RESEARCH ARTICLE OPEN ACCESS

Multiscale Feature Extraction For Content Based Image Retrieval Using Gabor Local Tetra Pattern

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Abstract-
In this project the image is retrieved using Local Tetra Pattern (LTrP) for Content Based Image Retrieval (CBIR). It gives the path to retrieve the needed information based on the image content. The earlier version of CBIR was based on Local Binary Pattern, Local Derivative Pattern and Local Ternary Pattern. These methods extract information based on the distribution of edges which are coded using only two directions. The performance of these methods is little less and thus it can be improved by differentiating the edges in more than two directions. So we propose local tetra pattern, in this we encodes the relationship between the referenced pixel and its neighbours based on the directions that can be calculated using second order derivatives in horizontal and vertical directions. The effectiveness of our proposed algorithm can be analyzed by combining it with the Gabor Transform. The performance of the proposed method is compared with the LBP, the LDP and the LTP based on the results obtained using benchmark image databases.

Index Terms- Content Based Image Retrieval (CBIR), Gabor Transform (GT), Local Binary Pattern (LBP), Local Tetra Pattern (LTrP), texture.

I. INTRODUCTION

A. General

Digital image libraries and other multimedia databases have been dramatically expanded in recent years. Storage and retrieval of images in such libraries has become a real demand in industrial, medical and other applications. Content Based Image Retrieval is considered as a solution. Feature extraction is the basis of CBIR. In a broad sense features may include both text based features (keywords, annotations) and visual features (color, texture, shape, faces). Within the visual feature scope, the features can be further classified as general features such as color, texture and shape. And domain specific features such as human faces and finger prints. The difficulty to find a single best representation of an image for all perceptual subjectivity due to the fact that the user may take photographs in different conditions such as view angle, illumination changes etc.

In February 1992 the US National Science Foundation(USNSF) organized a workshop in Redwood, California to identify major research area that should be addressed by researchers for visual information management systems that would be useful in scientific, industrial, medical, environmental, and other applications. Chellappa *et al.* used the Gaussian Markov Random Fields (GMRF) to model texture patterns based on statistical relationship between adjacent pixel intensity values [2]. Bovik *et al.* applied the Gabor filters to an image and then computed the average filter responses as features [3]. Weszka *et al.* applied the co-occurrence matrix to extract the mean intensity, contrast and correlation information from the texture image [4]. Wang *et al.* used wavelet domain information to index images [5]. Recently a wavelet based CBIR system called wavelet correlogram has been introduced by Moghaddam *et al.* [6]. Saadatmand *et al.* improve the performance of wavelet correlogram algorithm by optimizing the quantization threshold using genetic algorithm [7]. Birgale *et al.* and Subrahmanyam *et al.* combined the color(color histogram) and texture features(wavelet transform) for CBIR [8]. Subrahmanyam *et al.* proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets [9].

In the field of texture classification and retrieval the LBP feature has emerged as a silver lining. Ojala *et al.* proposed rotation and histogram equalization invariant features by observing the statistical distribution of the uniform LBP [10]. Minh B *et al.* have introduced Kullback- Leibler distance for providing greater accuracy and flexibility in capturing texture information using wavelet-based texture retrieval method [11] . Huang *et al.* extended the LBP method by calculating the derivative based

LBPs in the application of face alignment [12]. Yang *et al.* applied LBP for face recognition with Hamming distance constraint [13]. Chen *et al.* used statistical LBP for face recognition [14]. Mohanmed *et al.* applied hierarchical multiscale LBP with wavelet transform to recognize avatar faces [15].

B. Related Work

The LBP, the LDP and the LTP extract the information based on the distribution of edges which are coded using only two directions (positive and negative). Local Binary Pattern was used for texture classification and retrieval. This emerged method was very poor in capturing the intrinsic structural information of face appearance. In Local Derivative Pattern they encode directional pattern features based on the local derivative variations. The n^{th} order LDP is proposed to encode $(n-1)^{th}$ order local derivative direction variation. LDP extracts more detailed information is got than LBP. In Local Ternary Pattern the operator takes a local neighbourhood around each pixel, thresholds the pixels of neighbourhood and use the result as local image descriptors. LTP includes a 3-valued coding that includes a threshold around zero for improved resistance to noise. The versions of the LBP and LDP cannot adequately deals with the range of appearance variations that commonly occur in natural images due to illumination, pose, facial expressions, aging, partial occulation etc. In order to address these problems LTP has been introduced for face recognition under different lighting conditions.

