End-to-end Off-angle Iris Recognition Using CNN Based Iris Segmentation

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Abstract: While deep learning techniques are increasingly becoming a tool of choice for iris segmentation, yet there is no comprehensive recognition framework dedicated for off-angle iris recognition using such modules. In this work, we investigate the effect of different gaze-angles on the CNN based off-angle iris segmentations, and their recognition performance, introducing an improvement scheme to compensate for some segmentation degradations caused by the off-angle distortions. Also, we propose an off-angle parameterization algorithm to re-project the off-angle images back to frontal view. Taking benefit of these, we further investigate if: (i) improving the segmentation outputs and/or correcting the iris images before or after the segmentation, can compensate for off-angle distortions, or (ii) the generalization capability of the network can be improved, by training it on iris images of different gaze-angles. In each experimental step, segmentation accuracy and the recognition performance are evaluated, and the results are analyzed and compared.

Keywords: Off-angle iris segmentation, Off-angle iris recognition, Iris parameterization, Convolutional neural network, CNN.

1 Introduction

Iris recognition is known to be one of the most accurate biometric recognition techniques, widely adopted for many security needs in recent years. Accuracy of these systems, however, relies highly on the accurate segmentation of the iris texture in the captured eye images. Ever since the first iris recognition system proposed by John Daugman [Da09], a wide variety of techniques has been proposed to perform segmentation in eye images captured typically in a frontal view, under a controlled or constrained environment. In practice however, many of the users or operators of these systems are inexperienced and often capture images where the subjects are looking in the wrong direction due to inadvertent eye movement. Also, the emerging standoff iris biometric systems and the recent trend towards ”on-the-move-acquisition” are transforming iris biometric systems from being operated in well-controlled setup, to being smart standoff modalities. The iris images captured under such conditions are more likely to be off-angle, and incorporate additional off-angle related distortions.

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Segmentation tasks in such images become quite challenging as the iris boundaries are dilated, of elliptical shape, or even missing in the extreme off-angle images. Most classical segmentation approaches which are mainly based on the integro-differential, circular Hough Transform, and edge detection techniques, which rely on visibility of clear iris contours, fail to perform segmentation in such images. Consequently, also most feature comparison algorithms operating under the assumption that the iris texture lies on a flat frontal plane and possesses a circular geometric property, fail to perform the comparison task properly as well [ZA10]. Addressing such challenges, off-angle iris recognition has became a hot research topic within the biometrics community recently.

With recent advancement in deep learning techniques, some convolutional neural networks (CNN) were proposed for the challenging task of iris segmentation (*e.g.* [Ar18] [JU17]). While the proposed models proved to preform superior to the classical segmentation methods, yet the scarce researches dedicated to parameterization and normalization of obtained iris segmentations are just limited to frontal iris images, and no comprehensive recognition framework has been introduced for off-angle iris recognition using such modules. Jalilian *et al.* [JUK19] studied the effect of off-angle distortions on the segmentation performance of CNNs. We extend this study by specifically investigating the effect of different gaze-angles on the subsequent recognition performance. First, as a distinction to the segmentation studies in [JUK19], here we introduce a segmentation improvement scheme to compensate for some degradations in the segmentation masks, caused by the off-angle distortions. In this framework, we propose an off-angle parameterization method to determine the extent of off-angle-ness and to geometrically re-project the segmentations and their corresponding off-angle iris images back to frontal view. We further define several variants of end-to-end recognition pipelines to enable the usage of the CNN based segmentations for the final task of recognition. In the first approach, termed "improved-homogeneous", we train a dedicated CNN with homogeneous iris images of each distinct gaze-angle, and then carry out segmentation in iris images with certain gaze-angles. The segmentation outputs then are improved, and both the segmentation and recognition performance are evaluated afterwards. In the second approach, denoted as "improved-heterogeneous", we propose a heterogeneous-angle training, in which a network trained with iris images exhibiting different gaze-angles, is applied to iris images with any gaze-angle. Here we target to improve the generalization capability of the networks used in the improved-homogeneous approach, in a way that we can obtain hopefully better results than we obtained using the angle-specific training configuration. In the third approach we utilize our off-angle parameterization method (as explained in Section 3) to geometrically re-project the corresponding off-angle iris images back to frontal view before applying unwrapping and normalization. We denote this approach as "corrected-homogeneous." Doing so, we hope to correct the off-angle iris texture, compensating for the degradations imposed by the off-angle distortions, and thus enhance the biometric data encoded into it. And finally, by analogy to the corrected-homogeneous approach, we considered the "corrected-heterogeneous" approach, in which we investigate the effect of the correction mechanism on the recognition performance using a heterogeneous training configuration.

