

Adaptive Reflection Detection and Location in Iris Biometric Images by Using Computational Intelligence Techniques

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Abstract—Iris-based biometric systems identify individuals by comparing the characteristics of the iris captured by suited sensors. When reflections are present in the iris image, the portion of the iris covered by the reflections should not be considered in the comparison since it may produce erroneous matches. This paper presents an adaptive design methodology for reflection detection and location in iris biometric images based on inductive classifiers, such as neural networks. In particular, this paper proposes a set of features that can be extracted and measured from the iris image and that can effectively be used to achieve an accurate identification of the reflection position using a trained classifier. In addition, the use of radial symmetry transform (RST) is presented to identify the reflections in iris images. The proposed design methodology is general and can be used in any biometric system based on iris images.

Index Terms—Biometric system, iris, neural networks, radial symmetry transform (RST).

I. INTRODUCTION

BIOMETRIC systems exploit automated methods capable of recognizing individuals by analyzing their physiological and/or behavioral characteristics. Physiological biometrics is based on data derived from the direct measurement of a body part (e.g., fingerprints, face, retina, and iris), whereas behavioral biometrics is based on measurements and data extracted from human actions (e.g., gait and signature) [1], [2].

Iris biometric systems identify the user by performing the following steps: The first step is the acquisition of the iris image (*sample*) by the sensor module. The second step is the localization of the iris in the acquired image. All biometric systems can achieve their maximum accuracy in identification/verification only if the samples are correctly acquired [3]. For this reason, all exogenous elements that are superimposed to the real biometric information in the sample must be removed (e.g., in iris images, we may have reflections, eyelids, etc.). This operation can reduce the probability of erroneous matching. In the case of the iris sample, the exogenous elements are mainly the following: 1) eyelids; 2) lashes; and 3) reflections. In this step, the edges of the pupils and iris must initially be located

in the input image, and then the eyelids, lashes, and reflections must be identified and removed from the iris image. The third step aims at extracting the biometric template from the iris (*iris encoding*). This template will be used by the biometric system to perform comparisons (*matching*) with the templates used as reference [3], generally stored in a database or in an identification document typically using a smartcard-based technology.

In most of the cases, the sensor is a charge-coupled-device-based camera with a proper optics. Such systems can achieve remote acquisition (about 0.5–1.5 m) of a face portion containing one complete eye (Fig. 1). Most of the systems require about 100×100 pixels of resolution for the iris to suitably identify an individual. Nowadays, low-cost sensors, such as webcams, have also been considered to perform iris identification. Fig. 1 shows different iris images. Images (a) and (b) have been acquired with cameras working in the IR band by using optics with focal lengths of 8 and 54 mm, respectively, and image (c) has been produced by a low-cost sensor. Images (d) and (f) show two irises acquired by using visible light (ambient light and lamp light, respectively), whereas image (e) has been obtained by using a color webcam.

Reflections in iris images can occur in a great variety of applications and acquisition systems. This phenomenon is due to the particular shape and condition of the cornea (the spherical and wet transparent surface that protects the iris and the inner eye from the outside). The light coming from windows, screens, and the illumination system (which is almost always required to correctly acquire the iris image) is often reflected by the cornea. Additional reflections may be caused by occlusions such as contact lenses and eye glasses.

Unfortunately, reflections tend to be superimposed on the iris pattern, causing difficulties in the iris acquisition. Complex iris-based biometric systems use special illumination system (e.g., single point IR illuminators, optical filters, etc.) and require that users must be correctly positioned in front of the sensor. Consequently, reflections are confined in the pupil area, hence outside of the iris pattern. However, even in such cases, external reflections are often very frequently present in low-cost systems and in outdoor conditions.

This paper focuses on the creation of a pattern recognition system capable to locate the reflections that are present in the iris image. In particular, the contribution is twofold: the paper proposes 1) a highly effective set of features to be extracted from the iris image [based on the radial symmetry transform (RST)] and 2) an innovative adaptive design methodology

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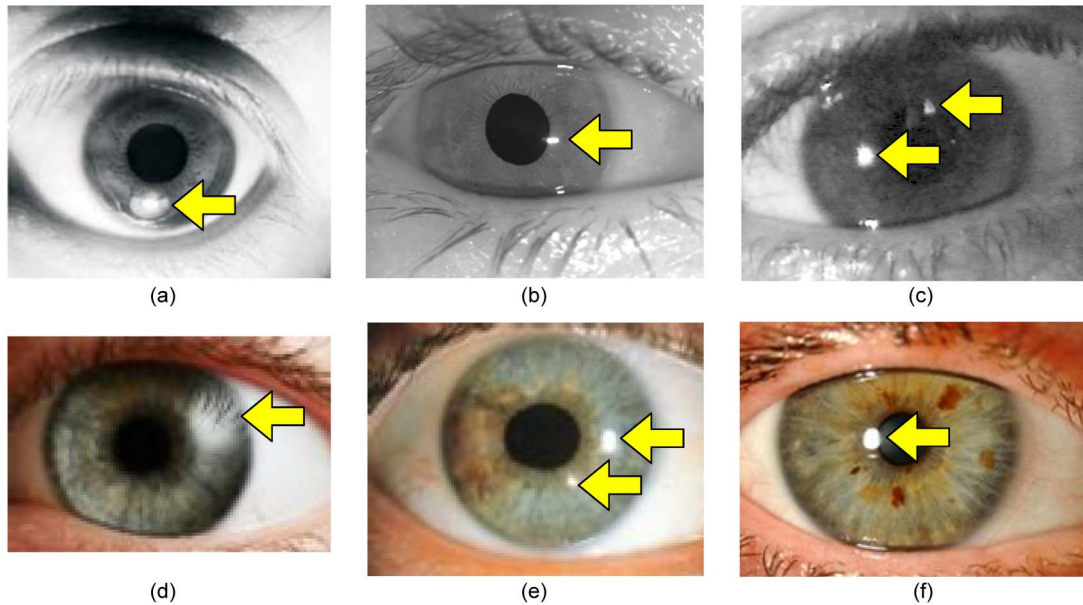


