Iris Texture Description Using Ordinal Co-occurrence Matrix Features

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Abstract. Feature extraction is one of the fundamental steps of any biometric recognition system. The biometric iris recognition is not an exception. In the last 30 years a lot of algorithms have been proposed seeking a better description of the texture image of the human iris. The problem still remains into find features that are robust to the different conditions in which the iris images are captured. This paper proposes a new iris texture description based on ordinal co-occurrence matrix features for iris recognition scheme that increases the recognition accuracy. The novelty of this work is the new strategy in applying robust feature extraction method for texture description in iris recognition. The experiments with the Casia-Interval, Casia-Thousands and Ubiris-v1 databases show that our scheme increases the recognition accuracy and it is robust to different condition of image capture.

Keywords: Feature extraction · Ordinal measures · Iris recognition

1 Introduction

The human iris has been proved to be a good and high-confident biometric characteristic for the person verification and identification due to its reliability, stability and uniqueness. One of the important tasks in iris recognition process is feature extraction from iris texture patterns. Analyzed the variety and large number of techniques found in the literature can say that has been a hot topic. However, the overall performances of such methods can be reduced in non-ideal conditions, such as non-voluntary on-the-move, or non-collaborative setups[1].

For iris feature extraction there are reported methods that perform signal processing in both: (1) spatial domain, using mathematical operators such as Laplacian of Gaussian filters [2] and (2) frequency domain, using transformed as Gabor [3,4] and Wavelets [5,6]. Another group uses statistical processing

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techniques such as LBP [7], Co-Occurrence [8]. The combined methods such as [9,10] make use of the feature fusion obtained from several individual methods.

In 2009 Sun and Tan [11] proposed Ordinal Measures (OMs) for iris recognition. Unlike traditional approaches that use quantitative values to represent features, OMs focus on qualitative values. These qualitative values may represent the results of ordinal comparisons between, for example, two groups of image regions, taken some intra and inter region parameters. The shape of the region, location of the region, average intensity values of pixels of the region, spatial configuration of the region, the region filtering (using different filters as Gabor, Wavelet, etc.); may be taken as parameters.

Tan, Zhang et al. [9] proposed an integrated scheme (OMs and color histogram for iris texture, texton representation and semantic label for eye patterns) to match visible light iris images in uncontrolled situations. Zhang, Sun et al. [12] used bandpass geometric information and lowpass ordinal features to address deformed iris image matching problem. Recently Rahulkar and Holambe [13] presented the directional ordinal measures scheme using their previous proposed filter new class of triplet half-band checkerboard shaped filter bank.

Motivated by the (promising) results obtained OMs and their flexibility for biometric recognition, in this work we propose and explore the use of ordinal co-occurrence matrix [14] to represent the features of iris texture. The flowchart of this method is shown in Fig. 1. Normalized iris images are taken as input. In feature extraction step normalized iris image is divided into regions. In each region, pixels are labeled based on ordinal comparisons. Then matrices of co occurrence of pairs of label pixel, with specific orientation and distance, are obtained as iris pattern texture features.

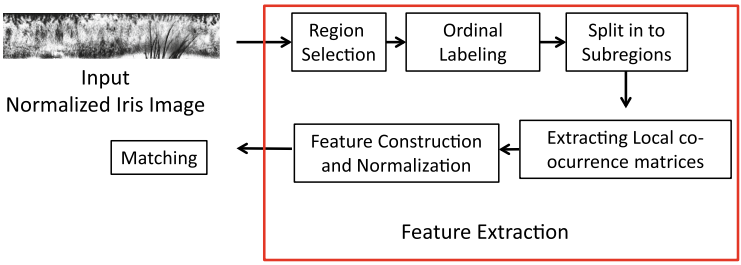

Fig. 1. A general description of proposed algorithm.

The remainder of this paper is organized as follows. Section 2 presents the proposed feature extraction method based on ordinal co-ocurrence matrix. Section 3 presents the principles of the experimental design. Section 4 presents a discussion of the experimental evaluation, and Section 5 gives the conclusion and future of this work.

