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A Novel Face Encoding Algorithm Based On Local Directional Number Pattern

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Abstract: Edge response in terms of direction and number will vary from person to person and expression to expression and can be used for face and expression recognition. Encoding these face features in a compact form is a must to obtain the discriminant information. This is a hot research topic and many works have already been done on the same. This paper proposes a novel algorithm based on Local Directional Number Pattern (LDN) for encoding edge responses and directional information of an image in an effective manner. Choice of appropriate edge detection method is very important for finding the absolute gradient magnitude for edges. Kirsch Compass Mask (KCM), a popular edge detection operator which uses the derivative approximation to find edges is used in this work. This paper also discusses two variants of edge detection namely Slow KCM (SKCM) approach which is computationally more complex and Fast KCM (FKCM) approach which is less complex. Analysis of edge responses in different expressions namely normal, smile, surprise, disgust, and sad, using the proposed algorithm is presented in this paper. The results show that LDN coded image can be used as unique feature descriptor in face and expression recognition.

Keywords: Local Directional Number Pattern, gradient magnitude, Kirsch Compass Mask, derivative approximation, Face and expression recognition.

I. INTRODUCTION

Edge in an image is a contour across which the brightness of the image changes abruptly. However, image data is discrete, so edges in an image often are defined as the local maxima of the gradient. An edge detector is basically a high pass filter that can be applied to extract the edge points in an image. The goal of edge detection is to mark the points in a digital image at which the luminance changes abruptly. The mathematical representation for the same is a convolution sequence given as [2].

$$g(x,y) = \sum_{I=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} I((x-k),(y-1))\, f(k,1) \qquad (1)$$

Where, $g(x,y)$ is the resultant image, and $I(x,y)$ is the input image and $f(x,y)$ is filter mask. Edge detection is extensively used for object recognition, face and expression recognition, target tracking, segmentation, and so on, and is considered to be one of the most important operations of image processing. Many edge detection methods are available in literature [2] namely, Sobel, Prewitt, Roberts, Canny. These methods have been proposed for detecting transitions in images. Early methods determined the best gradient operator to detect sharp intensity variations. Commonly used method for detecting edges is to apply derivative operators on images. Derivative based approaches can be categorized into two groups, namely first and second order derivative methods [3]-[5]. First order derivative based techniques depend on computing the gradient several directions and combining the result of each gradient. The value of the gradient magnitude and orientation is estimated using two differentiation masks. Kirsch Compass Mask (KCM) operators of dimensions 3×3 and 5×5 which can detect edges in eight and sixteen directions respectively are used in this work. The details of these edge detection operators are discussed in next sections.

In human-human communication the face conveys lot of information. Analyzing face in human-computer communication is the challenging task in the present scenarios. Most of the shape information of an image is enclosed in edges, which can be horizontal, vertical, or inclined. In face analysis, a key issue is the descriptor of the face appearance. Some methods which are available in literature are based on Eigen face using principle Component Analysis (PCA) [6]-[8], Fisher face using Linear Discriminative Analysis (LDA) [9] [10]. Some other coding techniques such as Local Binary Pattern (LBP) [11]-[14], Local Derivative Pattern (LD_eP) [15], Local Directional Pattern (LD_iP) [16], are used for Face Feature Extraction (FFE). These techniques have following limitations. They works only on low resolution images, highly sensitive to illumination variation, Random noise, Change in pose, less effective for facial expression, which is considered in this work are of these drawbacks. The details of KCM and LDN encoding are discussed in section A and section B.

A. Kirsch Compass mask

This is one of the types of compass edge detection, an alternative approach to differential gradient edge detection and appropriate way to estimate the magnitude and

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direction of an edge. Edge in an image can be regarded as the space gradient. An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel. A change of the image function can be described by a gradient that points in the direction of the largest growth of the image function [17].

$$Grad\,|\,g(x,y)\,|=\sqrt{\left(\frac{\partial g}{\partial x}\right)^2+\left(\frac{\partial g}{\partial y}\right)^2} \quad (2)$$

$$\psi=\arg\left(\frac{\partial g}{\partial x},\frac{\partial g}{\partial y}\right)=\tan^{-1}\left(\frac{\partial g}{\partial y}\Big/\frac{\partial g}{\partial x}\right) \quad (3)$$

Where $g(x,y)$ the central pixel neighborhood of an image is, $\frac{\partial g}{\partial x}$ is the intensity variation along x-axis, $\frac{\partial g}{\partial y}$ is the intensity variation along y-axis. ψ is the argument of along x-axis $\frac{\partial g}{\partial y}$ is the intensity variation along y-axis.