Fig. 1. Reflections present in iris images acquired with different sensors and optics.

for creating an inductive classifier to achieve reflection detection and location by a pixel-by-pixel approach. The proposed method can work with any close-up image of the eye, and it does not require any information concerning the iris position and other segmentation information. This allows for implementing flexible iris-based identification systems that are very robust to environmental and operating conditions.

This paper is structured as follows: Section II presents the state of the art, whereas Section III proposes the design methodology for reflection detection and location. Starting from the choice of the proper set of features to be extracted from the image, the design process encompasses the feature selection and composition phases, the creation and training of the classifiers, and a test session. In particular, Section III shows how the RST can be used and how to tune the parameters with respect to the input image. Section IV shows the application of the proposed design methodology with experimental results using computational intelligence techniques, such as neural networks. The creation of the training data set is discussed, whereas the results of the neural networks are compared with respect to traditional classification paradigms (e.g., the k -nearest neighbor classifiers) discussing accuracies and computational complexities.

II. STATE OF THE ART

The approaches presented in the literature traditionally consider the reflections as any other occlusion in the biometric images. A first kind of approach tries to evaluate the global quality of the iris acquisition by measuring the global property of the iris pattern. In [4], Ma *et al.* analyze the Fourier spectra of local iris regions to characterize defocusing, motion, and occlusion presence. Zhang and Salganicoff [5] examine the sharpness of the region between the pupil and the iris. Daugman [6] and Kang and Park [7] evaluate the iris quality by estimating the energy of high spatial frequencies over the entire image region. All of these techniques only consider one or two global

features extracted from the iris/eye image to estimate the quality of the image. These methods implicitly estimate the presence of occlusions since their presence tend to degrade the overall sample quality.

Differently, a second class of approaches uses a local analysis of the iris to achieve a proper segmentation of occlusions. In [8], Chen *et al.* use the local features extracted from one iris image by using a 2-D wavelet technique. A similar local approach is present in [4]. In [9], Zhu *et al.* propose a technique based on the analysis of a sequence of images by using wavelet coefficients.

In the literature, it is well known that the performance of an iris-based biometric system can be enhanced if the encoding phase of the iris pattern is performed after the reflections have been localized and removed from further comparisons. Reflection removal is typically achieved by localizing the reflections by means of a segmentation technique based on hard thresholding. Thresholding is performed by using one or more features extracted from the iris pattern, as previously described. A *mask image* will be created to mark each pixel that is supposed to belong to the iris pattern and not to occlusions (as, for example, in the well-known IrisCode technique proposed by J. Doughman [10]).

Traditionally, the approaches available in the literature consider binarization of the input grey-level image [8], [9], [12]. This is conceptually based on the fact that the reflections are caused by external light, and hence, they tend to be characterized by light grey intensities. This approach is very simple, but it is not robust since its accuracy strongly depends on the setup of the binarization threshold. It is very difficult to set a proper threshold suitable for different image types, even by using an adaptive threshold technique. In addition, some white image regions may not contain any reflection (e.g., in the sclera region). Therefore, the binarization approaches tend to produce large false detection rates since they classify white portions as reflections (e.g., the sclera region). In the following, we refer to this method with the name *BIN*.

Most of the papers available in the literature can be considered as ad hoc applications since they typically miss a proper and comprehensive methodological design approach. In the following section, we propose a generalized design methodology that can be used to design a detection and localization system for reflections by using a new set of features and a multiple classification system.

III. DESIGN METHODOLOGY

The design of a detection and localization system for iris reflections can be considered as a particular case of the design of a pattern-matching system. The peculiarities of the reflection patterns must be identified and exploited to perform localization. The proposed design methodology will therefore consist of the following steps, which are typical of this kind of method [13]:

- A) *acquisition* of data from the camera/sensor;
- B) *preprocessing* of data to reduce the noise, correct lens aberrations in the images, process contrast enhancement, and accomplish possible other similar tasks;
- C) *processing of the features* to extract important information concerning the reflection presence from the signal (also called feature extraction phase);
- D) *selection and composition/fusion* of the extracted features to better measure, describe, and detail the phenomena associated with the presence of reflections;
- E) *classification* of the features in a two-class output by evaluating the presence of the reflections;
- F) *error evaluation* of the detection and localization system.

