Half Iris Biometric System Based on HOG and LIOP

Raul Malutan, Simina Emerich, Olimpiu Pop
Communications Department
Technical University of Cluj-Napoca
Cluj-Napoca, Romania
e-mail: {Raul.Malutan, Simina.Emerich}@com.utcluj.ro,
olimpiu.pop@tvr.ro

László Lefkovits
Department of Electrical Engineering
Sapientia University
Târgu-Mureș, Romania
e-mail: lefkolaci@ms.sapientia.ro

Abstract—**Automatic iris recognition is becoming increasingly important technique for identity management and hence security. In the computer vision domain and mainly in the image recognition applications, the possibility to compare affined images, which could be distinguished just through small differences, is highly important. Using local image descriptors, similar images could be identified, although they are not part of the same scene or they have a changed parameter. Implemented systems show that HOG (Histogram of Oriented Gradients) and LIOP (Local Intensity Order Pattern) descriptors are promising for human recognition based on iris texture. Experimental results are reported on two public databases: UPOL and CASIA_V1.**

Keywords-iris recognition; biometrics; HOG; LIOP; ordinal measures; SVM

I. INTRODUCTION

In recent years, the interest in biometric based security systems has received a considerable attention.

Iris recognition, as a biometric method, can be defined as an approach of identifying persons based on unique patterns within the annular part which is placed between the pupil and the white sclera. Iris based biometric technology is more and more employed in applications with high security requirement, such as citizen identity cards, border control, military, banking, etc.

The pattern of the iris is unique, remains stable over time, the capture process is un-intrusive and is difficult to circumvent.

The researches in the field of iris recognition [1], [2] conclude that there are four modules in an iris biometrics system: image acquisition, iris region segmentation, iris texture feature extraction and the matching of iris representations. The acquisition process significantly affects the overall performance of the recognition system.

The iris region segmentation consists of two approaches: finding the pupillary and limbic boundaries and determining the regions that are occluded by eyelids, eyelashes, specular reflections, etc. There are some other particular cases, when the person wears glasses or contact lenses, and partially closed eyes. These cases are subject to other segmentation methods.

Usually, eyelid and eyelash occlusions are the major challenges for effective iris segmentation [3], [4], which pose problems not only for segmentation but also for recognition.

In our work we select for analyzing only the effective iris regions as indicated in Fig. 1. In the preprocessing step the left and right sideways will be retain, in order to minimize the effect of artifacts during recognition.

Once the iris is segmented the next steps are iris encoding and iris matching. Encoding is usually done after the unwrapping of the segmented image. Many approaches proposed in literature are using a multi-resolution analysis of the iris by applying Gabor filters.

The matching process produces a score by comparing different types of feature sets of two iris images and had been implemented in various ways [5]. The matching can be done either by computing the Hamming distance between two iris codes, or other complex approaches based on discrete cosine transforms, ordinal features, scale-invariant feature transforms etc. [6].

Our approach proposes two methods to extract the iris representative information: one is based on Histogram of Oriented Gradients (HOG) [7] and the second one uses Local Intensity Order Pattern (LIOP) ordinal features [8]. Related works has been done with the use of different local features such as LBP [9], SIFT [10] or LPQ [11].

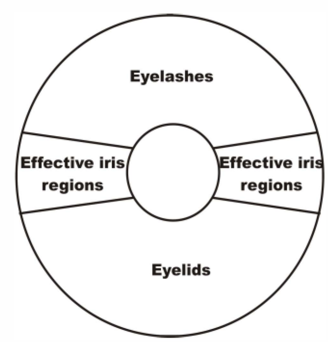

Figure 1. Distribution of the iris regions

II. FEATURE ENCODING ALGORITHMS

A. Histogram of Oriented Gradients (HOG)

The histogram of oriented gradients (HOG) is a feature descriptor used in image processing and computer vision for objects detection. HOG became one of the most popular low-level image representations in computer vision. These features are used to solve various problems for recognition, tracking or classification of different images.

The HOG descriptor technique counts occurrences of gradient orientation in different parts of an image – detection window or region of interest. The implementation is achieved by dividing the image in small connected regions, called cells and computing, for each cell, a histogram of gradient directions or edge orientations of the pixels within the cell. The orientations can range within the interval 0 – 180° for unsigned gradients or 0 - 360° for signed gradients.

The next important step in HOG feature extraction is creating the cell histograms, as in Fig. 2. Each pixel within the cell represents a weighted vote for an orientation-based histogram channel resulted in the gradient computation. The cells can have either rectangular or radial shape and the channels can be spread over 0 to 360 degrees. The weighted vote can be either the result of the gradient magnitude, the square root or the square of the gradient magnitude.

