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Local Directional Mask Maximum Edge Pattern for Image Retrieval

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ABSTRACT: The main objective of this project is to get the desired images easily. Irrespective of checking multiple images from million coordinates this project will try to get the particular images of particular areas. The method can also be used in biomedical image retrieval for the proper detection of diseases. It can also be used for the security purpose for the proper face recognition. Initially Local binary pattern (LBP) and LBP variants collect the relationship between the centre pixel and its surrounding neighbours in an image. Thus, LBP based features are very sensitive to the noise variations in an image. Therefore the proposed method is to collect the maximum edge patterns (MEP) and maximum edge position patterns (MEPP) from the magnitude directional edges of face/image. Further, the robustness of the proposed method will be increased by integrating it with the multiresolution Gaussian filters. Some new algorithm based on 8 or 10 directional mask will be used to increase the efficiency.

KEYWORDS: Image Retrieval, Gaussian Filter, MEPP, LDMaMEP

I.INTRODUCTION

Content-based image retrieval, 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 since the 1990s. 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. Before introducing the fundamental theory of content-based retrieval, we will take a brief look at its development. Early work on image retrieval can be traced back to the late 1970s. In 1979, a conference on Database Techniques for Pictorial Applications was held in Florence. Since then, the application potential of image database management techniques has attracted the attention of researchers. Early techniques were not generally based on visual features but on the textual annotation of images. In other words, images were first annotated with text and thensearched using a text-based approach from traditional database managementsystems. Text-based image retrieval uses traditional database techniques to manage images. Through text descriptions, images can be organized by topical or semantic hierarchies to facilitate easy navigation and browsing based on standard Boolean queries. . Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results. 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 typical content-based image retrieval systems (Figure 1-1), 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.

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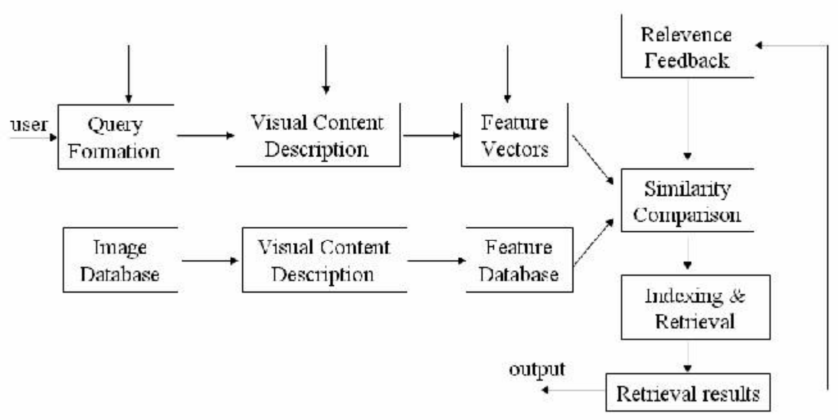

Figure 1 Diagram for content-based image retrieval system

II. LITERATURE SURVEY

The feature extraction is a key step in pattern recognition (PR) application. The effectiveness of feature extraction depends upon the descriptor adopted for extracting features from given images/ faces. In content based image retrieval (CBIR), the feature descriptor utilizes the visual contents, color, texture, shape, faces, spatial layout etc., to represent and index the database. These features can be further classified as general features such as color, texture, shape and domain specific features such as human faces, fingerprints, etc. These descriptors should have to show high variance between the different category images/faces and no or little variance between within the category images/faces. There is no single best representation of an image in various conditions such as illumination changes, noise and so on. Thus, there remain some challenging problems that attract the researcher's interest towards PR. The colour composition of an image can turn out to be a powerful feature for the purpose of CBIR, if extracted in a perceptually oriented way and kept semantically intact. Furthermore, colour structure in a visual scenery is robust to noise, image degradations, changes in size, resolution and orientation. Eventually most of the existing CBIR systems use various colour descriptors to retrieve relevant images (or visual multimedia material); however, their retrieval performance is usually limited especially on large databases due to lack of discrimination power of such colour descriptors. In early year's discrete wavelet transform (DWT) based features are used for texture analysis, such as texture classification and texture retrieval. However, the DWT has limited directional (0°, 90° and ±45°) selectivity. To address this directional limitation, Gabor transform (GT), rotated wavelet filters, dual-tree complex wavelet filters (DT-CWFs), DT rotated CWFs , and rotational invariant complex wavelet filters have been proposed for texture image retrieval. Further, the combination of colour and texture features has been used for image retrieval. Liu et al. have integrated the colour and texture features called multi-texton histogram (MTH) for image retrieval. MTH integrates the advantages of co-occurrence matrix and histogram by representing the attribute of co-occurrence matrix using histogram. Further they introduced the micro-structure descriptor which is built based on the underlying colours in micro-structures with similar edge orientation. The performance of these methods is excellent in constrained environment but their performance degrades in environmental variation. Recently, active researchers in image retrieval and face recognition using the pattern based features, due to their effectiveness and the ease of extracting it from the face/image. Ojalaet al. have proposed the local binary patterns (LBP) which can show better performance as well as less computational complexity for texture classification. Success of LBP variants in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification, face recognition, object tracking, image retrieval, fingerprint matching and interest point detection. Guo et al. developed the completed LBP (CLBP) scheme for texture classification. Further, they have developed the learning framework which can estimate the optimal pattern subset of interest by simultaneously considering the robustness, discriminative power and representation capability of texture features. They integrated these features with existing LBP variants such as conventional LBP, rotation invariant patterns, local patterns with anisotropic structure, CLBP and local ternary pattern (LTP) to derive new image features for texture classification. Zhang et al. proposed the local derivative patterns (LDP) for face recognition, where they

