Face and Expression Recognition Using Local Directional Number Pattern

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Abstract: ***Local directional number encodes the directional information of the face's textures in a dense way, producing a more discriminative code than current methods. We figure the structure of each micro-pattern with the support of a compass mask that extracts directional information, and encode such information using the well-known direction indices and sign .which allows us to distinguish among similar structural patterns that have different intensity transitions. Then we divide the face into several regions, and take out the distribution of the LDN features from them. Then, concatenate these features into a feature vector, and we use it as a face descriptor. In which descriptor performs consistently under illumination, noise, expression, and the time lapse variations.***

Keywords: Local pattern, directional number pattern, image descriptor, face descriptor, face recognition, expression recognition, and features

1. Introduction

1.1 Image Processing

Image processing is any form of a signal processing for which the input is an image, such as a photograph or video frame. Output of image processing may be either an image or a set of characteristics or parameters related to the image. The Most of the 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. The acquisition of images (producing the input image in the first place) is referred to as imaging.

An image may be defined as a two-dimensional function, f(x, y), where x and y are the spatial coordinates, and the amplitude of f at any couple of coordinates (x, y) is called the intensity or a gray level 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 pasture of digital image processing refers to digital images by means of a digital computer. A digital image is collection of a finite number of elements; each has a particular location and value. These elements known as as picture elements, image elements, and pixels is the term most commonly used to indicate the elements of a digital image.

In face analysis, a key issue is the descriptor of the face appearance [1], [2]. The efficiency of the descriptor depends on its representation and the ease of extracting it from the face. Perfectly, a good descriptor should have a high variance among classes (between different persons or expressions), but little or no difference within classes (same person or expression in various conditions). These descriptors are used in many areas, such as, facial expression and face recognition. Present two common approaches to extract facial features: geometric-feature-based and appearance-based methods [3].The former [4], [5] encodes the shape and locations of different facial components, which are joint into a feature vector that represents the face. An instance of these methods is the graph-based methods [6]–[10], which use several facial components to create a representation of the face and process it. Likewise, the Local-Global Graph algorithm [6]–[8] 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 varied into a local graph, and the algorithm creates an skeleton (global graph) by interrelating the local graphs to represent the topology of the face. Also, facial features are widely used in expression recognition, the pioneer work of Ekman and Friesen [11] identifying six basic emotions produced a system to categorize the expressions, known as Facial Action Coding System [12], and later it was simplified to the Emotional Facial Action Coding System [13]. However, the geometric-feature-based methods usually require accurate and reliable facial feature detection and tracking, which is difficult to put up in many situations. The appearance based methods [14], [15] use image filters, either on the whole face, to create holistic features, or some exact face-region, to create local features, to extract the appearance changes in the face image. The presentation of the appearance-based methods is excellent in constrained environment but their performance degrades in environmental variation [16]. In the literature, there are many methods for the holistic class, such as, Eigenfaces [17] and Fisherfaces [18], which are built on Principal Component Analysis (PCA) [17]; the more recent 2D PCA [19], and Linear Discriminant Analysis [20] are also examples of holistic methods. Local descriptors have gained attention because of their robustness to illumination and poses. Heisele et al. showed the validity of the component-based methods, and how they break holistic methods [21]. The local-feature methods compute the descriptor from parts of the face, and then collect the information into one descriptor. In that these methods are Local Features Analysis [22], Gabor features [23], Elastic Bunch Graph Matching [24], and Local Binary Pattern (LBP) [14], [25]. The last one is an extension of the LBP feature, that was originally considered for texture description [26], applied to face recognition. LBP achieved better performance than previous methods, thus it gained popularity. Newer methods tried to overcome the shortcomings of LBP, like Local Ternary Pattern (LTP) [27], and Local Directional Pattern (LDiP) [28-30]. The previous method encodes the directional information in the neighborhood, as an alternative of the intensity. Also, Zhang etal.[31,32] explored the use of higher order local derivatives (LDeP) to produce better results than LBP. Both methods use other information, as an alternative of intensity, to overcome noise and illumination difference problems. However, these methods still go through in non-monotonic illumination variation, unsystematic noise, and changes in pose, age, and different expression conditions. Although few methods, like Gradientfaces [33], have a high discrimination power under different illuminations, but they still have low recognition capabilities for expression and in variant age conditions. Some methods explored different features, such as, infrared [34], near infrared [32], and phase information [35], [36], to overcome the illumination problem while maintaining the performance under difficult conditions.