2 Iris Recognition Process Based on Ordinal Co-ocurrence Matrix Features

A new feature extraction method based on ordinal measure concept and using the ordinal co-ocurrence matrix [14] is proposed to describe the texture of iris patterns. Iris recognition process consists on the general steps (image capture, eye localization, segmentation, noise detection, normalization, feature extraction and matching). Nevertheless, these steps present some peculiarities when Ordinal Co-ocurrence Matrix Features (OCMF) is used in feature extraction stage, see Fig. 1. The main OCMF steps are explained in the followings subsection.

2.1 Region Selection

Normalized iris image T is divided into a set of overlapping regions R_p. $T = \{R_p | p = 1, 2, 3, ..., P\}$, where P is the number of regions in T. The regions are overlapped based on a certain value d of displacement between the central pixels cp of each region. This operation permits the local computation of texture features (see Fig. 2). Local ordinal co-occurrence matrices are then computed over these regions. Taking in to account the rectangular shape of the normalized iris images, we consider subregions to be rectangle blocks of size $n \times m$.

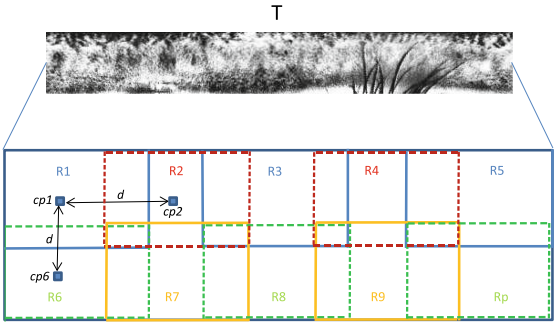

Fig. 2. Region selection.

2.2 Iris Ordinal Labeling

Based on the flexibility of ordinal measures, the selected regions should be labeled in order to retain the ordinal information of each region. The basic idea is to establish a labeling of the region following some criteria of comparison based only on ordinal relations. As in [14], the goal of this step is to represent the ordinal information of the local iris region in a compact manner allowing the efficient feature construction.

Two labels $(0, 1)$ are used to represent the values to be considered in the next step and another label (-1) for values that are not going to be consider,

following the next idea: first the mean intensity value V_m of the pixels in the region R_p and standard deviation S_d are calculated. Then intensity value of each pixel V_j is compared with the V_m and S_d, for ordinal labeling, by the following rule (Eq.1):

$$Lb = \begin{cases} 0 & \text{if} \quad (V_m - S_d) \leq V_j < V_m, \\ 1 & \text{if} \quad V_m \leq V_j \leq (V_m + S_d), \\ -1 & \text{if} \quad V_j > (V_m + S_d) \;\; or \;\; V_j < (V_m - S_d). \end{cases} \tag{1}$$

As shown in Eq.1 the pixels which intensity value is out of range $V_m \pm S_d$ are considered as noise pixel. With this strategy is possible extenuate some illumination problem in images taken in uncontrolled environment.

2.3 Split in to Subregions

In order to accelerate the process of feature extraction, each region R_p is subdivided into N subregions Sr_i, $R_p = \{Sr_i | r = 1, ..., N\}$. The regions are divided into rectangular shapes considering the size of each region. The most representative label value of each sub-region is taken as the value of the sub-region.

2.4 Iris Local Ordinal Co-occurrence Matrix

Iris local ordinal co-occurrence matrices can capture the co-occurrence of ordinal relations between label pixel in the representative values of the subregion in the normalized iris image. The columns of the matrices contain the occurrences detected in different directions o. Rows contain the occurrences at different distances d. The number of obtained ordinal matrices will depends on the number of used labels.

The proposed method utilize a binary labeling $(0, 1)$, then the possible patterns combinations, to be consider, between two label pixels are: $00, 01, 10, 11$. For each pattern one co-occurrence matrix is obtained. In total, four matrices representing the local characteristics of possible texture patterns.

Each co-occurrence matrix have a size of $N_o \times N_d$, where N_o, represents the number of orientations between pixels to be compared and N_d, represents the distance. The orientations used are: $235^0, 270^0, 315^0, 360^0$ degrees. With this strategy are not compared twice a couple of pixels, because will always be compared the central pixel with the neighbors pixels at the bottom and right. Further, when the distance is greater than 1 adjacent pixels to the left of each orientation are considered to be compared(see Fig. 3).

