Periocular Recognition Without The Iris And Sclera Using Deep Neural Networks

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Abstract- *A disruptive hypothesis for periocular biometrics in visible-light data, the recognition performance is optimized when the components inside the ocular globeare simply discarded, and the recognizer's response is exclusively based on the information from the surroundings of the eye.Based on deep neural networks a processing chain that defines the regions-of-interest in the input data that should be privileged in an implicit way, i.e., without masking out any areas in the learning/test samples.An ocular segmentation algorithm exclusively in the learning data.Using deep neural network we separate the ocular from the periocular parts.Alarge set of "multi-class" artificial samples is produced by interchanging the periocular and ocular parts from different subjects. Samples are used for data augmentation purposes and feed the learningphase of the DNN, always considering as label the ID of the periocular part.Every periocular region, the DNN receives multiple samples of different ocular classes, forcing it to conclude that such regions should not be considered in its response.Samples are provided without any segmentation mask during test phase.The network naturally disregards the ocular components, which contributes for improvements in performance.Experiments were carried out in full versions of two widely known data sets (UBIRIS.v2 and FRGC) and show that the proposed method consistently advanc*

Keywords- DeepNeuralNetwork,Softbiometrics,Periocular Recognition,Segmentation,Feature extraction.

I. INTRODUCTION

Periocular biometrics is one of the most discriminative regions of the face, gaining attention as an independent method for recognition or a complement to the faceand iris modalities under non-ideal conditions [1, 2]. The typical elements of the periocular region are labeled.This region can be acquired largely relaxing theacquisition conditions, in contraposition to the more carefullycontrolled conditions usually needed in face or iris modalities.Another advantage is that the problem of iris segmentation isavoided, which can be an issue in difficult images [3].This paper provides a review of periocular research work.The restricted Boltzmann machines (RBM) is a generativestochastic neural network that can learn a probabilitydistribution over a set of inputs. The convolutional RBM is onevariant of RBM to make it capable in deal with large resolutionimage data. The CRBM has been successfully utilized invarious applications, such as the handwriting recognition,image classification, and face verifications, *etc*. Compared withtraditional biometrics like fingerprint and palm print, theperiocular recognition is an emerging biometrics targeted toenhance iris or face recognition under visible illuminationusing at-a-distance imaging. In this study, the unsupervisedCRBM framework is firstly introduced to the periocularrecognition paradigm. Our work described in this paperpresents some encouraging results on larger publicly availablebenchmark periocular databaset.The biometrics domain, the covert recognition ofhumans (outdoor and non-cooperative) remains to be achieved,and will be a breakthrough in security/forensics applications.Here, the periocular region is a trade-off between using the irisand the face, with encouraging performance levels reported in the literature.

- When imaged under visible-light, the iris (particularly)and the sclera are prune to corneal reflections, resulting in the so-called Purkinje images;
- Along with the body and head movements, the components in the ocular globe are subjected to an additional motion source (eye gaze) that increases the probabilities of acquiring blurred data;
- The iris and the sclera are often partially occluded, due toeyelids and eyelashes movements;

According to the above points, this paper describes a periocularrecognition algorithm to work in poor quality visiblelightdata, relying on DNNs to model complex data patterns.

The key is a data augmentation strategy based in multiclassregions swapping, that implicitly induces the DNN toconsider that some regions in the input data are not reliablefor classification purposes.