The peculiarity of the computation intelligence techniques can be exploited in many steps of the design chain, giving interesting enhancement in the performances of the system. In [10], the use of these techniques is discussed in general by addressing the most important benefits and limits. In this paper, we focus on the application of computational intelligence mainly in the *feature fusion* and *classification* phases.

A. Acquisition and Detection of the Iris

Fig. 2 plots the structure of modules that consist the reflection detection and localization system. The first module (the detection module) acquires the eye image, preprocesses the input image (phase A), and localizes the iris in the eye image (phase B). In this module, detection of the eyelids is also typically accomplished. The output of this module is an image in which the iris area has been localized. In the literature, many different and effective techniques have been proposed to implement the tasks of the detection module (e.g., [4], [6], and [14]–[16]). The discussion of these techniques is beyond the scope of this paper.

In the following, we consider the detection module as a given block, and we assume the following: 1) the input to the reflection detection and localization system is an image in which the iris is present; 2) the iris center has roughly been located; and 3) the eyelids and the eye brushes may be present even if they are overlapping the iris. These hypotheses are very general, and they are fully satisfied by all the techniques mentioned.

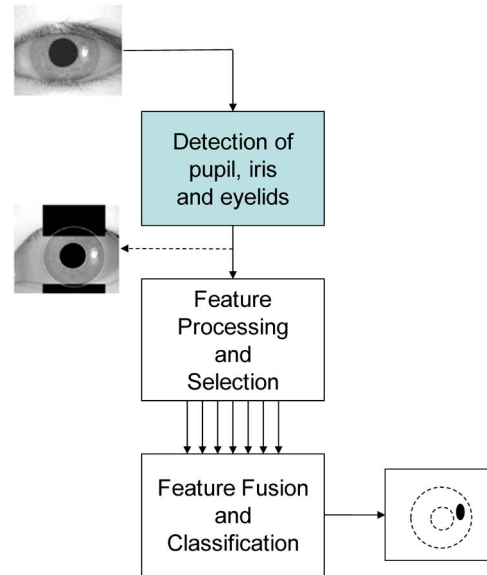


Fig. 2. Structure of the proposed system for reflection identification.

B. Iris Feature Processing and Selection

The second module in Fig. 2 is the feature processing module. Its input is the eye image. From the eye images, it extracts a set of features that can be used for detecting and localizing the reflections. This module can mainly work in two different modalities. The first modality consists of a global image analysis that returns a single vector of features extracted from the whole image (for example, a set of quality indexes of the input image). The second modality consists of a pixel-by-pixel analysis; this returns a transformed image (often called “map” or “transformation”) in which every pixel represents a feature value corresponding to the properties of the pixel in the input image in the same x - y coordinates.

These properties can be obtained by a single-pixel analysis (e.g., the thresholding binarization techniques based on the pixel intensity level) or by processing the local distribution of the intensities in the input image. In the following, we will consider both approaches. Since the first approach returns one global feature vector for each input image, it can be exploited only to produce a binary answer if a reflection is present or not in the input image. For example, if a reflection has been detected, then the input image can be discarded, and a new eye image can be requested to the iris acquisition and detection module.

The second approach is more general since it can be adopted to localize the reflections. In addition, the reflection coordinates can be used to compensate/mask the reflections themselves, and hence, it allows the biometric system for optimally using the acquired image. In the next section, we will present a method that adopts this second approach. Typically, the reflection presence on the iris pattern is measured by using the total amount of pixels classified as reflection by the classification system. If that value is lower than a given threshold, then the image can be used by the biometric system. Otherwise, the iris pattern is too much degraded to be processed as a valid sample.

In most of the cases, more than one feature is extracted from the input image to better analyze the reflection patterns (e.g., by

exploiting the physical knowledge of the phenomenon). Once a set of features has been extracted, a feature selection phase can be performed to identify which features are most significant and relevant for classification [10]. This task is frequently accomplished offline (e.g., during the design phase or in a fine-tuning activity), since the methods available in the literature are usually highly computational intensive, and they are not suitable for real-time applications. A comprehensive review of the feature selection techniques can be found in [11].

It is worth noting that the feature selection phase can be considered as an optional task. Therefore, it may be neglected in the first design stages of the biometrics system and then can be included in the final system optimization.

C. Feature Fusion and Classification

The third module shown in Fig. 2 performs the feature fusion and classification tasks. The feature fusion (often called “extraction”) is an optional step of the reflection detection and localization system that aims to intelligently compose the incoming features to obtain a reduced and more significant subset of features to be processed by the classifier. The feature fusion can also be described as a mapping of the input space into a—potentially reduced—subset of features, which are capable of augmenting the accuracy of the final classifier. A high number of techniques are available in the literature to perform this task. The more common technique is the principal component analysis (PCA), which can compress most of the variation measured in the input features into a minor number of components [17], [18].

Since the PCA-like mappings mix the input components into a reduced set of new features, the direct relationship between the features and their influence on the reflection classification is less explicit. Similar approaches in the literature are based on neural networks and genetic algorithms. A comprehensive review of these techniques can be found in [11]. This phase does not necessarily reduce the number of features to be measured, but very often an increased accuracy may be achieved. On the other hand, the effect of the lower dimensional representation of the inputs may produce a better generalization behavior of the classifiers [18].