2.5 Feature Construction and Normalization

The co-occurrence matrices obtained in each subregion are taken as features. Then to represent the features we built a feature vector, where each position contains the four co-occurrence matrices obtained in the previous stage.

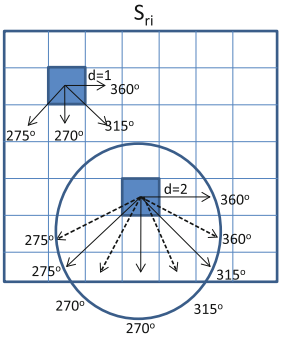

Fig. 3. Orientations and distances between pixels to be compared in each subregion.

3 Experimental Design

The main experimental scheme consisted in comparing the proposed approach with five (Daugman[1] and Masek, Ma, Monro[2] and OMs [11] two-lobe filters) different feature extraction methods in the verification task.

The protocol adopted for the experiments, compares the probe data with all labeled templates in the gallery. This sort of matching is also referred as 1:N matching. The evaluation of accuracy was assessed by the degree of influence on verification accuracy, estimated by Equal Error Rate(EER) and decidability index (d') [3]. The Equal Error Rate (EER) is the location on ROC curve, where the False Reject Rate (FRR) and False Accept Rate (FAR) are the same. The (d') combines the mean and standard deviation of the intra-class and inter-class measurement distributions.

The matching process between two normalized iris images is performed by comparing the correspondent matrices between each subregion of images. Matrices are compared using Euclidean distance and the result of each comparison is summed. The final score will be the sum of scores obtained from the comparison of each local regions.

3.1 Iris Databases

The proposed method was evaluated on three iris databases: CASIA-Interval, CASIA-Thousand and UBIRIS-V1.

CASIA-Interval[3], all iris images were collected under near infrared illumination with high quality, 320×280 pixel resolution and contains 2639 images from 395 subjects. For the experiments we used the whole database.

CASIA-Thousand[3] , contains 20,000 iris images from 1,000 subjects, collected using IKEMB-100 camera. The main sources of intra-class variations in CASIA-

[1] OSIRIS v4.1,http://svnext.it-sudparis.eu/svnview2-eph/ref_syst/
[2] USIT - University of Salzburg Iris Toolkit v1.0, http://www.wavelab.at/sources/
[3] CASIA-Interval and CASIA-Thousands, http://biometrics.idealtest.org/

Thousand are eyeglasses and specular reflections. For the experiments we used a subset composed by 3,960 images from the all subjects.

UBIRIS-v1 [15], database is comprised of 1,877 images collected from 241 subjects. This database incorporates images with several noise factors, simulating less constrained image acquisition environments. For the experiments we used a subset composed by 1,207 images from all the subjects.

All databases were segmented and normalized using OSIRIS[1]. Subsets images in (UBIRIS-v1 and Thousand) were chosen based on the quality of the result of this previous step.

4 Experimental Results

This section show the results obtained by the experimental design oriented to explore the capacity of the proposed feature extraction method to increase the recognition rates independently of the image quality.

Table 1 report the results of the recognition accuracy in EER at $\leq 0.01\%$ FAR and (d') on three databases. Fig. 4 show ROC curves.

Table 1. Experimental results on three iris image databases

Database	**Interval**		**Thousand**		**UBIRIS v1**	
Method	EER(%)	d'	EER(%)	d'	EER(%)	d'
Daugman	10.13	2.38	12.27	1.97	7.01	3.04
Masek	7.43	2.73	10.80	2.11	7.76	3.01
Ma	17.60	1.81	13.90	1.83	9.57	2.74
Monro	21.11	1.53	21.03	1.39	12.02	2.14
OMs	7.45	2.79	12.77	2.00	7.44	3.20
OCMF	**5.5**	**3.18**	**15.2**	**1.76**	**6.95**	**3.12**

The ROC curves in Fig. 4 show that, the OCMF marked improvement over five compared methods in Interval (top left), slightly perform better than Daugman in UBIRIS (down) and similar performance in Thousands (top right).

The experimental results, as shown in Table 1, indicate that the proposed OCMF allows and reduces the EER and increase the (d'). From the five evaluated feature extraction methods is possible to see that the proposed OCMF method obtains a better performance for two databases (Interval and UBIRIS-v1).

