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## AN IMPROVED LOCAL TETRA PATTERN FOR CONTENT BASED IMAGE RETRIEVAL

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**Abstract:** Content-based image retrieval (CBIR)- an application of computer vision technique, addresses the problem in searching for digital images in large databases. This emerging approach includes the Local Binary Pattern (LBP), Local Derivative Pattern (LDP), Local Ternary Pattern (LTP) and Magnitude Pattern. In this paper, local Tetra pattern (LTrP) for CBIR method based on horizontal and vertical direction and also includes the magnitude pattern refers the uniform pattern and non-uniform pattern (i.e all the pixel in an image) is proposed. Unlike the conventional method which encodes the relationship between the referenced pixel and its surrounding neighbours by computing gray-level difference and the magnitude pattern refers the uniform pattern only the proposed includes 1). Pre-processing and direction of pixel which uses the pre-processing technique namely resize and calculated the first order derivatives along with  $0^\circ$  and  $90^\circ$ . 2). Extraction of pattern using LTrP and LBP used to classify each pixel using tetra direction and separate into binary patterns 3). Extraction of magnitude pattern is collected using magnitudes of derivatives. 4). Finally, Hybrid method is established to extract the feature of image by combining LTrP, LBP and magnitude pattern which is use to improve the performance. The performance analysis shows that the proposed method improves the retrieval result from 73.4%/42.7% to 79.5%/47.8% in terms of average precision/average recall on database DB.

**Key Word:** Local derivative Pattern, Content Based Image Retrieval, Magnitude Pattern, Local Binary Pattern.

### INTRODUCTION

Recent years have seen a rapid increase in the size of digital image collections. Every day, both military and civilian equipment generates giga-bytes of images. A huge amount of information is out there. However, we cannot access or make use of the information unless it is organized so as to allow efficient browsing, searching, and retrieval. The process of retrieving desired images from a large collection of database is quite complicated task in most web based search engines. Content-based image retrieval (CBIR), is a technique which uses visual contents to search images from large scale image databases according to users' interests, has been an active and fast advancing research area. During the past decade, remarkable progress has been made in both theoretical research and system development. However, there remain many challenging research problems that continue to attract researchers from multiple disciplines.

Content-based image retrieval uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In content-based image retrieval systems, the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The

similarities /distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results [1].

Color and texture have close relationship via fundamental micro-structures in natural images and they are considered as the atoms for pre-attentive human visual perception. The "texton" is a very useful concept in texture analysis and has been utilized to develop efficient models in the context of texture recognition or object recognition [2-5]. However, few works were proposed to apply texton models to image retrieval. How to obtain texton features, and how to map the low-level texture features to textons need to be further studied. To this end, in this paper we propose a new descriptor for image retrieval. The content based image retrieval techniques aims to respond to a query image with query similar resultant images obtained from the image database. The query image also gets processed for extracting features which are compared with features of database images by applying appropriate similarity measures for retrieving query similar Images. In the area of CBIR, it overcomes the difficulties of manual annotations by using visual feature based representations, such as color, texture, shape, etc. However, after over a decade of intensified. The

major bottleneck of this approach is the gap between visual feature representations and semantic concepts of images. Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features.

Local Binary Pattern (LBP) operator is a texture descriptor for grayscale images. Texture in a 2D image grayscale image is a phenomenon which consists of spatial structure (pattern) and contrast (amount of texture). LBP operator quantifies the pattern of texture. Satisfactory texture descriptors aim to have some of following properties

- a. Efficient discrimination of different types of textures.
- b. Robustness to pose and scale variations.
- c. Robustness to illumination variations.
- d. Robustness to spatial non-uniformity.
- e. Should work well for fairly small sample sizes.
- f. Computational Latency will be less.

Local ternary patterns (LTP) are an extension of Local binary patterns (LBP). The Local Binary Patterns threshold the pixels into three 0 and 1 whereas the LTP uses a threshold constant to threshold pixels into three values. The content based Image retrieval technique has wide applications includes Biometric recognition, Facial expression recognition, Iris recognition, Fingerprint recognition, Hair based person detection, Image retrieval, Image segmentation, Inspection of surfaces and so on.