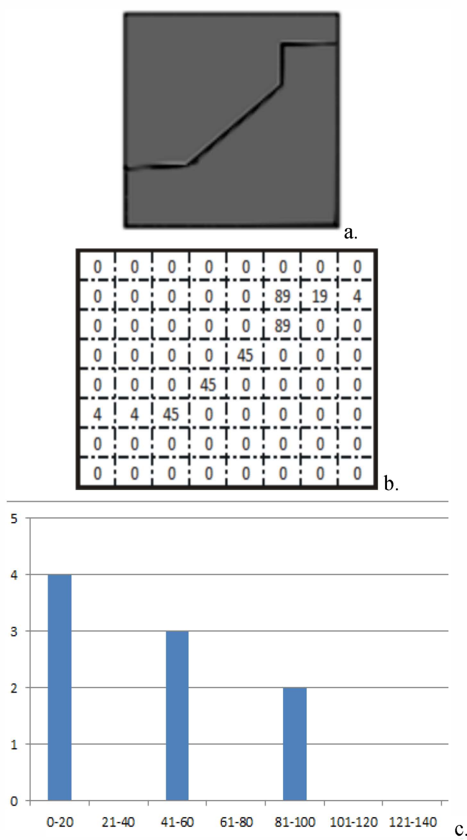

Figure 2. Computed HOG features for a cell within a window: a. the image corresponding to a 8x8 cell, b. the gradient orientation, c. histogram of oriented gradients

Further, the cells must be grouped together into larger spatially connected blocks. The concatenated vector of the components, of the normalized cell histograms from all the blocks is the resulted HOG descriptor. Blocks typically overlap, meaning that each cell contributes more than once in the resulting descriptor. In general, there are two main block geometries: rectangular R-HOG blocks and circular C-HOG blocks. R-HOG blocks appear similar to the SIFT descriptors and C-HOG blocks can be found with a single, central cell and with angularly divided central cell.

In their experiment, Dalal-Triggs [7] explored four different types of block normalization which showed a real improvement over the non-normalized data.

The final step in this process is to use the descriptors in a recognition system based on a supervised manner.

The size of the descriptor vector varies with the width of the windows, the height of the window, the block stride, the number of blocks, the number of cells within a block and the number of computed orientation for a pixel.

For the HOG features extraction we used two variants, the classical Dalal-Triggs [7] which computes the undirected gradients, and the approach of Felzenszwalb [12] which extracts both directed and undirected gradients and energy components.

B. *Local Intensity Order Pattern (LIOP)*

In the area of image recognition and classification, local invariant feature descriptors extraction methods can be separated in two design methods: Handcrafted Descriptors and Data-driven Descriptors. In the handcrafted category are included the classical methods like, SIFT, SURF, BRIEF, ORB and LIOP.

Local Intensity Order Pattern (LIOP) [8] is a method for feature description based on intensity order. The principle of this approach is that the relative order of pixel intensities remains unchanged when the intensity changes are monotonic.

The method uses the advantages offered by ordinal measurements to extract the descriptors. First, the overall image intensity order is used to divide a local patch into subregions called bins. Next, a Local Intensity Order Pattern (LIOP) of each point is defined, based on the relationships among the intensities of its neighboring sample points. Considering 4 neighboring points for each pixel, 24 possible permutations are obtained. Each permutation can be regarded as a local intensity order pattern. The final LIOP descriptor is built through accumulating the LIOPs of the points in each selected bin respectively, by concatenating them together.

III. IRIS ANALYSIS AND REPRESENTATION

Experiments were made on two public iris databases: CASIA-V1 (collected by the Chinese Academy of Sciences' Institute of Automation (CASIA)) and UPOL. The first one contains 756 greyscale iris images, collected from 108 Asian persons, whose upper eyelid is quite low. The iris pattern is often covered by eyelids and eyelashes (Fig. 3.a.) [13]. Ross et al. found in [14] that the iris content is less than 67%, for 11% of images. There are 7 different images for each individual, taken from the same eye, in two sessions.

The UPOL database includes 384 iris images captured from 64 persons (3 for the left and 3 for the right eye) [15]. It consists of high resolution and texture rich images. The iris area is not occluded due to eyelids or eyelashes and the specular reflection is located in the pupil region (Fig. 3.b.).