As the last step, classification is then performed in the third module. As previously described, the classification system can classify each single pixel of the image or produce a single binary answer concerning the presence of reflections in the overall input image, according to the approach adopted in the second module. In this paper, we focus on the single-pixel classification approach.

The single-pixel classification can be obtained by direct classification of the features or by using a two-phase approach in which a measure of the reflection presence (i.e., a real value in the 0–1 range) is first produced and then used by the classifier to generate the final binary output (reflection presence/absence). In both cases, it is possible to use a multiple classification system. In the literature, it has been shown that a combination of classifiers can improve the identification accuracy [11]. In this paper, we describe the results for both approaches. Since an exhaustive explicit relationship between the input iris patterns

and the presence of the reflections is not available nor an efficient algorithm has been identified, the use of an inductive classification system is valuable. An inductive classification system (e.g., neural networks, nearest neighbor classifiers, and support vector machines [17]) is in fact able to learn almost any relationship given a suited set of examples, usually under very loose conditions.

D. Accuracy Estimation of the Final System

The final step in the design methodology is directed to perform the following tasks: 1) tuning all the parameters; 2) classification system learning; and 3) estimating the accuracy of the final classifier. The parameter tuning depends on the techniques adopted for feature extraction. Each technique has a specific method to set all the parameters. Similarly, a suited learning algorithm for tuning the classification model on the given training data set should be provided for the specific classification paradigm (namely, neural networks, k -nearest neighbors, etc.) that was adopted.

To properly estimate the accuracy of the final system classifier, the example data set must be divided in two partitions, as requested by the cross-validation techniques. The first partition (the training data set) is used to tune the system’s parameters and to train the inductive classifier. In some approaches, the training data set is split in more parts, each used for one of these tasks: parameter tuning and classifier learning will be performed by using separated subsets of data [18]. For example, a subset of the training data set can be used to directly test the generalization capability of the classifier during the learning phase, as it is typical in neural networks [19].

The second partition (validation data set) is used only once to estimate the system classification error. More accurate techniques for classification error estimation can be used (e.g., the N -fold validation and leave one out), but their computational complexity becomes very high for large data sets [11], [18].

In most cases, the simple classification error is not sufficient to describe the accuracy of the system. To describe the performance of the classification system, we also need to use the false acceptance rate (FAR) and the false rejection rate (FRR). In addition, other related parameters (such as specificity, sensitivity, and confusion matrix) should be taken into account in the accuracy evaluation [12], [20]. If the classification system uses a final acceptance threshold (a very common situation, particularly when neural network are adopted), then the classification errors and the FAR/FRR values directly depend on the threshold value. In this case, the behavior of the overall system is better described by the receiver operating characteristic (ROC), which concisely represents the different FARs and FRRs of the system with respect to the possible threshold values. An ideal system achieves FAR and FRR equal to 0 for all threshold values.

Another important point concerns the estimation of the enhancements that a reflection identification system can produce in the accuracy of a complete iris identification system. This estimation requires the development of a complete experiment that encompasses a complete iris verification/identification system and a real-life large database of iris images where

reflections are present. Unfortunately, most public iris databases have been acquired in controlled environments, and the presence of reflections is carefully avoided. Although the complexity of the experiment, unfortunately, the obtained results have low generality since they depend on the chosen system and on the image databases. In [13] and [24], it has been shown that the overall effect of the occlusions in the iris images (eyelids, lashes, and reflections) on the accuracy of the system can be up to a few percent. In most biometric iris systems, the comparison between templates is achieved by comparing the bits of the templates with the exclusion of the masking bits related to the occlusions. Preliminary results show that the improvements due to the use of the masking bits are related to the percentage of masking bits that have correctly been classified as occlusions.

A better identification of the reflections can hence help to reduce the error of the overall biometric system. This positive factor can be very relevant when the system works in *identification applications*, since a great number of iris comparisons is required, and the single comparison error (the matching error) is correspondingly multiplied. In such applications, even small improvements in the accuracy are very relevant for the applicability and the usability of the system.

IV. APPLICATION OF THE METHODOLOGY AND EXPERIMENTAL RESULTS

In this section, we describe the application of the proposed methodology by starting from the feature selection step. In this step, all meaningful features that are useful to detect and locate the reflections should be extracted from the input image. In the literature, most of the papers focus on the grey intensity level or—when feasible—on the color information associated with the iris pattern. In this paper, we propose the use of a particular input image mapping called RST, which is capable of detecting and locating the reflections from their peculiar shape. This mapping tends to enhance the objects in the image that have radial symmetry (such as the reflections). To compute the RST, we use the fast RST proposed by Loy and Zelinsky [21].

Due to the spherical shape of the cornea, the reflections tend to be smaller than the pupil; moreover, they are generally circularly shaped. This kind of shape has a relatively high value in the RST. Fig. 3 shows the application of this mapping to different images. The RST has two main parameters. The first parameter is an array of candidate radii (N) that will be considered in the image analysis, whereas the second parameter is the radial strictness parameter (α). In the transformed image, only symmetrical objects whose radii are comparable with those in the N array will be enhanced (high contrast). Objects with low radial symmetry tend to be suppressed in the transformed image (low contrast). With small values of the parameter α (i.e., ≤ 1), image features also having bilateral symmetry will be enhanced. With higher values of α , only objects/features in the image with strict radial symmetry will be enhanced.

