Local descriptors fusion for mobile iris verification

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***Abstract*—This paper summarizes the proposal submitted by the joint team conformed by researchers from UPV and ULPGC to the Mobile Iris CHallenge Evaluation II. The approach makes use of a state-of-the-art iris segmentation technique, to later extract features making use of local descriptors. Those suitable to the problem are selected after evaluating a collection of 15 local descriptors, covering a range of different grid configuration setups. A Machine Learning approach is used, learning a supervised classifier to deal with the descriptors data. A classifier is obtained for each descriptor, and the best ones are combined in a multi-classifier system. The final step fuses the classifier outputs obtained for 5 different local descriptors, to compute the dissimilarity measure for a pair of iris images.**

I. Introduction

The literature on iris biometric has posed different challenges in the last ten years. Noisy conditions were for the first time exhaustively tackled within the NICE competitions [1]. However, the fast development in mobile technology has made evident the need to evaluate such scenario. With this intention in mind the first Mobile Iris CHallenge Evaluation (MICHE-I) [2] was defined.

After the successful achievements in MICHE-I, this year the 23rd International Conference on Pattern Recognition (ICPR) hosts as part of its Contest program a new edition of the Mobile Iris CHallenge Evaluation, i.e. MICHE II. As exposed in the challenge call for participation, biometric identification based on sensors located in mobile devices go further from traditional biometric systems, spreading the use of automatic identification technology. We address the interested reader to the MICHE-II technical report, which encloses comparative results and extensive details on the training and test datasets provided to participants.

This paper describes the approach adopted by the UPV-ULPGC joint team for iris verification. The proposal is based on the analysis of different local descriptors, that have been later evaluated making use of Weka [3] to select the best suited descriptors and classification combination for the provided data previous to the algorithm submission deadline.

II. The approach

This section describes the different steps involved in the iris verification proposal submitted to the MICHE-II challenge. An initial step is devoted to iris detection and normalization. Later different descriptors have been computed on the normalized iris pattern. In a final stage, those descriptors are evaluated with the available data considering different classification approaches. This is done to design a final combination of descriptors and classification schemes.

A. Detection and normalization

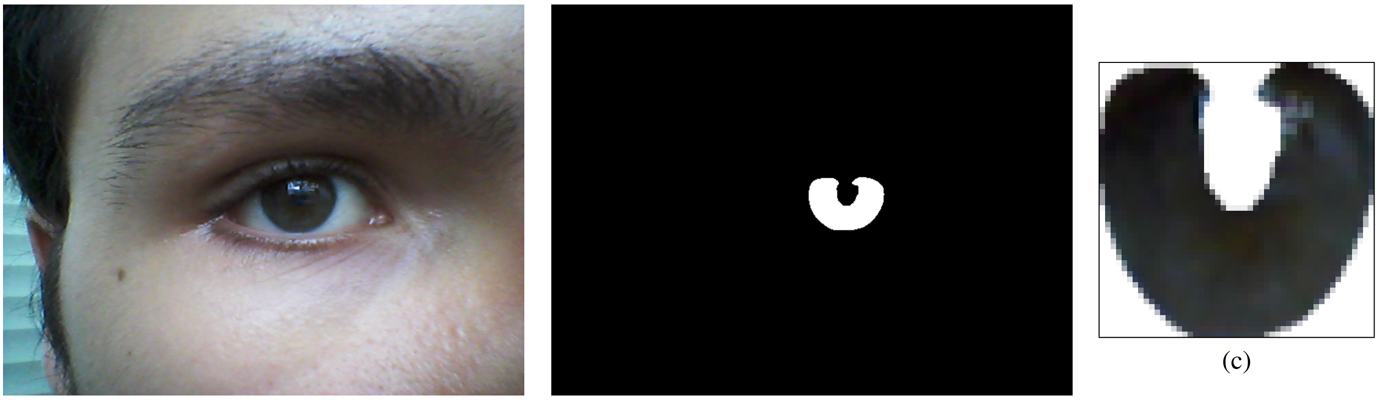
Any iris based identification system requires an initial step devoted to the detection of the iris trait in the captured image. For this purpose, as suggested by the MICHE-II submission protocol, we have adopted the unsupervised iris detection approach developed by Haindl et al. [4]. In Figure 1a-b, it can be observed a sample image captured by a mobile device, and the resulting iris mask provided by the iris segmentation technique by Haindl et al.