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considered LBP as non-directional first-order local patterns collected from the first-order derivatives and extended the same approach for nth order LDP . Xie et al. have proposed the local Gabor XOR patterns operator for face recognition. The versions of LBP in the open literature cannot adequately deal with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc. To address this problem, we propose a novel descriptor, local directional mask maximum edge patterns (LDMaMEP) for image retrieval and face recognition applications. The LDMaMEP encodes the structure of local region based on its directional information which is computed with the aid of eight directional mask windows. Further, the robustness of the proposed method is increased by integrating it with the Gaussian filters. The robustness of the proposed method is analysed with the help of sample image and experiments on four benchmark databases. The organisation of the paper is as follows: In Section 1, a brief review of image retrieval and related work is given. Section 2, presents a concise review of local patterns (LBP, LTP and LDP). Section 3, presents the concept of proposed feature extraction method, proposed system framework, analysis and query matching.

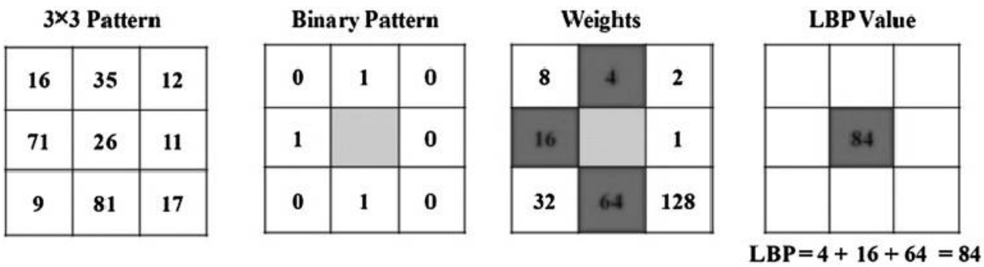

Fig. 2 Calculation of LBP

III. PROPOSED METHODOLOGY

3 Local directional mask maximum edge patterns Existing LBP based features collect the relationship between the centre pixel and its surrounding neighbours (based on the sign of edges) in an image. Thus, these features are largely sensitive to lighting changes and noise conditions. In literature, it’s already proved that the edge magnitudes are more robust to the noise and lighting changes. In this paper, we propose theLDMaMEP based on the magnitude of directional information (edges) which are collected from directional mask windows (see in Fig.2) for image retrieval and face recognition applications. The detailed description about LDMaMEP is given as follows.

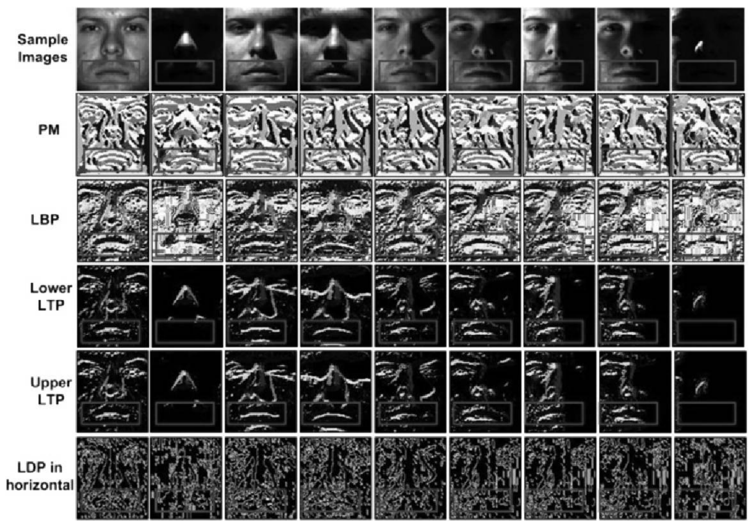

Fig. 3 Analysis of various pattern based methods on sample face images under illumination changes. PM: proposed method (LDMaMEP)

