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CONTENT BASED IMAGE RETRIEVAL USING MODIFIED LOCAL TETRA PATTERN

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ABSTRACT

Content based image retrieval (CBIR) is a method of retrieving images from large image database, which has been found according to user's interest. This paper represents high order local pattern descriptors. Image features are extracted using these descriptors. Image retrieval and indexing algorithm uses these local patterns for content-based image retrieval (CBIR). The local binary pattern (LBP) and local ternary pattern (LTP) encode the relationship between the referenced pixel and its neighbours by calculating gray-level difference. It can extract more detailed information than first order LBP. The local tetra pattern (LTrP) encodes the relationship between the referenced pixel and its surrounding neighbours, based on the directions that are calculated using the first-order derivatives in horizontal and vertical directions. To get more effective result we proposed new method that is modified local tetra pattern (MLTrP). It encodes relationship between pixel based on the directions which are calculated using first order derivatives in horizontal, vertical and diagonal direction. This will improve the performance of the system in terms of average precision and average recall.

KEYWORDS: *Content Based Image Retrieval, Local Binary Pattern, Local Ternary Pattern, Local Tetra Pattern, Modified Local Tetra Pattern*

I. INTRODUCTION

In recent years, digital image libraries and other multimedia databases have been expanded. Storage and retrieval of images in digital libraries has become a necessary requirement in industrial, medical, and other applications [1]. The traditional text-based image retrieval systems require manual annotation of images. So, annotating each image manually is quite difficult task for large image databases. So that we required a technique that can automatically search the desired image from the large database. Content based image indexing and retrieval (CBIR) is considered as a one of the best solution. Content based image retrieval uses low level and high level image features such as color, shape, texture, spatial layout and local patterns to represent and index the image. Images of the same category are expected to have similar characteristics. Similarity measurement is performed on the basis of image features. The basic structure of CBIR is as shown in Fig. 1

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 potential in extracting the prominent features [3], [4]. Texture retrieval is a branch of texture analysis that has attracted wide attention from industries since this is well suited for the identification of products such as ceramic tiles, marble, parquet slabs, etc. Ahmadian *et al.* have used the discrete wavelet transform (DWT) for texture classification [5]. Similar images are expected to have similar texture patterns, so texture features are important for content based image retrieval.

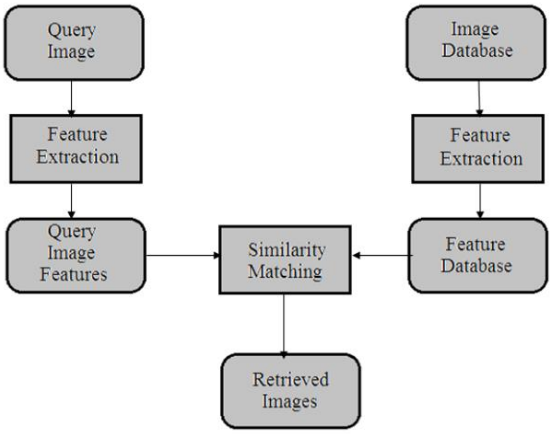

Figure 1. Basic CBIR Framework

The local binary pattern (LBP) feature has emerged as silver lining in the field of texture classification and retrieval. LBPs are converted to rotational invariant version of texture classification [6], [7]. Zhang *et al.* proposed Local Derivative Pattern (LDP) for face recognition, where they considered the LBP as non directional first order derivatives and extended the same approach for n^{th} order LDP [9]. To address the problem which has been occurred in the previous patterns, the Local Ternary Pattern (LTP) [10] has been introduced for face recognition under different lighting conditions. The LBP, LDP, and LTP extract the information on the basis of distribution of edges, which are coded using only two directions (positive direction and negative direction).Recently, Murala et al. has been introduced local tetra pattern (LTrP) and it considered the four direction code[11].

This paper is organized as follows. Section II describes the feature descriptors for content based image retrieval such as local binary pattern, local ternary pattern, local derivative pattern, local tetra pattern. Section III describes the proposed method and performance analysis. Finally, concluding remarks are given in Section IV.