Once the iris is segmented, the iris analysis literature have commonly adopted the dimensionless polar coordinate system before extracting features [5]. Our limited previous experience in iris processing has led us to initially extract features directly from the masked original iris image, that is normalized to 50×50 pixels as seen in Figure 1c. As it is visible in the sample normalized iris image, the occlusion of the upper iris area, provokes an affine deformation in the resulting iris image, whose influence in the recognition process has not been analyzed by the authors yet.

B. Features

The iris richness in texture provides enough variability to serve as a valid biometric trait. Therefore texture analysis has been an interesting source of tools to analyze the iris patterns. In this sense, the community is already aware of the use of local descriptors for iris recognition [6], [7] and even for spoofing detection in biometrics [8].

Our previous experience related to facial analysis, have motivated us to attempt their raw use in this challenge. Commonly, local descriptors describe an image/pattern in terms of codes that are summarized in a histogram, h_i, providing the side effect of compacting the representation of the information. Each histogram bin indicates for each descriptor code the number of occurrences present in the image. This concept follows a Bag of Words scheme [9]. Certainly, the use of histograms reduces the feature vector dimension, but has the drawback of losing spatial information. For that reason, since the work related to facial analysis by Ahonen et al. [10] an image is commonly divided into rectangular non overlapping cells, i.e. a grid of cells, to introduce spatial information in the descriptors, see Figure 2. According to each particular application, the system designer would define the number of



(a) (b) (c)

Fig. 1. (a) Input image sample, (b) its corresponding segmented iris mask, and (c) normalized iris (50×50 pixels).

horizontal and vertical cells, respectively cx and cy, with a total of $cx \times cy$ cells. Their respective histograms would conform the image feature vector, its length would be larger than a single histogram, but tuning the number of cells would keep it low while representative.

Summarizing, for a particular descriptor, d, the resulting image feature vector, is composed by the concatenation of $cx \times cy$ cell histograms, i.e. the resulting feature vector is defined as $x^d = \{h_1, h_2, ..., h_{cx \times cy}\}$, where h_i is the corresponding histogram of cell i. Given a number of bins per descriptor histogram, n_{bins}, the number of features would be $cx \times cy \times n_{bins}$.

For the challenge, we have evaluated different descriptors, variants and grid configurations, that describe from different point of views the image appearance information. The number of bins per cell histogram is presented in Table I. We briefly summarized the main features of the set of descriptors considered:

- Histogram of Oriented Gradients (HOG) [11]. These extensively used descriptor describes the image in terms of gradient orientations in each image cell.
- Local Binary Patterns (LBP) and uniform Local Binary Patterns (LBP^{u2}) [10]. Robust texture descriptor that encodes each image pixel attending to whether it is greater or not each of its neighbors, composing a binary code. LBP^{u2} reduces the codes dictionary considering only the most common codes in texture images.
- Local Gradient Patterns (LGP) [12]. LBP makes use of the pixel gray values in the neighborhood, LGP integrates the neighborhood gradient values to encode each pixel value.
- Local Ternary Patterns (LTP) [13]. Unlike LBP that considers two possible relations of a pixel with its neighborhood, LTP considers three possible relations obtaining a ternary code that may be separated into high and low parts. Both parts are evaluated separately, i.e. LTP$_{low}$ and LTP$_{high}$.
- Local Salient Patterns (LSP) [14]. This LBP alternative focuses on the largest differences computed within each pixel neighborhood. This is done to reduce noise influence when gray pixel values are quite similar. Five different variants are evaluated: LSP$_0$, LSP$_1$, LSP$_2$, LSP$_{01}$ and LSP$_{012}$.
- Weber Local Descriptor (WLD) [15]. Based on Weber's Law, observes that human perception of a pattern depends both on the change of a stimulus and also on its original intensity.
- Local Phase Quantization (LPQ) [16]. Insensitive to centrally symmetric blur, it is computed using the short-term Fourier transform (STFT) within the neighborhood.
- Intensity based Local Binary Patterns (NILBP) [17]. Computes the difference of each neighborhood pixel with the neighborhood mean, instead of the central pixel gray value.
- Local Oriented Statistics Information Booster (LOSIB) [18]. Texture enhancer based on LBP, that computes the local oriented statistical information in the whole cell.