## RELATED WORK

Texture is the main difficulty in a segmentation method. Many texture segmentation algorithms require the estimation of texture model parameters which is a very difficult task. 'JSEG' segmentation proposed in [6] overcomes these problems. Instead of trying to estimate a specific model for texture region, it tests for the homogeneity of a given color-texture pattern. 'JSEG' consists of two steps. In the first step, image colors are quantized to several classes. Replacing the image pixels by their corresponding color class labels, we can obtain a class-map of the image. Spatial segmentation is then performed on this class-map which can be viewed as a special type of texture composition [7]. The wavelet transform proposed in [8] provides a multi-resolution approach to texture analysis and classification. Studies of human visual system support a multi-scale texture analysis approach, since researchers have found that the visual cortex can be modeled as a set of independent channels, each tuned to a particular orientation and spatial frequency band. That is why wavelet transforms are found to be useful for texture feature extraction.

In [9] the use of Gauss mixture vector quantization (GMVQ) was proposed as a quantization method for color histogram generation. GMVQ is known to be robust for quantizer mismatch, which motivates its use in making color histograms for both the query image and the images in the database. Results show that the histograms made by GMVQ with a penalized log-likelihood (LL) distortion yield better retrieval performance for color images than the conventional methods of uniform quantization and VQ with squared error distortion. One simple but popular quantization method is uniform quantization of each color channel for every

pixel.[9] However, uniform quantization not only ignores the interdependency among pixels but also does not consider any actual color distributions in a given image database (DB). A new feature extractor and descriptor, namely Multi-Texton Histogram (MTH) was presented in [10], for image retrieval. MTH can be viewed as an improved version of TCM. It is specially designed for natural image analysis and can achieve higher retrieval precision than that of Edge Orientation Auto-correlogram (EOAC) [11] and TCM [12]. It integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram, and can represent the spatial correlation of color and texture orientation.

The prominent boundary detection based hierarchical approach with region feature extraction would significantly improve the quality of retrieval results. Many state of the art techniques suggest that semantic domain based image retrieval systems, comparing meaningful concepts improve quality of retrieved image set. Effective learning and inferring of meaningful concepts may get proved critical for such systems. The state of the art image retrieval techniques have a scope of under-going significant technical evolution [13]. A novel manifold learning algorithm, called GIR, for image retrieval was defined. The standard spectral technique is then used to find an optimal projection, which respects the graph structure. This way, the Euclidean distances in the reduced subspace can reflect the semantic structure in the data to some extent. The proposed framework in [14] can be efficiently merged textual and image features for image retrieval systems. To incorporate an image analysis algorithm into the text-based image search engines without degrading their response time, the framework of multi-threaded processing is developed. In a high-level semantic retrieval system, the search engine to retrieve a large number of images using a given text based query was utilized. In low-level image retrieval process, the system provides a similar image search function.

Various techniques for extraction and representation of image features like histograms local (corresponding to regions or sub-image ) or global, color layouts, gradients, edges, contours, boundaries & regions, textures and shapes have been reported in the literature. Histogram is one of the simplest image features [15]. Despite being invariant to translation and rotation about viewing axis, lack of inclusion of spatial information is its major drawback. Many totally dissimilar images may have similar histograms as spatial information of pixels is not reflected in the histograms. Consequently, many histogram refinement techniques have been reported in the literature. Histogram intersection based method for comparing model and image histograms was proposed in [16] for object identification.

## PROPOSED METHOD

The goal of the proposed system is to detect the most relevant images from the databases. In this paper, the LTrP includes LDP, LBP, LTP and Magnitude Pattern which are used to retrieve feature from the images.

### *Preprocessing and computing the direction of pixel:*

The initial step in processing the image is Pre-Processing. Pre-Processing, in general, processing of an image in order

to prepare it for the primary processing. There are several preprocessing techniques such as Dominated variables, Tightening bounds, Make A sparser, Scaling and so on. The proposed system uses the pre-processing technique namely Image Resize. The method is applied to improves the image retrieval time.

Given image I, the first-order derivatives along 0° and 90° directions are denoted as  $I_0^1(g_p)$  and  $I_{90}^1(g_p)$  where  $g_p$  denoted as neighboring pixels of an image. Based on vertical, horizontal direction pixel values calculate the first order derivatives for every individual pixel. The first-order derivatives along 0° and 90° directions are denoted as

$$I_0^1(g_c) = I(g_h) - (g_c) \quad (1)$$

$$I_{90}^1(g_c) = I(g_v) - (g_c) \quad (2)$$

Where,  $g_c$  – Center pixel and  $g_h, g_v$  – horizontal and vertical direction of center pixel.

