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FACE ANALYSIS BY LOCAL DIRECTIONAL NUMBER PATTERN

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Abstract— In Face analysis, the Local directional number pattern method encodes the directional information of the face's textures producing a more discriminative code than current methods. We compute the structure of every micro pattern with the support of a compass mask, which extracts directional information, and we encode such information using prominent direction indices and sign, which allows us to distinguish among similar structural patterns that have different intensity transitions. We divide the face into many regions, and extracting the distribution of the LDN features from them. Then, concatenating these features into a feature vector, and we use it as a face descriptor. The descriptor performs consistently under noise, illumination, expression, and the time lapse variations.

Keywords— Features, local pattern, directional number pattern, image descriptor, face descriptor, face recognition, expression recognition

[1] Introduction

A photograph or video frame is the input to the Image processing; the output of the image processing may be either an image or a set of characteristics related to the image. The acquisition of images (producing the input image in the first place) is referred to as imaging. Image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. The Image processing usually refers to digital image processing, but optical and the analog image processing also are possible. An image may be defined as a two-dimensional function, f(x, y), where x and y are coordinates, and the amplitude of f at any couple of coordinates (x, y) is called the intensity of the image at that point. When x, y, and an amplitude values of f are all finite, separate quantities, we call the image a digital image. The digital image is the collection of a finite number of elements, pixels is the term most commonly used to indicate the elements of a digital image.

Face recognition is one of the most successful applications of image analysis; It has recently received important attention, especially during the past few years. With constant growing of image analysis and pattern recognition technology, facial expression recognition has attracted more attention, and it generally contains three processes: image acquisition, feature extraction and expression classification, in which key point is the feature extraction. And the performance of an expression recognition method more critically depends on the extracted expression features with better discrimination capability. There are two common approaches to extract facial features: geometric-feature-based and appearance based methods [1-3]. The Geometric feature based methods extracts the shape and locations of facial components (including mouth, eyes, and nose) to represent the face geometry [45], [46].

Appearance-based methods deal with the whole face or specific face-regions to extract appearance changes of face using image filters such as Gabor-wavelet and local binary pattern (LBP) [47],[13]. The performance of the appearance-based methods is fantabulous in constrained environment but their performance degrades in environmental variation [15]. The face and expression features are recognized in different applications in different conditions. The descriptor of the face appearance is the key issue in face analysis [48],[49]. The descriptor efficiency depends on its representation and the ease of extracting it from the face, a good descriptor should have a high variance among classes (between different persons or expressions), but little variation within classes (same person or expression in different conditions). Descriptors are used in facial expression and face recognition. The two common approaches to extract facial Features are geometric-feature-based and appearance-based methods [4]. The former [50], [6] encodes the shape and locations of different facial components; they are combined into a feature vector that represents the face. An instance of these methods is the graph-based methods [5]–[9], which use some facial components to create a representation of the face and process it. Furthermore The Local-Global Graph algorithm [5]–[7] is an interesting approach that uses Voronoi tessellation and Delaunay graphs to segment local features and builds a graph for face and expression recognition. These features are combined into a local graph; the algorithm creates a skeleton (global graph) by interrelating the local graphs to represent the topology of the face. Moreover the facial features are widely used in expression recognition as the work done by Ekman and Friesen [12] identifying six basic emotions produced a system to categorize the expressions, known as Facial Action Coding System [11], and later it was simplified to the Emotional Facial Action Coding System [14]. However the geometric feature- based methods requires accurate and reliable facial feature detection and tracking, which is difficult to put up in many situations. The appearance based methods [13], [16] use image filters, either some exact face-region, to create local features, or on the whole face, to create holistic features, to extract the appearance changes in the face image.