The first differences of the image $g(x,y)$ in the vertical direction (for fixed x) and in the horizontal direction (for fixed y) are

$$\Delta g(x,y)=g(x,y)-g(x-n,y) \quad (4)$$

$$\Delta g(x,y)=g(x,y)-g(x,y-n) \quad (5)$$

Where n is an integer, value of which should be chosen small enough to provide a good approximation to the derivative, but large enough to neglect unimportant changes in the image function. There are some gradient operators, such as Sobel, Robert, Kirsch etc. The Kirsch-operator is a non-linear edge detector that finds the total edge strength in a few predetermined directions and a mask of direction 3x3 will rotate 45^0 apart and obtain the edge responses in eight different directions namely East (E), North-East (NE), North-West (NW), West (W), South-West (SW), South (S), and South-East (SE). These masks templates in these directions will be represented by matrices M_0 through M_7 respectively. As Kirsch operator can adjust the threshold automatically according to the character of the image, the Kirsch gradient operator is chosen to extract the contour of the object. Each templates of KCM operator find the positive intensity gradient in respective direction. 5x5 KCM which can detect edges in sixteen different directions will also be considered in this work for enhanced edge detection.

$$\begin{bmatrix}-3&-3&5\\-3&0&5\\-3&-3&5\end{bmatrix}$$
East(E) directional Mask (M_0)

$$\begin{bmatrix}-3&5&5\\-3&0&5\\-3&-3&-3\end{bmatrix}$$
North-East (NE) directional Mask (M_1)

$$\begin{bmatrix}5&5&5\\-3&0&-3\\-3&-3&-3\end{bmatrix}$$
North (N) directional Mask (M_2)

$$\begin{bmatrix}5&5&-3\\5&0&-3\\-3&-3&-3\end{bmatrix}$$
North-West (NW) directional Mask (M_3)

$$\begin{bmatrix}5&-3&-3\\5&0&-3\\5&-3&-3\end{bmatrix}$$
West (W) directional Mask (M_4)

$$\begin{bmatrix}-3&-3&-3\\5&0&-3\\5&5&-3\end{bmatrix}$$
South-West (SW) directional Mask (M_5)

$$\begin{bmatrix}-3&-3&-3\\-3&0&-3\\5&5&5\end{bmatrix}$$
South (S) directional Mask (M_6)

$$\begin{bmatrix}-3&-3&-3\\-3&0&5\\-3&5&5\end{bmatrix}$$
South-East (SE) directional Mask (M_7)

Fig. 1 (a): 3×3 KCM templates.

When using compass edge detection the image is convolved with a set of (3×3 KCM) convolution kernels, each of which sensitive to edges in a different direction/orientation. For each pixel the local edge gradient magnitude is estimated with the maximum response of all eight kernels at this pixel location.

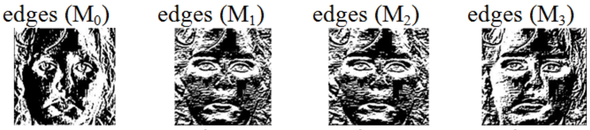
Mathematically represented as

$$|G|=Max\left(|G_i|:i=1,2,\ldots,n\right)$$

Where $|G_i|$ is the response of the kernel i at the particular pixel position, n is the number of convolution kernels based on this working principle the KCM edge detection algorithm uses a 3×3 template of pixels. Therefore this template of pixels is called convolution template because it moves across the image in a convolution style algorithm and the edge responses by using 3×3 KCM is shown in Fig

Fig. 1 (b): Original image of normal expression.

East direction edges (M_0) | North-East direction edges (M_1) | North direction edges (M_2) | North-West direction edges (M_3)



West direction edges (M_4) | South-West direction edges (M_5). | South direction edges (M_6) | South-East direction edges (M_7)

Fig. 1 (c): Edge responses of normal expression using 3×3 KCM.

