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MRI and CT Images Indexing and Retrieval Using LBP and LMEPVEP

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ABSTRACT: *Recently, the content based image retrieval has become the exclusive topic and the techniques of content based image retrieval have achieved a great development. In many areas of commerce, government, academics and hospitals, large collections of digital images are being created. Many of these collections are the product of digitizing existing collection of analog photographs, drawings, etc., usually, the only way of searching these collections was by keyword indexing, or simply by browsing. Digital images database open the way to Content based searching. Image retrieval methods based on, texture, shape and semantic image are discussed, analysed and compared. Content based image retrieval can be performed by two methods – LBP (Local Binary Pattern) and LMePVEP (Local mesh peak valley edge patterns). The LBP extracts the gray scale relationship between the center pixel and its surrounding s in an image. LMePVEP extracts the gray scale relationship among the s for a given center pixel in an image. The relations among the s are peak or valley edges which are obtained by performing the first-order derivative. The performances of the two methods are tested by conducting experiments on the sample images from the MRI and CT scan database.*

Keywords*: LMePVEP, indexing, retrieval, peak edges, valley edges, first-order derivative.*

I. INTRODUCTION

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools. Image search is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be meta tags, colour distribution in images, region/shape attributes, etc.

- Image meta search - search of images based on associated metadata such as keywords, text, etc.
- Content-based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colours, shapes etc.) to a user-supplied query image or user-specified image features.
- List of CBIR Engines - list of engines which search for images based image visual content such as colour, texture, shape/object, etc.
- Image collection exploration - search of images based on the use of novel exploration paradigms.
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II. TEXT-BASED IMAGE RETRIEVAL

Searching for interesting and useful images from among the enormous number of images available generally relies either on content-based image retrieval using visual image features or text based search using text queries to search for images based on textual annotations of the images. In text-based image retrieval, the Incomplete Annotation Problem (IAP) can greatly degrade retrieval effectiveness. Often it is difficult to find a sample image to use as a query image for visual search, and thus the text-based method is often the most commonly used by search engine vendors such as Google, Bing and Yahoo. Where high quality detailed annotations are available, the text-based method can be very effective. However, annotations are unfortunately often found to be noisy or incomplete, e.g. Picasa1, Flickr2.The annotations are generally provided by those contributing the images that often only provide very brief or sometimes inaccurate details. These issues of poor image annotation can greatly affect image retrieval effectiveness based on textual metadata. Without complete textual description of an image, it is difficult to reliably match the image with text queries, Since relevant images may not contain useful annotation terms. Thus is not possible for the retrieval system to return the relevant images with high accuracy. This effect is referred as the incomplete annotation problem (IAP) in image retrieval. Manual annotation is impossible for a large database. Manual annotation is not accurate. A picture is worth a thousand words, so retrieval is so difficult. Surrounding text may not describe the image.

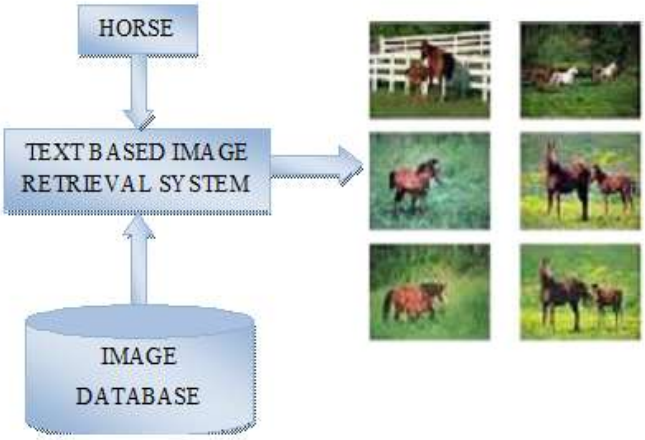

Fig.1 Text based image retrieval

III. CONTENT BASED IMAGE RETRIEVAL

CBIR or Content Based Image Retrieval is also known as QBIC or Query by Image Content. It was developed by IBM, Almaden Research Centre, to allow users to graphically pose and refine queries based on multiple visual properties such as, texture and shape. It supports queries based on input images, user-constructed sketches, and selected and texture patterns. Visual features, such as colour, texture, and shape information, of images are extracted automatically. Similarities of images are based on the distances between features.

