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Multi-Model Biometric Recognition Using Local Directional Number Pattern

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ABSTRACT

Novel local feature descriptor and local directional number pattern (LDN) are used for iris analysis. LDN encodes the directional information of the iris's textures (i.e., the texture's structure) in a compact way, constructing a more discriminative code than current methods.LDN for robust iris recognition that encodes the structural information and the intensity variations of the iris's texture. LDN encodes the structure of a local neighborhood by analyzing its directional information. Consequently, to compute the edge responses in the neighborhood, in eight dissimilar directions with a compass mask. To compute the structure of each micro-pattern with the aid of a compass mask that extracts directional information, and encode such information using the prominent direction indices (directional numbers) and sign which allows us to distinguish among similar structural patterns that have different intensity transitions. Divide the iris into several regions, and extract the allocation of the LDN features from them. Then concatenate these features into a feature vector, and use it as a iris descriptor. The experiments are carried out using CASIA iris dataset. Previous research has shown that the face feature vector can be calculated using LDN. We are combining the iris along with the face of the same person. The features for face and iris are extracted. The experiment is set upped as, by retrieving the face image of a person for the given iris image. This provides more security than unimodel biometrics. Also the face database need not to be updated.

Keywords

Directional number pattern, iris descriptor, recognition, feature, image descriptor, local pattern.

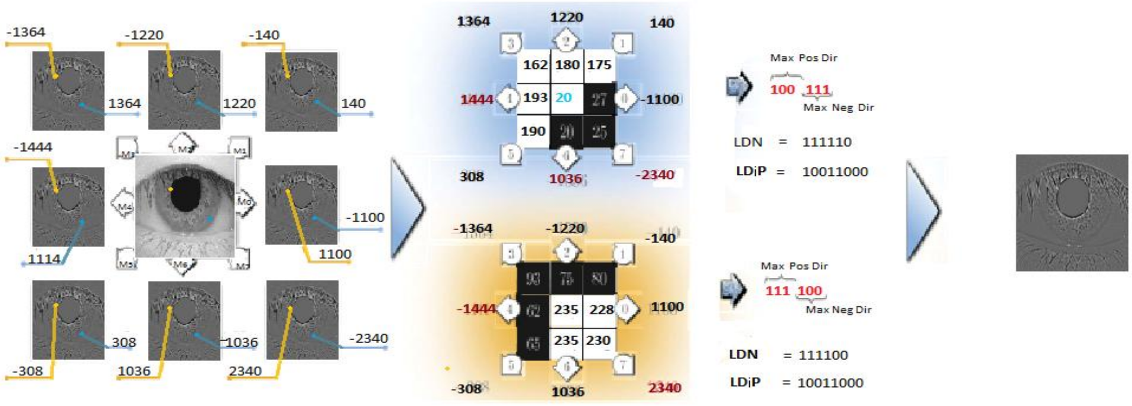
1. INTRODUCTION

The preface to IRIS recognition is one of the biometric detection and validation that employs pattern recognition expertise with the aid of high resolution images of iris of eye of a exacting person. Iris recognition is totally diverse than Retina Scan Technology. This technology provides unambiguous and wonderful identification of an individual. IRIS recognition is the unique biometric recognition technology entirely suited for one to many identification.

An Iris investigation, a key matter is the descriptor of the iris demonstration [1]. The efficiency of the descriptor depends on its demonstration and the simplicity of extracting it from the iris. In an ideal world, a superior descriptor should have a high dissent surrounded by course (between different persons), but slight or no discrepancy within course (same person in different conditions). These descriptors are used in numerous areas, such as, iris and face recognition.