Based on the first order derivatives value of pixel, the direction of every pixel can be calculated as

$$I_{Dir}^1(g_c) = \begin{cases} 1, & I_0^1(g_c) \geq 0 \text{ and } I_{90}^1(g_c) \geq 0 \\ 2, & I_0^1(g_c) < 0 \text{ and } I_{90}^1(g_c) \geq 0 \\ 3, & I_0^1(g_c) < 0 \text{ and } I_{90}^1(g_c) < 0 \\ 4, & I_0^1(g_c) \geq 0 \text{ and } I_{90}^1(g_c) < 0 \end{cases} \quad (3)$$

Where,  $I_0^1(g_c)$  – Value of center pixel in horizontal direction,  $I_{90}^1(g_c)$  – value of center pixel in horizontal direction

**Input:** query image; **Output:** Direction of pixel values

**Steps:**

- Load and resize the image and convert into grayscale values.
- Based on vertical, horizontal direction pixel values calculate the first order derivatives for every individual pixel.
- Using First order derivative values the direction of the pixel can be calculated.

From (3), it is obvious that the possible direction for each center pixel can be either 1, 2, 3, or 4, and finally, the image is converted into four values, i.e., directions.

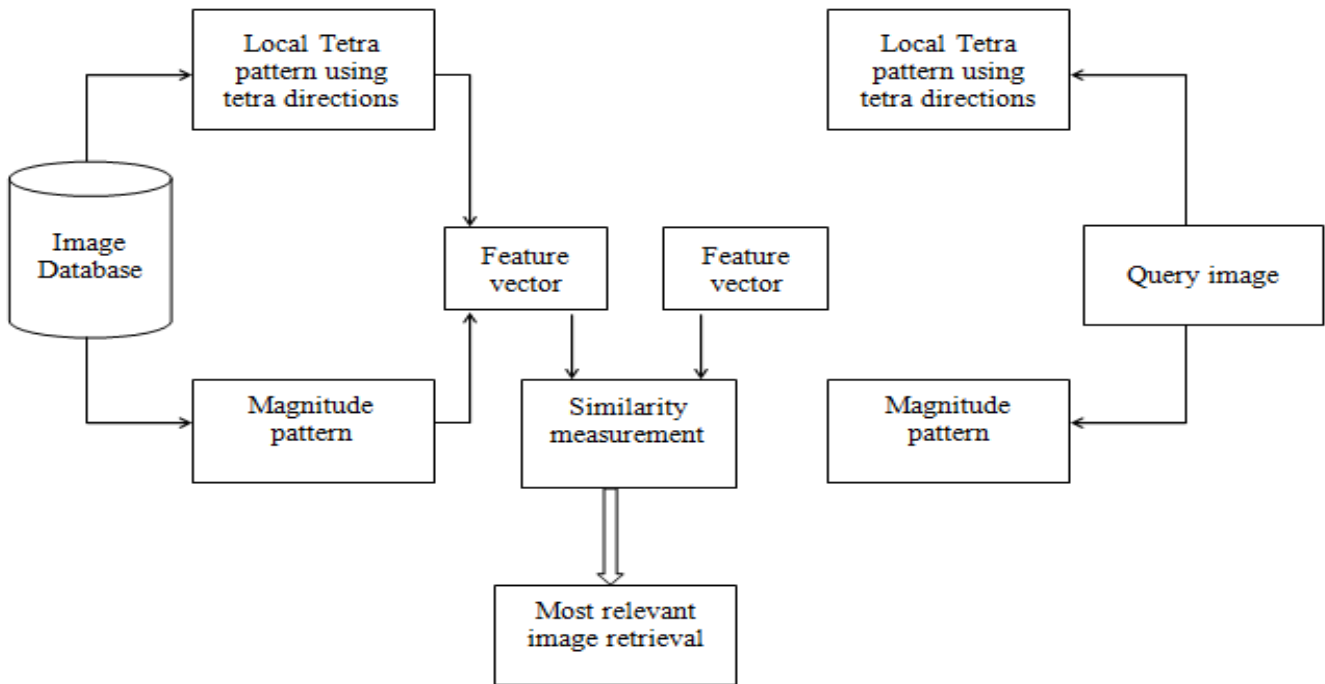


Figure: 1 Block diagram of proposed system

**Constructing Terra Pattern:**

The LTrP is able to encode images with four distinct values as it is able to extract more detailed information. LTrP encodes the relationship between the center pixel and its neighbors based on directions that are calculated with the help of (n-1) th-order derivatives. The second-order LTrP<sup>2</sup>( $g_c$ ) is defined as