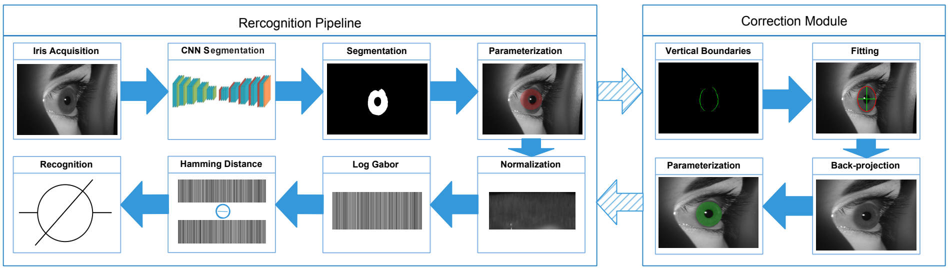

Figure 1: Recognition pipeline and the correction module

2 Related Work

Several different techniques have been proposed to address the off-angle iris segmentation and recognition problem. For example Daugman proposed to detect inner and outer off-angle iris boundaries using an active contour method, based on the discrete Fourier series expansion of the contour data [Da06]. Shah and Ross combined snakes segmentation with geometric active contours [SR09]. Zuo *et al.* [ZS09] used intensity, shape, and localization features from the iris and pupil to automatically segment non-ideal iris images. Their method demonstrated performance improvement on challenging iris images up to 30°. Price *et al.* [R-07] developed a generalized eye model to correct for perspective and refractive distortion of the iris pattern using ray tracing techniques. They reported a median reduction of Hamming Distance for synthetic eyes with gaze up to 60°. Recent advances in deep learning techniques enabled the application of deep neural networks for iris segmentation. For example Liu *et al.* [Li16b] proposed two iris segmentation techniques based on different topologies of CNNs (hierarchical convolutional neural networks and multi-scale fully convolutional networks). The method presented by Arsalan *et al.* [Ar17] roughly estimates the iris region using an edge detection algorithm and then classifies the pixels in two classes (iris and non-iris) by using a CNN. The study presented in [JU17] utilized a fully convolutional encoder-decoder network trained for classifying iris and non-iris pixels in images acquired in a wide set of heterogeneous conditions, including off-angle images. The work presented in [Ar18] proposed a deep network called IrisDenseNet, which is based on VGG-16, to deal with low quality iris images, such as side views, glasses, off-angle eye images and rotated eyes. There are far more approaches dedicated for eff-angle iris segmentation/recognition. Yet due to the space limitation, we narrowed our review to the methods presented above. To review further approaches please refer to *e.g.* [S-16].

3 Off-angle Iris Parameterization and Segmentation Improvement

Off-angle iris parameterization: The available algorithms used for parameterization of the iris region in the CNN based segmentation are limited to the frontal segmentation outputs, where circular Hough transform is used to parameterize the iris region. The main obstacle to apply an elliptic parameterization (as the iris shape looks in the off-angle view) is the tendency of such models to overly oblong or obround, due to occlusion of the iris by eyelids or eyelashes. To resolve this issue, we propose to search only for the vertical edges in the segmentation outputs. The resulting edge points secure the proper fitting of an ellipse to the actual iris region (see Figure 1 for an example). In the next step, we extract the horizontal and vertical axes information of the ellipse, and use them for re-projecting (correcting) the segmentation outputs and their corresponding off-angle iris images back to frontal view as follows. Assuming that our ellipse is in the following parametric form:

$$x = x_0 + Q \times \begin{bmatrix} a \times cos(\theta) \\ b \times sin(\theta) \end{bmatrix}, \tag{1}$$

where x and x_0 are 2-dimensional vectors, and $a > b > 0$ correspond to the horizontal and vertical axes of the ellipse, respectively. Q is the rotation matrix, and θ represent the rotation angle. We assume a vertical ellipse, Thus:

$$Q = \begin{bmatrix} cos(90) & -sin(90) \\ sin(90) & cos(90) \end{bmatrix}. \tag{2}$$

We want our transformation to produce y in the shifted, rotated coordinates:

$$y = \begin{bmatrix} 1 & 0 \\ 0 & a/b \end{bmatrix} \begin{bmatrix} a \times cos(\theta) \\ b \times sin(\theta) \end{bmatrix}, \tag{3}$$

and x in the original coordinates. Submitting to the equation (1), we can infer the affine transformation matrix we need to re-project the parameterized ellipse back to frontal view, so that it possess circular shape:

$$x = \left[Q \begin{bmatrix} 1 & 0 \\ 0 & a/b \end{bmatrix} Q' \right] x + \left[\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - Q \begin{bmatrix} 1 & 0 \\ 0 & a/b \end{bmatrix} Q' \right] x_0. \tag{4}$$

Segmentation Improvement: We improved the segmentation outputs by applying some morphological operations. It was already understood that the network tends to produce some false-positive detection, in specific, along the segmentation output masks borders [JUK19]. So, we first defined a marginal area (A) along each border of the segmentation output masks (with a width (in pixel) equal to $1/5$ of the length of the same border), and then performed an opening operation with a big (disk-shape) structuring element (B):

$$A \circ B = (A \ominus B) \oplus B, \tag{5}$$

Figure 2: Sample iris image with P0 gaze-angle and its corresponding segmentation (green-color) and error mask (red-color) before (middle), and after correction (right), using the network trained on P0 images

where $\ominus$ and $\oplus$ denote erosion and dilation, respectively. We further performed another opening operation on the whole segmentation outputs using a small (disk-shape) structuring element to remove small false-positive detections outside the iris region. Figure 2 shows a sample segmentation output and its corresponding improved segmentation mask.

4 Experimental Framework

Dataset: For our experiments we used a subset (containing 4400 left eye iris images captured from 40 subjects) of an off-angle iris database [Ka13]. The iris images in this database are captured by two near-infrared sensitive IDS-UI-3240ML-NIR cameras. Images at 0°gaze-angle were captured by a frontal fixed camera, and off-angle images were captured by a frontal moving camera rotating horizontally from -50°(N50) to +50°(P50) in angle with a 10°step-size. Each camera captured 10 iris images per stop, giving 10 frontal and 100 off-angle iris images captured from each subject, to comprise 400 images per angle (examples of images in the database are presented in Figure 3). The database is accessible on request (from the authors), and further details about it can be found in [Ka13]. We developed the ground-truth labels (required for training the network) for all images available in the dataset using the iris, pupil, upper and lower eyelid parameters specified manually. For our experiments we divided the whole dataset into two equal parts (each containing iris images of 20 separate subjects), and used one part as our testing data and the other one as our training data.