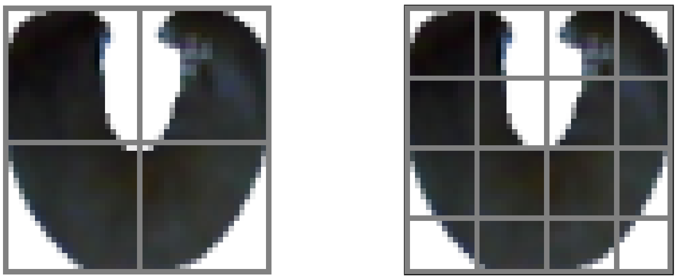
TABLE I
NUMBER OF BINS PER CELL HISTOGRAM.

Descriptor	Number of bins
HOG	9
LBP^{u2}, NILBP	59
LBP, LGP, LPQ, WLD, LTP$_{high}$ LTP$_{low}$	256
LOSIB	8
LSP$_0$, LSP$_1$, LSP$_2$	57
LSP$_{01}$	114
LSP$_{012}$	171

It is worth noticing that the iris obtained from the original images can vary in size and shape, as shown in Figure 3. To overcome that variability, the iris image is resized to a fixed size. In this approach, a 50x50 size has been selected.

C. Classification

The provided dataset data is composed of samples of 75 individuals, who have been captured with different mobile sensors, making a total of 3146 sample images. This dataset



(a) (b)

Fig. 2. Normalized masked iris patterns at (a) 2×2 and (b) 4×4 grid setups, respectively.

TABLE II
BEST RESUTS USING KNN

Descriptor	Grid	Recognition rate (%)
LBP^{u2}	4×4	64.82
LPQ	2×2	63.68
LPQ$_{012}$	4×4	63.68
NILBP	4×4	64.38
WLD	2×2	65.84
WLD	3×3	66.09

has been used to explore different classification alternatives. A 10 fold cross validation has been used to that end.

As mentioned above, Weka [3] was adopted to evaluate different descriptors, grid configurations and classifiers, to determine those that are better suited for the problem. Later, a subset of descriptors is used to combine their decisions. According to our previous experience, the combination of descriptors has proven to be of interest in gender classification reducing both error and ambiguous cases [19], [20]. This evidence has also been argued by other authors in different applications.

Basically the challenge proposes the problem of given two captures, determine whether they belong to the same individual or not. Once that the iris has been segmented in both images and normalized, the process continues as follows:

1) Each normalized iris, ni_a and ni_b, is classified separately based on their respective feature vectors $x^d_{ni_a}$ and $x^d_{ni_b}$. Several classifier paradigms have been used, being K-NN the one which has obtained the best results.
2) The resulting posterior distribution histograms are used to compute a distance that is used as dissimilarity measure. For that purpose, we have adopted the Histogram Difference.
3) If more than one descriptor is used, the histogram mode is computed for each classifier and class, later and similarly to a single descriptor approach, the respective image histograms are used to compute the dissimilarity measure.

The single descriptors which have obtained the best results in the classification phase are presented in Table II. Other classifiers have been tested as well, but in general significantly worse results are obtained. For instance, Decision Tree models obtain an accuracy less than 20%, while Naive Bayes model obtains results around 22%.