However on Thousands database this behavior is different, though OCMF maintains a similar level of accuracy than the rest of the algorithms outperforming only one of them (Monro) on the value of ERR. This fact could be caused by the presence of eyeglasses and specular reflections in this database. This behavior can also be produced by an incorrect selection of quantity and region distribution in the OCMF representation. This problem should be addressed in our future researches.

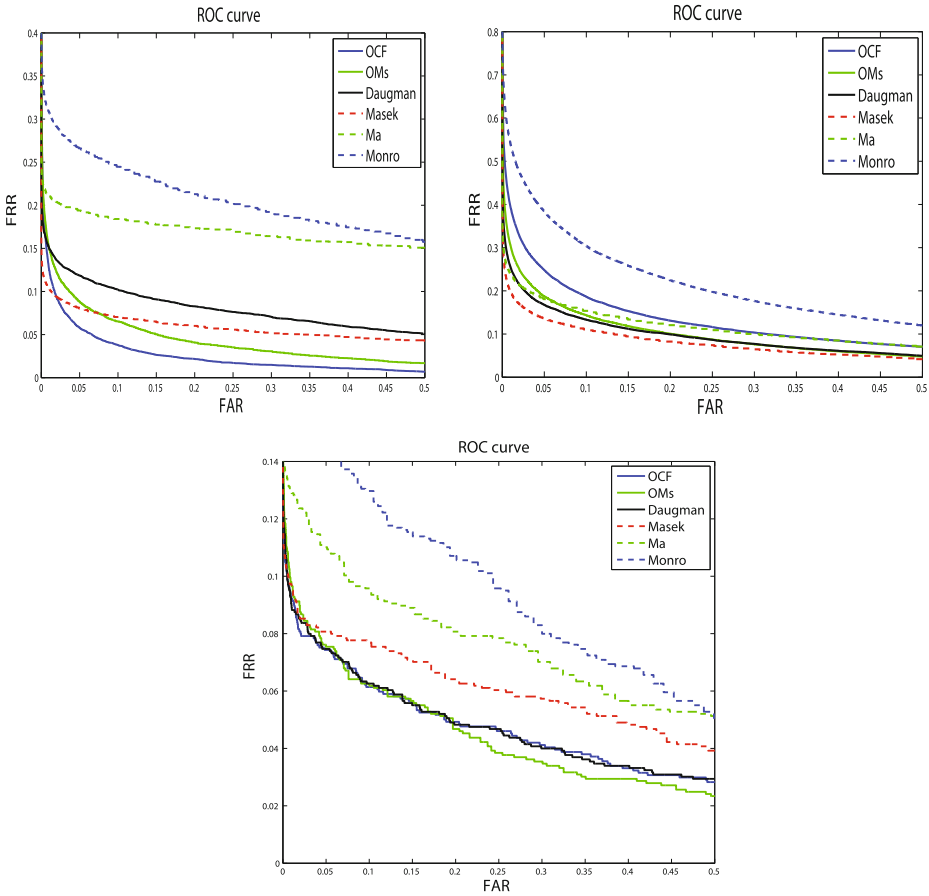

Fig. 4. ROC curves for Interval (top left), Thousand (top right) and UBIRIS-v1 (down).

From the results in the UBIRIS-v1 database containing iris images taken in the visible spectrum, under less controlled conditions than the images of Interval databases, the performance of our method outperforms the rest of the analyzed algorithms. It can also be possible to foresee that it would be a promising technique to address the problem of identification by iris in less cooperative environments and different types of iris sensors.

5 Conclusions and Future Work

In this paper we have presented a new feature extraction method for texture iris representation based on the Ordinal Co-occurrence Matrix Features. The characteristics obtained are invariant to monotonic gray-level changes in the pixel values, therefore can be applied to the iris images which may be obtained, for example, under different illumination conditions.

Experiments conducted on three databases and compared with five state-of-the-art feature extraction algorithms demonstrate the ability of the proposed representation to address the problem of robust feature extraction of iris allowing the recognition of people with greater accuracy.

Some aspects must still be researched to achieve a better performance of the proposed representation. The correct selection of sizes and the number of regions based on the characteristics of the sensor and images taken by it is an area that requires more research and experimentation.

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