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Iris Recognition- Image Processing

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ABSTRACT: Biometrics systems have significantly improved person identification and authentication, playing an important role in personal, national, and global security. Iris segmentation algorithms are of great significance in complete iris recognition systems, and directly affect the iris revivification and recognition results. However, the conventional iris segmentation algorithms have poor adaptability and are not sufficiently robust when applied to noisy iris databases captured under unconstrained conditions. In addition, there are currently no large iris databases; thus, their is segmentation algorithms cannot maximize the benefits of convolutional neural networks (CNNs). The main work of this paper is as follows: first, we propose an architecture based on CNNs combined with dense blocks for iris segmentation, referred to as a dense-fully convolution network (DFCN), and adopt some popular optimizer methods, such as batch normalization (BN) and dropout. Second, because the public ground-truth masks of the CASIA-Interval-v4 and IITD iris databases do not include the labeled eyelash regions, we label these regions that occlude the iris regions using the Label me software package. Finally, the promising results of experiments based on the CASIA-Interval-v4, IITD, and UBIRIS.V2 iris databases captured under different conditions reveal that the iris segmentation network proposed in this paper outperforms all of the conventional and most of the CNN-based iris segmentation algorithms with which we compared our algorithm's results in terms of various metrics, including the accuracy, precision, recall, f1 score, and nice1 and nice2 error scores, reflecting the robustness of our proposed network. The results strongly indicate that spoofing detection systems based on convolution networks can be robust to attacks already known and possibly adapted, with little effort, to image-based attacks that are yet to come.

I. INTRODUCTION

Iris texture plays an important role in national defense and security because of its unique, stable, noncontact and anticounterfeiting characteristics. A complete iris recognition system usually consists of the following steps: initially, iris images are obtained by an imaging device. Then, the iris regions of the eye images are located by iris segmentation algorithms. Next, iris features are extracted by feature extraction algorithms. Finally, the extracted iris features are used for iris verification or recognition. As shown in FIGURE 1,with the exception of the iris regions, the iris images consist of not only the iris regions but also other regions, i.e., pupil, eyelid, eyelashes and sclera [1]. The non-iris regions degrade the iris segmentation performance. Iris segmentation algorithms are designed to eliminate the effects of the no iris regions and accurately segment the iris regions from The associate editor coordinating the review of this manuscript and approving it for publication was Genny Tortora. the eye images. Iris segmentation algorithms are of great significance in iris recognition systems. The accuracy and robustness of the algorithms directly affect the subsequentiris extraction, verification and recognition stages [2]. Underideal conditions—i.e., the iris regions are not occluded by the eyelids or eyelashes, the iris images are clear, and users are absolutely cooperative; thus, most existing iris segmentation algorithms can accurately segment the iris regions. However, under non ideal conditions, it is still challenging to design robust iris segmentation algorithms that accurately segment the iris regions despite the effects of eyelids, eyelashes, light, and user cooperation.

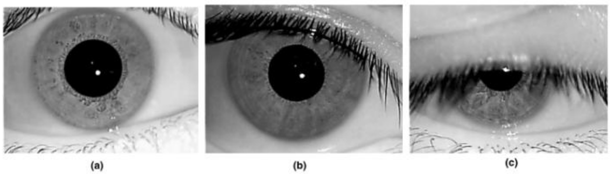

FIGURE 1. Samples of iris images under ideal and nonideal conditions. (a) Ideal iris images. (b) Iris images slightly occluded.(c) Iris images severely occluded

Deep Learning

In this paper, we do not focus on custom-tailored solutions. Instead, inspired by the recent success of Deep Learningin several vision tasks, and by the ability of the technique to leverage data, we focus on two general-purpose approaches

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to build image-based anti-spoofing systems with convolutional networks for several attack types in three biometric modalities, namely iris, face, and fingerprint. The first technique that we explore is hyperparameter optimization of network architectures that we henceforth call architecture optimization, while the second lies at the core of convolutional networks and consists of learning filter weights via the well-known back-propagation algorithm, hereinafter referred to as filter optimization. Fig. 1 illustrates how such techniques are used. The archi-tecture optimization (AO) approach is presented on the left and is highlighted in blue while the filter optimization (FO) approach is presented on the right and is highlighted in red.