The RST algorithm maps the local radial symmetry of an image $I(\mathbf{p})$, where $\mathbf{p} = \{x, y\}$ is a point in the image, into a

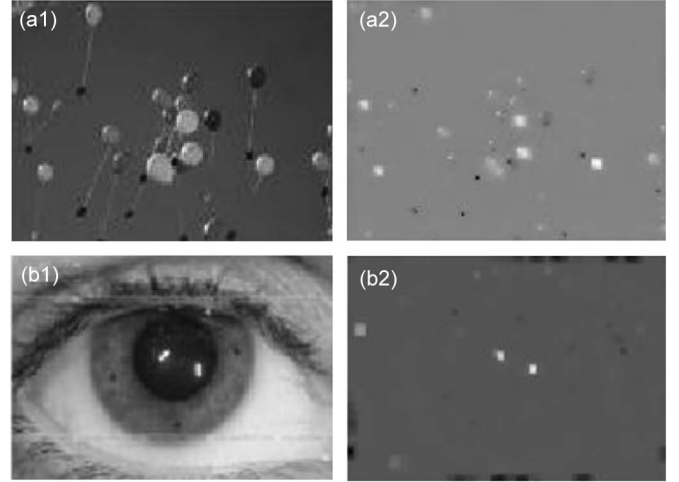


Fig. 3. Application of the fast RST to an image containing spherical objects (a1) and to an iris image (b1). Local maxima (white pixels) in the transformed images (a2) and (b2) are related to white objects in the input image with high radial symmetry.

transformed image $S(\mathbf{p})$ with a low computational complexity with respect to other methods available in the literature.

The output image S is calculated with one or more radii n belonging to the set of radii N (e.g., ranging from 1 to 5 pixels) by the following sum:

$$S(\mathbf{p}) = \text{RST}(I(\mathbf{p})) = \frac{1}{|N|} \sum_{n=1}^N S_n \quad (1)$$

where S_n is the radial symmetry contribution at radius n defined as the following convolution:

$$S_n = F_n * A_N. \quad (2)$$

In (2), A_N is a 2-D Gaussian kernel, and F_n is a transformed image obtained by

$$F_n(\mathbf{p}) = \frac{M_n(\mathbf{p})}{k_n} \left(\frac{|\tilde{O}_n(\mathbf{p})|}{k_n} \right)^\alpha \quad (3)$$

where α represents the *radial strictness parameter*, and

$$\tilde{O}_n(p) = \begin{cases} O_n(p), & \text{if } O_n(p) < k_n \\ k_n, & \text{otherwise} \end{cases} \quad (4)$$

where k_n is the scaling factor of the maps M_n (the magnitude projection image) and O_n (the orientation projection image). M_n and O_n are obtained by examining the gradient vector $\mathbf{g}(\mathbf{p})$ in peculiar points called *positively affected pixels* and *negatively affected pixels*. Loy and Zelinsky defined the positively affected pixel as “the pixel that the gradient vector $\mathbf{g}(\mathbf{p})$ is pointing to, a distance n away from $\mathbf{p}$ ” and the negatively affected pixel as “the pixel a distance n away that the gradient is pointing directly away from” [21]. Gradient vector images can suitably be processed by a simple 3×3 Sobel operator.

A. Data Set

In this paper, we used a data set of eye images captured by different sensors (as described in Section I) and classified by

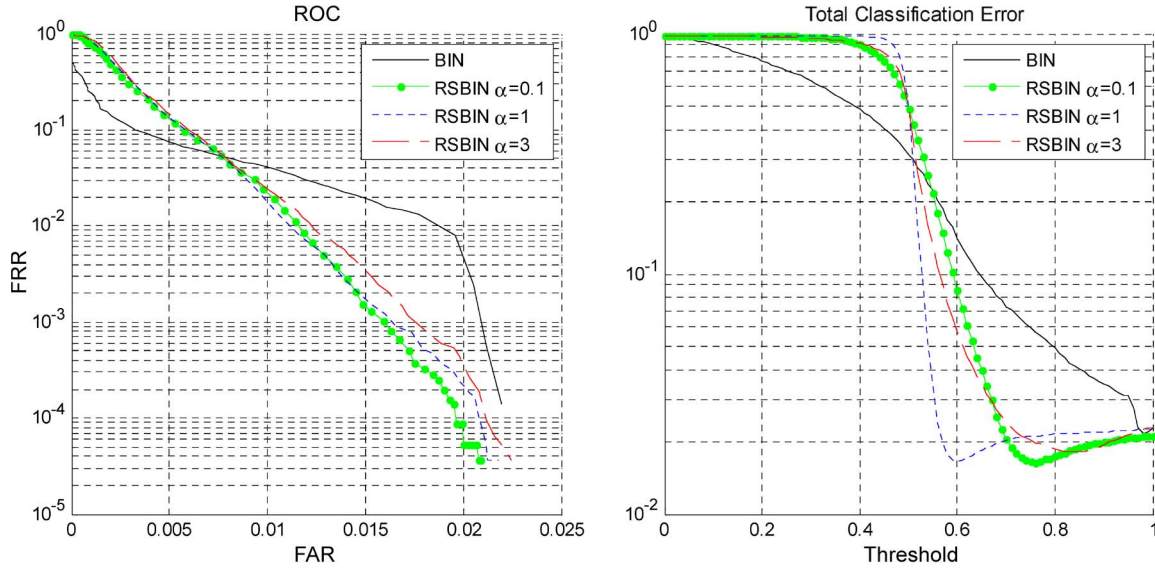


Fig. 4. (Left) ROC curves of the traditional binarization method (*BIN*) and the proposed radial symmetry binarization method (*RSBIN*) at different α . (Right) Total classification error with respect to the threshold level.