We propose a face descriptor, local Directional Number Pattern (LDN), for robust face recognition that encodes the structural information and the intensity variations of the face's texture. LDN gives the structure of a local neighborhood by analyzing its directional information. Accordingly, we compute the edge responses in the neighborhood, in eight distinct directions with a compass mask. And then, from all the directions, we select the top positive and negative directions to produce a meaningful descriptor for different textures with similar structural patterns. This approach allows us to differentiate intensity changes (e.g., from bright to dark and vice versa) in the texture, yet it is more compact-as it is 6 bit long. It uses the information of the entire neighborhood, instead of using sparse points for its computation like LBP. So, our approach conveys more information into the code.

[2] LITERATURE REVIEW

The two common approaches to extract facial Features are geometric-feature-based and appearance-based methods [4]. Eigen faces [18] and Fisher faces [17] are some methods for the holistic class, which are built on Principal Component Analysis (PCA) [18]; the more recent 2D PCA [20], and Linear Discriminant Analysis [19] are also examples of holistic methods. Local descriptors have gained attention because of their robustness to illumination and pose variations. Heisele et al. presented the validity of the component based methods, and how they perform holistic methods [22]. The local-feature methods calculate the descriptor from parts of the face, and then collect the information into one descriptor. In that these methods are Local Features Analysis [21], Gabor features [24], Elastic Bunch Graph Matching [23], and Local Binary Pattern (LBP) [13], [26]. The last one is an extension of the LBP feature, that was designed for texture description [25], applied to face recognition. LBP gained popularity because; it achieved better performance than previous methods. Newer methods tried to overcome the shortcomings of LBP, like Local Ternary Pattern (LTP) [28], and Local Directional Pattern (LDiP) [27-29], The previous method encodes the directional information in the neighborhood as an alternative of the intensity. Zhang et al.[32,31] explored the use of higher order local derivatives (LDeP) to produce better results than LBP. Both these methods use other information as alternative of intensity to overcome illumination and noise difference problems. However, these methods still suffer in nonmonotonic illumination variation, unsystematic noise, and changes in age, pose, and different expression conditions. Few methods, like Gradient faces [34], have a high discrimination power under different illuminations, but they still have low recognition capabilities for expression and in variant age conditions. However some methods explored different features, such as, infrared [33], near infrared [31], and phase information [36], [35], to overcome the illumination problem while maintaining the performance under difficult conditions.

I.Kotsia and I.Pitas [6] proposed facial expression recognition in facial image sequences are presented. The user has to place few Candide grid nodes to face landmarks depicted at the first frame of the image sequence under assessment. Grid-tracking and deformation system is used based on deformable models, select the grid in successive video frames eventually, as the facial expression evolves, in anticipation of the frame that corresponds to the greatest facial expression intensity. The geometrical displacement of selected certain Candide nodes, characterized as the dissimilarity of the node coordinates between the first and the greatest facial expression intensity frame also used as an input to a novel multiclass Support Vector Machine (SVM) system of classifiers that are used to identify either a set of chosen Facial Action Units (FAUs) or the six basic facial expressions.

M. Pantic and L. J. M. Rothkrantz [15] proposed the Face Expression Recognition and Analysis: The State of the Art in this automatic face and expression recognition the characteristics of an ideal system, Databases that have been used and the advances made in terms of their standardization and a detailed summary of the state of the art and discusses facial parameterization using FACS Action Units (AUs) and MPEG-4 Facial Animation Parameters (FAPs) and the recent advances in face tracking, detection, feature extraction methods. Observations have also been provided on emotions, expressions and facial features, conversation on the six prototypic expressions and the recent studies on expression classifiers.

L.Wiskott,J.-M.Fellous,N.Kuiger and C. von der Malsburg[23] proposed Face Recognition by Elastic Bunch Graph Matching ,it presents a system for recognizing human faces from single images out of a large database consisting one image per person. The task is hard because of image variation in terms of expression, position, size, and pose. The system collapses majority of this variance by extracting concise face descriptions in the form of the image graphs. In these, fiducial points on the face (eyes, mouth, etc.) are described by sets of wavelet components (jets). Image graph extraction is based on a novel approach, the bunch graph, that is developed from a little set of sample image graphs. Recognition is based on simple comparison of image graphs.