II. LITERATURE SURVEY

The first three of such benchmarks consist of spoofing attempts for iris recognition systems, Biosec, Warsa, and MobBIOfake. Replay-Attack and 3DMAD are the benchmarks considered for faces, while Biometrika, CrossMatch, Italdata, and Swipe are the fingerprint benchmarks here considered, all them recently used in the 2013 Fingerprint Liveness Detection Competition (LivDet'13). Results outperform state-of-the-art counterparts in eight of the nine cases and observe a balance in terms of performance between AO and FO, with one performing better than the other depending on the sample size and problem difficulty. In some cases, we also show that when both approaches are combined, we can obtain performance levels that neither one can obtain by itself.
Moreover, by observing the behaviour of AO and FO, we take advantage of domain knowledge to propose a single new convolutional architecture that push performance in five problems even further, sometimes by a large margin, as in CrossMatch (68.80%v.98.23%). The experimental results strongly indicate that convolutional networks can be readily used for robust spoofing detection. Indeed, we believe that data-driven solutions based on deep representations might be a valuable direction to this field of research, allowing the construction of systems with little effort even to image-based attack types yet to come. We organized the remainder of this work into five sections. Section II presents previous anti-spoofing systems for the three biometric modalities covered in this paper, while Section III presents the considered benchmarks. Section IV describes the methodology adopted for architecture optimization (AO) and filter optimization (FO) while Section V presents experiments, results, and comparisons with state-of-the-art methods. Finally, Section VI concludes the paper and discusses some possible future directions.
A Survey Based on Fingerprint, Face and Iris Biometric Recognition System, Image Quality Assessment and Fake Biometric
This paper introduce three biometric techniques which are face recognition, fingerprint recognition, and iris recognition (Multi Biometric System) and also introduce the attacks on that system and by using Image Quality Assessment For Liveness Detection how to protect the system from fake biometrics.
Advantages
Hardware-based schemes generally present a higher fake detection rate, at the same time software-based techniques are in general less expensive (like no extra device is needed), and less intrusive since their implementation is clear to the user.
Disadvantages
Fingerprints have been used from long time for identifying individuals.

III. IRIS SYSTEM IMPLEMENTATION

3.1 Acquiring the Picture

Beginning with a 320x280 pixel photograph of the eye taken from 4 cenimeters away using a near infrared camera. The near infrared spectrum emphasizes the texture patterns of the iris making the measurements taken during iris recognition more precise. All images tested in this program were taken from the Chinese Academy of Sciences Institute of Automation (CASIA) iris database.

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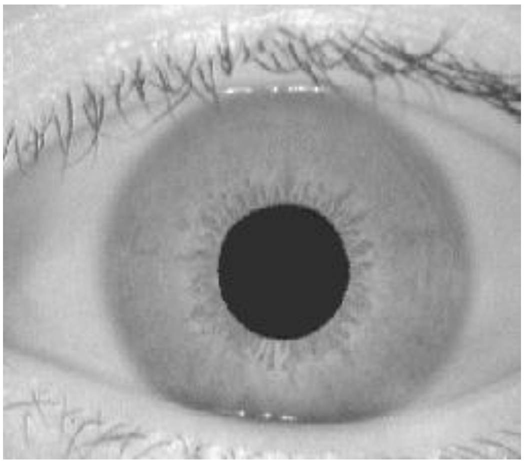

Figure 1: Near-infrared image of eye from CASIA Database

3.2 Edge Detection

Since the picture was acquired using an infrared camera the pupil is a very distinct black circle. The pupil is in fact so black relative to everything else in the picture a simple edge detection should be able to find its outside edge very easily. Furthermore, the thresholding on the edge detection can be set very high as to ignore smaller less contrasting edges while still being able to retrieve the entire perimeter of the pupil.

The best edge detection algorithm for outlining the pupil is canny edge detection. This algorithm uses horizontal and vertical gradients in order to deduce edges in the image. After running the canny edge detection on the image a circle is clearly present along the pupil boundary.