an expert user at pixel level. Each pixel has been labeled by using two classes: 1) *reflection* and 2) *nonreflection*. Images have been collected by using different sensor and optics to test the generality of the method in different applicative contexts. In particular, as detailed in Section I, we used cameras working in the IR band (by using low and high focal length optic), low-cost sensors (two different off-the-shelf color webcams), and industrial cameras using visible light (ambient light and lamp light). The data set consists of 153 876 classified pixels. The occurrence of reflection pixels in the image data set is about 2.34%. The probability of an iris pixel to be a reflection is about 6.92%.

B. Application of the RST

The first implementation of the method for reflection detection and localization that we propose in this paper is based on the RST followed by of a simple thresholding technique. This simple approach demonstrates the good intrinsic capability of the RST to identify reflections.

Once the RST has been performed, reflections are detected and localized by selecting the pixels in the map that have an RST value of higher than a predefined threshold t ; hence

$$RSBIN(p) = \begin{cases} 1, & \text{if } RST(I(p)) > \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

The RST has low sensitivity to the average brightness of the images (since the presence of derivative components in the algorithm); hence, it is not particularly difficult to tune the threshold t . Experiments showed that a threshold value of

$$t = \alpha \max(RSBIN(p)) \quad (6)$$

allows for a correct reflection identification with $\alpha = 0.6$. If the input images have a larger variability in the light conditions, then the triangular binarization method can also be considered since it is capable of producing a very robust and adaptive

method for reflection identification via RST. On the current data set, the results are comparable; hence, the method in (6) is preferred because of its simplicity and low sensitivity with respect to the value of the α parameter.

By using this approach, it is possible to detect the reflections from the shape information given by the RST without using the direct values of pixel intensities. The information extracted by this method relies on the local distribution of the pixel intensities around the selected pixel. Since both *BIN* and *RSBIN* approaches depend on the threshold value (which has to be suitably set by the designers), a fair comparison between these techniques can be performed by using the ROC curves. ROC curves allow for identifying the best method for the ranges of FAR and FRR in the considered application.

Fig. 4 shows the ROC curves of the traditional *BIN* algorithm with respect to the ROC curves of the proposed *RSBIN* method with different values of the parameter α . The ideal algorithm should produce FAR and FRR equal to zero for all the threshold values (i.e., the ROC curve should coincide with the axes). The plots show very different behaviors of the two algorithms. The traditional *BIN* algorithm has a better behavior in the left part of the ROC curve than the proposed *RSBIN* algorithm. Conversely, in the right part of the ROC curve, *RSBIN* achieves better results. For example, the classification error of the sclera as a reflection typical of the *BIN* algorithm produces in the ROC curve a large FAR rate. In Fig. 4, the plot on the right side shows the total classification error (i.e., the sum of FAR and FRR) of the *BIN* and *RSBIN* algorithms. The *BIN* algorithm has a minimum total classification error when the threshold is 1 (i.e., all image pixels are classified as non-reflections): in this working point, the *BIN* classifier is totally useless. On the contrary, the proposed *RSBIN* algorithm has a threshold value that can effectively minimize the sum of FAR and FRR in useful working conditions. The best performance is obtained with the *RSBIN* method when $\alpha = 1$.

Fig. 5 plots four different iris images (first column) and the corresponding RSTs (second column). Notably, this mapping



Fig. 5. Application of the RST and reflection compensation.

properly detects the positions of the reflections in the iris. It can be seen that the reflections correspond to the positions of the local maxima in the transformed maps (the second column in Fig. 5). The third column plots the binarized values of the RSTs by using the threshold value expressed in (5) with $\alpha = 0.6$. The last column shows the final compensated images. The pixels belonging to the reflections have been compensated by processing the mean intensity value of a 10-pixel neighborhood to qualitatively show on the eye image the effect of the classification accuracy of the method: false-positive classifications produce overwritten iris pixels, and false-negative classifications are visible as uncompensated reflections.

C. Feature Fusion and Classification by Using Neural Networks

To perform classification, a more discriminative and significant set of features can be obtained by using the RSTs, possibly integrated with other classical features (e.g., the normalized pixel intensity). This set of features can be used as input to a neural network that performs reflection detection and localization better than the traditional thresholding method. In this section, the traditional approaches are compared with the proposed technique based on the RSTs.