T. Ahonen, A. Hadid, and M. Pietik¨ainen [26] proposed a Face Description with Local Binary Patterns: Application to Face Recognition in that the face image is divided into several regions from which the LBP feature distributions are extracted and combined into an enhanced feature vector to be used as a face descriptor. The act of the proposed method is evaluated in the face recognition problem under different challenges

T. Xu, J. Zhou, and Y. Wang presented an effective image description for facial expression recognition, which is a variation of local directional pattern (LDP), and introduced weightings on the modular's LDP and investigated the effect on recognition rates with different weightings. Finally, the overlapped block is proposed when using LDP and proposed method. For recognition, it adopts PCA+LDP subspace method for feature reduction, and the nearest neighbor classifier is used in the classification. The results of extensive experiments on benchmark datasets JAFFE and Cohn-Kanade illustrated that the proposed method not only can obtain better recognition rate but also have speed advantage. Furthermore, the appropriately selected weightings and regional overlapping can improve recognition rates for both proposed method and LDP method [44].

[3] LOCAL DIRECTIONAL NUMBER PATTERN

The proposed Local Directional Number Pattern (LDN) is a six bit binary code allotted to each pixel of an input image that represents the structure of the texture and its intensity transitions. The previous research [38], [37] proved, edge magnitudes are largely unresponsive to lighting changes. Accordingly, we create our pattern by calculating the edge response of the neighborhood using a compass mask, and by considering the top directional numbers, which is the most positive and negative directions of those edge responses. We represent this coding scheme in fig. 1. The positive and negative responses yield valuable information of the structure of the neighborhood, as they reveal the gradient direction of bright and dark areas in the neighborhood. Thereby, this differentiation between dark and bright responses, allows LDN to distinguish between blocks with the positive and the negative direction exchanged (which is equivalent to swap the bright and the dark areas of the neighborhood, as demonstrated in the middle of fig. 1) by developing a different code for each instance, as other methods may mistake the swapped regions as one. Moreover, these transitions occur frequently in the face, for example, the top and bottom edges of the eyebrows and mouth have different intensity

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transitions. Thus, it is very important to differentiate among them; LDN can perform this task as it assigns a specific code to each of them.