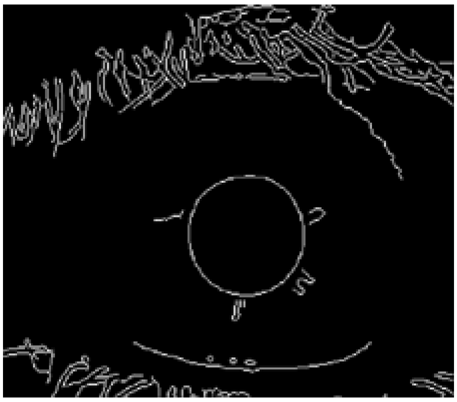

Figure 2: Canny edge detected image of the eye

3.3 Image Clean Up

A variety of other filters can be used in order decrease the extraneous data found in the edge detection stage. The first step in cleaning up the image is to dilate all the edge detected lines. By increasing the size of the lines nearby edge detected components are likely to coalesce into a larger line segment. In this way complete edges not fully linked by the edge detector can form. Thus the dilation will give us a higher probability that the perimeter of the pupil is a complete circle.

Knowing that the pupil is well defined more filters can be used without fear of throwing out that important information. Assuming the image is centered a filter can be used to fill in the circle defined by the pupil's perimeter. In this way we clearly define the entire area of the pupil. After this, a filter which simply throws out sections of connected pixels with an area below a threshold can be used effectively to throw out smaller disconnected parts of the image the edge detector found. Finally, any holes in the pupil caused by reflections or other distortions can be filled, by looking for sections of blank pixels with an area below a threshold. After this processing we achieve a picture that highlights the pupil area while being fairly clean of extraneous data.

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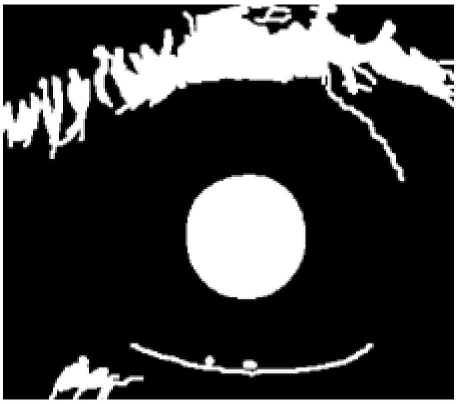

Figure 3: Image after final filters

3.4 Pupil Information Extraction

Having pre-processed the image sufficiently the extraction of the pupil center and radius can begin. By computing the euclidean distance from any non-zero point to the nearest zero valued point an overall spectrum can be found. This spectrum shows the largest filled circle that can be formed within a set of pixels. Since the pupil is the largest filled circle in the image the overall intensity of this spectrum will peak in it.

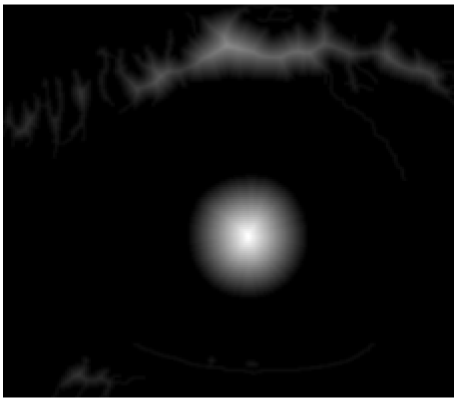

Figure 4: Image after computing minimal euclidean distance to non-white pixel

In the pupil circle the exact center will have the highest value. This is due to the simple fact that the center is the one point inside the circle that is farthest from the edges of the circle. Thus the maximum value must correspond to the pupil center, and furthermore the value at that maximum (distance from that point to nearest non-zero) must be equal to the pupil radius.