Fully convolution neural network (FCN): We selected the RefineNet [Li16a] to perform the iris segmentations in our experiments. The network is already proven to enable high-resolution prediction, and at the same time, preserve the boundary information (which is needed for our parameterization mechanism). The network is a multi-resolution refinement network, which employs a 4-cascaded architecture with 4 Refining units, each of which directly connects to the output of one Residual net [He15] block, as well as to the preceding Refining block in the cascade. Each Refining unit consists of two residual convolution units (RCU), which include two alternative ReLU and 3×3 convolutional layers. The output of the RCU units are processed by 3×3 convolution and up-sampling layers incorporated in multi-resolution fusion blocks. A chain of multiple pooling blocks, each consisting a 5×5 max-pooling layer and a 3×3 convolution layer, next operate on the feature maps, so that one pooling block takes the output of the previous pooling block as input. Therefore, the current pooling block is able to re-use the result from the previous

Figure 3: Sample iris images with P0 (left), N50 (middle), and P50 (right) gaze-angles

pooling operation and thus access the features from a large region without using a large pooling window. Finally, the outputs of all pooling blocks are fused together with the input feature maps through summation of residual connections. We used ADAM optimizer with learning rate of 0.0001, executing 40,000 iteration to train the network. The implementation of the network was realized in Keras using TensorFlow back-end.

Recognition Pipeline: The output segmentations (after applying correction or improvement), are parameterized using the technique introduced in [HJU19]. The extracted iris patterns are normalized by unwrapping the circular region into a rectangular block of constant dimensions. The algorithm repeats the last pixel for a given angle if no values are available. Each isolated iris pattern is then demodulated to extract its phase information (feature) using quadrature 1-D Gabor wavelets. To compare the unique extracted features to each other, the Hamming distance with rotation correction were calculated in the comparison phase. We used the University of Salzburg implementation of these algorithms, as provided in the Iris Toolkit (USIT)[3]. Figure 1 illustrates the overall recognition pipeline, along with the proposed parameterization and correction module.

Segmentation Evaluation and Measures: In order to facilitate proper quantification of the accuracy of the segmentations in each experiment, we considered the $nice1$ iris segmentation error rate, which is based on the NICE1 protocol[4], as used in several iris segmentation challenges. Accordingly, the segmentation error rate $(nice1)$ for each segmentation output mask I_i is given by the proportion of corresponding disagreeing pixels (through the logical exclusive-or operator) with the ground-truth mask, over all the output mask as:

$$nice1 = \frac{1}{c \times r} \sum_{c'} \sum_{r'} O(c', r') \otimes C(c', r'), \tag{6}$$

where c and r are the dimensions of the segmentation, and $O(c', r')$ and $C(c', r')$ are, respectively, pixels of the segmentation and the ground-truth mask. The value of $(nice1)$ is in the [0, 1] interval, and 1 and 0 are the worst and the best scores, respectively.