Features

- Colour features computed are the 3D average colour vector of an object or the whole image in RGB, YIQ, Lab, and Munsell colour space and a 256-dimensional RGB colour histogram.
- The texture features used in CBIR are modified versions of the coarseness, contrast, and directionality features proposed by Tamura.
- The shape features consist of shape area, circularity, eccentricity, major axis orientation and a set of algebraic moment invariants.

The major axis orientation and the eccentricity are computed from the second order covariance matrix of the boundary pixels. The major axis orientation as the direction of the largest eigenvector and eccentricity as the ratio of the smallest eigen value to the largest one. For the database images, the shape features are extracted for all the object contours, semi automatically computed in the database population step. In this process, the user enters an approximate object outline, which is automatically aligned with the nearby image edges, using the active contours technique. In this object identification step, the user can also associate text to the outlined objects.

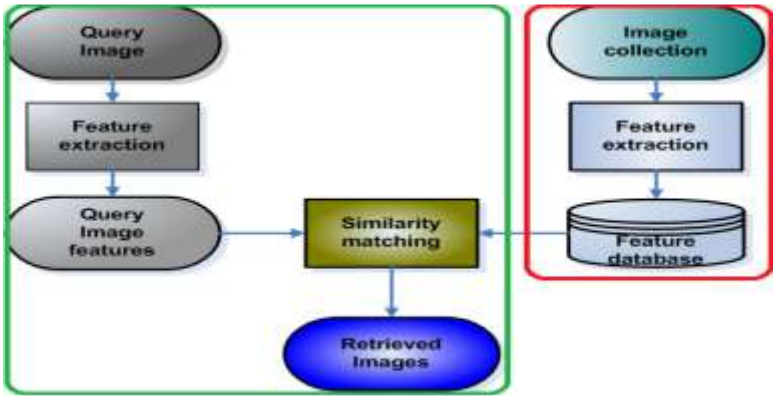

Fig.2 Content Based Image Retrieval (CBIR)

CBIR also implemented a method of retrieving images based on a rough user sketch. For this purpose, a reduced binary map of edge points represents images in the database. This is obtained as follows: first, the colour image is converted to a single band luminance using a Canny edge detector, the binary edge image is computed and is next reduced to size 64´64. Finally this reduced image is thinned.

Querying CBIR allows queries based on example images, user-constructed sketches and selected colour and texture patterns. In the last case, the user chooses colours or textures from a sampler. The percentage of a desired colour in an image is adjusted by moving sliders.

Matching For the average colour, the distance between a query object and database object is a weighted Euclidean distance, where the weights are the inverse standard eviation for each component over the samples in the database. In matching two colour histograms, two distance measures are used, one low dimensional, easy to compute (the average colour distance) and one much more computationally expensive (the quadratic histogram distance). The first one (which is computed for all the images in the database) acts as a filter, limiting the expensive matching computation to the small set of images retrieved by the first matching. Two shapes are matched also by a similar weighted Euclidean distance between shape feature vectors. In a query by sketch, after reducing the binary sketch image drawn by the user to size 64´64, a correlation based matching is performed, a kind of template matching. This is done by partitioning the user sketch into 8´8 blocks of 8´8 pixels and fined the maximum correlation of each block of the sketch within a search area of 6´16pixels in the image database (this is done by shifting the 8´8 block in the search area). This local correlation score is computed on the pixel level using logical operations. The matching score of a database image is the sum of the correlation scores of all local blocks.

Indexing CBIR was one of the first systems that applied multidimensional indexing to enhance the speed performance of the system. The average colour and the texture features (both3D vectors) are indexed using trees. The 18 dimensional moment-based shape feature vector is first reduced using the KL transform and then indexed by using R*-trees.