Computation intelligence techniques may be advantageous for reflection classification. In particular, neural networks can combine the extracted features in a nonlinear manner to create better reflection classifiers. We aim in fact to train a neural

network to mimic the behavior of a traditional *BIN* classifier in the left part of the ROC curve (Fig. 4) and to learn the behavior of the proposed classifier based on the radial symmetry in the right part of the ROC curve. The basic idea is to induce the neural networks to learn the desired best behavior in the different regions of the image by using more than one feature. In our experiments, neural networks have been trained by using a training data set of 8000 classified pixels, which were obtained by random extraction from the original data set of 153 876 pixels. The trained neural networks have been verified by using the validation data set according to the cross-validation technique. In this paper, we only analyzed the use of neural networks for the pixel-by-pixel approach.

A first implementation based on our approach obtains the reflection classification by using two inputs: 1) the grey level intensity of each pixel and 2) the corresponding value of the RST. This input configuration has been tested by considering a set of feedforward neural networks with a number of hidden neurons ranging from 1 to 30, which were trained ten times with the Levenberg–Marquardt method (chosen for its convergence properties) and the Bayesian regularization (chosen for the capability to enhance the generalization property of the neural network) [11], [19].

The minimum total error rate has been obtained by using a feedforward neural network with four neurons in the hidden layer (*FFNNI* in Fig. 6). This neural network achieved a total error rate of 1.64%, and its ROC curve is much better than the *BIN* and *RSBIN* approaches in a wide range of the

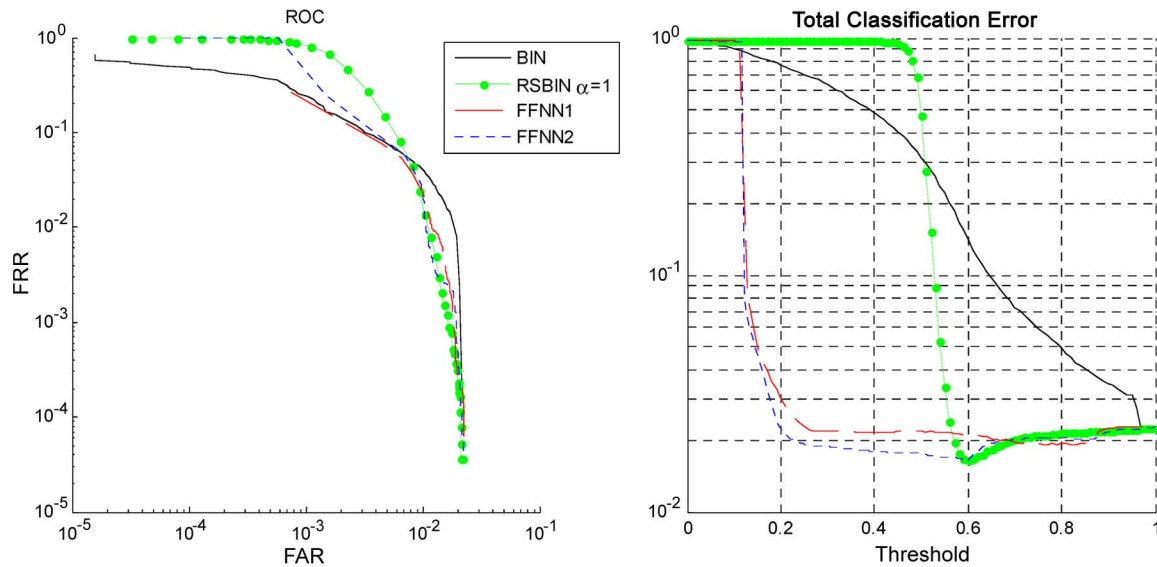


Fig. 6. Application of the RST and fusion of features by using neural networks.

curve. A similar behavior has been obtained by using a neural network with six neurons in the hidden layer (*FFNN2* in Fig. 6): although it is only better in some limited ranges, it is globally a bit worse than the previous solution. Hence, very interestingly, the use of the FFNN method instead of the *RSBIN* or *BIN* method can achieve a more robust behavior of the system with respect to the threshold value. As a matter of fact, the total classification error of the FFNN method is more stable for a wider range of threshold values than for the *RSBIN* and *BIN* methods.

A set of k nearest-neighbor (kNN) classifiers with k ranging from 1 to 15, with the Euclidean norm, has been tested as reference. The best results have been obtained with $k = 1$. Since no threshold needs to be set in the nearest-neighbor classifier, there is no ROC curve, but only a single value for FAR and FRR. The best kNN classifier has FAR = 1.62%, FRR = 1.66%, and total error rate = 3.28%.

The computational complexity of the kNN model can be estimated with respect to the best neural network by measuring the execution times of the two classifiers. In our experiments, the execution time has been measured on a real processor (Intel P4 2 GHz with 750-MB RAM running the Microsoft Windows XP operating system) by removing unnecessary operating system processes. Measures were averaged over 100 presentations of the whole data set for each benchmark to reduce the influence of the variability of the operating system processes. The whole system has been implemented in Matlab by exploiting the available Neural Network Toolbox and PRTOOL [23]. The kNN model was shown to be about 190 times more complex than the best neural network.