$$LTrP^2(g_c) = \{f_2(I_{Dir}^1(g_c), I_{Dir}^1(g_1)), \dots, f_2(I_{Dir}^1(g_c), I_{Dir}^1(g_p))\} p=8 \quad (4)$$

$$f_2(I_{Dir}^1(g_c), I_{Dir}^1(g_p)) = \begin{cases} 0, & I_{Dir}^1(g_c) = I_{Dir}^1(g_p) \\ I_{Dir}^1(g_p), & \text{else} \end{cases} \quad (5)$$

LTrP encodes the relationship based on the direction of the center pixel and its neighbors, which are calculated by combining (n-1)th - order derivatives of the 0° and 90° directions.

**Input:** Direction of pixel values; **Output:** 8-bit tetra pattern

**Steps:**

- Select a pixel and consider it as a center pixel.
- Choose its 8 neighboring pixels around it.

- c. Compare the center pixel value with neighbor pixel values.
- d. If the neighbor pixel value matches the center pixel value replace it by '0'. Otherwise retained the same neighbor pixel value.
- e. Finally, it gives 8-bit tetra pattern for every pixel.

From (4) and (5), we get 8-bit tetra pattern for each center pixel. Then, we separate all patterns into four parts based on the direction of center pixel. Finally, the tetra patterns for each part (direction) are converted to three binary patterns.

The Local Binary Pattern (LBP) is an operator for image description that is based on the signs of differences of neighboring pixels. It is fast to compute and invariant to monotonic gray-scale changes of the image. so the direction

of center pixel  $I_{Dir}^1(g_c)$  obtained using (4) be "1"; then,  $LTrP^2$  can be defined by segregating it into three binary patterns. Every tetra pattern separate into 3 binary patterns based on direction of pixel values. Similarly, the other three tetra patterns for remaining three directions (parts) of center pixels are converted to binary patterns. Thus, we get 12 (4 X 3) binary patterns.

**Constructing the Magnitude Pattern:**

Although the sign component extracts more useful information as compared with the magnitude constituent, exploiting the combination of sign and magnitude mechanisms can provide better clues, which are not evident in any one individual constituent. This concept has motivated us to propose the 13th binary pattern by using the magnitudes of horizontal and vertical first-order derivatives.

137	138	132	135	138
125	127	130	134	124
134	125	124	125	122
133	131	134	129	122
152	147	152	147	144