IV. METHODOLOGY

Local binary patterns (LBP)

Local binary pattern (LBP) is a type of feature used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990.LBP was first described in 1994.It has since been found to be a powerful feature for texture classification. It has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets.

Given a center pixel in the image, LBP value is computed by comparing its gray value with its neighbors.The local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholded by its centre pixel value, multiplied by powers of two and then summed to obtain a label for the centre 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 centre and the pixels in the neighbourhood.

The LBP value is calculated by,

$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \text{ X } f1(I(gi) - I(gc)) \qquad (1)$$

$$f1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{else} \end{cases} \qquad (2)$$

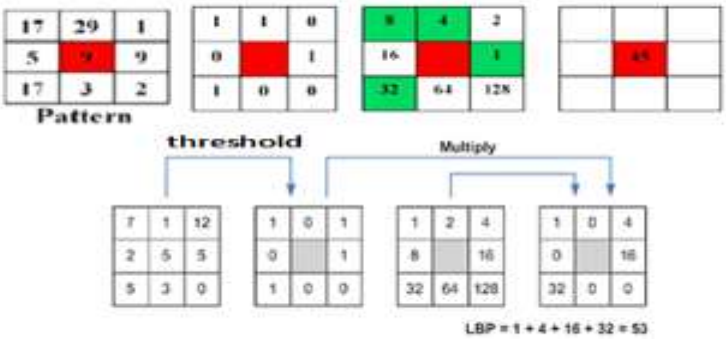

Fig.3 Calculation of LBP operator

Local Mesh Peak Valley Edge Patterns (LMePVEPs)

The ideas of the LBP and peak valley edge patterns (PVEP) have been motivated us to propose the LMePVEP for biomedical image retrieval. The mesh patterns (LMeP) are computed based on the relationship among the surrounding neighbours for a given centre pixel in an image. The local pattern is coded to peak pattern when two directions are approaching the centre and valley pattern when two directions are leaving from the centre. For a given centre pixel in an image, the LMePVEP value is computed based on the relationship among the surrounding neighbours using forward and backward first-order derivatives. The forward and backward first-order derivatives among the neighbours for a given centre pixel are calculated. The forward first-order derivative among P neighbours.

Feature extraction

Proposed system frame work

- Load the image.
- Perform the forward and backward first-order derivatives among the neighbours for a given centre pixel.
- Calculate the ternary LMePVEP.
- Separate the ternary LMePVEP into binary LMePEP and LMeVEP.
- Construct the histogram.
- Construct the feature vector by concatenating histograms.
- Compare the query image with the image in the database.
- Retrieve the images based on the best matches.

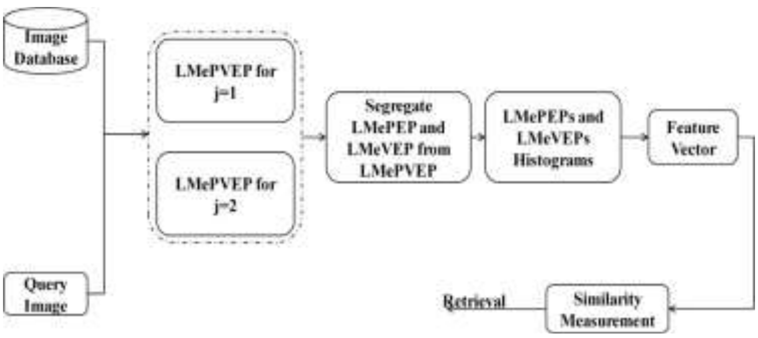

Fig.4 Flow Diagram for CBIR using LMePVEP

The detailed representation of these two patterns is shown in Fig.7. Fig.7 illustrates the example for LMePVEP calculation and then segregation them into LMePEP and LMeVEP for a given centre pixel in an image. For calculating forward and backward first-order derivative, a 3 x 3 matrix in an image is considered. The forward first order derivative is calculated for a given centre pixel $I(g_c)$.

$$I_{P,R}(g_c , g_i) = I(g_{a1}) – I(g_i),\ \ i=1,2,3…………P \qquad (3)$$
$$a1 = 1 + mod((i+P+j-1),P),\ \ j=1,2,………..(P/2) \qquad (4)$$

where j is the distance for first-order derivative.