B. Local Directional Number Pattern (LDN)

The LDN is a six bit binary code assigned to each 3×3 window of an input image that represents the structure of the texture and its intensity transitions. Hence, the pattern will be created by computing the edge response of the neighborhood using a Kirsch Compass Mask (KCM) and by taking the most positive and negative directions of those edge responses.

The positive and negative responses provide valuable information on the structure of the neighborhood, as they reveal the gradient direction of bright and dark areas in the neighborhood [1]. 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.

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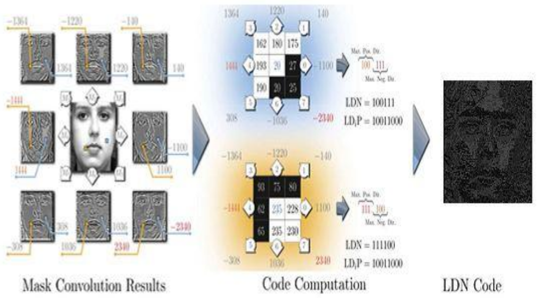

Fig. 1(d): LDN code computation.

LDN code is generated by analyzing the edge response of 3×3 KCMs M_0 through M_7, which represents the edge significance in its respective direction, and by combining the dominant directional numbers. Given that the edge responses are not equally important the presence of a high negative or positive value signals a prominent dark or bright area.

Hence, to encode these prominent regions, the sign information is implicitly used, as we assign a fixed position for the top positive directional number, as the three most significant bits in the code, and the three least significant bits are the top negative directional number.
Therefore for 3x3 KCM, LDN code is defined as

$$LDN(x,y) = 8i(x,y) + j(x,y) \tag{6}$$

For 5x5 KCM, LDN code is defined as

$$LDN(x,y) = 16i(x,y) + j(x,y) \tag{7}$$

In general for higher dimensions of KCM, LDN code is defined as

$$LDN(x,y) = 4(n-1) * i(x,y) + j(x,y) \tag{8}$$

Where (x,y) is the central pixel of the neighborhood being coded, n is the order of KCM, $i(x,y)$ is the directional number of the maximum positive response, and $j(x,y)$ is the directional number of the maximum negative response.

II. PROPOSED WORK

The authors of [1] adopted the 3×3 KCM to generate the LDN coded image by analyzing the edge responses in eight directions. In this work we use two variants of edge detection namely, 3×3 Fast KCM (FKCM) in which we move 3×3 pixel neighborhood in window by window fashion and, 3×3 Slow KCM (SKCM) in which we move 3×3 pixel neighborhood in pixel by pixel fashion.

In both the cases KCM templates are the same. Similarly we design the higher dimension of KCM (i.e. 5×5 KCM) and in this case also categorize the 5×5 KCM into 5×5 Fast KCM (FKCM) and 5×5 Slow KCM (SKCM). 5x5 KCM, compared to 3x3 KCM can detect edges in sixteen different directions and are more robust against noise and change in illumination. SKCM approach is computationally more complex and gives a better accuracy than FKCM and for the same reason we use the SKCM to generate LDN coded image.

Calculating the presence and direction of edges using convolution masks involves two major steps. They are, calculating the derivatives in all the intended directions and find the corresponding mask index and direction of maximum derivatives.

A. *Methodology*

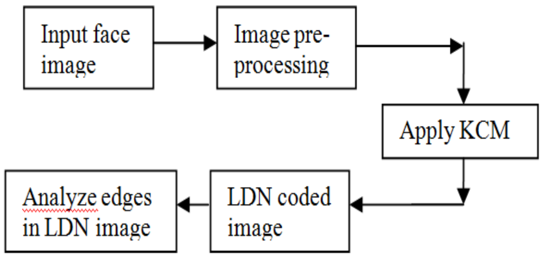

Fig. 2 (a): Overview of the proposed work.

First and foremost step in feature extraction is image pre-processing. In this stage face region from the original input image is detected and extracted using viola-john algorithm.

The extracted face region is then normalized into required dimension. KCM is applied to the preprocessed image to obtain edges in all directions. From the KCM output, edge information is then encoded using LDN.

B. Design and working of higher (5x5) dimension KCM

As suggested by Mcleod a larger mask offers more immunity to noise and detects more number of edges, so we consider the design of the 5×5 KCM.

It is same as that of the 3×3 KCM only differences being the dimension of the mask. A 3×3 KCM detects edges in eight directions and has to be rotated 45^0 apart, to obtain filter template in next direction.