II. LITERATURE SURVEY

The advantages of biometrics recognition using periocularimages in comparison with iris recognition have beendemonstrated in [4]. Its feasibility was comprehensivelyinvestigated by using various local descriptors, such as LocalBinary Pattern (LBP), Histogram of Oriented Gradients (HOG)and Shift Invariant Feature Transform (SIFT) *etc*. As one of themost representative models in deep learning, the deep beliefnetwork (DBN) [5] is a generative graphical model whichcontains a layer of visible units and multiple layers of hiddenunits. Each layer encodes correlations in the units of next layer.DBNs and related unsupervised learning algorithms such asauto encoders [1] and sparse coding [9]-[10] have been usedto learn higher-level feature representations from unlabeleddata. A lot of related works have been successfully applied forthe visual recognition and classifications [5]-[7]. MetricLearning is a method to learn a transformation matrix from thetraining data so that the new metric can perform better than theEuclidean space. Learning this target is identical to the learningof Mahalanobis distance. Metric learning has been applied inthe face verification [11] and image recognition [9] domains.Several researchers proposed many techniques for explaining the privacy while the computation of associations rules when the database is partitioned horizontally. Each technique is explained as follows.Shubhra Rana et.al [1] has proposed a solution named Paillier additive homomorphismcryptosystem. Pattern count tree is used for making the data structure. The main advantages of this system is that it is built in single I/O scan. The Hierarchical Homomorphic Encryption scheme is used for providing security.Tamir Tassa [2] also proposed an idea named Fast Distributed Mining for finding frequent item set. Thisalgorithm is a extended version of Apriority. It deals two algorithms called secure multi party algorithm. This solution provide complicated inequality verification to check set inclusion while providing security.

III. EXISTING SYSTEM

A. Image Alignment

Periocular images across subjects contain some commoncomponents (e.g., iris, sclera, and eyelids) that can be representedin a common coordinate system. Once a common areaof interest is localized, a global representation scheme can beused. The iris or eyelids are good candidates for the alignmentprocess. Even though both the iris and eyelids exhibit motion,such variations are not significant in the periocular images used in the research. While frontal iris detection can be performedfairly well due to the approximately circular geometry of theiris and the clear contrast between the iris and sclera, accuratedetection of the eyelids is more difficult. The inner and outercorners of the eye can also be considered as anchor points, butthere can be multiple candidates as shown in Fig. 2. Therefore,we primarily use the iris for image alignment. A public domainiris detector based on the Hough transformation is used forlocalizing the iris [25]. The iris can be used for translation andscale normalization of the image, but not for rotation normalization.However, we overcome the small rotation variationsusing a rotation tolerant feature representation. The iris-basedimage alignment is only required by the global matchingscheme. The local matcher does not require image alignmentbecause the descriptors corresponding to the key points can beindependently compared with each other.a periocularrecognition algorithm to work in poor quality visiblelightdata, relying on CNNs to model complex data patterns.The key is a data augmentation strategy based in multiclassregions swapping, that implicitly induces the CNN toconsider that some regions in the input data are not reliablefor classification purposes.1) Effectiveness of incorporating the eyebrows, 2) Use of side information (left or right) in matching,3) Manual versus automatic segmentation schemes, 4) local versusglobal feature extraction schemes, 5) Fusion of face and periocular biometrics, 6) Use of the periocular biometric in partially occluded face images, 7) Effect of disguising the eyebrows, 8) Effect of pose variation and occlusion, 9) Effect of masking the iris and eye region,and 10) Effect of template aging on matching performance**.**The above mentioned are the various aspects of periocular biometric system.Even under ideal conditions characterized by favorablelighting conditions and an optimal standoff distance, if thesubject blinks or closes his eye, the iris information cannotbe reliably acquired.While conjunctival vasculature can be imaged at a distance,the curvature of the sclera, the specular reflections in theimage, and the fineness of the vascular patterns can confoundthe feature extraction and matching modules of thebiometric system.by considering a small region around the eye as an additionalbiometric. We refer to this region as the periocular region. Weexplore the potential of the periocular region as a biometric incolor images pertaining to the visible spectral band.