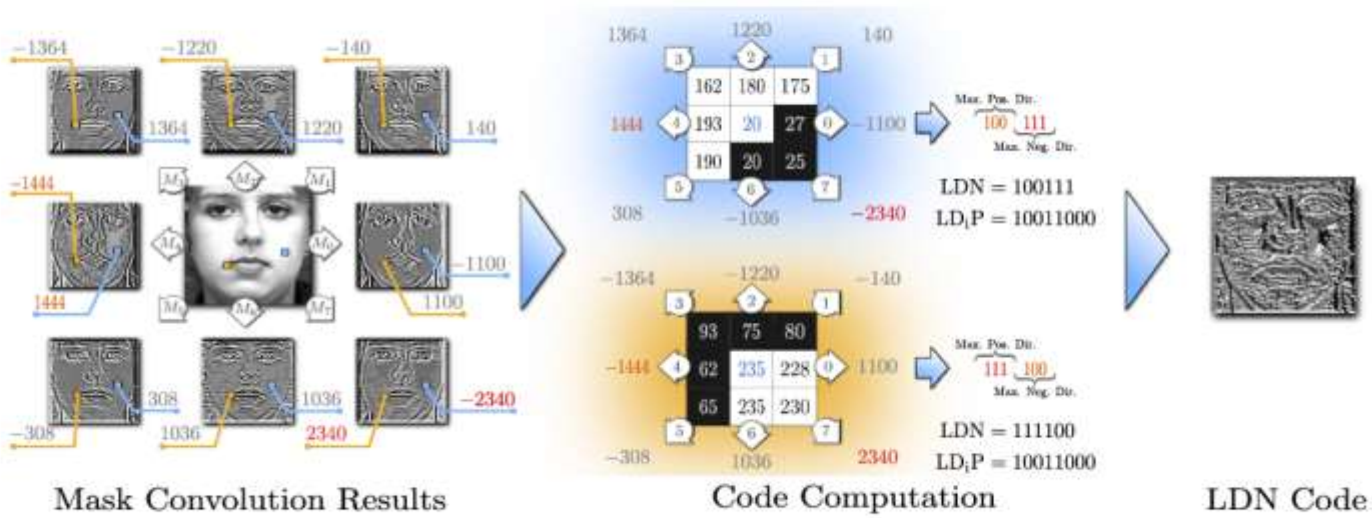

Fig. 1. LDN code computation. The (Kirsch) compass masks are convoluted with the original image to extract the edge response images (shown in the left). From these images, we choose the prominent directional numbers (positive and negative directions) to encode the texture in the neighborhood. We show an example of a neighborhood in the middle-top, that corresponds to the colored marks on the edge response images. It shows the different response values, the top directional numbers (in red and orange), and the final LDN code (shown in the right). Moreover, LDN can detect changes in the intensity regions by producing a different code (as shown in the middle-bottom) while other directional patterns cannot (like LD_iP), as they produce the same code for different textures.

3.1 COMPARISON WITH PREVIOUS WORK

Current methods have several disadvantages. For example, LBP [26] encodes the local neighborhood intensity by using the centre pixel as a threshold for a sparse sample of the neighboring pixels. Some number of pixels used in this method introduces several problems: First, it limits the precision of the method. Second, the method rejects most of the information in the neighborhood. Lastly, it makes the method very sensitive to noise. Furthermore, these disadvantages are more apparent for bigger neighborhoods. Accordingly, to avoid these problems more information from the neighborhood can be used, as other methods do [28], [27], [32], [36], [35]. Even though the use of more information makes these methods more constant, they still encode the information in a same way as LBP: by marking certain characteristics in a bit string. And in spite of the simplicity of the bit string coding strategy, it discards most information of the neighborhood. For example, the directional (LDiP) [27] and derivative (LDeP) [32] methods miss some directional information (the responses' sign) by considering all directions equally. Also, they are responsive to illumination changes and noise, while the bits in the code will flip and the code will represent a totally different feature. To avoid these problems, we investigate a new coding scheme, that implicitly utilizes the sign of the directional numbers to increase the encoded structural information, with two dissimilar masks: a derivative-Gaussian (to avoid the noise disturbance, and to set up our method robust to illumination changes, as previous methods showed [34]) and a Kirsch compass mask. Figure 1 demonstrates how LDN produces distinct codes in different scenarios, while LDiP [27] produces the same code (note that LDeP will have a same result). hence, the use of the directional numbers produces a more robust code than a simple bit string. Furthermore, the use of principal directions may be similar to a weighted coding strategy, in the sense that not all directions have the same prominence. In contrast, previous weighting methods [33] 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. Accordingly, we pick the prominent information of each pixel's neighborhood. So, our method filters and gives more importance to the local information before coding it, while other methods weight the grouped (coded) information. the important points of our proposed method are: (1) the coding scheme is based on directional numbers, instead of bit strings, that encodes the information of the neighborhood in a more effective way; (2) the inexplicit use of sign information, in comparison with preceding directional and derivative methods we encode more information in less space, and, at the same time, differentiate more textures; and (3) the use of gradient information makes the method strong against illumination changes and noise.