2. Literature Review

Face recognition is one of the most successful applications of image analysis and understanding, face recognition has recently received important attention, especially during the past few years. There are two common approaches to extract facial features: geometric-feature-based and appearance-based methods. The performance of the appearance-based methods is excellent in constrained environment but their performance degrades in environmental variation. The face and expression features are recognized in different applications in different conditions.

I.Kotsia and I.Pitas [5] proposed facial expression recognition in facial image sequences are presented. The user has to manually place few Candide grid nodes to face landmarks depicted at the first frame of the image sequence under assessment. The grid-tracking and deformation system is used based on deformable models, tracks 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, defined 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 recognize either the six basic facial expressions or a set of chosen Facial Action Units (FAUs).

M. Pantic and L. J. M. Rothkrantz [16] 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 detection, tracking, feature extraction methods. Observations have also been offered 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 [24] proposed Face Recognition by Elastic Bunch Graph Matching it present a system for recognizing human faces from single images out of a large database containing one image per person. The task is difficult because of image variation in terms of position, expression, size, and pose. The system collapses most of this variance by extracting concise face descriptions in the form of 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, which is developed from a small set of sample image graphs. Recognition is based on a simple comparison of image graphs. We statement recognition experiments on the FERET database as well as the Bochum database, as well as recognition across pose.

T. Ahonen, A. Hadid, and M. Pietik¨ainen [25] 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 concatenated into an enhanced feature vector to be used as a face descriptor. The act of the proposed method is assessed in the face recognition problem under different challenges

3. Local Directional Number Pattern

The proposed Local Directional Number Pattern (LDN) is a six bit binary code assigned to each pixel of an input image that represents the structure of the texture and its intensity transitions. As previous research [37], [38] , edge magnitudes are largely insensitive to lighting changes. Accordingly, we create our pattern by computing the edge response of the neighborhood using a compass mask, and by captivating the top directional numbers, that is positive and negative directions of those edge responses. We show this coding scheme in fig. 1. The positive and negative responses give valuable information of the structure of the neighborhood, as they expose the gradient direction of bright and dark areas in the neighborhood. Thus, this distinction, between dark and bright responses, allows LDN to discriminate between blocks with the positive and the negative direction swapped (which is equivalent to swap the bright and the dark areas of the neighborhood, as shown in fig. 1) by generating a different code for each case, while other methods may mistake the swapped regions as one. also, these transitions occur repeatedly in the face, for example, the top and bottom edges of the eyebrows and mouth have different intensity transitions. Thus, it is important to distinguish among them; LDN can accomplish this task as it assigns a specific code to each of them.

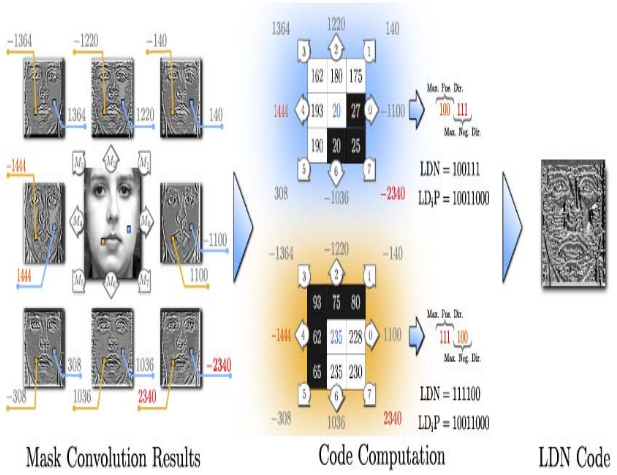

Fig. 1. LDN code computation. The (Kirsch) compass masks are convoluted with the original image to extract the edge response images (shown in the left). From these images, we choose the prominent directional numbers (positive and negative directions) to encode the texture in the neighborhood. We show 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$_i$P), as they produce the same code for different textures.