IV. PROPOSED SYSTEM

A. Deep Neural Network

We use one of the most popular deep learning architecturesfor image classification: Convolution Neural Networks(CNNs), which are a biologically inspired variant ofmultilayer perceptron networks (MLPs) particularly suitablefor image classification. By making some assumptions aboutthe nature of the input data (e.g., stationarity of statistics andlocality of pixel dependencies), CNNs have much fewer connectionsthan MLPs, making learning a feasible task. In particular,we adopt a CNN architecture based in AlexNet [9], shown In this section we propose a system which tries to cover the challenges presented in Existing system. In the proposed system will provide more security and work without any complex data structure. Its strength is its simplicity.Acquisition setups include still images and videos with a varietyof sensors in VW and NIR range such as: digital cameras,webcams, videocameras, smartphones, or close-up iris sensors. Although many databases have distance variability (e.g.FRGC, Compass, UBIRIS v2, UBIPr), acquisition is mostlydone with the subject standing at several stand-off distances.

B. Convolutional RBM

In the CRBM model all nodes in the convolution andvisible layers share one CRBM weight. The model consists oftwo layers: an input layer D and a convolution layer C. Theinput layer consists of an array of real value units.The convolution layer consists of K groups, where each groupis an array of binary units, resulting in hiddenunits. Each of the K group is associated with a filter .The filter weights area across all thehidden units within the group. In addition, each hidden grouphas a biasand all visible units share a single bias *b*.The number of hidden nodes is far more than the visiblelayers. In order to reduce the computation burden and also betolerant to small translational misalignment, the pooling stageis included. In the pooling stage, the convolution layer ispartition to blocks of and each block a is connected to exactly one binary unit in the pooling layer. The resultingstructure of the CRBM model is as illustrated in figure 3.

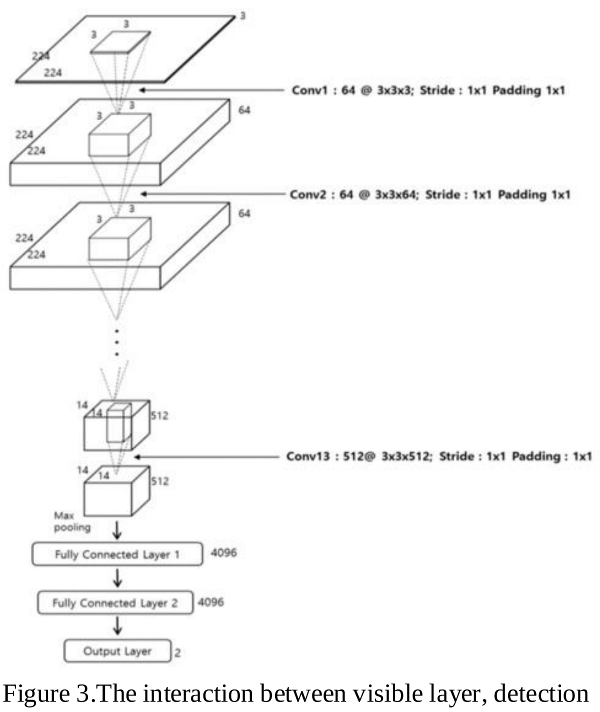

Figure 3.The interaction between visible layer, detection layer and pooling layer.

