A Performance Comparison between Circular and Spline-based Methods for Iris Segmentation

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Abstract—Iris segmentation is an important module of iris recognition that can substantially affect recognition performance. Since iris and pupil boundaries usually are not exactly circular, spline-based methods have been used to model irregular iris and pupil boundaries recently. However, in most existing methods, many other factors or modules in the iris recognition pipeline are evaluated together and their mixed effects are assumed to be negligible. More importantly, the splines that model irregularity of the boundaries could not be enough to model the internal nonlinear deformations of an iris pattern (e.g., caused by iris dilation). As a result, it remains unclear whether spline-based methods can provide significant improvements. In this paper, we conduct a complete performance comparison between circular and spline-based methods. There are mainly two contributions. Firstly, for the purpose of comparison, we propose a spline estimator that is robust to outliers caused by eyelashes, eyelids, highlights, and shadows. Secondly, we analyze the relation between iris matching distances and segmentation results by using circular and spline-based methods. Based on our experiments, we found that, even with the proposed robust spline estimator, the improvement of recognition performance is still limited (around 6%). Therefore, in case that less robust spline estimators are used due to the real-time requirement in practical systems, the actual recognition improvement by using splines could be far below the expectation.

I. INTRODUCTION

The iris region has been reported as one of the most accurate biometric characteristics. An iris recognition pipeline usually consists of five modules: iris segmentation, eyelids/eyelashes detection, iris feature extraction, feature representation, and iris matching. The goal of iris segmentation is to find iris regions that are consistent over a set of eye images that could have different scales/gaze changes, irregular boundaries, nonlinear deformations inside the iris region, and occlusions from eyelids, eyelashes, and highlights. In most access control applications, users are required or instructed to face the acquisition systems including long range systems [1], [2]. Hence, the majority of iris images are frontal or contain small eye gaze changes as shown in benchmark iris databases [3], [4] and the UBIRIS non-ideal iris database [5].

The commonly used iris segmentation is to estimate iris and pupil boundaries. These two boundaries could be modeled by circles, ellipses, and splines. Intuitively, we expect that more accurate models could result in better recognition performance. It could be one of reasons that spline models are widely adopted in the area of iris recognition.

However, this expectation is based on two assumptions. Firstly, it assumes that the spline estimators are as robust as circle estimators. The comparison between two kinds of estimators can be considered as an example of model selection. Since a good model selection strategy needs to balance between goodness of fit and simplicity, a more complicated model is often not a better model (i.e., the over-fitting problem). In a typical eye image, the majority of pixels or edges could be treated as noises and outliers that could be caused by eyelashes, shadows, and highlights. Thus, it remains unclear which kind of estimators for iris segmentation could provide more robust performance. Second, it assumes that splines can fully model the nonlinear deformations of an iris pattern. This may not be a valid assumption in general. Splines that only model the irregularity of iris and pupil boundaries could not be enough to model the internal nonlinear deformations of an iris pattern. The internal nonlinear deformations could be caused by iris dilation/constriction. It has been shown that iris dilation is also an important factor to affect recognition performance [6].

In many existing algorithms, different estimators of iris and pupil boundaries are evaluated together with other factors or modules (e.g., iris image enhancement and iris encoding) in the iris recognition pipeline. This kind of evaluation strategy could not reflect the actual performance of spline-based methods since it assumes that these factors or modules are independent to each other or their mixed effects are negligible.

In this paper, we investigate the impact of spline models on recognition performance. In order to do this, we need to design proper experiments by fixing or removing irrelevant factors and modules in the iris recognition pipeline. Firstly, we propose a robust spline estimator that can largely remove the outliers caused by occlusions. The goal is to obtain the most accurate spline models for the boundaries. Second, we fix other modules, such as image enhancements, feature extraction and representation, and eyelids/eyelashes detection. These modules can greatly affect the recognition performance. Since it is difficult to evaluate combined effects over a large amount of parameters or thresholds, it is necessary to fix them during experiments. We adopt widely-used or the state-of-the-art algorithms for these modules. Third, iris images are selected...
uniformly across different databases acquired by close-range and long range systems. Hence, the effects from different acquisition systems are reduced to minimum.

The remaining of this paper is organized as follows. Section 2 introduces different estimators in iris segmentation. Section 3 proposes a robust spline estimator based on RANSAC [7]. Section 4 discusses other components of the recognition pipeline used in our experiment. Section 5 describes our evaluation method for iris segmentation. A statistical analysis is given in section 6 followed by the conclusion in section 7.