There are two familiar approaches to extract iris features: geometric feature based and appearance based methods. The former [2] encodes geometric properties of a convex polyhedral cone throughout the central rays in their convex polyhedral cones and that templates protected in a technique extended from iris code can be out of order into shape and locations of dissimilar iris components, which are united into a feature vector that represents the iris. Furthermore, to increase performance of a single biometric matcher based on vectors of quality actions combined with biometric data are expressed by values of Quality of Sample (QS) index and Confidence in matching Scores (CS), respectively. The third method, Quality Sample and Template features (QST) [6]. The Covert Iris [10] Noisy Iris Challenge Evaluation (NICE), an iris biometric evaluation scheme that received worldwide participation and whose foremost modernism is the use of heavily degraded data obtained in the visible wavelength and uncontrolled arrangements, with subjects moving and at widely varying distances. Fuzzy matching [13] strategy with invariant properties, which can provide a robust and efficient matching scheme for two sets of iris feature points. Iris Matching based on Personalized Weight Map

[10] every human iris has its unique visual pattern and neighborhood image features also differ from region to region, which guides to significant differentiations in robustness and uniqueness among the feature codes derived from different iris regions.



Mask Convolution Results **Code Computation** **LDN Code**

Fig 1: LDN code computation. The (Kirsch) compass masks are convoluted with the original image to take out the edge response images (shown in the left). From these images we decide the peak directional numbers (+ve and –ve directions) to instruct the texture in the region. It shows the dissimilar response values, the peak directional numbers and the last LDN code (shown in the right). Additionally, LDN can detect changes in the intensity regions by producing a different code (as shown in the center base) while other directional patterns cannot (like LDiP), as they make the similar code for dissimilar textures.

techniques tried to overcome the shortcomings of LBP, like Local Ternary Pattern (LTP), and Local Directional Pattern (LD¡P) [15]. The last technique encodes the directional information in the neighborhood, as an alternative of the intensity.

In the literature, there are lots of techniques for the holistic class, such as, Kernel Learning [3] and Sperical model [4] methods have been studied Iris Center localization technique based on the detail that the elliptical shape (ES) of the iris varies according to the alternation of the eyeball. The other modern Bi-orthogonal Triplet Half-Band Filter Bank [7] presents a shift, scale, and rotation-in-variant method for iris feature demonstration and fused post categorization at the decision-level to develop the accuracy and speed of the iris recognition system. Acquired Face Images [8] develops multiple higher order local pixel dependencies to robustly classify the eye region pixels into iris or non-iris regions. The original Average of Synthetic Exact Filters (ASEF) formulation, demonstrating that its exactness can be enhanced if adequate illumination correction, spatial priors and cross-filter reactions are exploited for eye localization [4]. The sparse combination [5] explains ellipse parameters by linearly combining a division of data points rather than the entire data points. The local feature process compute the descriptor from element of the iris, and then collect the information into one descriptor. Along with these process are Local Features Analysis [14], Gabor features [12], and Local Binary Pattern (LBP) [11]. LBP get better performance than previous process, hence it gained popularity, and was studied extensively. Newer

In this paper, we propose a iris descriptor, Local Directional Number Pattern (LDN), for robust iris recognition that codes the structural information and the intensity deviations of the iris's texture. LDN codes the structure of a local neighborhood by evaluating its directional information. So, we calculate the edge responses in the region, in eight dissimilar directions with a compass mask. Next, from all the directions, we decide the top positive and negative directions to construct a meaningful descriptor for different textures with similar structural patterns. This move toward allows us to distinguish intensity changes (e.g., from bright to dark and vice versa) in the texture, that otherwise will be missed see Fig. 1. Moreover, our descriptor uses the information of the total neighborhood, instead of using sparse points for its calculation like LBP. Thus, our approach communicates more information into the code, so far it is more compact as it is six bit long. Likewise, we trial with dissimilar masks and resolutions of the mask to obtain characteristics that may be abandoned by just one, and merge them to extend the encoded information. We found that the addition of multiple encoding levels produces an improvement in the detection process.

This paper is organized as follows: In Section 2 we initiate our proposed coding system. Then, in Section 3 detail the use of the proposed descriptor for iris recognition.

We evaluate the performance of the proposed descriptor and discuss its results in Section 4. At last, we present concluding remarks in Section 5.