A binary mask **B** that discriminates between the ocular **O**(iris and sclera) and the remaining components **P** (henceforthdesignated as periocular, including the eyebrows, eyelids,eyelashes and skin) in each learning sample. Next, a setof artificial samples is created, interchanging the ocular andperiocular parts from different subjects, but always consideringas label the ID provided by the periocular part. Thisway, during the learning phase, the DNN receives, for eachperiocular part, samples of different ocular classes, forcingit to conclude that such regions should not be considered inits response (i.e., the ID). During the test phase (*Test* box),samples are provided to the network without any segmentationmask, yielding four key properties: 1) the DNN testingperformance is not conditioned by the effectiveness of the segmentation step, known to be a primary error source in computer vision tasks; 2) the DNN naturally ignores the ocularcomponents, focusing in the most discriminating information;3) the learning and test data have similar appearance, whichcontributes to the CNN's generalization capability; and 4) froma data augmentation perspective, the set of artificial samplesprovided to the network also improves the CNN performance.As shown in the bottom part of Fig. 2, any other combinationof learning/test data (using explicit region masking) will notkeep these four properties simultaneously.As outcome of this work, the resulting periocular recognizer outperforms consistently the state-of-the-art, decreasing theEERs and improving the Rank-1 values with respect to thebaseline methods. Note that these results were obtained in twowidely known data sets and using the entire set of images inboth sets, i.e., without disregarding even the poorest qualitysamples.Tests were conducted over a "small" (899 images, 30subjects, 2 sessions) database of frontal periocular images,acquired in the VW. Although face matching achieving 100%rank-1 recognition accuracy, the reported recognition for periocularrange from 62.5% when using HOG features, to 80.8%when fusing them with SIFT results. Curiously, combining thethree descriptors didn't overcome those results, although jointperformance was very close: 80%.Changes in subjects' expression significantly lowered theperformance of LBP and HOG, although on SIFT, more robustto distortions, a slightly increase was registered. Masking theiris and the entire eye also caused performance to decrease, thistime being SIFT the more disfavored. Top accuracy for singleclassifiers was 79.49%, achieved through SIFT on unmaskedperiocular images, manually segmented with the eyebrow,when compared to an image captured from the same side andexpression.

(a) (b)

Figure 4.Example images of a subject from the FRGC database [15] with (a) neutraland (b) smiling expressions

C. Data Augmentation

1) Ocular/Periocular Regions Swapping: Let **I**i and **I** j be150×200×3 RGB images from two different subjects. Using the segmentation method described in [17], we obtain two binary masks **B**i and **B**j (150 × 200 pixels) that discriminate between the ocular (iris and sclera) and the periocular componentsin **I**.. Let **O**. and **P**. denote the ocular and periocular partsof **I**.. The goal is to create an artificial sample **P***i***O***j* composedof the periocular region of **I***i* overlapping the ocular part of **I** *j* ,which requires to find the scale and translation parameters,such that **O***j* optimally fits the ocular whole of **P***i*. Let **b**. be the*n* ×1 vectorized version of **B**. *(*n = 30 000*)*. The convolution“*” between **b***i* and **b***j* is given in matrix form by:

$$\mathbf{b}_i \text{ X } \mathbf{b}_j = \mathbf{T}(\mathbf{b}_i)\, \mathbf{b}_j .$$

Initial periocular studies were focused on feature extractiononly (with the periocular region manually extracted), but automatic detection and segmentation has increasingly becomea research target in itself.summarizes existing research aimed at locatingthe eye position directly. Eye detection can be a decisive preprocessing to ensure successful iris segmentation in difficult images, as in using correlation filters over the difficultFOCS database.

V. CONCLUSION

This paper describes a periocular recognition algorithmfor visible-light data that is based in deep neural networks (DNNs). The advantage is that, by augmenting thelearning data using multi-class artificial samples, it is possibleto implicitly transmit prior information to the network aboutthe regions in the input data that are not reliable for biometricrecognition. Such conclusion, if left to be autonomously drew by the DNN would require additional amounts of learning data,which might not be available.Two important conclusions with respect to the periocular biometrics domain.1) for visible-light data, performanceimproves when the information in the ocular globeis disregarded, and the recogniser's response is solely basedin the surrounding eye's components; and 2) disregarding theiris/sclera regions can be done without explicitly segmentingthese regions during the recognition step. As main result,the proposed method advances the state-of-the-art performancein the *closed-world* scenario for two of the most used data setsin this field (UBIRIS.v2 and FRGC).

VI. ACKNOWLEDGMENT

We would like to thank, first and foremost, Almighty God, without his support this work would not have been possible. We would also like to thank all the faculty members of Mount Zion college of engineering, for their immense support.

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