A. Difference with previous work

Current methods have several shortcomings. For example, LBP [25] encodes the local neighborhood intensity by using the center pixel as a threshold for a sparse sample of the neighboring pixels. The a small number of number of pixels used in this method begin several problems: First, it restrict the accuracy 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 drawbacks are more evident for bigger neighborhoods. Accordingly, to avoid these problems more information from the neighborhood can be used, as other methods do [27], [28], [31], [35], [36]. Although the use of more information makes these methods more constant, they still encode the information in a similar way as LBP: by marking certain characteristics in a bit string. And despite the effortlessness of the bit string coding strategy, it rejects most information of the neighborhood. For example, the directional (LDiP) [28] and derivative (LDeP) [31] methods miss some directional information (the responses' sign) by treating all directions similarly. Also, they are sensitive to illumination changes and noise, the bits in the code will flip and the code will represent a totally different features. To avoid these problems, we investigate a new coding scheme, that completely uses the sign of the directional numbers to increase the encoded structural information, by two different masks: a derivative-Gaussian (to avoid the noise perturbation, and to make the method robust to illumination changes, as previous methods showed [33]) and a Kirsch compass mask. Fig 1 shows how LDN produces different codes in different scenarios, while LDiP [28] produces the same code (note that LDeP will have a related result). so, the use of the directional numbers produces a more robust code than a simple bit string. In addition, the use of principal directions may be similar to a weighted coding scheme, in the intellect that not all directions have the same importance. In difference, previous weighting methods [34] treat the code (again) as a bit string, pick all the information of the neighborhood, and weight only the addition 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. Therefore, the method filters and gives more importance to the local information before coding it, while other methods weight the grouped information. In review, the key points of our proposed method are: (1) the coding scheme is based on directional numbers, as an alternative of bit strings, which encodes the in order of the neighborhood in a more efficient way; (2) the implicit use of sign information, in relationship with previous directional and derivative methods we encode more information in less space, and, at the same time, categorize more textures; and (3) the use of gradient information makes the method robust against illumination changes and noise.

B. Coding scheme

In our coding scheme, we create the code, LDN, by analyzing the edge response of each mask, $\{M^0, \ldots, M^7\}$, that represents the edge significance in its particular direction, and by combining the leading directional numbers. Given that the edge responses are not similarly important. The presence of a high negative or positive value signals a prominent dark or bright area. Therefore to encode these major regions, we implicitly use the sign information, as we assign a fixed position for the top positive directional number, as the three most important bits in the code, and the three least important bits are the top negative directional number, as shown in fig. 1. Therefore the code is

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

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

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

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

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

$$\mathbb{I}^i = I * M^i. \tag{4}$$

C. Compass masks

We use the gradient space, instead of the intensity feature space, to calculate our code. The former has more information than the later, as it holds the associations among pixels implicitly. Also, due to these relations the gradient space reveals the underlying structure of the image. Accordingly, the gradient space has more discriminating power to discover key facial features. In addition, we explore the use of a Gaussian to smooth the image, which makes the gradient estimation more stable. These operations make our method more robust; similarly previous research [28], [31], [33] used the gradient space to calculate their code. Consequently, our method is robust against illumination due to the gradient space, and to noise suitable to the smoothing.

To create the LDN code, we need a compass mask to compute the edge responses. In this we analyze our proposed code using two different asymmetric masks: Kirsch and derivative-Gaussian (shown in figs. 2&3). Both masks operate in the gradient space, which reveals the face structure. Furthermore, we explore the use of Gaussian smoothing to stabilize the code in presence of noise by using the derivative-Gaussian mask. The Kirsch mask [39] is rotated $45°$ apart to obtain the edge response in eight different directions, as in fig. 2. We indicate the use of this mask to produce the LDN code by LDNK. Moreover, inspired by the Kirsch mask [39], we use the derivative of a skewed Gaussian to create an asymmetric compass mask that we use to compute the edge response on the smoothed face. This mask is strong against noise and illumination changes, while producing strong edge responses. Therefore, given a Gaussian mask defined by:

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

where x, y are location positions, and σ is the width of the Gaussian bell; we define 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, where*is the convolution operation, & k is the offset of the Gaussian regarding to its center—in our experiments we use one fourth of the mask diameter for this offset. Then, we create a compass mask, $\{M^0_\sigma,\ldots,M^7_\sigma\}$, by rotating M_σ, $45°$ apart, in eight different directions. Hence, 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 indicate that the code generated through this mask as LDN^G_σ, where σ determines 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.

