

A Novel Gradient Based Algorithm for Facial Expression Recognition

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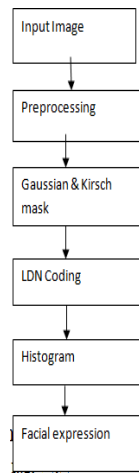
ABSTRACT: This paper proposes a new recognition technique for facial expression of a human image using Local Direction Number Pattern method. LBP is used to encode local neighborhood intensity by using center pixel as threshold. The problem in this method is it is sensitive to noise, which affects the accuracy of the image. The next version of LBP: Local Directional Pattern (LDiP), Local Derivative Pattern (LDeP). Both these methods treat all direction equally, due to this effect the bits in the code will flip which is very vulnerable to the biggest neighborhood.

I. INTRODUCTION

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. Ideally, a good descriptor should have a high variance among classes (between different persons or expressions), but little or no variation within classes (same person or expression in different conditions). These descriptors are used in several areas, such as, facial expression and face recognition. There are 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 combined into a feature vector that represents the face. An instance of these methods are the graph-based methods [6]–[10], which use several facial components to create a representation of the face and process it.Moreover,the Local-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 mixed into a local graph, and then the algorithm creates an skeleton (global graph) by interrelating the local graphs to represent the topology of the face. Furthermore, facial features are widely used in expression recognition, as 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 accommodate in many situations. The appearance-based methods [14], [15] use image filters, either on the whole-face, to create holistic features, or some specific face-region, to create local features, to extract the appearance changes in the face image. The performance of the appearance-based methods is excellent in constrained environment but their performance degrade in environmental variation [16].

ARCHITECTURE OVERVIEW

In this method of facial expression recognition we get the input image from the user and it is checked for whether the image is a human image or the repeated image, Then the preprocessing of the image is done by converting the RGB image into the gray scale image. The method that is used to implement the LDN methods are the Derivative Gaussian mask and the Kirsch compass mask. The Derivative Gaussian mask is used to avoid noise and helps in filtering of the image, It also reduces the changes in illumination. when coming to kirsch compass mask it gains the number of directions and 45 degree rotation to find the edge response.



The directional information is the key characteristics which helps to discover many key facial features. The LDN coding uses the direction pattern of the most top most positive directional number(MSB) and top negative number(LSB).It helps in the convolution of the image with mth mask. The histogram is the graphical way of representing the project it helps in finding the micropattern of an image without the location information.

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. Edge magnitudes are largely insensitive to lighting changes. Consequently, we create our pattern by computing the edge response of the neighborhood using a compass mask, and by taking the top directional numbers, that is, the most positive and negative directions of those edge responses. The positive and negative responses provide valuable information of the structure of the neighborhood, as they reveal the gradient direction of bright and dark areas in the neighborhood. Thereby, this distinction, between dark and bright responses, allows LDN to differentiate between blocks with the positive and the negative direction swapped by generating a different code for each instance, while other methods may mistake the swapped regions as one. Furthermore, these transitions occur often in the face, for example, the top and bottom edges of the eyebrows and mouth have different intensity transitions. Thus, it is important to differentiate among them; LDN can accomplish this task as it assigns a specific code to each of them.

II. RELATED WORK (EXISTING SYSTEM)

In existing system, they have tried to use Local binary pattern which encodes local binary neighborhood intensity by using centre pixel as the threshold, it limits accuracy and discards most of the neighborhood information. The LBP treats all the direction equally which limits in gaining the accurate results. The next version of LBP was Local directional pattern and Local derivative pattern, which are sensitive to illumination changes and noise that affects the bit in the code and causes the bit to flip thus the entire code will totally represent different characteristics. These two codes uses different codes in different scenarios,both these treats tall the directions equally.

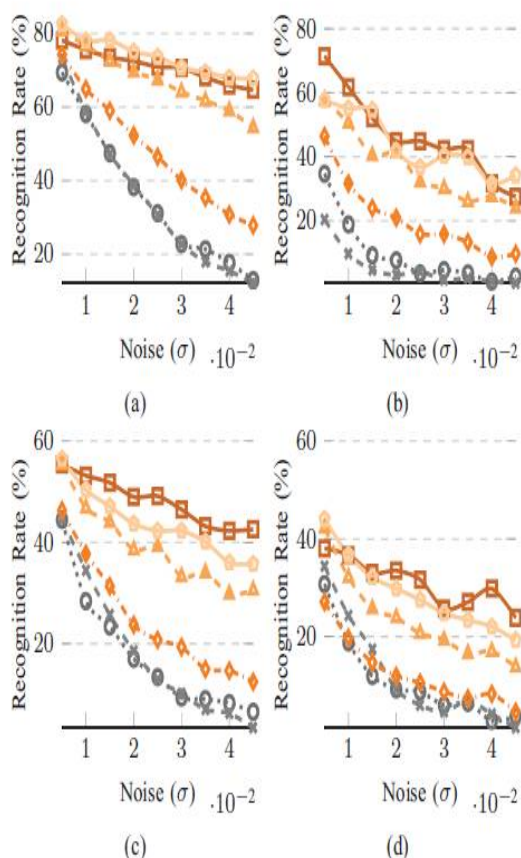
PROPOSED SYSTEM

In our proposed work, we have tried to reduce the changes in the illumination and to reduce noise by using the Local Directional Number pattern, it uses both bit strings and direction values thus the sign of the direction number increases the structural information. LDN uses different code in different scenarios, the implicit use of sign information in comparison with the previous methods gives out the accurate expression of the information. Thus the use of gradient information makes the method robust against illumination changes and noise. 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. This LDN can be implemented with two methods Derivative Gaussian mask and Kirsch compass mask.

III. EXPERIMENTAL RESULTS

We performed several experiments to evaluate the performance of the proposed coding scheme for face recognition and expression classification. We analyzed the former under expression, time lapse, pose, and illumination variation. Also, we tested the proposed code for expression recognition with six and seven expressions. 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, LDNK has a length of 56, and the LDNG codes have a length of $56n$, 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(in the uniform case) is 59, LDiP is 56, LDeP is 1024, LPQ is 256, LTP [33] (coded as two uniform LBP codes) is 128, and general LTP is 38. However, multi-scale codes, like HGPP [35], have huge lengths, as the global version (GGPP) length is $256 ns$, and the local version (LGPP) length is $256 nsno$ (where $ns = 5$ is the number of scales, and $no = 8$ is the number of orientations). Furthermore, HGPP is a combination of the local and global versions, which will combine its lengths (note that the use of real and imaginary values will double the length). Due to the length of the HGPP descriptor, we will not compare against it in the following section—see the end of next section for more details on the differences with the literature. Additionally, all these lengths should be multiplied by the grid size. In comparison, our multi-scale descriptor is extremely compact, and the single scale is more compact than other descriptors. Moreover, the execution time of our code is, in average, 37 ms on images of size 100×100 for one mask—we produced this time using a Dual-Core CPU with 2.5 GHz, using un-optimized MATLAB code. Moreover, the codes that use n different sigmas will take, in average, n times more.



IV. CONCLUSION

In this paper we introduced a novel encoding scheme, 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, 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 different intensity transitions—*e.g.*, from dark to bright and vice versa.

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