Similarly 5×5 KCM can detect edges in sixteen directions and a rotation of 22.5^0 is needed to obtain the filter template in next direction. As we increase the dimension of KCM, the number of direction in which edges can be detected is increased.

Therefore, 3×3 KCM has eight directions and rotates 45^0 apart and 5×5 KCM has sixteen directions and rotates 22.5^0 apart.

In general KCM of dimension n x n can detect edges in $4(n-1)$ directions and has to be rotated $\left(\frac{360}{4(n-1)}\right)^0$ to obtain filter template in next direction. Templates of the 5x5 KCM are shown below.

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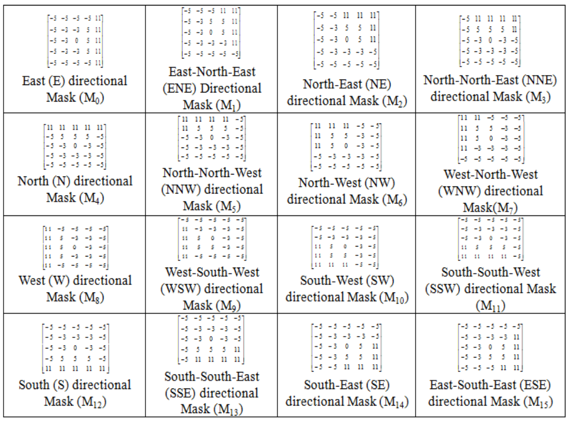

Fig. 2 (b): 5×5 KCM templates

The working of the 5x5 KCM is same as the 3x3 KCM except for the fact that we need to consider 5x5 pixel neighborhood instead of 3x3 to detect edges in sixteen directions. Analyzing the edge responses by using 5×5 KCM is shown in Fig. 2 (c).

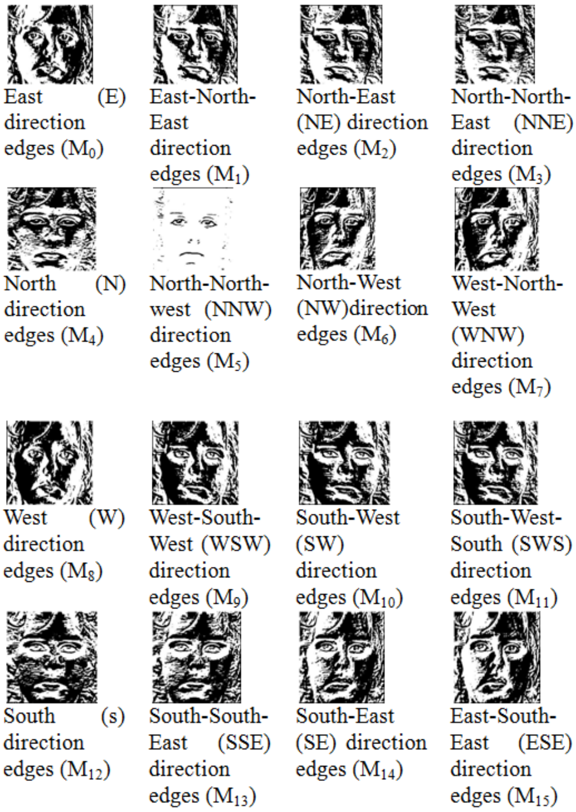

Fig. 2 (c): Sixteen-directional edge responses of normal expression using 5×5 KCM

C. LDN code using FKCM

Step 1: First step is to detect and extract face region (image pre-processing) from the standard cohn-Kanade data sets using viola-john algorithm.

Step 2: Apply the compass mask to the pre-processed image.

a) Consider the first *nxn* window pre-processed image.
b) Initialize the index matrix of dimension 1x4(*n*-1) with elements 0 through 4(*n*-1)-1. Also initialize the mask template in the mth direction, where, m=0 through 4(*n*-1)-1 are indices corresponding to 4(*n*-1) directions starting from east in anticlockwise sense.
c) Apply the mth KCM in ith nxn window (W) and save the values as mth element in a row matrix (R)
d) Check whether m=4(*n*-1)-1. If no increment m by 1 and repeat step c. If yes go to step.
e) Find the maximum positive value in R and save the corresponding index value in $i_{x,y}$, similarly find the most negative value in R and save the corresponding index value in $j_{x,y}$.
f) Calculate the LDN code by using equation (8) and save the values as corresponding elements in a matrix to get LDN coded image.
g) Repeat (c) for each window.