The segmentation process was made according to the algorithm proposed by Libor Masek, in [16] and the iris region is unwrapped by using the Cartesian to Polar Transformation [17]. The segmentation method has a success rate of 83% for CASIA_V1 non-ideal database [18] consequently 93 classes were selected, respectively a 100% success rate for UPOL where all 64 classes were used in the proposed system.

The unwrapped images, from both databases, are resized to a fixed dimension (61x610). The iris zone is divided into 10 equal parts and only 4 of them, corresponding to the interest area, are selected for analysis. Hence, each sideway region (left and right) has a size equal with 61x122 pixels as shown in Fig. 4.

On both left and right sides the same processing techniques are employed, based on HOG respectively LIOP descriptors and the results are than concatenated into the final feature vector. The HOG and LIOP features are computed using VLFeat, a library of Computer Vision algorithms [19].

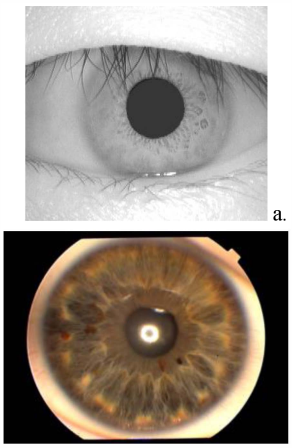

Figure 3. Iris image from: a. CASIA_V1; b. UPOL database

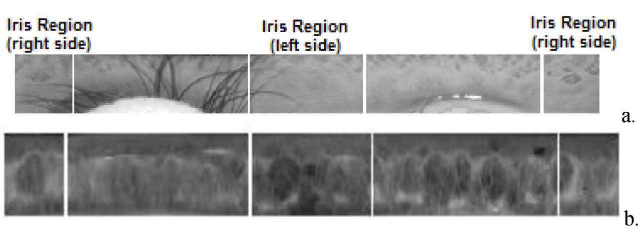

Figure 4. Iris polar representation for a. CASIA_V1 image; b. UPOL image

A. HOG Based Iris Analysis

The region of interest is divided into 8x8 squared cells and the HOG descriptor is computed for each cell, in order to collect the gradient orientation of the iris area. In our experiments we choose 8 or 4 orientations. The original HOG method, further denoted by Dalal et al. computes the undirected gradients. The modified version proposed by Felzenszwalb, further denoted by UoCTTI, computes directed and undirected gradients, 4 texture-energy features and also uses a compression algorithm.

Fig. 5 illustrates the left side region extracted from the UPOL iris image. The HOG representation from Fig. 6, is obtained from the previous image, for cell size equal with 8 and 8 orientations.

Figure 5. Selected iris region (the left side)

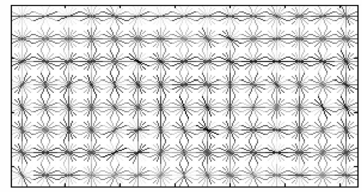

Figure 6. Corresponding HOG descriptors

B. LIOP Based Iris Analysis

The LIOP technique encodes the intensity order information into a descriptor and could be computed only from square images with odd length. Consequently, for each iris side two images will be considered (of 61x61 pixels each of them).

The input image is divided into regions (or bins) with the same intensity, as shown in Fig. 7.

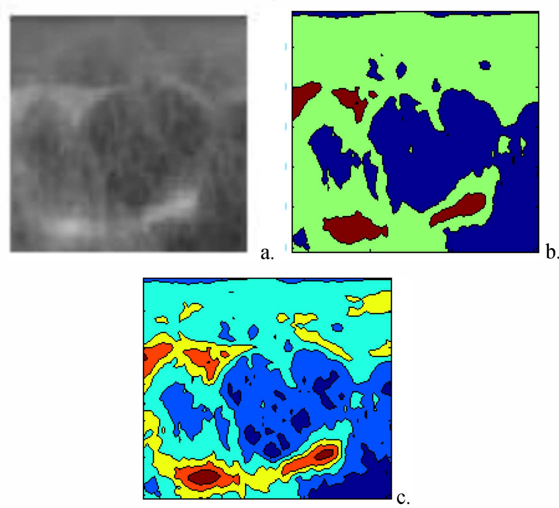

Figure 7. Input image region (a) and the region division into 3 bins (b) and 6 bins (c).