[3] http://www.wavelab.at/sources/USIT
[4] http://nice1.di.ubi.pt/

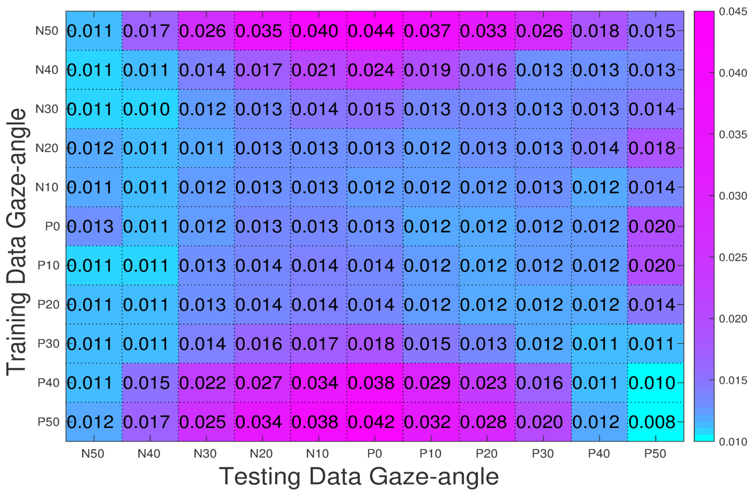

Figure 4: Segmentation performance using the improved-homogeneous approach

5 Experiments and Analysis

We initiated our experiments by investigating the effect of different gaze-angles on the CNN based off-angle iris segmentations, after the improvement, as well as evaluating their subsequent recognition performance (under the improved-homogeneous approach). To focus our experiments on this objective, we considered an ideal (but unrealistic) condition, in which the true images' gaze-angles are already known. "Theoretically," one may use the horizontal and vertical axes information to estimate the images gaze-angles (D) using: $D = acosinus(HorizontalAxis/VertcialAxis)$. So, we trained a dedicated network with iris images belonging to each distinct gaze-angle separately, and then performed segmentation in all our testing data, and improved the segmenation outputs as already described in Section 3. Figure 4 shows the results, as average *nice*1 error for this experiment. Affirming to what we found using the identical training scheme (Homogeneous) and network (RefineNet) already in [JUK19], we can see the direct relation of the network performance to the similarity of gaze-angles of the training and testing images, here after the morphological improvement too. Yet the key new finding is that, the performance gradually improves as the gaze-angles of the training and testing data converge in terms of angle but may also diverge in terms of the direction. To be more precise, the network is able to detect the symmetric iris elliptical features in the images captured from the same angle (with respect to frontal view), but in opposite direction. The applied improvement, which in fact compensated for some false-positive detections (caused by the off-angle distortions), allowed us to figure out this capability of the network. Overall, the applied improvement resulted in considerable enhancements in almost all segmentation results (especially for the right off-angle (P) images), compared to the segmentation results obtained in [JUK19], as the average error decreased (about 47%) from 0.030 to 0.016.

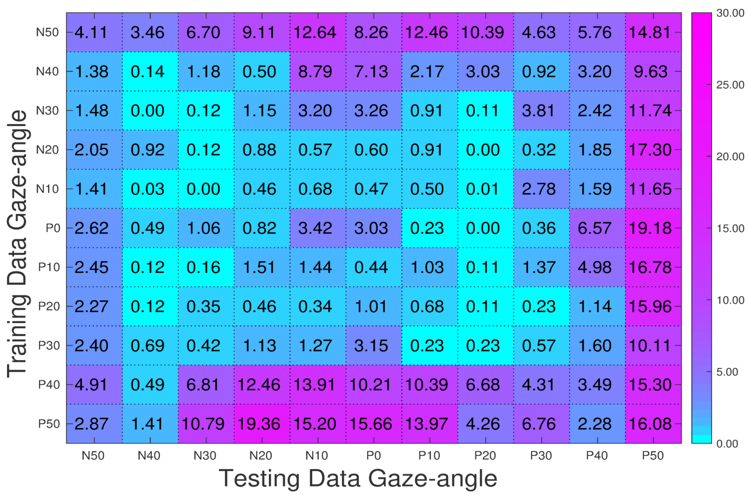

Figure 5: Recognition performance using the improved-homogeneous approach

In the next step, we fed the improved segmentations along with their corresponding images to the recognition pipeline to investigate the recognition performance in terms of EER. Figure 5 shows the results for this experiment. Expectedly, we can observe that the segmentation results are translated into the recognition scores, following the same trends already discussed in the segmentation experiments. The only visible difference here is the lower recognition performance of the extreme gaze-angle images (*i.e*. N50 and specially P50). This seems mainly to be due to the extreme 3D and perspective erosion of the extracted iris texture, which leads to the lower recognition performance on these images. In the improved-heterogeneous approach, we considered to investigate if we can improve the generalizability of the network by switching to a heterogeneous training setting, where we include iris images with different gaze-angles into the training data. We tested the trained network in all iris images in our testing data, applied the improvement, and evaluated performance afterward, differentiating and grouping results into the different gaze-angles available. While the heterogeneous configuration was expected to deliver good results (compared to the angle-specific training configuration), based on the findings in [JUK19], here we (i) evaluated the extent to which the improvement applied can enhance the segmentation performance, and (ii) verified if the improved segmentations can eventually improve the recognition performance, beyond the improved angle-specific training configuration. Figure 6 demonstrates the segmentation results for this experiment in the form of Boxplot for each gaze-angle group (after the improvement). As the results show, applying the improvement, we obtained a considerable enhancement in almost all segmentation results (especially for the right off-angle (P) images), compared to the angle-specific improved-homogeneous results already obtained, as well as those obtained in the identical heterogeneous configuration without improvement in [JUK19], as the average segmentation error decreased (about 4.5 times) from 0.023 to 0.005. Figure 7 shows