2. LOCAL DIRECTIONAL NUMBER PATTERN

The proposed Local Directional Number Pattern (LDN) is a six bit binary code system assigned to each pixel of an input image that represents the structure of the texture and its intensity transitions. Accordingly, we form our pattern by computing the edge reply of the region using a compass mask, and by taking the peak directional numbers, that is, the majority positive and negative directions of those edge responses. We point up this coding scheme in Fig. 1. The positive and negative responses offer important information of the structure of the region, as they expose the slope direction of bright and dark areas in the region. Thereby, this peculiarity, involving dark and bright responses, allows LDN to discriminate among blocks with the positive and the negative direction swapped (which is similar to exchange the bright and the dark areas of the region, as shown in the middle of Fig. 1) by generating a individual code for each one occurrence, while further methods may blunder the exchanged regions as one. M oreover, these transitions happen frequently in the iris, for example, edges of the pupil and sclera have dissimilar intensity conversions. Thus, it is vital to distinguish amongst them; LDN can realize this assignment as it allocates an unambiguous code to each one of them.

2.1 Difference with previous work

In progress methods have several shortcomings. For example, LBP [13] encodes the local neighborhood intensity by using the center pixel as a threshold for a sparse sample of the neighboring pixels. The few number of pixels used in this method introduce several problems. First, it limits the accuracy of the method. Second, the technique rejects most of the information in the neighborhood. Moreover, these drawbacks are more evident for bigger neighborhoods. Consequently, to avoid these problems more information from the neighborhood can be used, as other methods do [17], [18], [19], [22]. Although the use of more information makes these methods more stable, they still encode the information in a similar way as LBP: by marking certain characteristics in a bit string. And despite the simplicity of the bit string coding strategy, it discards most information of the neighborhood. For example, the directional ($\mathrm{LD_iP}$) [15] and derivative ($\mathrm{LD_eP}$) [16] methods miss some directional information (the responses sign) by treating all directions equally. In addition, they are sensitive to illumination changes and noise, since the bits in the code will flip and the code will represent a totally different characteristic. To avoid these problems, we investigate a new coding scheme, that implicitly uses the sign of the directional numbers to increase the encoded structural information, with two different masks: a derivative-Gaussian (to avoid the noise perturbation, and to make our method robust to illumination changes, as previous methods showed [20]) and a Kirsch compass mask. Fig. 1 shows how LDN produces different codes in different scenarios, while $\mathrm{LD_iP}$ [15] produces the same code (note that $\mathrm{LD_eP}$ will have a similar result). Thus, the use of the directional numbers produces a more robust code than a simple bit string. Moreover, the use of principal directions may be similar to a weighted coding scheme, in the sense that not all directions have the same importance. In contrast, previous weighting methods [21] treat the code (again) as a bit string, picking all the information of the neighborhood, and weight only the inclusion of each code into the descriptor. However, we (equally) use the two principal directional numbers of each neighborhood (and code them into a single number) instead of assigning weights to them. Consequently, we pick the prominent information of each pixel's neighborhood. Therefore, our method filters and gives more importance to the local information before coding it, while other methods weight the grouped (coded) information.

In review, the key positions of our proposed method are: 1) the coding scheme is based on directional numbers, instead of bit strings, which encodes the information of the neighborhood in a more efficient way; 2) the implicit use of sign information, in comparison with previous directional and derivative methods we encode more information in less space, and, at the same time, discriminate more textures; and 3) the use of gradient information makes the method robust against illumination changes and noise.

2.2 Coding scheme

In our coding design, we produce the code, LDN, by analyzing the edge response of each mask, $\{M^0,\ldots,M^7\}$, that represents the edge significance in its relevant direction, and by combining the dominant directional numbers. Given that the edge responses are not evenly vital, being there of a elevated negative or positive rate signals a top dark or bright area. Consequently, to encode these top regions, we absolutely use the sign information, as we allot a fixed pose for the top positive directional number, as the three a large amount significant bits in the code,

$$\underset{M^0}{\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}}\underset{M^1}{\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}}\underset{M^2}{\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}\underset{M^3}{\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}}$$

$$\underset{M^4}{\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}}\underset{M^5}{\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}}\underset{M^6}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}}\underset{M^7}{\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}}$$