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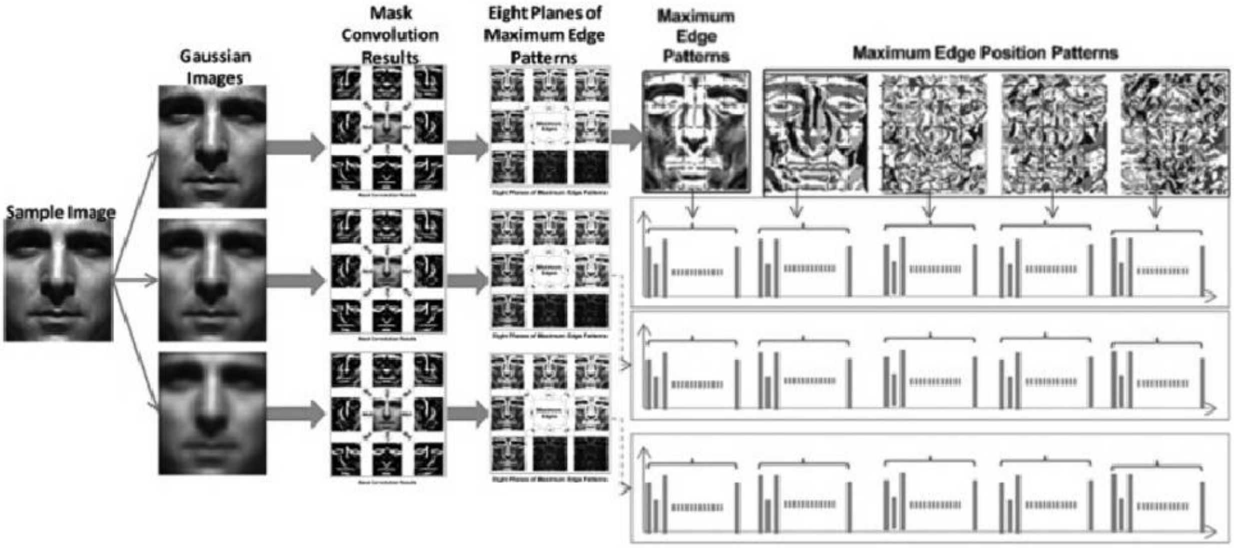

Fig. 4 Proposed feature extraction framework

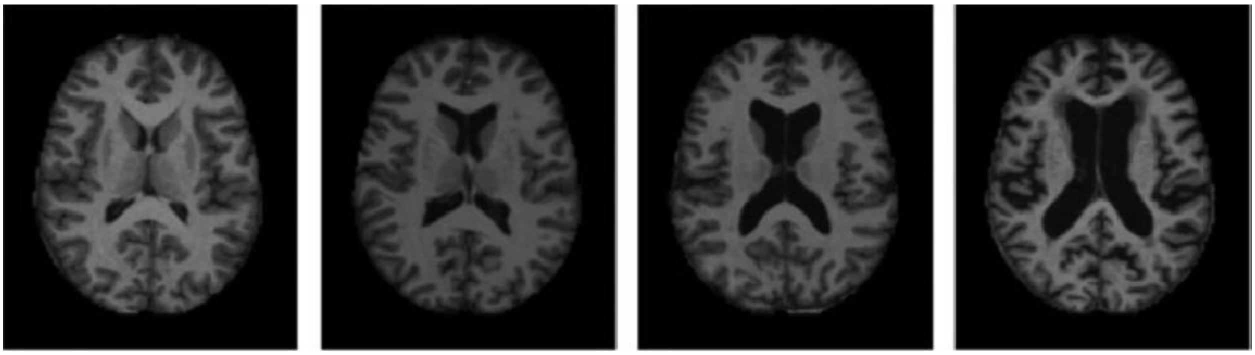

Fig. 5 Sample images from OASIS database (one image per category)