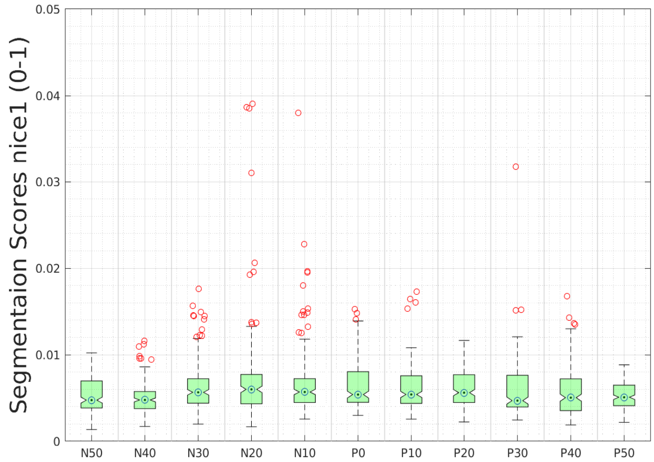

Figure 6: Segmentation performance using the improved-heterogeneous approach

the subsequent recognition results obtained using the corresponding images. Excluding a slight declination in the recognition results of N40 gaze-angle images, all other results show considerable improvements, compared to the angle-specific configuration results (the improved-homogeneous) shown in Figure 5. Of course, this is a positive result, as it enables us to refrain from the angle-specific training strategy, and even better, there is no need to determine the iris images gaze-angles or carry out the correction.

In the corrected-homogeneous approach, we target to address if re-projecting the off-angle iris images back to frontal view and correcting the off-angle iris texture can compensate for the degradations imposed by the off-angle distortions, and eventually improve the system recognition performance. To address this, we first applied our parameterization algorithm (already explained in Section 3) to the improved segmentation outputs obtained in the previous step, and subsequently re-projected them along with their corresponding iris images back to frontal view. The corrected data then was fed into the recognition pipeline to evaluate the recognition performance. Figure 8 shows the recognition results for this experiment. When comparing the results to those obtained using the improved-homogeneous approach, we can only observe slight improvements in the results of configurations where the training and testing data are close to frontal (*i.e.* P0, P10, P20, ...) view, as well as the extreme gaze-angles (*i.e.* , P50 and N50), where the gaze-angles of the training and teasing data are the same. For the rest of configurations, the results gradually degrade as we move towards the right and, in specific, the left sides of the table (compared to the