II. RELATED WORK

Iris and pupil boundaries are often modeled as circles in [8], [9], [10]. It could be estimated by an intergrodifferential operator that searches for the maximal integral of radial derivatives [8]. It could also be estimated by circular Hough transform [10]. Edge points are often used as input to the Hough transform. Since direct usage of these estimators is not robust to outliers, many variant approaches (e.g., [9], [11]) are proposed to reduce the outlier rate before the estimation.

In the event of eye gaze changes, iris and pupil boundaries are closer to ellipses. Li [12] used ellipse fitting of edge points to deal with off-angle eye images. Recently, it has been found that iris and pupil boundaries possess irregular shapes that can be better fitting by splines [13], [14], [15]. Daugman [13] proposed an algorithm to detect and model boundaries with active contours. Along with other methods, such as statistical inference methods for eyelash and shadow detection. Without using the iris masks, performances of circular and spline models are very similar. When all the methods are applied, performance is much better, however, the impact of spline models is still unknown. Similar to [13], a set of other methods have been proposed in [14], such as reflection removal, eyelid estimation, and statistical inference methods for eyelash and shadow detection. The iris boundaries could be very different in iris images with and without occlusions using this treatment (e.g., half-open v.s. fully opened). Hence, this could further increase the nonlinear deformations of iris patterns when uniform sampling is used during the iris normalization. In our method, this behavior is greatly reduced by using data point sampling and the circle estimation before the sampling.

Robust spline estimator could increase the burden of real-time iris recognition, and could not be robust when there is a high outlier rate. Therefore, in this paper, we would like to find out whether spline models are robust enough to outliers for iris recognition and whether spline models improve recognition performance significantly.

III. ROBUST SPLINE ESTIMATION

In this section, we propose a method of spline estimation for pupil and iris boundary that is robust against outliers such as irregularity in boundary and occlusions. Our method starts with a number of sampled points close to the circular estimation of the boundary derived by the Hough transform. The sample points are chosen based on characteristics of the boundary such as gradient and intensity. Part of the outliers from occlusions are removed using a statistical inference method. However, since it is difficult to define fixed thresholds or cost functions to distinguish outliers for all kinds of iris images, a RANSAC outlier removal method is then applied. At last, a closed smooth spline is generated from the resulting points.

A. Data Point Sampling at Pupil and Iris Boundary

In this section, we collect data points for spline fitting based on the rough location of the boundary obtained by the circle-based localization method. The basic idea is to collect data points in each radial direction with the greatest gradient value. The radial direction is obtained according to the circular boundary estimated by the Hough transform. This is based on the assumption that the ground truth boundary should be close to the circular boundary and should hold the greatest contrast values in the radial direction. However, occlusions such as eyelash, eyelid and highlight will also produce big contrast values, which may lead to outliers in the collected data points.

Our solution is to use a statistical inference strategy to avoid part of the possible outliers when we are collecting the sample data. Here, we use the intensity as a measurement to see if a possible data point belongs to the expected intensity range of a boundary. Firstly, we collect data points in a small range around circle boundaries in each radial direction, here we use \((-3,+3)\) as the search range. Then we separately compute the intensity median for points in and out of the circle. We assume that the intensity of the ground truth boundary points are within the ranges of the inner median or outer median. We now get two intensity ranges: \([\text{median}_{\text{inner}} - \alpha, \text{median}_{\text{inner}} + \alpha]\) and \([\text{median}_{\text{outer}} - \alpha, \text{median}_{\text{outer}} + \alpha]\), in which we set \(\alpha = 20\) for pupil boundary and \(\alpha = 12\) for iris boundary. We now search for the greatest gradient value points in radial directions. If one such point belongs to the above intensity ranges, we regard it as the sampled data in its direction. Otherwise, it could be a point on a patch of highlight or eyelashes, which should be discarded. In this situation, we use the point on the circle boundary as sampled data point in this direction.

B. RANSAC

After data sampling, we use RANSAC to remove outliers and find a best matching spline with the greatest number of inliers. In each iteration of the algorithm, we repeatedly estimate a spline from a randomly selected subset of the current sample points, and in this process try to find a best spline with the highest number of inliers from all current points. And we do this iteration until the iteration time exceeds the maximum
trial times (in this paper we set it to 1000) or the current \( N \), the number of trials to ensure we pick with probability \( p \), a data set with no outlier, which will be updated according to the current best matched model [7].

We use a function to avoid the problem of degenerate model caused by non-uniform starting subset points. This function is to make sure our randomly chosen starting subset data points are evenly distributed on a circle. We use standard deviation and angular range as a metric to filter out bad starting subsets.