II. LOCAL PATTERNS

Automatic face analysis includes, face recognition and facial expression recognition has become a very active topic in computer vision research. Finding good descriptors for the appearance of local facial regions is an open issue. These descriptors should be easy to compute and have high extra-class variance and low intra-class variance, which means that the descriptor should be robust with respect to aging of the subjects, alternating illumination and other factors. At first we investigate the representation of face images by means of Local Binary Pattern features.

A. Local Binary Patterns

The Local Binary Pattern operator was introduced for texture classification and it has been widely used in various applications. Given a centre pixel in the image, the LBP value is computed by comparing its gray value with its neighbours. A LBP is called Uniform Pattern if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa.

B. Local Derivative Patterns

Local Derivative Patterns considers the Local Binary Patterns as the non-directional first order local pattern operator and extended it to higher order called the Local Derivative Patterns. It has more detailed discriminative features as compared with the LBP. The second order LDP can capture directional derivative changes among local neighbour and encode the turning point of the direction. The n^{th} order LDP captures the detailed relationship in a local neighbourhood. Gabor real and imaginary features for face recognition can effectively enhance the performance of the LDP. The Local Derivative Pattern features are directly extracted from gray-level images without any training procedure. LDP is a micro pattern representation modelled by histogram to preserve the information.

C. Local Ternary Patterns

The Local Binary Pattern is extended to a three valued code called Local Ternary Pattern, in which gray value in the zone of width ±t around g_c are quantized to zero, those above (g_c+t) are quantized to +1 and those below (g_c-1) are quantized to -1. Local Ternary Pattern partially solves the noise-sensitive problem by encoding the small pixel differences into a separate state. When the ternary code is split into a positive LBP code and a negative LBP code it may result in a significant information loss.

D. Local Tetra Patterns

The Local Tetra Pattern describes the spatial structure of the local texture using the direction of the centre gray pixel g_c. Given image I, the first-order derivatives along 0º and 90º directions are denoted as $I^1_\theta(g_p)|_{\theta=0^o,90^o}$. Let g_c denote the centre pixel in I and let g_h and g_v denote the horizontal and vertical neighbourhoods of g_c. Then the first-order derivatives at the centre pixel g_c can be written as

$$I^1_{0^o}(g_c) = I(g_h) - I(g_c) \qquad (1)$$

$$I^1_{90^o}(g_c) = I(g_v) - I(g_c) \qquad (2)$$

and the direction of the centre pixel can be calculated as

$$I^1_{Dir.}(g_c) = \begin{cases} 1, & I^1_{0^o}(g_c) \geq 0 \text{ and } I^1_{90^o}(g_c) \geq 0 \\ 2, & I^1_{0^o}(g_c) < 0 \text{ and } I^1_{90^o}(g_c) \geq 0 \\ 3, & I^1_{0^o}(g_c) < 0 \text{ and } I^1_{90^o}(g_c) < 0 \\ 4, & I^1_{0^o}(g_c) \geq 0 \text{ and } I^1_{90^o}(g_c) < 0 \end{cases} \qquad (3)$$

Then the second-order $LTrP^2(g_c)$ is defined as

$$LTrP^2(g_c)$$

$$= \{f_3(I^1_{Dir.}(g_c), I^1_{Dir.}(g_1)),\ f_3(I^1_{Dir.}(g_c), I^1_{Dir.}(g_2)), \ldots\ldots,\ f_3(I^1_{Dir.}(g_c), I^1_{Dir.}(g_p))\}|_{p=8} \quad (4)$$

Where,

$$f_3(I^1_{Dir.}(g_c), I^1_{Dir.}(g_p)) = \begin{cases} 0, & I^1_{Dir.}(g_p) = I^1_{Dir.}(g_p) \\ I^1_{Dir.}(g_p), & \text{else.} \end{cases} \quad (5)$$

We separate all patterns into four parts based on the direction of centre pixel. Finally, the tetra patterns for each part are converted to three binary patterns. Let the direction of centre pixel obtained be '1', then $LTrP^2$ can be defined by segregating it into three binary patterns as follows:

$$LTrP^2|_{Direction=2,3,4}$$

$$= \sum_{p=1}^{P} 2^{(p-1)} \times f_4(LTrP^2(g_c))|_{Direction=2,3,4} \quad (6)$$

Where,

$$f_4(LTrP^2(g_c))|_{Direction=2,3,4}$$

$$= \begin{cases} 1, & if\ LTrP^2(g) \\ 0, & else \end{cases} \quad (7)$$

Similarly the other three tetra patterns for remaining three directions of centre pixels are converted to binary patterns. Thus we get 12 binary patterns. The sign and magnitude components can provide better clues, this can be motivated to propose the 13^{th} binary pattern (LP) by using the magnitudes of horizontal and vertical first-order derivatives using

$$M'_{I\ (gp)} = \sqrt{(I^1_{0^o}(g_p))^2 + (I^1_{90^o}(g_p))} \quad (8)$$

Then,

$$LP = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(M'_{I\ (gp)} - M'_{I\ (gc)})|_{p=8} \quad (9)$$