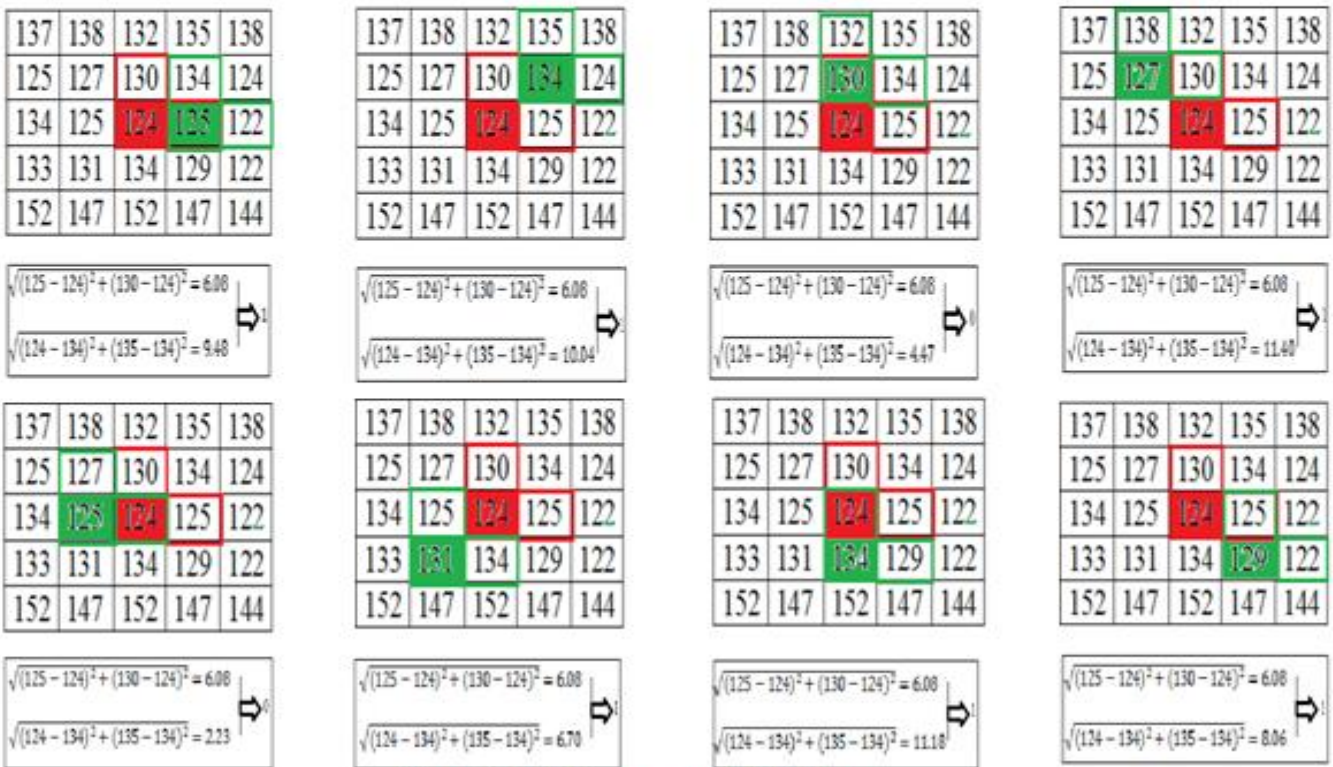


Figure. 2. Shows an example to obtain the magnitude patterns. For the magnitude pattern, the bit is coded with "1" when the magnitude of the focus pixel is less than the magnitude of its neighbor, or else "0."

**Input:** Query image; **Output:** Magnitude pattern

**Steps:**

- a. Select a pixel and choose the adjacent pixel in horizontal and vertical position, Calculate the difference between a pixel and adjacent pixels.
- b. Similarly choose its 8 neighboring pixels around it, calculate difference between all the neighboring pixels and its adjacent pixels.

- c. Compare the difference of a pixel value and the differences 8 neighboring pixel values.
- d. If the difference value of a pixel is lesser than the difference value neighboring pixels means it gives '1' as a magnitude pattern values.
- e. If the difference value of a pixel is greater than the difference value neighboring pixels means it gives '0' as a magnitude pattern values



For the local pattern with neighborhoods,  $2^P$  variations of LBPs are possible, resulting in the feature vector length of  $2^P$ . The computational cost of this feature vector is calculated for both uniform and non-uniform patterns. After identifying the local pattern (the LBP, the LTP, the LDP, or the 13-binary-pattern form LTrP), the whole image is represented by building a histogram.

In order to reduce the computational cost, we think through the uniform patterns. The uniform pattern refers to the uniform presence pattern that has limited incoherence in the circular binary representation. In this paper, those patterns that have less than or equal to two incoherence in the circular binary image are referred to as the uniform patterns, and the residual patterns are referred to as nonuniform. Thus, the distinct uniform patterns for a given query image would be  $P(P-1)+2$ . After identifying the local pattern (the LBP, the LTP, the LDP, or the 13-binary-pattern form LTrP), the whole image is represented by building a histogram.

**Compute feature vector and query matching:**

Extracting the feature vector from the combined 13(4X3+magnitude LBP) binary pattern using histograms. Finally, measure the similarity and retrieve the most relevant matches. Calculate the feature vector for the every image in

the database. Compare the query image with the images in the database and Select the top-matched images by measuring the distance between the query image and the images in database using

$$D(Q, DB) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{j,i}} - f_{Q_i}}{1 + f_{DB_{j,i}} + f_{Q_i}} \right|$$

Where,  $f_{DB_{j,i}}$  is the  $i$ th feature of  $j$ th image in the database DB and  $f_{Q_i}$  is the feature of query image.