Fig 2: Kirsch compass masks

and the three smallest amount significant bits are the top negative directional number, as shown in Fig. 1. Therefore, we define the code as:

$$LDN(x, y) = 8 i_{x,y} + j_{x,y} \quad (1)$$

where (x, y) is the middle pixel of the region organism coded, $i_{x,y}$ is the directional number of the utmost positive response, and $j_{x,y}$ is the directional number of the least amount negative response defined by:

$$i_{x,y} = \arg\max_{i} \{ \mathbb{I}^i(x, y) \mid 0 \le i \le 7 \} \quad (2)$$

$$j_{x,y} = \arg\min_{j} \{ \mathbb{I}^j(x, y) \mid 0 \le j \le 7 \} \quad (3)$$

where $\mathbb{I}^i$ is the convolution of the original image, I, and the ith mask, M^i defined by:

$$\mathbb{I}^i = I * M^i \quad (4)$$

2.3 Compass masks

We apply the gradient space, instead of the strength feature space, to work out our code. The former has additional information than the afterward, as it holds the relatives amongst pixels absolutely (while the strength space ignores these relatives). Moreover, due to these relatives the gradient space exposes the essential structure of the image. Consequently, the gradient space has additional perceptive power to realize key iris features. Additionally, we investigate the application of a Gaussian to soft the image, which makes the gradient computation more stable. These operations build our process additional robust; alike earlier research [18], [19], [20] used the gradient space to compute their code. Consequently, our process is robust in opposition to illumination due to the gradient space, and to noise due to the smoothing.

To generate the LDN code, we necessitate a compass mask to work out the edge responses. In this paper, we examine our proposed code using two dissimilar asymmetric masks: Kirsch and derivative-Gaussian (shown in Figs. 2 and 3). Equally masks work in the gradient space, which reveals the structure of the iris. Besides, we investigate the use of Gaussian smoothing to become stable the code in being there of noise by using the derivative-Gaussian mask.

The Kirsch mask [22] is rotated 45° not together to attain the edge response in eight dissimilar directions, as shown in Fig. 2. We indicate the use of this mask to construct the LDN code by LDN^k. Furthermore, motivated by the Kirsch mask [22], we use the derived of a skewed Gaussian to generate an asymmetric compass mask that we use to work out the edge response on the soft iris. This mask is robust beside noise, although producing well-built edge responses. Consequently, given a Gaussian mask defined by:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (5)$$

where x, y are location positions, and σ is the width of the Gaussian bell; we define our mask as:

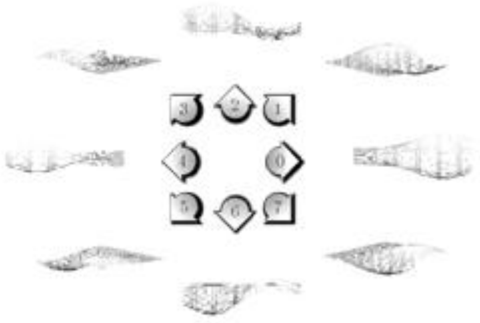


Fig 3: Derivative of Gaussian compass masks,computed by (6)

$$M_\sigma(x, y) = G'_\sigma(x + k, y) * G_\sigma(x, y) \quad (6)$$

where G'_σ is the derivative of G_σ with respect to x, σ is the width of the Gaussian bell, $*$ is the convolution process, and k is the offset of the Gaussian with respect to its center in our experiments we use one fourth of the mask diameter for this offset. Then, we generate a compass mask, $\{M^0, \ldots, M^7\}$, by rotating M_σ, 45° apart, in eight different directions. Thus, we obtain a set of masks similar to those shown in Fig. 3. Due to the rotation of the mask, M_σ, there is no need of computing the derivative with respect to y (because it is equivalent to the 90° rotated mask) or other combination of these variables. We denote the code generated through this mask as LDN_σ^G, where σ determines the parameter for the Gaussian.