3.2. CODING SCHEME

In this coding scheme, we develop the LDN code, by analyzing the edge response of all mask, $\{M^0,...,M^7\}$ that represents the edge significance in its respective direction, and by totaling the dominant directional numbers. Given that the edge responses are not evenly important, the presence of a high negative or positive value signals a salient dark or bright area. Therefore, to encode these salient regions, we implicitly use the sign information, as we allot a fixed position for the top positive directional number, the three most significant bits in the code and three least significant bits are the top negative directional number, as presented in fig.1.
Therefore, the code is:

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

where (x,y) is the central pixel of the neighborhood to be coded, $i_{x,y}$ is the directional number of the maximum positive response, and the $j_{x,y}$ is the directional number of the minimum negative response represented by:

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

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

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

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

3.3 COMPASS MASKS

To compute our code, we use the gradient space instead of the intensity feature space. The former has more information than the later, because it holds the relations among pixels implicitly (while the intensity space ignores these relations). Furthermore, the gradient space reveals the underlying structure of the image due to these relations. Accordingly, the gradient space has more incisive power to detect key facial features. Additionally, we explore the utilization of a Gaussian to smooth the image, that makes the gradient computation more constant. These operations make our method more robust; likewise previous research [27], [32], [34] used the gradient space to calculate their code. So, our method is robust against illumination due to the gradient space, and noise due to the smoothing. We need a compass mask to compute the edge responses, to produce the LDN code,. In this paper, we analyze our proposed code using two different asymmetric masks: Kirsch and derivative-Gaussian (illustrated in figs 2 , and 3).

These masks operate in the gradient space, as it reveals the structure of the face. Moreover, we explore the use of Gaussian smoothing to stabilize the code in presence of noise by using the derivative-Gaussian mask. The Kirsch mask [40] is rotated 45^0 apart to get the edge response in eight different directions, as shown in fig. 2. We express the use of this mask to produce the LDN code by

LDN^K. Furthermore, inspired by the Kirsch mask [40], we use the derivative of a skewed Gaussian to create an asymmetric compass mask that we use to calculate the edge response on the smoothed face. This mask is robust against illumination changes and noise. while producing strong edge responses. Therefore, given a Gaussian mask represented by:

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

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

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

where G'_σ is the derivative of G_σ with respect to x, σ is the width of the Gaussian bell, $*$ is the convolution operation, k is the offset of the Gaussian with respect to its center—in our experiments for this offset we use one fourth of the mask diameter. Then, we develop a compass mask, $\{M_\sigma^0, \ldots, M_\sigma^7\}$, by rotating M_σ, 45^O apart in eight different directions. Thus, we get a set of masks similar to those shown in fig. 3. Because of the rotation of the mask, M_σ, there is no need of calculating the derivative with respect to y (because it is equivalent to the 90^0 rotated mask) or other combination of these variables. We express the code developed through this mask as LDN_σ^G , where σ represents the parameter for the Gaussian.

$$\underset{M_0}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \underset{M_1}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \underset{M_2}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \underset{M_3}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{M_4}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \underset{M_5}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \underset{M_6}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \underset{M_7}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

Fig. 2. Kirsch compass masks.

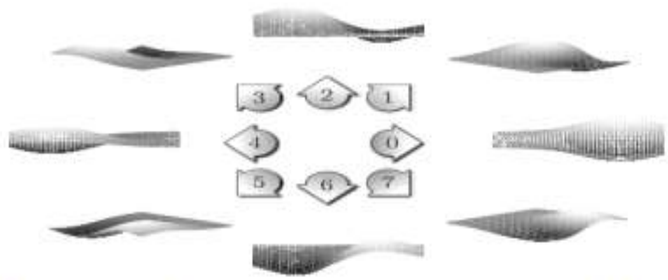

Fig. 3. Derivative of Gaussian compass masks, computed by Eq. (6).