**EXPERIMENTATION RESULTS**

This database consists of a large number of images of various contents ranging from animals to outdoor sports to natural images. These images have been pre-characterized into different categories each of size 100 by domain experts.

The images in the database contains the different dimensions and its collected into single database images. The performance of the proposed method is measured in terms of average precision and average recall. Performance analysis shows that the proposed method improves the retrieval result from 73.4%/42.7% to 79.5%/47.8% in terms of average precision/average recall on database DB

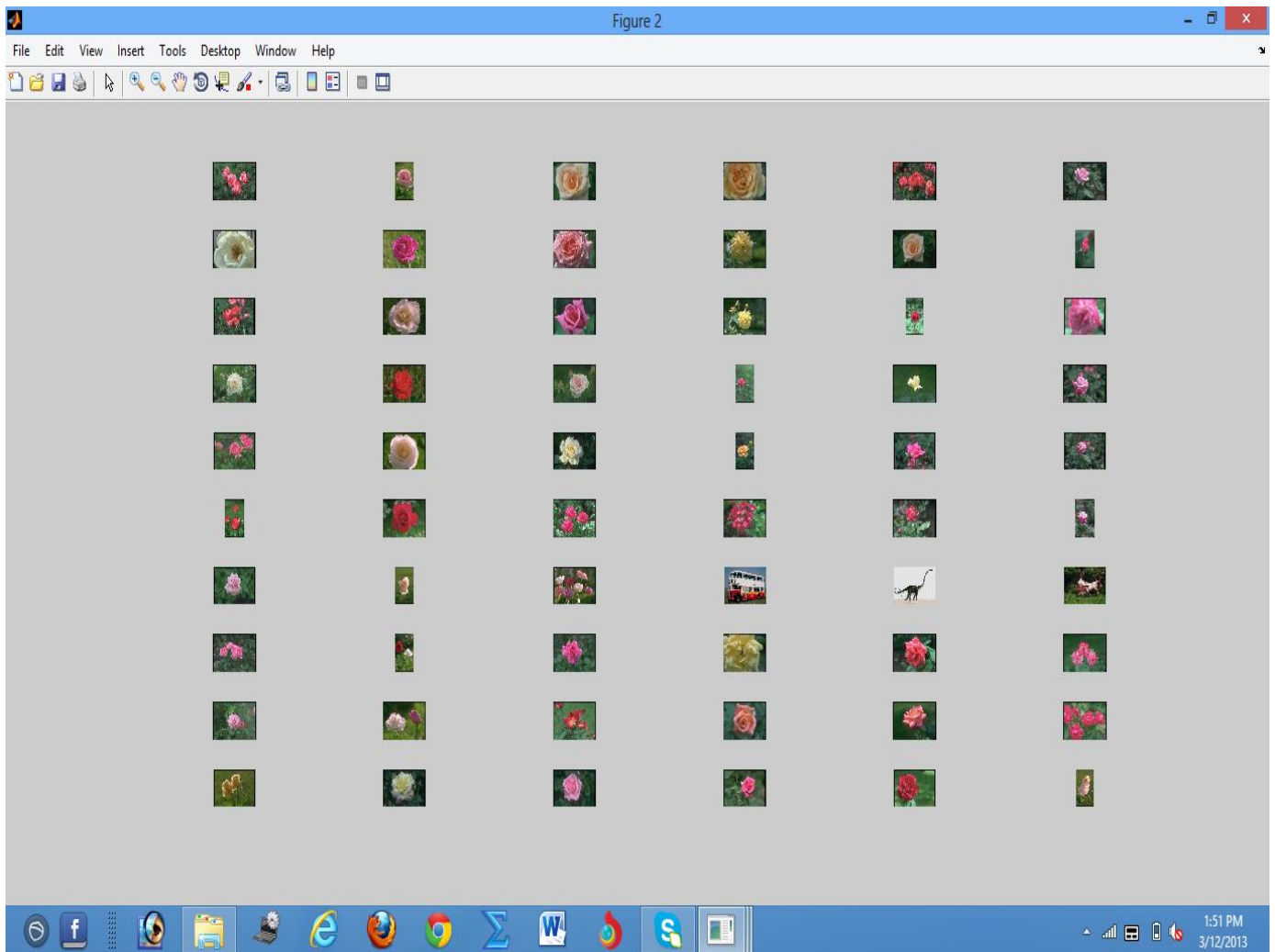


Figure 3: Sample retrieval results from DB for given query image (Rose)