\( N \) is the number of iterations, which is used to ensure that at least one random sample does not include any outlier with the probability of \( P \) (we set it to 0.99). \( N \) is computed by \( N = \frac{\log(1 - P)}{\log(1 - s^t)} \), where \( s \) stands for the probability that any selected data point is an inlier and \( t \) denotes the minimum number of points required in a start subset. In our case, \( s = \frac{\text{Num inliers}}{\text{Num total sample}} \), \( \text{Num inliers} \) is the number of inliers under the current model, and \( \text{Num total sample} \) is the total number of the sampled data points. In our algorithm, if \( N \) exceeds 1000, we will stop the iterations. That is because, generally speaking, 1000 iterations can ensure \( s \geq 0.7 \), which is good enough for a spline when taking into account outliers such as eyelids, eyelash and the method’s time consumption. Figure 1 shows an example of RANSAC outlier removal.

We find during experiment that even with RANSAC, there are still a number of failure cases in our test data which produce inaccurate spline results. This tells us the iterative methods also could not give 100% accuracy. This is because the outlier rate in some iris images reaches the breakpoint of the estimator.

### C. Closed Spline

In this section, we introduce close cubic smoothing spline to localize the boundaries [16].

Let \( P_k = (x_k, y_k), k = 1..n \) be \( n \) points in the plane, with \( x_1 < x_2 < ... < x_n \). Let \( W_k, k = 1..n \) be positive real numbers (“weighting factors”) associated with \( P_k, k = 1..n \) respectively. The problem is to determine the set of \( 4(n - 1) \) coefficients of periodic cubic spline \( f \) on \([x_1, x_n]\) with knots at \( x_1, x_2, ..., x_n \), such that for a given parameter \( p \in (0, 1) \) and \( N \) points, the following will be minimized [17]:

\[
p \sum_{i=1}^{N} \left[ \frac{f(x_i) - y_i}{W_i} \right]^2 + (1 - p) \int_{x_1}^{x_n} f(x)^p dx \tag{1}
\]

where \( f \) is a cubic spline on \([x_1, x_n]\) if, for each \( k = 1..n - 1 \), there exist real numbers \( a_k, b_k, c_k, d_k \) such that

\[
f(x) = f_k(x) = a_k + b_k(x - x_k) + c_k(x - x_k)^2 + d_k(x - x_k)^3 \tag{2}
\]

Contrary to cubic spline, the cubic smoothing spline provide arbitrary control between the closeness to data and smoothing. \( p \) is the smoothing parameter, which could balance the contradictory demands of having \( f \) be smooth vs. be close to the data. For \( p = 0 \), \( f \) is the least-square straight line fit to the data, while, for \( p = 1 \), is the “natural” cubic spline interpolant. As \( p \) moves from 0 to 1, the smoothing spline changes from one extreme to the other. In this paper, we use \( p = 0.85 \) for the pupil boundary and \( p = 0.5 \) for the iris boundary localization. Comparing with our closed cubic smoothing spline, “natural end” spline will cause the curve to either close up with a noticeable discontinuity, or not close at all when the input data present a periodic feature, such as in our iris boundary, a closed curve.

The cubic spline \( f \) is said to be closed if it satisfies the following boundary conditions:

\[
\begin{align*}
  f(x_1) &= f(x_n) \\
  f'(x_1) &= f'(x_n) \\
  f''(x_1) &= f''(x_n) \tag{3}
\end{align*}
\]

However, a “natural end” cubic spline satisfies the so-
Fig. 2. The comparison between “natural” end spline and closed spline. (a) The input data points. (b) Localization of the boundaries by “natural” end spline. (c) Localization of the boundaries by closed spline.

called “natural end conditions”: \( f''(x_n) = f''(x_1) = 0 \). Detailed solution can be found in [16].

IV. THE IRIS RECOGNITION PIPELINE

In order to conduct a direct comparison between circular and spline-based iris segmentation, the two methods are performed within the same iris recognition pipeline, which helps to eliminate possible interferences on the recognition performance caused by changes of modules, parameters and thresholds. The pipeline consists of modules using state-of-the-art or widely used algorithms.

At the preprocessing stage, the contrast of the input image is adjusted to enhance contrast in the eye region. For pupil and iris localization, we use either the spline-based method, or circular estimation by performing the Hough transform on the edge map of the iris image [10]. Eyelid localization is done by fitting a parabolic curve on a vertical edge map of the ROI of the iris image, and the eyelash and shadow area is detected by estimating a threshold value from the intensity distributions of different iris regions [14].

After the iris pattern is extracted, its background illumination is estimated to compensate for local intensity variation [18]. We then extract the binary coded feature vectors using the 2D Gabor filter and the subsequent phase quantization [8]. The similarity score of two iris images is calculated by the Hamming Distance between their corresponding feature vectors.