Maximum edge patterns (MEP)

The MEP is coded based on the magnitude of directional information. Given an image I, the directional information is collected with the aid of eight directional masks (see in Fig. 2)

$$D_{\alpha}(x, y) = \sum_{s} \sum_{t} I((x - s, y - t) \times Ma_{\alpha}^{*}(s, t);$$

$$\forall \alpha = 1, 2, \ldots, 8$$

The maximum edges are obtained by the magnitude of eight directional edge information as shown below

$$\alpha_k(x, y) = \arg_{\alpha}\left(\max{}^{k}\left(|D_1(x, y)|, |D_2(x, y)|, \ldots, |D_8(x, y)|\right)\right)$$

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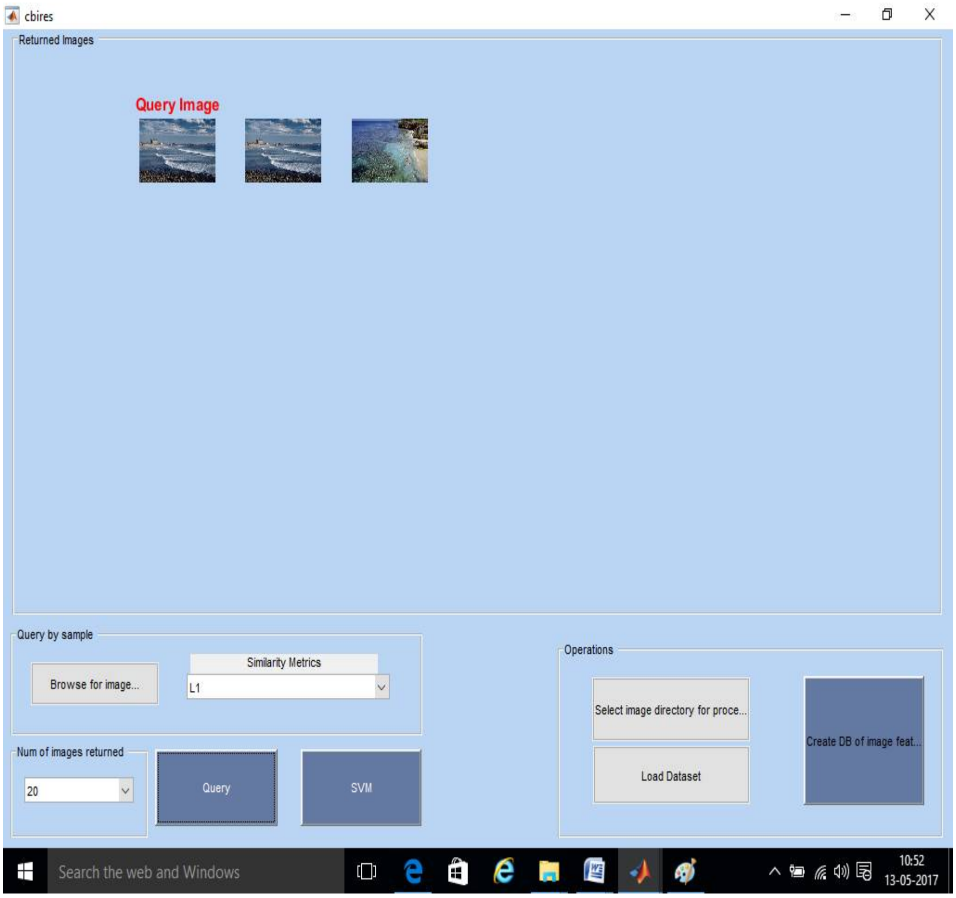
IV. EXPERIMENTAL RESULTS

L1 METRIC

Given a collection of n points in the plane, we exhibit an algorithm that computes the nearest neighbor in the north-east (first quadrant) of each point, in the L_1 metric. By applying a suitable transformation to the input points, the same procedure can be used to compute the L_1 nearest neighbor in any given octant of each point. This is the basis of an algorithm for computing the minimum spanning tree of the n points in the L_1 metric. All three algorithms run in O(n lg n) total time and O(n) space