V. CONCLUSION

This paper has presented an adaptive design methodology for reflection detection and localization systems in iris biometric images. The proposed methodology addresses the main steps of system design: feature extraction, feature selection, feature fusion, creation of the suited classification system, and its

error estimation. The methodology presented here is based on an innovative approach for the detection and localization of reflections. A suited set of features is extracted from the iris pattern, and an inductive classifier is then used to perform the reflection segmentation. In particular, we introduced the use of the RST as a new significant feature, and we focused on neural networks as classifiers. Results show that the RST can be considered as a very good feature to detect and localize reflections. This feature can easily be used, with a thresholding approach, to quickly perform detection and localization of the reflections, although not very accurately. A more discriminative and significant set of features can be adopted by considering the RSTs and other classical features (e.g., the normalized pixel intensity). This set of features has successfully been used to achieve much higher accuracy by means of neural networks.

The proposed methodology allowed for creating reflection detection and localization systems that have been proved to be much more accurate than those obtained using the traditional thresholding methods. The low computational complexity of the proposed systems is very suitable for real-time applications. The proposed method is very general and can be used in any biometric system based on iris images.

REFERENCES

- [1] A. K. Jain, R. Bolle, and S. Pankanti, *Biometrics: Personal Identification in Networked Society*. Norwell, MA: Kluwer, 1999.
- [2] R. Bolle, S. Pankanti, and A. K. Jain, "Biometrics: The future of identification," *Computer*, vol. 33, no. 2, pp. 46–49, Feb. 2000.
- [3] J. Wayman, A. Jain, D. Maltoni, and D. Maio, *Biometric Systems: Technology, Design and Performance Evaluation*. Berlin, Germany: Springer-Verlag, 2005.
- [4] L. Ma, T. Tan, Y. Wang, and D. Zhang, "Personal identification based on iris texture analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1519–1533, Dec. 2003.
- [5] G. Zhang and M. Salganicoff, "Method of measuring the focus of close-up image of eyes," U.S. Patent 5 953 440, Sep. 14, 1999.
- [6] J. G. Daugman, "How iris recognition works," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 14, no. 1, pp. 21–30, Jan. 2004.
- [7] B. J. Kang and K. R. Park, "A study on iris image restoration," in *Audio- and Video-Based Biometric Person Authentication*, vol. 3546. Berlin, Germany: Springer-Verlag, Jul. 2005, pp. 31–40.

- [8] Y. Chen, S. Dass, and A. Jain, *Localized Iris Quality Using 2-D Wavelets*. Hong Kong: ICBA, 2006.
- [9] X. Zhu, Y. Liu, X. Ming, and Q. Cui, "A quality evaluation method of iris images sequence based on wavelet coefficients in 'region of interest'," in *Proc. 4th Int. Conf. Comput. Inf. Technol.*, Sep. 2004, pp. 24–27.
- [10] A. Blum and P. Langley, "Selection of relevant features and examples in machine learning," *Artif. Intell.*, vol. 97, no. 1/2, pp. 245–271, Dec. 1997.
- [11] A. K. Jain, R. P. W. Duin, and J. Mao, "Statistical pattern recognition: A review," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 1, pp. 4–37, Jan. 2000.
- [12] A. Webb, *Statistical Pattern Recognition*. New York: Wiley, 2002.
- [13] J. Daugman, "Recognising persons by their iris patterns," in *Advances in Biometric Person Authentication*. Berlin, Germany: Springer-Verlag, 2004, pp. 5–25.
- [14] H. Proenca and L. A. Alexandre, "Iris segmentation methodology for non-cooperative recognition," *Proc. Inst. Elect. Eng.—Vis. Image Signal Process.*, vol. 153, no. 2, pp. 199–205, Apr. 2006.
- [15] T. A. Camus and R. Wildes, "Reliable and fast eye finding in closeup images," in *Proc. IEEE 16th Int. Conf. Pattern Recog.*, QC, Canada, 2004, pp. 389–394.
- [16] L. Ma, T. Tan, Y. Wang, and D. Zhang, "Personal identification based on iris texture analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1519–1533, Dec. 2003.
- [17] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. New York: Wiley, 2001.
- [18] K. Fukunaga, *Introduction to Statistical Pattern Recognition*. New York: Academic, 1990.
- [19] F. Girosi, M. Jones, and T. Poggio, "Regularization theory and neural networks architectures," *Neural Comput.*, vol. 7, no. 2, pp. 219–269, Mar. 1995.
- [20] R. A. Johnson and D. W. Wichern, *Applied Multivariate Statistical Analysis*. Englewood Cliffs, NJ: Prentice-Hall, 2007.
- [21] G. Loy and A. Zelinsky, "Fast radial symmetry for detecting points of interest," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 8, pp. 959–973, Aug. 2003.
- [22] X. Liu, K. W. Bowyer, and P. J. Flynn, "Experiments with an improved iris segmentation algorithm," in *Proc. IEEE Workshop Autom. Identification Adv. Technol. AutoID*, 2005, pp. 118–123.
- [23] F. van der Heiden, R. Duin, D. de Ridder, and D. Tax, *Classification, Parameter Estimation, State Estimation: An Engineering Approach Using MatLab*. New York: Wiley, 2004.
- [24] S. Cimato, M. Gamassi, V. Piuri, R. Sassi, and F. Scotti, "A multi-biometric verification system for the privacy protection of iris templates," in *Proc. Int. Workshop CISIS*, Genova, Italy, Oct. 23–24, 2008, pp. 227–234.



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