The backward first order derivative is calculated for a given centre pixel $I(g_c)$.

$$I_{P,R}(g_c , g_i) = \begin{cases} I(g_{(P+i-j)}) - I(g_i), & \text{if } j \geq i \\ I(g_{(i-j)}) - I(g_i), & \text{else} \end{cases} \qquad (5)$$

Consider forward and backward first-order derivatives as x and y respectively.

$$f(x,y) = \begin{cases} 1 \text{ if } x>0 \text{ and } y>0 \\ 2 \text{ if } x<0 \text{ and } y<0 \\ 0 \text{ else} \end{cases} \qquad (6)$$

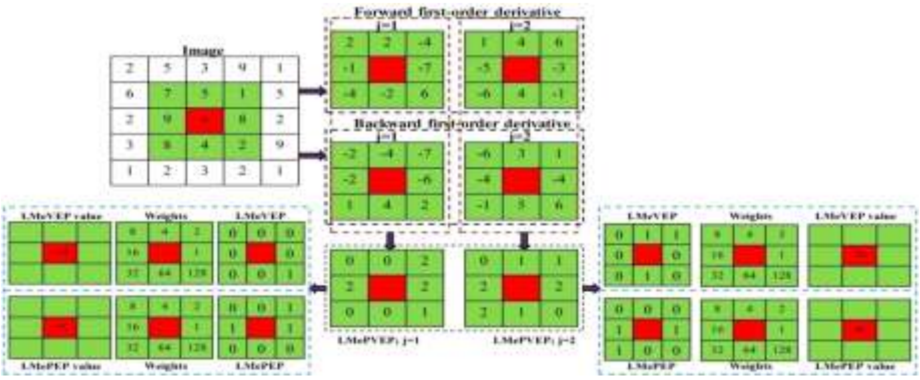

Fig.5 Calculation of operator

The obtained matrix is the LMePVEP for corresponding j values. From the obtained LMePVEP matrix, the LMeVEP and LMePEP matrix are obtained. After the patterns are calculated, the whole image is represented by building a histogram. The evaluation of different feature maps on sample image is shown in Fig 3.8. The sample image is chosen as it provides the results which are visibly comprehensible to differentiate the effectiveness of these approaches. It is observed that the LMePVEP yields more edge information as compared to LBP. The experimental results demonstrate that the proposed LMePVEP shows better performance as compared to LBP, indicating that it can capture more edge information than LBP for texture extraction.