## CONCLUSION

In this paper, a novel approach referred as LTrPs for CBIR was presented. The LTrP encodes the images based on the direction of pixels that are calculated by horizontal and vertical derivatives. As this method uses calculation of the magnitude pattern for all pixel in the image, it improves the image retrieval rate and image retrieval time. In this proposed system, only horizontal and vertical pixels have been used for derivative calculation. Results can be further improved by considering the diagonal pixels for derivative calculations in addition to horizontal and vertical directions. Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

## REFERENCES

- [1] Dr. Fuhui Long, Dr. Hongjiang Zhang and Prof. David Dagan Feng, Fundamentals of Content-Based Image Retrieval.
- [2] Guang-Hai Liu a, \_, LeiZhang b, Ying-KunHou d, Zuo-Yong Li c, Jing-YuYang, Image retrieval based on multi-texton histogram, Pattern Recognition, 43 (2010) , 2380–2389
- [3] B. Julesz, Textons, the elements of texture perception and their interactions, Nature 290 (5802) (1981) 91–97.
- [4] T.Leung, J.Malik, Representing and recognizing the visual appearance of materials using three-dimensional textons, International Journal of Computer Vision, 43(1)(2001), 29–44.
- [5] J. Winn, A. Criminisi, T. Minka, Object categorization by learned universal visual dictionary, in: Proceedings of the 10th IEEE International Conference on Computer Vision, (2005) pp. 1800–1807.
- [6] Ying Liua, Dengsheng Zhanga, Guojun Lua, Wei-Ying Mab, "A survey of content-based image retrieval with high-level semantics", journal of pattern recognition society, Elsevier, 40, 262-282, 2007."
- [7] Y. Deng, B.S. Manjunath, Unsupervised segmentation of color-texture regions in images and video, IEEE Trans. Pattern Anal. Mach. Learn. (PAMI) 23 (8) (2001) 800–810.
- [8] Narendra Gali, B.Venkateshwar Rao, Abdul Subhani Shaik, Color and Texture Features for Image Indexing and Retrieval, International Journal of Electronics Communication and Computer Engineering, Vol 3, No.1, 2012.
- [9] SangohJeong, Chee Sun Won, and Robert M. Gray, Image retrieval using color histograms generated by Gauss mixture vector quantization, computer vision and image understanding, Elsevier, 94, 44-66.
- [10] Guang-Hai Liu, LeiZhang, Ying-KunHou, Zuo-YongLi, Jing-YuYang, Image retrieval based on multi-texton histogram, Pattern Recognition 43 (2010) 2380–2389.
- [11] F. Mahmoudi, J. Shanbehzadeh, et al., Image retrieval based on shape similarity by edge orientation autocorrelogram, Pattern Recognition 36 (8) (2003) 1725–1736.
- [12] G.-H. Liu, J.-Y. Yang, Image retrieval based on the texton co-occurrence matrix, Pattern Recognition 41 (12) (2008) 3521–3527.
- [13] Darshak G. Thakore<sup>1</sup>, A. I. Trivedi, Content based image retrieval techniques – Issues, analysis and the state of the art.
- [14] P.Jayaprabha, R.Somasundaram, Content Based Image Retrieval Methods Using Graphical Image Retrieval Algorithm (GIRA), International Journal of Information and Communication Technology Research, Volume 2 No. 1, January 2012.
- [15] Jayaprabha, Somasundaram, Content Based Image Retrieval Methods Using Graphical Image Retrieval Algorithm, International Journal of Information and Communication Technology Research, Volume 2 No. 1, January 2012
- [16] Subrahmanyam Murala, R. P. Maheshwari, Local Tetra Patterns: A New Feature Descriptor for Content-Based Image Retrieval, IEEE Transactions on Image Processing, Vol. 21, No. 5, May 2012.

### Short Bio Data for the Author



K. Thangadurai was born in Tamil Nadu, India, in 1989. He received a B.E degree in Computer Science and Engineering from Anna University, Chennai, India in 2010. He is currently pursuing M.E in Computer Science and Engineering under Anna University, Coimbatore, India.



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