V. EVALUATION OF IRIS SEGMENTATION

We use two metrics to describe the difference of the pupil/iris boundary estimated by circular and spline-based segmentation algorithms: perimetric distance and area difference. The perimetric distance \( D_G \) is defined by the average of the distances between corresponding points on the circle and spline divided by the power mean of the pupil and iris radii.

\[
D_G = \frac{\sum_{i=1}^{N} \| P_c(\frac{2\pi i}{N}) - P_s(\frac{2\pi i}{N}) \|}{N \cdot r_c},
\]

where \( P_c(\theta) \) and \( P_s(\theta) \) are the intersection points of respectively the circle and spline, with a ray originating from the center of the circle, at angle \( \theta \). \( N \) is the number of points sampled on the circle/spline, and \( r_c \) is the radius of the circle.

The area difference \( D_A \) is defined by the sum of non-overlapping portions of the circle and spline areas for the pupil and iris, divided by the difference of overlapping portions of the circle and spline areas for the pupil and iris.

\[
D_A = \frac{\text{Area}(C_{Iris} \oplus S_{Iris}) + \text{Area}(C_{Pupil} \oplus S_{Pupil})}{\text{Area}(C_{Iris} \cap S_{Iris})} - \frac{\text{Area}(C_{Pupil} \cap S_{Pupil})}{\text{Area}(C_{Iris} \cap S_{Iris})},
\]

where \( C \) and \( S \) represent the area covered by the estimated circle and spline respectively, and \( \oplus \) represents the XOR operation.

VI. STATISTICAL ANALYSIS

A. Data Set

We compare the circular and spline-based segmentation using iris images selected from our own iris acquisition system and the ICE database. We experiment on around 1000 images of 80 different eyes. For each eye, a certain number (i.e., 1-5) of clearer, frontal eye images are picked as enrollment images, the rest as test. To fully evaluate the performance of the spline estimation algorithm, we have also included about 120 non-ideal eye images, with imperfections such as irregular pupil/iris shape, heavier occlusion, and more eye gaze deviation.

For either algorithm, we calculate the similarity score, i.e., Hamming Distance, between the enrollment and test images of each eye, with both normal and non-ideal data. The difference of performance between the two algorithms is then analyzed by investigating the difference of the scores they generate.
B. Analysis

In our experiment, the score difference between circular and spline-based segmentation algorithms is first calculated by subtracting the spline-based score from the circle-based score. Figure 4 and Figure 5 display score difference with regard to circle-spline distance in terms of perimetric distance and area difference respectively. Instances of superior spline-based performance are represented by data points above the zero lines, and those of inferior performance otherwise. From the figures, we find that the score differences are normally distributed with means slightly higher than zero. There are also a large amount of score differences that are negative. Further statistics in Table I and Figure 6 shows that the average intra-class Hamming distances of two methods are 0.2065 and 0.1934 respectively, which indicates an reduction of 6% on average.

We also notice that the score difference rises very slightly as the perimetric difference between circle and spline goes up as shown in Figure 4 and Figure 5. This could be an indication that the spline-based segmentation algorithm tend to be more advantageous in accuracy when the pupil/iris boundary less resembles a circle. However, the robust spline estimator tends to fail when the outlier rate is large. In our experiments, we manually inspect all the segmentation results and remove around 3% inaccurate spline models that would result in false recognitions (the same set of circular models are also removed for a fair comparison). Notice that existing close-form methods, which are commonly adopted due to speed concerns, could not be as accurate as the RANSAC-based estimator. Therefore, the percentage of false spline models could be higher, especially when long-range acquisition systems are used. This means that the overall performance improvement in practice could be below the common belief.

The most notable factor that prevents the spline-based segmentation algorithm from significantly surpassing the performance of its circular counterpart is nonlinear deformation in the iris region. Iris is the muscle to control the pupil diameter. The muscle movement caused by iris dilation/constriction or gaze changes could be nonlinear. As shown in [6], dilation degrades recognition performance. Figure 7 shows an example that intensity appearances of internal iris textures from the same eye could be quite different. We can find that even accurate spline models could not fully model the nonlinear deformation inside the iris pattern. Some possible solutions, such as more robust feature extractors, non-uniform sampling during iris normalization, and iris matching other than the Hamming distance, could be used to reduce this problem.

VII. Conclusion

In this paper, we have performed a complete comparison of iris recognition performance between circular and spline-
based segmentation algorithm. To this end, we developed a spline boundary estimator robust to deformation, occlusion and change of eye gaze. In our experiment with iris images from well-known database and our own acquisition system, we find that the improvement of recognition performance from the spline-based estimator is limited due to internal nonlinear deformations. One possible direction in our future work is to develop a more sophisticated iris matching algorithm that is not sensitive to nonlinear deformations.

REFERENCES