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 threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighbourhood consists of 8 pixels, a total of $2^8 = 256$ different labels can be obtained depending on the relative gray values of the center and the pixels in the neighbourhood, i.e., the LBP value is computed by comparing its gray value with its neighbours. Example of LBP is shown in Fig. 2

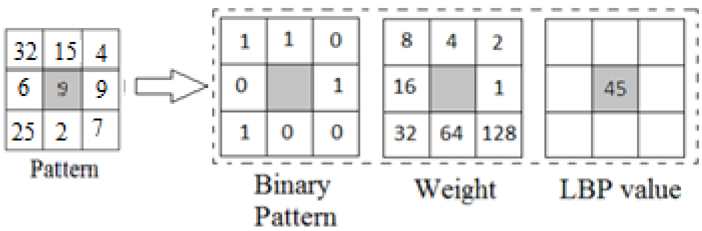

Figure 2. Example of obtaining LBP pattern

2.2. Local Tetra Pattern

Murula *et al.*[1] proposed the LTrP that describes the spatial structure of the local texture using the direction of the center gray pixel g_c. 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 are denoted as $I_\theta^1(g_p)$ |ɵ=0º, 90º. Let g_c denote the centre pixel in I, and let g_h and g_v horizontal and vertical neighbourhood of g_c, 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. PROPOSED METHOD AND EXPERIMENTATION

3.1. Proposed method

In the proposed technique a feature database is created using modified local tetra pattern (MLTrP). This system basically divided into two parts realtime and non realtime. There are two inputs to the proposed system, one is the image database and the other is a query image as shown in Fig. 5. The preprocessing is performed on both the inputs. Then we apply the first order derivatives at center pixel can be calculated as

$$I'_{0^\circ}(g_c) = I(g_h) - I(g_c) \qquad (1)$$
$$I'_{90^\circ}(g_c) = I(g_v) - I(g_c) \qquad (2)$$
$$I'_{45^\circ}(g_c) = I(g_d) - I(g_c) \qquad (3)$$

And direction of center pixel can be calculated as

$$I^1_{Dir}(g_c) = \begin{cases} 1, & I^1_{0^\circ}(g_c) \ge 0,\ I^1_{90^\circ}(g_c) \ge 0,\ I^1_{45^\circ}(g_c) \ge 0 \\ 2, & I^1_{0^\circ}(g_c) \ge 0,\ I^1_{90^\circ}(g_c) \ge 0,\ I^1_{45^\circ}(g_c) < 0 \\ 3, & I^1_{0^\circ}(g_c) < 0,\ I^1_{90^\circ}(g_c) \ge 0,\ I^1_{45^\circ}(g_c) \ge 0 \\ 4, & I^1_{0^\circ}(g_c) < 0,\ I^1_{90^\circ}(g_c) \ge 0,\ I^1_{45^\circ}(g_c) < 0 \\ 5, & I^1_{0^\circ}(g_c) < 0,\ I^1_{90^\circ}(g_c) < 0,\ I^1_{45^\circ}(g_c) > 0 \\ 6, & I^1_{0^\circ}(g_c) < 0,\ I^1_{90^\circ}(g_c) < 0,\ I^1_{45^\circ}(g_c) < 0 \\ 7, & I^1_{0^\circ}(g_c) \ge 0,\ I^1_{90^\circ}(g_c) < 0,\ I^1_{45^\circ}(g_c) \ge 0 \\ 8, & I^1_{0^\circ}(g_c) \ge 0,\ I^1_{90^\circ}(g_c) < 0,\ I^1_{45^\circ}(g_c) < 0 \end{cases} \qquad (4)$$

Based on distinct direction of center pixel, we compute the modified tetra pattern and separate them into binary patterns. On the basis of binary patterns compute the histograms of them. Construct the feature vector for each image which is stored in the image database. Finally, system matches the query image histogram with the histogram of images in the database using similarity distance metric. Similarity matching is done using Manhattan distance. The retrieved images are the set of best K images. Success definition is given by the precision and recall. Block diagram of the proposed system architecture is as shown below