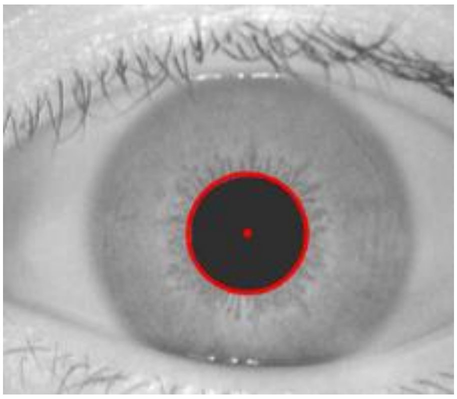

Figure 5: The original image of the eye with the pupil center and perimeter, found with the algorithm, highlighted

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3.5 Iris Recognition: Detecting the Iris

3.5.1 Iris Detection

With the information on the pupil discovered the location of the iris can now begin. It is important to note that the pupil and iris are not concentric. Consequently, the pupil information does not help directly determine the same parameters for the iris. However, the pupil information does give a good starting point, the pupil center.

Most modern iris detection algorithms use random circles to determine the iris parameters. Having a starting point at the pupil, these algorithms guess potential iris centers and radii. They then integrate over the circumference in order to determine if it is on the border of the iris. While this is highly accurate the process can consume a lot of time. This module explains an alternate approach which is much more lightweight but with higher error rates.

3.5.2 Iris Radius Approximation

The first step in finding the actual iris radius is to find an approximation of the iris radius. This approximation can then be fine tuned to find the actual iris parameters. In order to find this approximation a single edge of the iris must be found. Knowing that eyes are most likely to be distorted in the top and bottom parts due to eyelashes and eyelids, the best choice for finding an unobstructed edge is along the horizontal line through the pupil center.

Having decided on where to attempt to detect the iris edge, the question of how to do it arises. It seems obvious that some type of edge detection should be used. It happens that for any edge detection it is a good idea to blur the image to subtract any noise prior to running the algorithm, but too much blurring can dilate the boundaries of an edge, or make it very difficult to detect. Consequently, a special smoothing filter such as the median filter should be used on the original image. This type of eliminates sparse noise while preserving image boundaries. The image may need to have its contrast increased after the median filter.

Now that the image is prepped the edge detection can be done. Since there is such a noticeable rising edge in luminescence at the edge of the iris, filtering with a haar wavelet should act as a simple edge detector. The area of interest is not just the single horizontal line through the iris, but the portion of that line to the left of the pupil. This is so that the rising luminescence from the transition from iris to white is the only major step.

The iris should represent the steepest luminence change in the area of interest. Consequently, this area of the image should correspond to the highest valued componenet of the the output from the filter. By finding this maximal value the edge of the iris to the right of the pupil should be found. It should be noted that since the iris may not be concentric with the pupil the distance from the pupil center to this edge may not correspond to the iris' radius.

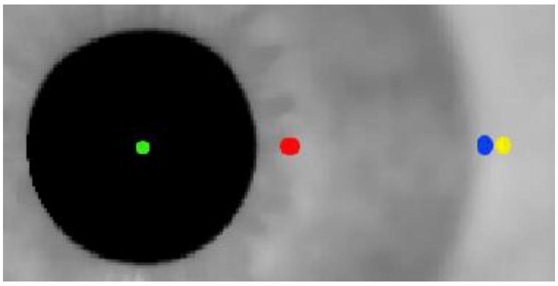

Figure 3: The green point is the pupil center found using the pupil detection techniques of part 1. The red point indicates the starting point of the area of interest. The blue point is the approximate radius found. The yellow point is the padded radius for use in finding the actual iris parameters.

3.6 Iris Translation

Having acquired an approximate radius, a small pad of this value should produce a circle centered on the pupil which contains the entire iris. Furthermore, with the perimeter of the pupil known, an annulus may be formed which should have the majority of it's area filled by the iris. This annulus can then be unrolled into cartestian coordinates through a straight discretized transformation. (r --> y, θ --> x) The details of this procedure are described in Step 3.

If the iris is perfectly centered on the pupil, the unrolled image should have a perfectly straight line along its top. However, if the iris is off center even a little this line will be wavy. The line represents the overall distance the iris is at from the pupil center. It is this line which will help to determine the iris' center and radius. Consequently, an edge detection algorith m must be run on the strip in order to determine the line's exact location. Once again canny edge detection is used. However, before the edge detection can be run the image should undergo some simple pre-processing to increase the contrast of the line. This will allow for a higher thresholding on the edge detection to eliminate extraneous data.