[4] FACE DESCRIPTION

As shown in fig. 4(a), each face is represented by a LDN histogram (LH). The LH contains fine to coarse information of an image, such as corners, spots ,edges, and other local texture features. The histogram only encodes the occurrence of certain micro-patterns without location information, to combine the location information to the descriptor, we divide the face image into small parts, $\{R^1,\ldots,R^N\}$, and extract a histogram H^i from each region R^i . We generate the histogram H^i, using each code as a bin, and then gathering all the codes in the region in their respective bin by:

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

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

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

Where N is the number of regions of the divided face, and Π is the concatenation operation. The spatially combined LH plays the role of a global face feature for the granted face. The use of the derivative-Gaussian mask allows us to freely vary the size of the mask. The alter in the size allows the coding scheme, LDN^G, to capture distinct characteristics of the face. Therefore, a fine to coarse representation is achieved by finding the LDN^G_σ code at n different σ_i (which we represent by $\mathrm{LDN}^G_{\sigma_1,\ldots,\sigma_n}$), and by concatenating the histogram of each σ_i, $\mathrm{H}^j_{\sigma_i}$, which is computed in the same way as Eq.(7) by using LDN^G_σ, we can merge the characteristics at different resolutions [as presented in fig. 4(b)]. We call this mixture of resolutions a multi-LDN histogram (MLH), and it is calculated by:

$$\mathrm{MLH}_{\sigma_1,\ldots,\sigma_n} = \prod_{j=1}^{N} \prod_{i=1}^{n} \mathrm{H}^j_{\sigma_i}, \qquad (9)$$

Where $\prod$ is the concatenation operation, $\mathrm{H}^j_{\sigma_i}$ is the histogram of the $\mathrm{LDN}^G_{\sigma_i}$ code at the R^j region, and n is the number of σ's used—in our experiments we limit ourselves to three. The modification in the mask's size allows our method to capture features in the face that otherwise may be overlooked. As previous research showed [39], it is critical to provide descriptive features for long range pixel interaction. Even so, previous works do not take into account the long range pixel interaction that takes place outside the coverage of their neighbourhood system. We find that joining the local shape information, the relationship between the edge responses, relating the information from different resolutions can better characterize the face's characteristics. We represent the face using a single-feature histogram, by using LH, or by a multi-feature histogram, by using the MLH. The LDN code in LH is LDN^K or LDN^G_σ and the code in MLH must be a $\mathrm{LDN}^G_{\sigma_1,\ldots,\sigma_n}$

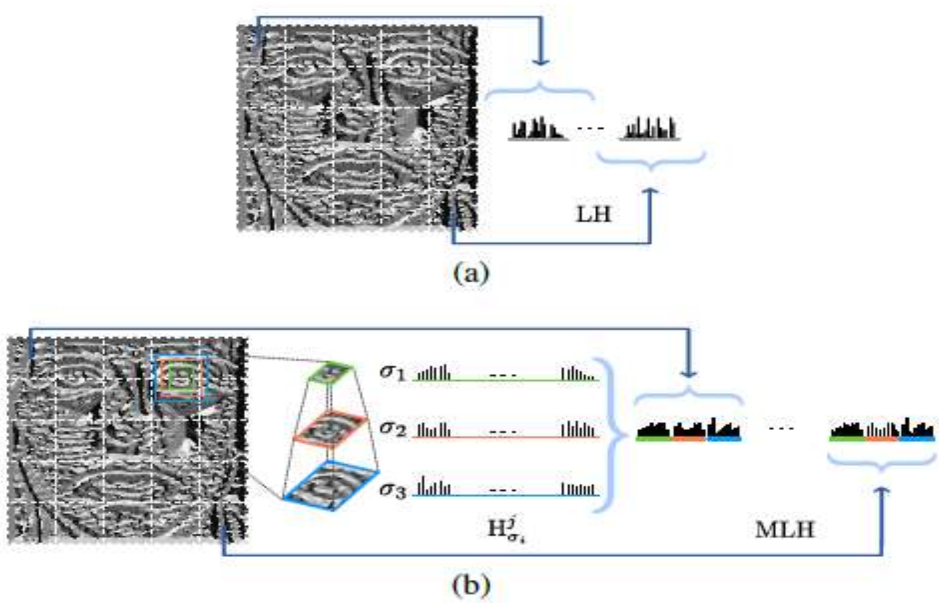

Fig. 4. Face descriptor using uniform grid for histogram extraction. (a) LDN histogram (LH), and (b) multi-LDN histogram (MLH).