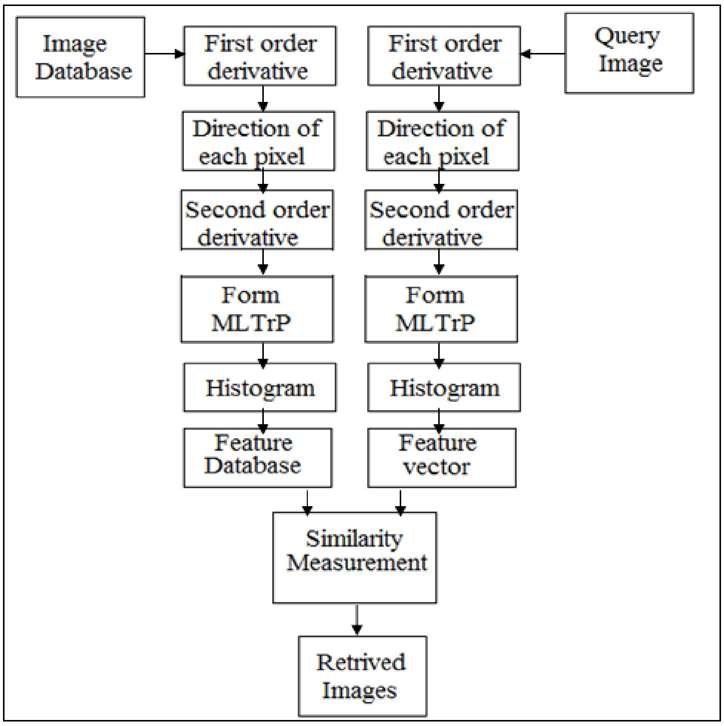

Figure 3. Proposed system architecture

3.2. Dataset

Images from the Corel database have been used for the experiment. This database consists of large number of images of various contents ranging from animals to outdoor sports to natural images [1]. 1000 Corel images are divided into 10 categories are Africans. Beach, Red bus, Flowers, Dinosaurs, Faces, Architecture, Elephants, Snow Mountain and Food. And each category contains 100 images of similar type. Size of all images is either 256X384 or 384X256. Fig.4 shows sample images from corel dataset.

Figure 4. Sample images from corel database

3.3. Result Analysis

We described the concept of modified local tetra pattern (MLTrP) and feature extraction process. The performance of proposed image retrieval system is compared with local binary pattern (LBP) and local tetra pattern (LTrP). Based on this analysis, we find that proposed method is powerful and effective in capturing information accurately which is a key to feature based CBIR. Because the ground truth of the whole database is known, every image in the database is used as a query. For each query, the precision for the retrievals at each level of recall (10%, 20%,...100%) is obtained. These precision values are then averaged to produce the average precision for the 1000 images in the database. The performance of the proposed method is measured in terms of average precision at different recall and is as shown in table 1 and Figure.5.

Table 1. Similarity matching using different methods

	Manhattan Distance		
% Recall	**LBP**	**LTrP**	**MLTrP**
10	46.03	55.43	80.75
20	51.15	66.31	84.08
30	51.65	70.17	86.49
40	48.66	64.37	80.71
50	41.1	55.11	70.4
60	31.3	41.59	56.79
70	26.36	33.08	46.6
80	22.43	28.6	42.35
90	19.92	24.72	39.28
100	18.51	21.74	34.07

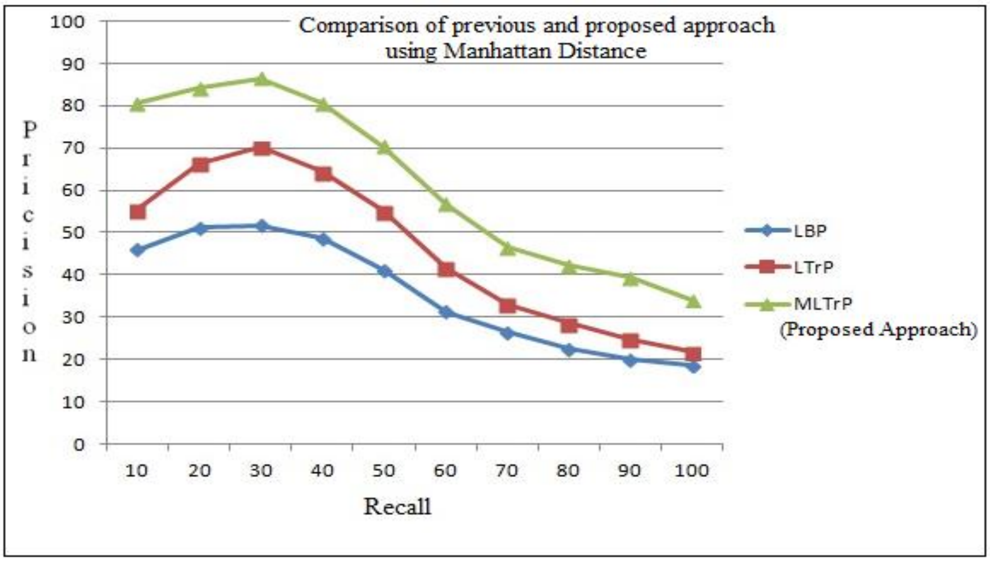

Figure 5. Performance Analysis

IV. Conclusions

This paper presents the modified local tetra pattern is a prominent feature descriptor for content based image retrieval. This pattern encodes the image based on distinct directions of pixels that are calculated by derivatives of horizontal, vertical and diagonal pixel. The performance improvement of proposed system has been compared with the existing method. As compared to the existing systems, proposed system gives the better retrieval results. This local pattern can be suitable for the various content based image retrieval systems. And it will improve the performance for CBIR systems in terms of percentage precision at different recall. Further the proposed system can be applied for different pattern recognition applications like fingerprint recognition, face recognition etc.

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