Step 3: Analyze of edge information using histogram of the LDN coded image.

D. LDN code using SKCM

LDN code using slow KCM is similar to Fast KCM, in that we move n×n pixel neighbourhood in pixel by pixel fashion.

SKCM approach which is computationally more complex and give a better accuracy than FKCM for this purpose we use the SKCM to generate LDN coded image.

III. EXPERIMENTAL RESULTS AND ANALYSIS

The Cohn-Kanade image database [1] is considered, it consists of set of images of dimension 640*490 of different expressions and different illumination, detect and extract the face region from the original input image using viola-john algorithm, normalize extracted face region into 225x225 dimensions, For experimental purpose, Image processing and Computer vision toolboxes are used in this work .

A. Comparison Table for LDN coded image using SKCM and FKCM (i) For FKCM:

Person 1	Normal expression	Smile expression	Surprise expression	Disgust expression	Sad expression
Original image					
LDN coded image using 3×3 FKCM					
LDN coded image using 5×5 FKCM	Edges are not detected	Edges are not detected	Edges are not detected	Edges are not detected	Edges are not detected

Table 1: Persons-1 LDN coded image using FKCM.

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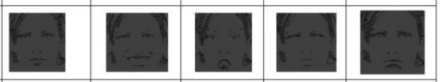
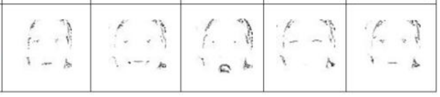
Person 2	Normal expression	Smile expression	Surprise expression	Disgust expression	Sad expression
Original image					
LDN coded image using 3×3 FKCM					
LDN coded image using 5×5 FKCM					

Table 2: Persons-2 LDN coded image using FKCM.

(ii) For SKCM:

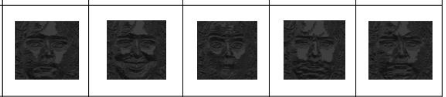
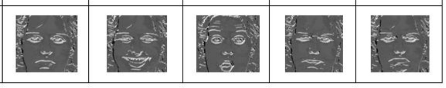
Person 1	Normal expression	Smile expression	Surprise expression	Disgust expression	Sad expression
Original image					
LDN coded image using 3×3 SKCM					
LDN coded image using 5×5 SKCM					

Table 3: Persons-1 LDN coded image using SKCM.

B. Histogram comparison of LDN coded image.

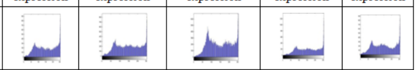
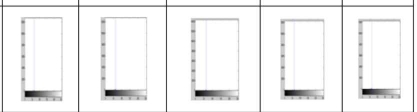
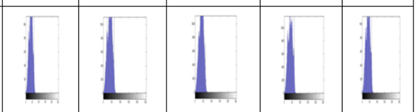
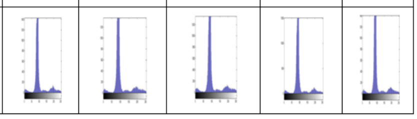
Person 1	Normal expression	Smile expression	Surprise expression	Disgust expression	Sad expression
Original image histogram					
Histogram of LDN coded image using 3×3 FKCM					
Histogram of LDN coded image using 3×3 SKCM					
Histogram of LDN coded image using 5×5 SKCM					

Table 3: Persons-3 Histogram comparison of LDN coded image.

IV. CONCLUSION AND FURTHER WORK

A novel algorithm for encoding face feature based on LDN, that takes advantage of the structure of the face's textures and that encodes it efficiently into a compact code is proposed in this paper. We have used this algorithm to obtain the directional information of different persons and expressions. The results shows that LDN coded images, which provides detailed discriminant information regarding face feature can be used for face and expression recognition. LDN uses directional information that is more stable against noise than intensity, to code the different patterns from the face's textures. We also presented the design aspects of higher order KCM which can detect edges in more number of directions, taking 5×5 KCM as an example. Ongoing work includes Face and expression recognition based on the proposed algorithm and analysis of enhanced edge detection on face and expression recognition accuracy.

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