4.1 FACE RECOGNITION

During the face recognition process, the LH and MLH are used. The purpose is to compare the encoded feature vector from one person with all other candidate's feature vector with the Chi-Square dissimilarity measure. Measure between two feature vectors, F1& F2, of length N is defined as:

$$\chi^2(\mathrm{F}_1, \mathrm{F}_2) = \sum_{i=1}^{N} \frac{(\mathrm{F}_1(i) - \mathrm{F}_2(i))^2}{\mathrm{F}_1(i) + \mathrm{F}_2(i)}. \qquad (10)$$

The related face of the feature vector with the lowest measured value indicates the match found

4.2 EXPRESSION RECOGNITION

To evaluate the performance of the proposed method, we perform the facial expression recognition by using a Support Vector Machine (SVM). SVM[42] is a supervised machine learning technique that implicitly maps the data into a higher dimensional feature space . Accordingly, it finds a linear hyperplane, with a maximal margin, to segregate the data in different classes in this higher dimensional space.

Assume a training set of M labeled examples

$T=\{(x_{i,} y_i) \mid i=1,...,M\}$,

where $x_i \in \mathbb{R}^n$ and $y_i \in \{-1,1\}$,the test data is classified by:

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

where α_i are Lagrange multipliers of dual optimization problem, b is the bias, and K(.,.) is a kernel function. Make a note that SVM allows domain-specific selection of the kernel function. As though many kernels have been proposed, the most often used kernel functions are the linear, polynomial, and Radial Basis Function (RBF) kernels. Given that SVM forms binary decisions, multi-class classification can be accomplished 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 [41]. We perform a grid-search on the hyper-parameters in a 10-fold cross-validation scheme for parameter selection, as advised by Hsu et al. [43]. The parameter setting bring out the best cross-validation accuracy was picked.

IV. CONCLUSION

The LDN uses directional information that is more stable against noise than intensity, to code the distinct patterns from the face's textures .It takes advantage of the structure of the face's textures and that encodes it efficiently into a compact code. And also, we analyzed the use of two different compass masks (a derivative-Gaussian and Kirsch) to extract this directional information. In general, LDN, implicitly, uses the sign information of the directional numbers which allows it to distinguish similar texture's structures with different intensity transitions—e.g., from bright to dark and vice versa. The derivative-Gaussian mask is more stable against illumination variation and noise, which makes LDN^G a reliable and stable coding scheme for face identification. Moreover, the use of Kirsch mask makes the code suitable for expression recognition, as the LDN^K code is more robust to find structural expression features than features for identification. Furthermore, the proposed face descriptor that combines the information from several neighborhoods at different sizes to encode micro patterns at those levels. Accordingly, LDN recovers more information, and uses it to boost its discriminating power.

Moreover, the combination of different sizes (small, medium and large) gives better recognition rates for certain conditions. For example, the combination of 5 x 5, 7 x 7, and 9 x 9 neighborhoods, in the LDN^G code, gives better results for expression and time lapse variation, in general. For noise intense environments large neighborhood's sizes perform better than other combinations, and in such environments the Kirsch mask performs as well as the derivative-Gaussian mask. Also, we analyzed LDN under expression, illumination variations and time lapse, and found that it is reliable and robust throughout all these conditions, unlike other methods. For example, Gradient faces had excellent results under illumination variation but failed with expression and time lapse variation. Also, LBP and LD_iP recognition rate deteriorates faster than LDN in presence of illumination changes and noise

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