3. IRIS DESCRIPTION

Each iris is represented by a LDN histogram (LH) as shown in Fig. 4(a). The LH holds fine to coarse information of an picture, such as edges, spots, corners and other local texture features. Certain that the histogram only encodes the occasion of certain micro-patterns without locality information, to aggregate the locality information to the descriptor, we divide the iris image into small regions, $\{R^1, \ldots, R^N\}$, and extract a histogram H^i from each region R^i. We create the histogram, H^i, using each code as a bin, and then accumulate all the codes in the region in their respective bin by:

$$H^i(c) = \sum_{\substack{(x,y)\in R^i \\ \mathrm{LDN}(x,y)=c}} v, \qquad \forall c \qquad (7)$$

where c is a LDN code, and (x, y) is a pixel position in the region R^i, $LDN(x, y)$ is the LDN code for the position (x, y), and v is the accumulation value normally the accumulation value is one. Lastly, the LH is calculated by concatenating those histograms:

$$LH = \prod_{i=1}^{N} H^i \qquad (8)$$

where Π is the concatenation operation, and N is the number of regions of the divided iris. The spatially combined LH plays the role of a global iris feature for the given iris.

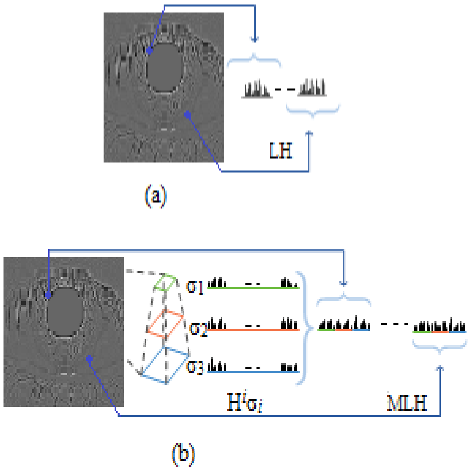


Fig 4: Iris descriptor using uniform gid for histogram extraction. (a) LDN histogram (LH) and (b) Multi-LDN histogram (MLH)

The use of the derivative-Gaussian mask allows us to freely vary the size of the mask. The change in the size allows the coding scheme, LDN^G, to capture dissimilar characteristics of the iris. Hence, a fine to coarse representation is achieved by computing the LDN^G_σ code at n different σ_i (which we represent by $LDN^G_{\sigma_1,\ldots,\sigma_n}$), and by concatenating the histogram of each σ_i, $H^i_{\sigma_i}$, which is computed in the same way as Eq. (7) by using LDN^G_σ, we can merge the characteristics at different resolutions [as shown in Fig. 4(b)]. We call this mixture of resolutions a multi-LDN histogram (MLH), and it is computed by:

$$MLH_{\sigma 1,\ldots,\sigma n} = \prod_{j=1}^{N} \prod_{i=1}^{n} H^j_{\sigma_i} \qquad (9)$$

where Π is the concatenation operation, $H^j_{\sigma_i}$ is the histogram of the $LDN^G_{\sigma_i}$ code at the R^j region, and n is the number of σ's used in our experiments we limit ourselves to three. The change in the mask's size allows our method to capture features in the iris that otherwise may be overlooked. However, previous works do not take into account the long range pixel interaction that takes place outside the coverage of their neighborhood system. We find that combining the local shape information, the relation between the edge responses, and relating the information from different resolutions can better characterize the iris's characteristics.

In other words, we represent the iris using a single feature histogram, by using LH, or with a multi-feature histogram, by using MLH. The LDN code in LH can be LDN^k or LDN^G_σ, and the code in MLH must be a $LDN^G_{\sigma_1,\ldots,\sigma_n}$.

3.1 Iris recognition

The LH and MLH are used during the iris recognition process. The objective is to compare the encoded feature vector from one person with all other candidate's feature vector with the Chi-Square dissimilarity measure. This measure between two feature vectors, F_1 and F_2, of length N is defined as:

$$X^2(F_1, F_2) = \sum_{i=1}^{N} \frac{(F_1(i) - F_2(i))^2}{F_1(i) + F_2(i)} \qquad (10)$$

The corresponding iris of the feature vector with the lowest measured value indicates the match found.

