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CONTENT BASED IMAGE RETRIEVAL USING ENHANCED LOCAL TETRA PATTERNS

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ABSTRACT

Content-based image retrieval (CBIR) is a technique to search the desired image from the homogeneous or heterogeneous database. Image is analyzed using features like shape, size, texture etc. which forms the basis of image retrieval. In CBIR, the existing approaches uses local binary patterns(LBP) and local ternary patterns(LTP) encode the relationship between the referenced pixel and its surrounding neighbors by computing gray level difference. The LBP, the LTP extract the information based on the distribution of edges, which are coded using only two directions (positive and negative). Thus to increase the performance a method called local tetra patterns (LTrPs) is introduced which uses four direction code. LTrPs encodes the relationship based on directions that are calculated using first order as well as the nth order derivative for CBIR. The issue that arises with this approach is that only horizontal and vertical pixels have been used for derivation calculation. The proposed work will be implemented to include the diagonal pixels for derivation calculations besides calculating the horizontal and vertical directions in LBP and LTP. This will increase the effectiveness of the method in pattern recognition for image retrieval.

Keywords: Content-based image retrieval (CBIR), local binary pattern (LBP), local tetra pattern (LTP), texture

I. INTRODUCTION

The EXPLOSIVE growth of digital libraries due to Web cameras, digital cameras, and mobile phones equipped with such devices is making the database management by human annotation an extremely tedious and clumsy task. Thus, there exists a dire need for developing an efficient expert technique that can automatically search the desired image from the huge database. Content-based image retrieval (CBIR) is one of the commonly adopted solutions for such applications. The feature extraction in CBIR is a prominent step whose effectiveness depends upon the method adopted for extracting features from given images. The CBIR utilizes visual contents of an image such as color, texture, shape, faces, spatial layout, etc., to represent and index the image database. These features can be further classified as general features such as color, texture, and shape, and domain-specific

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features such as human faces, fingerprints, etc. The difficulty to find a single best representation of an image for all perceptual subjectivity is due to the fact that the user may take photographs in different conditions such as view angle, illumination changes, etc.Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features. Texture is prominent and important visual property of an image. Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potentialin extracting the prominent features. Texture retrieval is a branch of texture analysis that has attracted wide attention from industries since this is well suited for the identification ofproducts such as ceramic tiles, marble, parquet slabs, etc. Similar images are expected to have similar texture patterns, so texture features are important for content based image retrieval.

II. LOCAL DESCRIPTORS

2.1 Local Binary Pattern

LBP was proposed by Ojala et.al for a grayscale invariant and as a local texture descriptor. LBP can be conceptually considered as a non directional first-order local pattern, which is the binary result of the first order derivative in images. LBP has shown excellent performance in terms of speed and discrimination performance [12], [13], [14]. The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholdby its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of 28 = 256 differentlabels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood, i.e., the LBP value is computed by comparing its gray value with its neighbors.

2.2 Local Tetra Pattern

The LTrP describes the spatial structure of the local texture using the direction of the centre gray pixel. Given image I, the first-order derivatives along 0º and 90º directions. Let denote the centre pixel in I, and let and horizontal and vertical neighbourhood of , respectively. Then, the first-order derivatives at the centre pixel and the direction of the centre pixel can be calculated.

From the second order derivative, 8-bit tetra pattern for each centre pixel. Then, all patterns separate into four parts based on the direction of centre pixel. Finally, the tetra patterns for each part (direction) are converted to three binary patterns. Similarly, the other three tetra patterns for remaining three directions (parts) of centre pixels are converted to binary
patterns.

III. RELATED WORK

***Meenakshi Madugunki, Sonali Bhadoria** used different methods for extracting color and texture features. For similarity measurements three methods are used and compared the results. They conclude that Discrete Wavelet Transform method gives us better precision and Canberra distance methods gives better performance than the other methods*

A.Bhagyalakshmi and V.Vijayachamundeeswari*reviewed the main CBIR components including low level descriptors for feature extraction such as color, texture, shape and various image retrieval methods using local binary operators. These operators generate the local binary patterns and local code for every pixel in an image. Once the codes are generated, Histogram is constructed. Results shows that the similar images have the same histogram value.*

Nitin Naravankar and Sanjay Dhaygude *presented an approach for texture feature using local tetra patterns. The LTrPs encodes the image based on the direction of pixels that are calculated by horizontal and vertical derivatives.*

T.Pratibha and Soniah Darathi *appliedan image retrieval technique referred as LTrPs for CBIR. The LTrPs encodes the image based on the direction of pixels. Proposed method improves the retrieval result as compared with the standard LBP*

IV. METHODOLOGY

The proposed work will be implemented to include the diagonal pixels with horizontal and vertical pixels for derivation calculations besides only calculating the horizontal and vertical directions in LBP and LTP. This will increase the effectiveness of the method in pattern recognition for image retrieval.

Algorithm for the proposed methodology

1. *Load the image, and convert it into gray scale.*
2. *Apply the first order derivatives in horizontal and vertical axis.*
3. *Calculate the direction for very pixel.*
4. *Divide the patterns into four parts based on the direction of center pixel.*
5. *Calculate the tetra patterns, and separate them into three binary patterns.*
6. *Calculate the histograms of binary patterns.*
7. *Calculate the magnitude of center pixels.*
8. *Construct the binary patterns, and calculate their histograms.*
9. *Combine the histograms calculated form 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 best matches.*

V. CONCLUSION AND FUTURE WORK

In this paper we have implemented a technique to include the diagonal pixels with including horizontal and verticalpixels for derivation calculations besides calculating only the horizontal and vertical directions in LBP and LTP. This will increase the effectiveness of the method in pattern recognition for image retrieval.

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