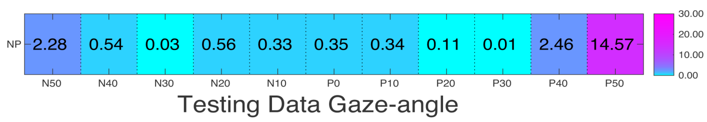

Figure 7: Recognition performance using the improved-heterogeneous approach

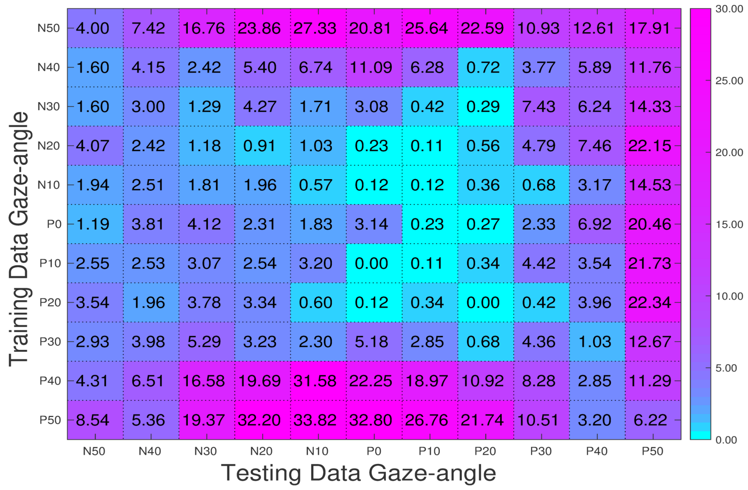

Figure 8: Recognition performance using the corrected-homogeneous approach

corresponding results, obtained using the improved-homogeneous approach, presented in the table in Figure 5. We can infer two degradation factors analyzing these results. First, the interpolation applied during the correction procedure starts to agonize the biometric features encoded in the iris texture, as the images' gaze-angle get far from frontal view, and the amount of the interpolation applied increases. Second, possible imperfections of the correction algorithm, may result in some differences in iris images belonging to each distinct subject, which eventually lead to degradation of genuine scores and subsequent recognition performance of the system. The pattern and scale of the changes in the results are a function of influence of these two factors.

We further considered the corrected-heterogeneous approach, in which we investigated if correcting the off-angle iris texture can compensate for the degradations imposed by the off-angle distortions, and thus improve the recognition performance, within a heterogeneous training configuration. So here, after training the network on iris images with different gaze-angles, and testing it on the images of each gaze-angle separately, the segmentation outputs were morphologically improved, parameterized and re-projected back to frontal view, and the recognition performance was evaluated subsequently. Figure 9 demonstrates the results for this experiment per gaze-angle. As it can be seen in the figure, the performance pattern is similar to what we found already in the corrected-homogeneous

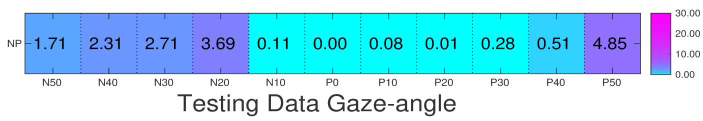

Figure 9: Recognition performance using the corrected-heterogeneous approach

approach. To be more precise, while we can see considerable improvements in the overall recognition results (compared to the corresponding results obtained using the angle-specific corrected-homogeneous approach) due to the supremacy of the heterogeneous configuration used, yet the same performance degradations (*i.e*. in the results of N40, N30, P30 gaze-angles) and enhancements (*i.e*. in the results of N50, P0, P10, P50 gaze-angles), as observed in the corrected-homogeneous approach, are visible here too.

6 Conclusion

The morphological improvement technique proved to compensate for some off-angle related segmentation degradations, enhancing the segmentation and the recognition results beyond those obtained in [JUK19], in identical configurations. The experiments carried out under the improved-homogeneous approach showed that the network performance gradually improves as the gaze-angle of the training and testing data converges in terms of angle but diverges in terms of direction. This showed the capability of the network to detect the symmetric iris contents in the images captured from the same angle, but in the opposite direction, which was figured out as the result of the segmentation improvement done. The experimental results of the viewing angle correction based approaches showed that the interpolation applied during the correction procedure and the possible imperfections of the correction algorithm, can dominantly influence the distinction of the iris images and thus undermine their subsequent recognition performance. This leads us to the conclusion that: Unless applying it to iris images with closed-to-frontal gaze-angles (*i.e*. up to 20°), and performing perfect (error free) correction, this angle correction based approaches are not expected to deliver promising recognition results (specially on the +20°off-angle images), when applied on the CNN based off-angle segmentations. While the heterogeneous training approaches were already expected to deliver good results (compared to the angle-specific homogeneous training configurations), based on the findings in [JUK19], yet our experiments actually showed that the applied segmentation improvement enhances the segmentation results, beyond those obtained using the same configuration (heterogeneous) in [JUK19], as well as improving the recognition results beyond the angle-specific training configuration results. In practice, this was very positive result, as it enabled us to refrain from the angle-specific training strategy, and even from the need for correcting the images' gaze-angles before being able to deploy the recognition systems.

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