Result Of L1 Matric



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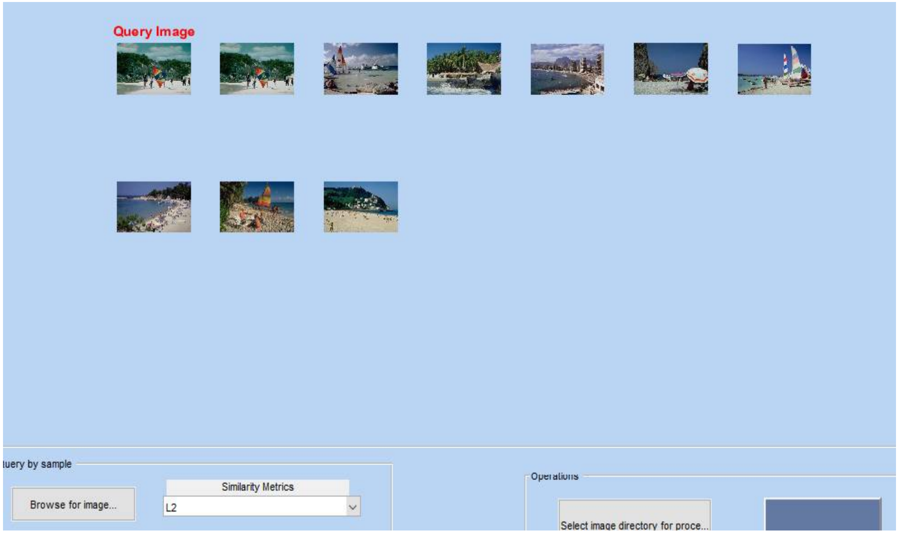
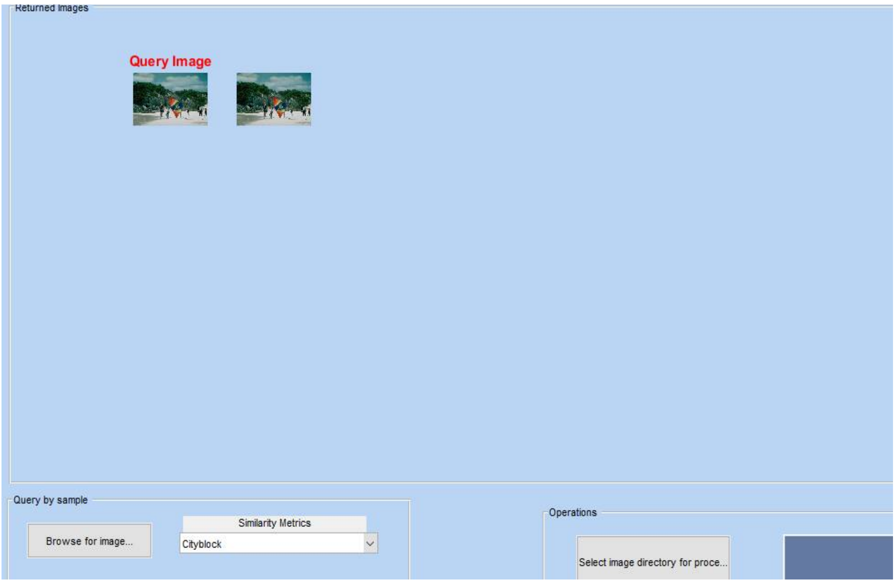
Result Of L2 Matric



Comparison between L1 and L2

When you are dealing with error measures (such as residuals in a regression model), L2 tends to produce worse overall fit (greater average error) than L1 in exchange for mitigating the worst errors. Which is better depends on how sensitive you are to occasional large screw-ups v. generally mediocre estimates. L1 can allow sparse solutions (solution vectors with many zeroed values) as an optimum and if you have a suitable method like gradient or quadratic linear approx methods you might get to those solutions. These are useful properties when looking for PCA feature selection problems or other matrix decomposition problems.

Result Of Standardised L2 Filter



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V. CONCLUSION

Here we have presented a novel approach referred as LDMaMEP for image retrieval and face recognition. LDMaMEP encodes the structure of local region based on its directional information which is computed with the aid of eight directionalmask windows. Further, the robustness of the proposed method will be increased by integrating it with the Gaussian filters. The performance of the proposed method will be tested by conducting different experiments and different algorithms which will further help in better efficiency and extraction of accurate data easily. With the above results, we can say that the city block filter and relative deviation filter response are better when an image is searched form the local database or we can say that with the help of different filters the efficiency to find accurate image can be increased. Some filters show some images and some show different images. And when the result of all the images are compared we can reach to the conclusion image easily. The efficiency of these filters is increased to almost 90%. Gaussian filter's efficiency was 60% and these images resulted in 90% efficiency.

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