After identifying the local pattern PTN (the LBP, the LDP, the LTP, or the 13-binary pattern from LTrP), the whole image is represented by building a histogram using

$$H_s(l) = \frac{1}{N1 \times N2} \sum_{j=1}^{N1} \sum_{k=1}^{N2} f_5(PTN(j,k),l);$$

$$l \in [0, P(P-1)+2] \quad (10)$$

Where,

$$f_5(x,y) = \begin{cases} 1, & if\ x = y \\ 0, & else \end{cases} \quad (11)$$

and

N1×N2 represents the size of the input image

For generating a tetra pattern the bit is coded with the direction of neighbour when the direction of the centre pixel and its neighbour are different otherwise "0". For the magnitude pattern the bit is coded with "1" when the magnitude of the centre pixel is less than the magnitude of its neighbour, otherwise "0". Each pixel of the original image is considered as the centre pixel and it is coded by using the LBP, LTP, LDP and LTrP descriptors with the help of neighbours. The LTrP extracts additional directional information as compared with other patterns.

E. Advantages of the LTrP Over other Patterns

The advantages of the LTrP over the LBP, the LDP and the LTP can be justified with the help of three points.

1. The LBP, the LDP and the LTP are able to encode images with only two (either "0" or "1"), two ("0 " or "1"), and three ("0", "1" or "-1") distinct values respectively. However the LTrP is able to encode images with four distinct values as it is able to extract more detailed information.
2. The LBP and the LTP encodes the relationship between the gray value of the centre pixel and its neighbours, whereas the LTrP encodes the relationship between the centre pixel and its neighbours based on directions that are calculated with the help of $(n-1)^{th}$ order derivatives.
3. The LDP encodes the relationship between the $(n-1)^{th}$ order derivatives of the centre pixel and its neighbours in 0°, 45°, 90° and 135° directions separately, whereas the LTrP encodes the relationship based on the direction of the centre pixel and its neighbours which are calculated by combining $(n-1)^{th}$ order derivatives of 0° and 90° directions.

III. MULTISCALE FEATURE EXTRACTION

A. Proposed System Framework

Algorithm:

Input: Query image

Output: Retrieval result

1. Load the image and convert it into grayscale.
2. Apply the first-order derivatives in horizontal and vertical axis.
3. Calculate the direction for every pixel.
4. Divide the patterns into four parts based on the direction of the centre pixel.
5. Calculate the tetra patterns and separate them into three binary patterns.
6. Calculate the histogram of binary patterns.
7. Calculate the magnitudes of centre pixels.
8. Construct the binary patterns and calculate their histogram.
9. Combine the histogram calculated from step 6 and 8.
10. Construct the feature vector.
11. Compare the query image with the images in the database.
12. Retrieve the images based on the best matches.

This algorithm is also applied on Gabor Wavelet subbands for GLTrP.