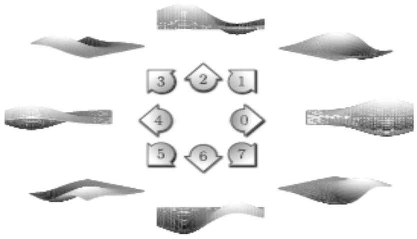

Fig. 3. Derivative of Gaussian compass masks, computed by Eq. (6).

4. Face Description

Each face is represented by a LDN histogram (LH) as shown in fig4(a). The LH contains fine to common information of an image, such as spots, edges, corners and other local texture features. Given histogram only encodes the occurrence of certain micro-patterns without location information, to collect the location information to the descriptor, we divide face image into the 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, & then accumulating all the codes in the region in their respective bin by:

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

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

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

where $\prod$ is the concatenation operation, and N is the number of regions of divided face. The spatially shared LH plays the role of a global face feature for the given 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 different characteristics of the face. Therefore, a fine to coarse representation is achieved by computing 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, $\mathrm{H}^i_{\sigma_i}$ which is computed in the same way as Eq. (7) by using LDN^G_σ, we can merge the characteristics at different resolutions [as in fig. 4(b)]. We call this mixture of resolutions a multi-LDN histogram (MLH), and it is computed by:

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

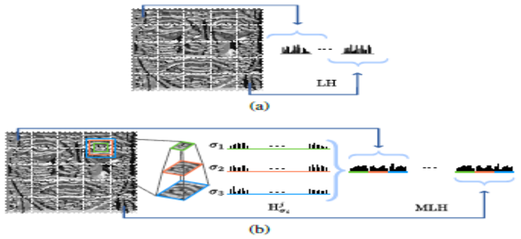

Fig. 4. Face descriptor using uniform grid for histogram extraction. (a) LDN histogram (LH), and (b) multi-LDN histogram (MLH).

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 alteration in the mask's size allows our method to capture features in the face that otherwise may be overlooked. As previous research showed [40], it is vital to provide descriptive features for long range pixel interaction. Though, 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 join the local shape information, and the relation between the edge responses, relating the information from different resolutions can better characterize the face's characteristics.

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

A. Face Recognition

The LH and MLH are used during the face recognition process. 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 matching face of the feature vector with the lowest measured value indicates the match found.

B. Expression Recognition

We perform the facial expression recognition by using a Support Vector Machine (SVM) to evaluate the performance of the proposed method. SVM [41] 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 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 $x_i\in\mathbb{R}^n$ and $y_i\in\{-1,1\}$, the test data is classified by:

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

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

Given that SVM makes binary decisions, the 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 [42]. We perform a grid-search on the hyper-parameters in a 10-fold cross validation scheme for parameter selection, as suggested by Hsu et al [43]. The parameter setting producing the best cross validation accuracy was picked.

5. Conclusion

The LDN, that takes advantage of the structure of the face'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 face's textures. Additionally, 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 dark to bright and vice versa. The derivative-Gaussian mask is more stable against noise and illumination variation in the face recognition problem, which makes LDN^G, a reliable and stable coding scheme for person identification. Furthermore, the use of Kirsch mask makes the code suitable for expression recognition, as the LDN^K code is more robust to detect structural expression features than features for identification. Moreover, the proposed face descriptor that combines the information from several neighborhoods at different sizes to encode micro patterns at those levels. Consequently, LDN recovers more information, and uses it to increase its discriminating power. Furthermore, the combination of different sizes (small, medium and large) gives better recognition rates for certain conditions. For example, the combination of 5×5, 7×7, and 9×9 neighborhoods, in the LDN^G, code, yields better results for expression and time lapse variation, in general. And for noise intense environments large neighborhood's sizes perform better than other combinations, and that in such environments the Kirsch mask performs as well as the derivative-Gaussian mask. Also, we evaluated LDN under expression, time lapse and illumination variations, and found that it is reliable and robust throughout all these conditions, unlike other methods. For example, Gradientfaces had excellent results under illumination variation but failed with expression and time lapse variation. Also, LBP and $\mathrm{LD_iP}$recognition rate deteriorates faster than LDN in presence of noise and illumination changes.

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