D. Classifier Combination

The final model is a multi-classifier system which combines five among the different descriptors; those chosen to be fused were LBP^{u2} using a 4×4 grid, LPQ using a 2×2 grid, LSP$_{012}$ using a 4×4 grid, NILBP using a 4×4 grid and WLD using a 3×3 grid. This selection is based on their respective single descriptor obtained accuracy.

The performed combination is shown in Figure 4. As it can be seen, for the received two images the same process is performed: once the segmented irises are isolated, and resized to 50x50 pixel images, the five descriptors are calculated, and a classification is made for each one, hence obtaining five a posteriori probability distributions (one for each classifier) for each input image. For each of the m classes considered, the final histogram contains the mode of the a posteriori values given by the usde five classifiers, i.e., in the ith position, the most repeated value among $h_{i1}, h_{i2}, h_{i3}, h_{i4}, h_{i5}$ is the one which appears as F_i. For instance, if the five a posteriori values obtained for the ith class value are $0.05, 0.05, 0.90, 0.90, 0.90$, the value of F_j would be 0.90.

Then, and in order to obtain a single distribution for each of the two images, a merge is performed among the five histograms, obtaining only one which contains, for each class value, the mode of the obtained five values.

Finally, two histograms are obtained, and the dissimilarity of the iris images is computed as the difference between them.

III. Discussion

First of all, this challenge was the first authors attempt to tackle the problem of iris recognition. Unfortunately, before the algorithm submission deadline we were unable to cover a larger exploration of alternatives. This circumstance suggests us directions for future work. In this sense, as the reader may observe in the normalized sample image, the normalization process may be criticized. Firstly, we have not explored the typical normalization based on polar coordinates [5], and secondly the simple scaling applied is not keeping the pattern aspect ratio if occlusions are present. For both situations, we are currently not aware of their influence in the recognition process, and that must be evaluated in the close future.

Another circumstance have been the limited exploration of descriptor fusion alternatives. We certainly have combined five descriptors, but we can not argue that such combination is the best possible fusion for the problem. Indeed the authors time limitations before the submission deadline, reduced the possibility to further explore grids were the number of horizontal and vertical cells are not identical, and cover any possible combination of descriptors and grid resolution. Certainly, we do not consider that the fusion of the best individual descriptors will provide the best fusion approach. Indeed they might share features, instead it would be more interesting to combine descriptors that are providing complementary information to describe the iris pattern.