We perform the various iris recognition by using a Support Vector Machine (SVM) to evaluate the performance of the proposed method. SVM [24] is a supervised machine learning technique that implicitly maps the data into a higher dimensional feature space. Consequently, it finds a linear hyperplane, with a maximal margin, to separate the data in different classes in this higher dimensional space.

Given a training set of M labeled examples $T = \{(x_i, y_i) \mid i = 1, \ldots, M\}$, where $x_i \in R^n$ and $y_i \in \{-1, 1\}$, the test data is classified by:

$$f(x) = sign\left(\sum_{i=1}^{M} \alpha_i y_i \; K(x_i, x) + b\right) \qquad (11)$$

where α_i are Lagrange multipliers of dual optimization problem, b is a bias, and $K(\cdot,\cdot)$ is a kernel function. Reminder that SVM allows domain-specific selection of the kernel function. Although many kernels have been proposed, the most frequently used kernel functions are the linear, polynomial, and Radial Basis Function (RBF) kernels.

Given that SVM makes binary decisions, multi-class classification can be achieved by adopting the one-against-one or one-against-all techniques. In our work, we opt for one-against-one technique, which constructs $k(k-1)/2$ classifiers,that are trained with data from two classes [23]. We perform a grid-search on the hyper-parameters in a 10-fold cross-validation scheme for parameter selection. The parameter setting producing the best cross- validation accuracy was picked.

4. EXPERIMENTS

We performed several experiments to evaluate the performance of the proposed coding scheme for face recognition and expression classification. We examined the former under time lapse, and illumination variant. Also, regarding the length of the proposed descriptor, the basic LDN has 56 different values, and the length of the final descriptor will be a multiple of this length. Consequently, LDN^K has a length of 56, and the LDN^G codes have a length of 56 n, where n is the number of sigmas used (in our experiments we set $n = 3$). Note that similar methods have descriptors with greater lengths. For example, the basic length of: LBP [25] (in the uniform case) is 59, $\mathrm{LD_iP}$ [28] is 56, $\mathrm{LD_eP}$ [31] is 1024, LPQ [36] is 256, LTP [33] (coded as two uniform LBP codes) is 128, and general LTP is 3^8.

4.1 Iris recognition

4.1.1 CASIA results: We tested the performance of the methods, for the iris recognition problem, in accordance to the Iris Identification Evaluation System with images from the CASIA database. In this problem, given a gallery containing labeled iris image, we classify a new set of probe images. This discrimination comes from the use of the Kirsch mask, which extracts more robust structural features than our proposed derivative-Gaussian mask. Therefore, we can accommodate the mask that is used to extract the features according to the target application.

4.1.2 Noise evaluation: To evaluate the robustness of the proposed method against noise, we corrupted the probe iris images, in the CASIA database, with white Gaussian noise, and then try to identify them using the same process as described before. We perform this research with different levels of noise. The robustness of LDN, against noise, is notable as it outperforms the other methods for every level of noise in every data set. $\mathrm{LD_iP}$ and LBP have problems overcoming the errors introduced by the noise.

5. CONCLUSION

In this paper we introduced a novel encoding scheme, LDN, that takes advantage of the structure of the iris's textures and that encodes it efficiently into a compact code. LDN uses directional information that is more stable against noise than intensity, to code the different patterns from the iris's textures. Additionally, we analyzed the use of two different compass masks (a derivative-Gaussian and Kirsch) to extract this directional information, and their performance on different applications. In general, LDN, implicitly, uses the sign information of the directional numbers which allows it to distinguish similar texture's structures with dissimilar intensity conversions *e.g.,* from dark to bright and vice versa.

We found that the derivative-Gaussian mask is more stable against noise and illumination variation in the iris recognition problem. This provides high security among all other biometric triats. Since iris feature will not change right from birth till death. If we use face recognition alone we need to update the features often for every 10 to 15 years. In order to overcome this we combine the iris features along with the face to provide high security. This prevents frequent updation of face features.

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