V. SIMULATION RESULT

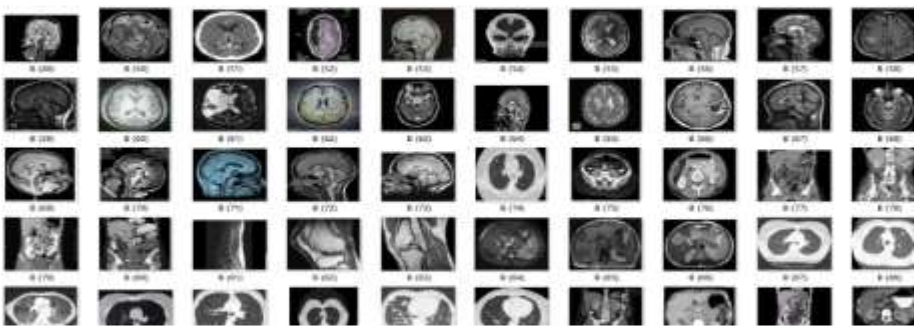

Fig.9 Fig. 6 Images in the database

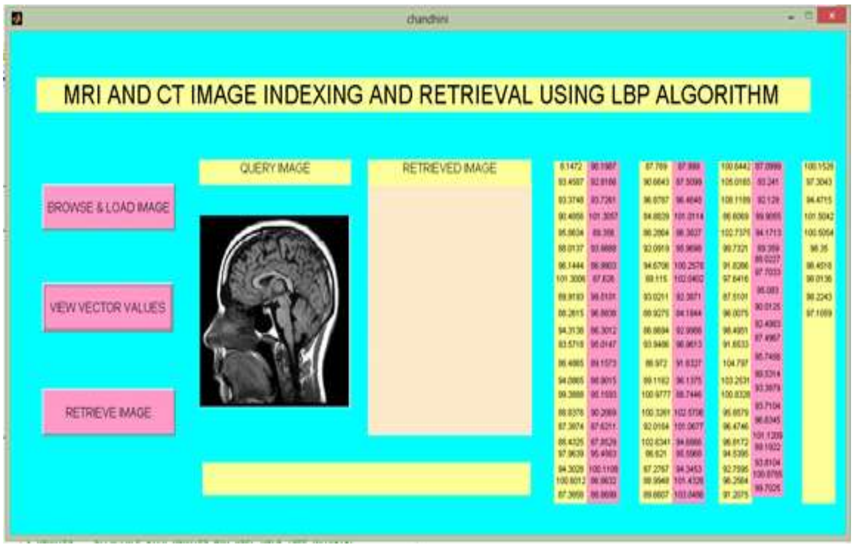

Fig. 7 Calculated vector values

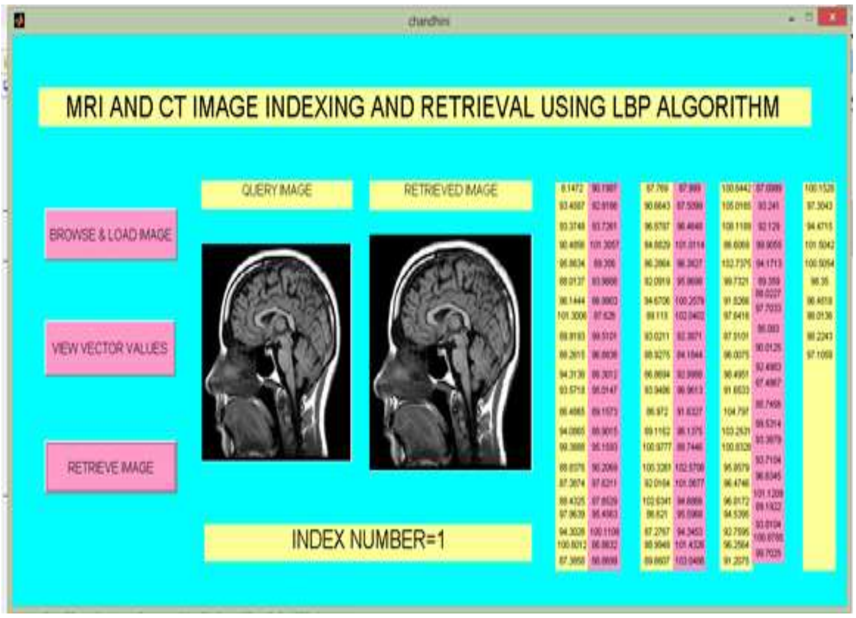

Fig. 8 Retrieval of similar image from the database

VI. CONCLUSION

Content Based Image Retrieval in an efficient way for indexing and retrieval of images. A technique that effectively uses most of the information from image is backbone of an efficient CBIR system for medical databases. The development of an image retrieval system based on various techniques such as feature extraction and similarity measurements are analysed. A novel pattern based image indexing and retrieval algorithms, local binary pattern (LBP) and local mesh peak valley edge patterns (LMePVEP) is proposed. The LBP extracts the gray scale relationship between the center pixel and its surrounding neighbours in an image. The LMePVEP extracts the relationship among the neighbours for a given center pixel in an image using forward and backward first–order derivatives. LMePVEP is a ternary pattern which is further converted into two binary patterns i.e. local mesh peak edge pattern (LMePEP) and local mesh valley edge pattern (LMePVEP). Thus either by LBP or LMePVEP, the given query image is compared with the images in the database and the similar image is retrieved.

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