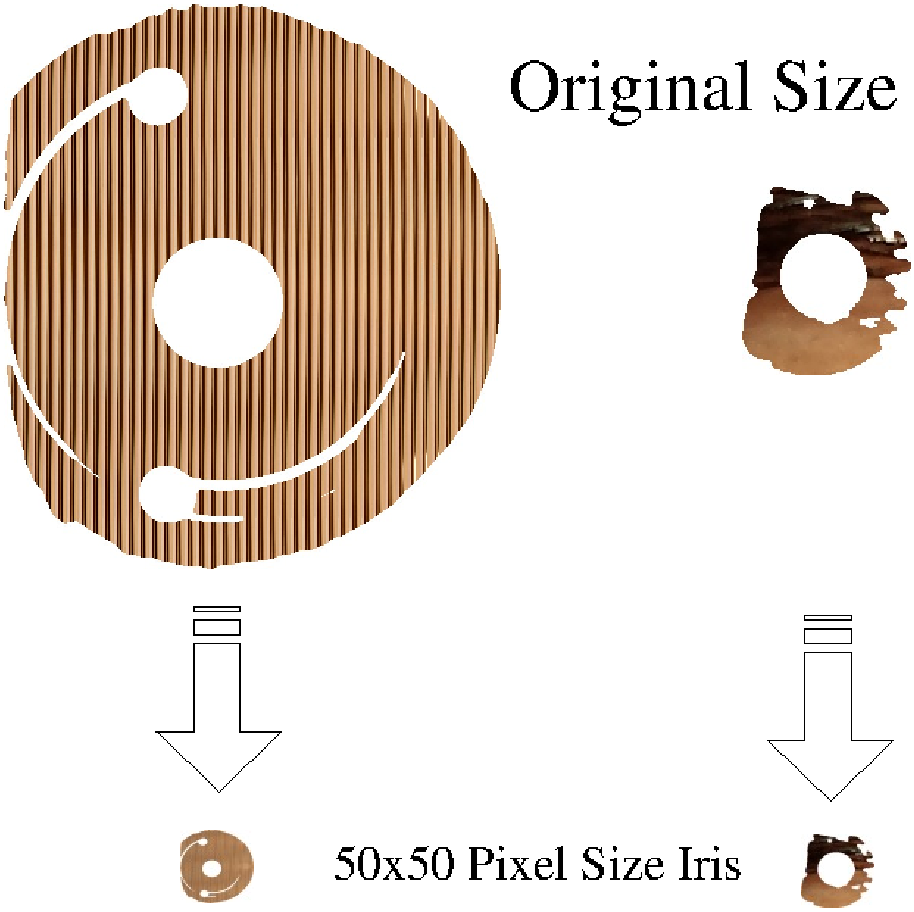


Fig. 3. Different sizes of the original iris images are to be tackled

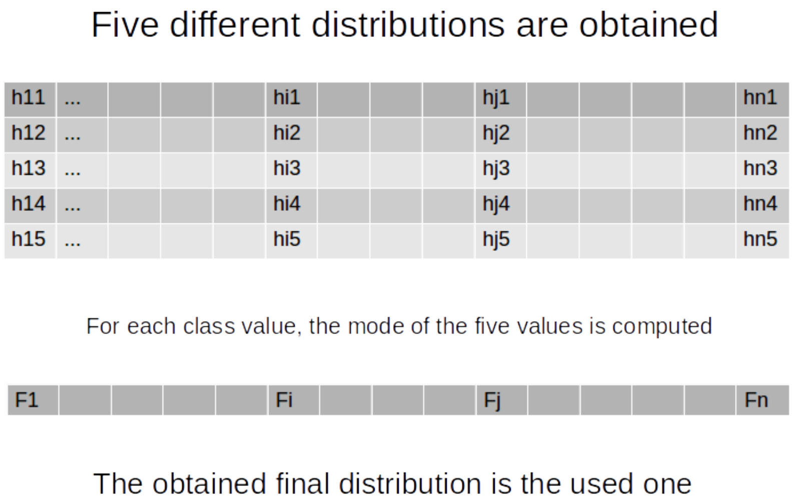


Fig. 4. Classifier Combination Approach

Other classification approaches may be explored, including classifier combination techniques which could improve the obtained results. The authors aim is to apply the Stacked Generalization approach they developed [21] and perform a Classifier Subset Selection as well. This is for sure the next step of the present research work.

Different histogram distances are also to be tested. Difference is used, but other could be more appropriated for the dissimilarity purpose. Kulback-Leibler, Chi Square, Mahalanobis or Jeffrey divergence are the most used ones, and would be tested as future work.

IV. Conclusion

In this paper a new approach is presented to deal with iris verification. Machine Learning paradigms, as well as Computer Vision techniques, are used to this end. Descriptors are obtained based on well known approaches, such as LBP, LPQ, WLD and so forth. The idea is to use them individually in order to construct a classifier, and then combine some of them to outperform the obtained accuracy. The model sent combines the single best five descriptors to obtain a dissimilarity measure of the given two iris images.

Machine Learning classifiers have been used to perform the classification, and hence to obtain the a posteriori probability distribution for each of the two iris images. Histogram distance between the two distributions is used to compute the dissimilarity.

To perform the final classifier combination, five different classifiers are used, each of one giving a different a posteriori distribution for each image. The mode of each a posteriory probability for each class value is used to combine the five classifiers, and the distance of the two mode histograms (one for each iris image) is used as dissimilarity measure.

As future work, and due to the fast schedule of the MICHE II Challenge, some improvements are to be applied: different classifiers, histogram distances, image descriptors, and classifier combination techniques could be applied, and some of them are to be investigated as following steps to this paper.

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