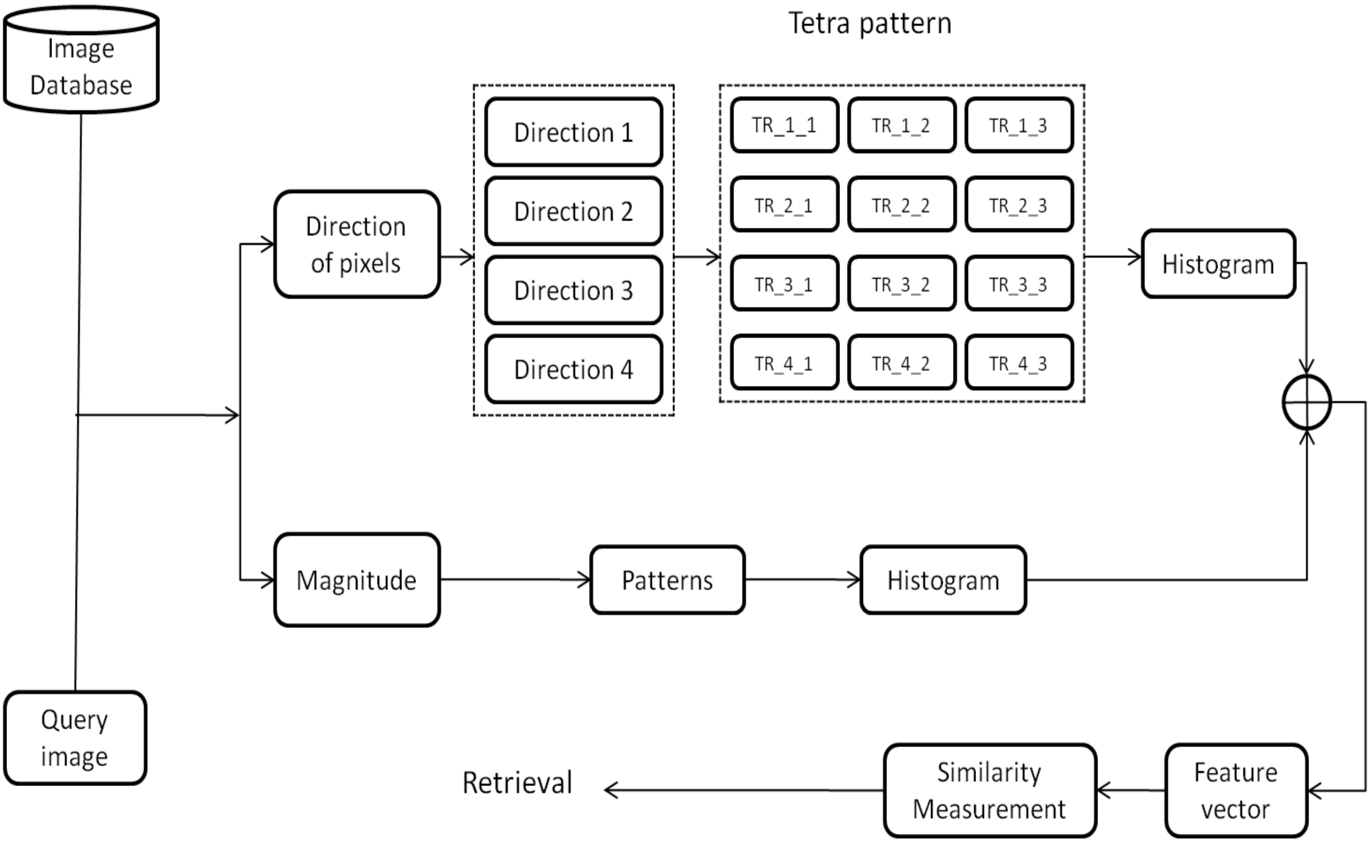

Fig.1 Proposed image retrieval system framework.

B. Query matching

The feature vector for the query image Q represented as $f_{Q=} (f_{Q1}, f_{Q1}, \ldots, f_{QL})$ is obtained from feature extraction. Similarity each image in the database is represented with the feature vector $f_{DB}= (f_{DB1}, f_{DB1}, \ldots, f_{DBL})$. The goal is to select the *n* best images that resemble the query image. This involves the selection of *n* top-matched images by measuring the distance between the query image and the images in database. In order to match the images we use d_1 similarity distance metric computed using

$$D(Q,DB)= \frac{fDB - fQ}{1 + fDB + fQ} \qquad (12)$$

Given below are the abbreviations used in the analysis of the result.

LBP	Local Binary Pattern.
GLBP	LBP with GT.
LDP	Local Derivative Pattern.
GLDP	LDP with GT.
LTP	Local Ternary Pattern.
GLTP	LTP with GT.
LTrP	Local Tetra Pattern.
GLTrP	LTrP with GT.
CBIR	Content Based Image Retrieval

IV. CONCLUSION

Content Based Image Retrieval (CBIR) also known as Query By Image Content (QBIC), it is the application of computer vision techniques. This project enhances the novel approach referred as Local Tetra Pattern along with vertical and horizontal directions also adds the color features. The Local Tetra Pattern encodes the images based on the direction of pixels that are calculated by horizontal and vertical derivatives. The magnitude of the binary pattern is collected using magnitudes of derivatives. The effectiveness of the proposed approach has been also analyzed by combining it with the Gabor Transform. Local Tetra Pattern encodes the relationship between centre pixel and its neighbour based on the directions that are calculated with the help of (n-1) order derivatives and so the combinations are more that makes easy searchable of images in the internet and the image labelling more efficient. So the retrieval of image is accurate with less computational cost. Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as fingerprint recognition.

ACKNOWLEDGEMENT

The authors would like to thank Mr. A. B. Gonde, Dr. D. K. Rajoriya, and Mr. P. Aravind (Research Scholars), Department of Electrical Engineering, and Mr. D. Gangodkar (Research Scholar), Department of Electronics and Computer Engineering, Indian Institute of Technology Roorkee, Roorkee, for their valuable technical discussions for this paper. They would also like to thank the associate editor and anonymous reviewers for insightful comments and helpful suggestions to improve the quality, which have been incorporated in this paper.

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