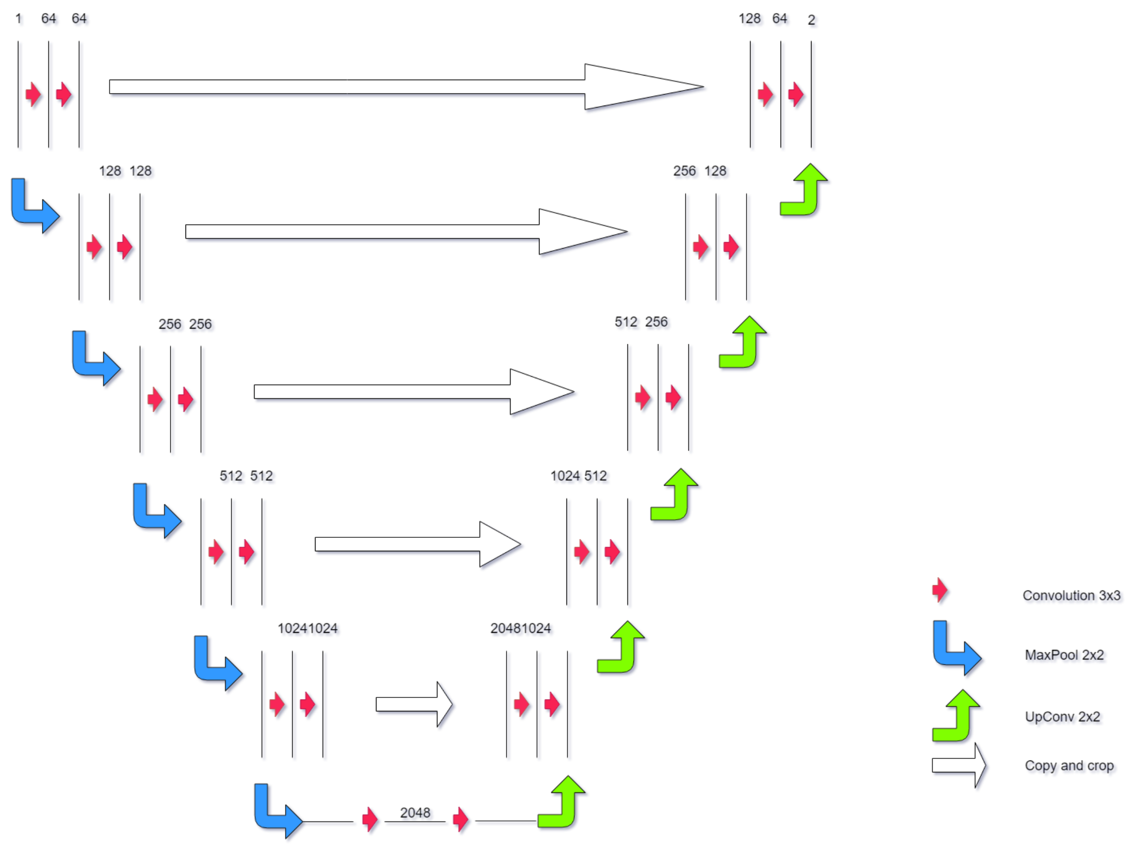

Figure 7: Graphical representation of Model.

4 Results and Future Scope

In our series of experiments, we found that the U-Net architecture gave significantly better results than the other methods on images without specular illumination. The model achieved an overall accuracy of 94.80 percent which is significantly higher than the traditional methods. For images with illumination, we found that the accuracy dipped significantly to 85.70 percent which is below par in case of iris images which have high amounts of details. Traditional methods of illumination removal seemed to work better than deep learning techniques in terms of average precision. Hence, the next step would be to take the best of both worlds and work on an architecture that removes illumination first and then goes for iris segmentation.
Hence, we see that the U-Net based segmentation model proved to be very successful at segmenting the iris, while also outperforming all considered baseline methods(for certain cases). The model didn't require a great amount of training data and worked well without the use of data augmentation during training. In conclusion the use of deep learning methods in iris recognition may provide an increase in performance in an area of biometrics compared to conventional methods

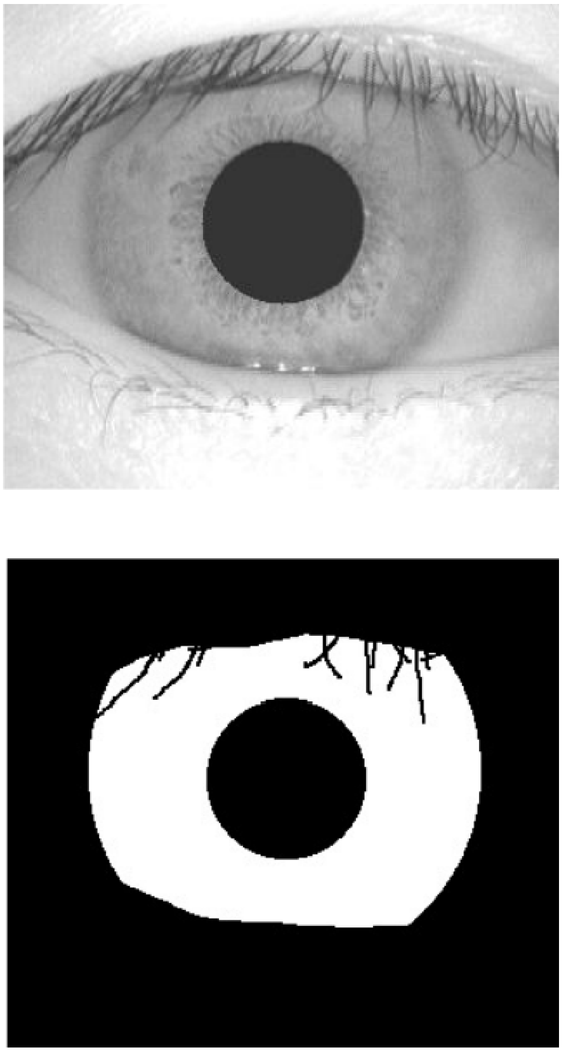

Figure 8: Iris segmentation using U-Net. The first image is the original image and the second image is the binary mask(the output of the model) which when multiplied with the original image gives the iris.

References

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