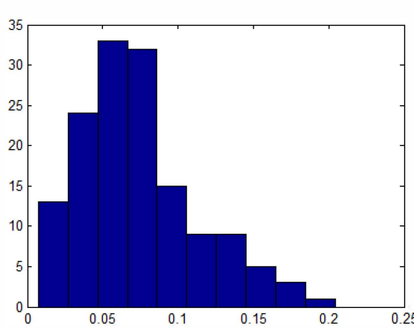

Figure 8. Example of LIOP histogram

IV. Experimental Approach

For the classification task, the Support Vector Machine *libsvm* package [20] with linear and RBF kernel, was used. Best performances were obtained for C=100, gamma=0.01 and d=5.

The proposed system based on UPOL database comprises 64 different classes (enrolled users), and the one based on CASIA_V1, 93 classes. The distribution of training /test instances was 1/3 for UPOL, respectively 3/2 for CASIA_V1 database. The considered items were collected from one eye, for each individual.

Daugman has shown in [21] that there are differences between human left and right irises, so they could be considered independent sources of information for a biometric system.

Thus, a multi-instance scenario has been also proposed for UPOL database, where irises from both eyes are available. The classifier was trained with one left eye and one right eye images, and tested with the rest of four images (two left and two right irises), for each user.

A. *Half Iris Biometric System Based on HOG*

Different tests were designed to determine which combination (regarding the size of the cells and the number of orientations) offers best performances in terms of accuracy and speed.

If the whole sideway image regions are considered, the length of the feature vector is very high (for instance 6720 characteristics in case of UoCTTI variant, 8 cell size and 8 orientations).

For this reason we apply the Discrete Bidimensional Wavelet Transform for a number of 2 iterations and we further consider the images resulted from the approximation coefficients. Recognition rates for the proposed HOG based systems are presented in Table I.

TABLE I. Recognition Rates for HOG Based Systems

System	Train/test Instances per user	Accuracy (%) SVM Kernel Linear	Accuracy (%) SVM Kernel RBF	HOG Variant	CellSize & Orient.	Feature vector
CASIA	3/2	91.93	91.93	Dalal	8 & 8	512
		98.38	97.84	UoCTTI	8 & 8	448
		83.33	82.25	Dalal	8 & 4	256
		95.69	96.23	UoCTTI	8 & 4	256
UPOL	1/2	100	100	Dalal	8 & 8	512
		100	100	UoCTTI	8 & 8	448
		95.31	95.31	Dalal	8 & 4	256
		100	100	UoCTTI	8 & 4	256
UPOL multi instance	2/4	99.6	100	UoCTTI	8 & 8	512
		98.82	98.82	UoCTTI	8 & 4	448

B. *Half Iris Biometric System Based on LIOP*

Local Intensity Order Pattern (LIOP) descriptor was computed for 3 respectively 6 bins. Four neighbors samples were involved in the construction of the order pattern for each pixel and the radius of the circular neighborhood was set to 5. The length of the final feature vector is dramatically influenced by these parameters.

In order to ensure rotation invariance, the neighboring points are sampled in a locally rotation invariant coordinate system. The results obtained for the implemented LIOP based systems are described in Table II.

TABLE II. Recognition Rates for LIOP Based Systems

System	Train/test Instances per user	Accuracy (%) SVM Kernel Linear	Accuracy (%) SVM Kernel RBF	LIOP bins nr.	Feature vector
CASIA	3/2	96.77	96.77	3	288
		96.23	96.23	6	576
UPOL	1/2	100	100	3	288
		100	100	6	576
UPOL multi instance	2/4	100	100	3	288
		100	100	6	576

C. *Discussions*

In a real scenario, the proposed multi-instance system could be implemented in a serial or parallel mode. In the serial one the information is processed sequentially. For example, if a user identification or verification could not be accomplished from the left iris, the right iris is further considered. This scheme could be very useful in large scale biometric system.

For an increase security, the parallel mode is more appropriate. Both sources (left and right irises) are processed in the same time and after fusion the system could establish if the user is accepted or rejected.

V. Conclusions

Image descriptors play a high key role when designing an iris biometric system. The first approach involves two variants of the HOG method, the original version and a modified one. Both of them are combined with wavelet analysis to reduce the feature vector dimension. The HOG modified version (UoCTTI) offers better classification rate, even for a smaller number of features.

In the second approach, another local descriptor, LIOP, is employed in order to explore the intensity order information. LIOP descriptor ensures invariance to monotonic brightness change and to rotations.

Experimental results obtained on UPOL and non-ideal CASIA-V1 databases, emphasize that UoCTTI HOG and LIOP descriptors are able to capture the relevant information from the iris images.

In recent years, due to their advantages, ordinal descriptors are explored increasingly more for object recognition. In future we intend to propose new image analysis and coding techniques based on ordinal measurements, with application in biometrics.

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