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Figure 4(a): The unrolled iris before and after edge detection

Figure 4(b): The unrolled iris before and after edge detection

3.7 Iris Information Extraction

In order to extrapolate the iris' center and radius, two chords of the actual iris through the pupil must be found. This can be easily accomplished with the information gained in the previous step. By examing points with x values on the strip offset by half of the length of the strip a chord of the iris is formed through the pupil center. It is important to pick the vectors for these chords so they are both maximally independent of each other, while also being far from areas where eyelids or eyelashes may interfere.

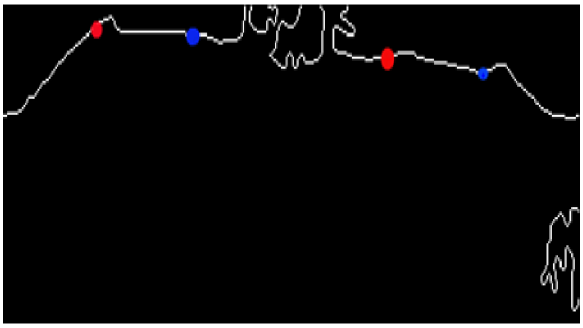

Figure 5(a): The points selected on the strip to form the chords of the iris through the pupil

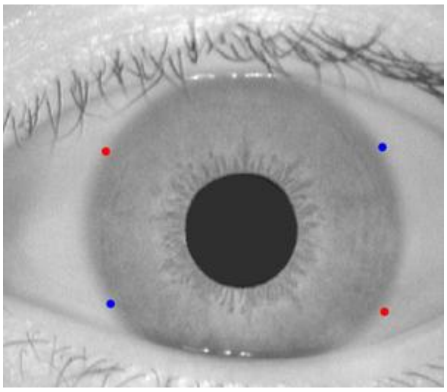

Figure 5(b): The points selected on the strip to form the chords of the iris through the pupil

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IV. CONCLUSION

Iris segmentation algorithms play an important role in iris recognition systems and directly affect the accuracy of iris verifification and recognition. We proposed an iris segmentation architecture based on CNNs combined with denseblocks, referred to as DFCN. The encoder of DFCN consists of dense blocks, and the decoder of DFCN obtains the output prediction masks via transpose convolution. To evaluate the performance of DFCN, we adopted three public iris databases captured under different conditions, namely, CASIA-Interval-V4, IITD and UBIRIS.v2, with thecorresponding ground-truth masks. Moreover, we labeledthe eyelash regions occluding the iris regions of theCASIA-Interval-V4 and IITD iris databases using theLabelme software package, which is also used for trainingand testing. To reflflect the superiority of DFCN in terns of many aspects, we adopted a variety of metrics used forevaluating the iris segmentation algorithms, i.e., the accuracy, precision, recall, f1 score, and nice1 and nice2 error scores. In addition, we compared some conventional and CNN-based iris segmentation algorithms. The results of the experiments reveal that the iris segmentation architecture proposed inthis paper outperforms most of the other algorithms, which demonstrates its superiority and robustness. Nevertheless, the performance of DFCN on the public ground-truth masksis better than that on our labeled ground-truth masks; this fifinding is related to the adopted public iris databases andthe method of labeling. Thus, more attention is needed inthe future for the design of more robust iris segmentation algorithms for iris databases under nonideal conditions andfor more effective ways of labeling.

V. FUTURE WORK

For future work, we intend to evaluate such datasets using the proposed approaches here and also consider other biometric modalities such as palm, vein, and gait. As evident from the results, it is possible to create, relatively easily, an algorithm to detect and recognize irises to a calculated degree of confidence. In addition, after a little research , it is clear that more sophisticated algorithms exist that give zero false acceptance--something many other authentication techniques simply cannot deliver. One specific algorithm patented by Dr. Daugman, is currently the most accepted and widely used in iris code recognition systems. This embodiment of the algorithm uses robust algorithms in each part of the implementation (pupil and iris detection, masking, Gabor correlation), and has experimentally proven to be extremely accurate. In the largest deployment of iris recognition systems, this algorithm does 3.8 billion comparisons a day in the United Arab Emirates (story here).

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