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CONTENT BASED MEDICAL IMAGE RETRIEVAL USING TEXTURE DESCRIPTOR

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ABSTRACT

The focus of this paper is to using texture information for browsing and retrieval of large Medical image database. In this paper a feature, named structured local binary Haar pattern(SLBHP), is used for pixel based graphics retrieval the SLBHP is a hybrid of local binary pattern(LBP) and Haar wavelet. The SLBHP encodes the polarity rather than the magnitude of the difference between accumulated grey values of adjacent rectangles. The polarity relationships are then considered as a binary value as in LBP. Experiment results on graphics retrieval show that the discriminative power of SLBHP is good even in noisy condition[1]. The performed technique has three system components: feature extraction, image data base indexing and similarity retrieval.

I. INTRODUCTION

CBIR for medical images has become a major necessity with the growing technological advancements. The contents of an image have to be carefully extracted, classified with efficient techniques for easy retrieval. Content-Based Image Retrieval (CBIR) refers to image retrieval system that is based on visual properties of image objects rather than textual annotation. Contents of an image can be of various forms like, texture, color, and shape etc. In this work, texture is selected as a primary feature in indexing the image database[8]. Medical images are usually fused, subject to high inconsistency and composed of different minor structures. So there is a necessity for feature extraction and classification of images for easy retrieval. Among visual features, texture is widely used for content-based access to medical images [11]. Through textural analysis, it is possible to discover the texture signature of a medical image relevant to the diagnostic problem. The effectiveness of textural analysis depends on the methods used to extract meaningful features [9]. Content-based image retrieval (CBIR) systems normally return the retrieval results according to the similarity between features extracted from the query image and candidate images. In CBIR system; the processing steps are getting the input images, extracting the feature of the images, classifying the images and finally storing the images in an image feature database which is available for retrieval of similar images from the feature database.

A. Texture features:

Visual features were classified in [5] into *primitive* features such as color or shape. Among visual features, texture is widely used for content-based access to medical images [2]. Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. In short, it is a feature that describes the distinctive physical composition of a surface. Through textural analysis, it is possible to discover the texture signature of a medical image relevant to the diagnostic problem. The effectiveness of textural analysis depends on the methods used to extract meaningful features [8]. These texture measures try to capture the characteristics of the image or image parts with respect to changes in certain directions and the scale of the changes. This is most useful for regions or images with homogeneous texture. There have been several methods of textural feature extraction, such as gray level co-occurrence matrices [12] and Tamura’s textual features [10],wavelets [13,14] and Gabor filters [15,16,17].

B. Use of image retrieval in medical application:

The huge volume of medical images generated in hospitals creates a need to develop new tools to retrieve such visual information. In the medical field, images, and especially digital images, are produced in ever increasing quantities and used for diagnostics and therapy. The task of content-based image retrieval (CBIR) in the medical field is to help radiologists to retrieve images with similar contents. Content based access to medical images for supporting clinical decision making has been proposed that would ease the management of clinical data and scenarios for the integration of content-based access methods into Picture Archiving and Communication Systems (PACS) have been created [7]. In earlier study on the diagnostic use of medical image retrieval also shows an improvement in diagnostic techniques such as radiology, histopathology, and computerized tomography when using CBIRs which underline the potential importance of this technique. CBIRs can be of great use in managing large medical image databases.

The solution initially proposed was to extract the primitive features of a query image and compare them to those of database images. Using matching and comparison algorithms, the texture features of one image are compared and matched to the corresponding features of another image. This comparison is performed using texture and distance metrics. In the end, these metrics are performed one after another, so as to retrieve database images that are similar to the query. The similarity between features was to be calculated using algorithms Euclidean distance Algorithm.

II. ALGORITHM USED

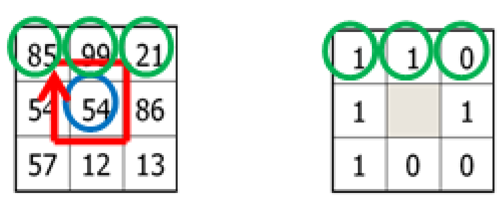
A. Structured local binary Haar pattern [1]

Local feature-based approaches have had great success in object detection and recognition in recent years. The original local binary pattern (LBP) descriptor was proposed by Ojala et al. [3] and was proved a powerful means for texture description. Haar features [4] encode the difference between accumulated grey values of adjacent rectangles. It is widely and successfully used in face and pedestrian detection. In this Letter, based on the similar idea of multi-block local binary pattern features [5, 6], a descriptor structured local binary Haar pattern (SLBHP) is modified from LBP with Haar wavelet. The proposed SLBHP adopts four types of Haar features, which capture the changes of grey values along the horizontal, the vertical and the diagonal directions as shown in Fig. 1a. Only the polarity of Haar feature is involved in SLBHP, while the magnitude is discarded. The polarity relationships are then considered as a binary value as in LBP.

B. Original Local Binary Pattern [19]

Ojala et al [20] propose a robust way for describing pure local binary patterns (LBP) in a texture. In the two-level version, there are only 2^8= 256 possible texture units. In binary case, the original 3x3 neighborhood is thresholded by the value of the center pixel. The values of the pixels in the thresholded neighborhood are multiplied by the weights given to the corresponding pixels. The result for this example is shown in. Finally, the values of the eight pixels are summed to obtain the number (211) of this texture unit that become the new value of center pixel. LBP method is gray scale invariant and can be easily combined with a simple contrast measure by computing for each neighborhood the difference of the average gray level of those pixels which have the value 1, and those which have the value 0, respectively.

An origin image (Fig.1a) can be converted to its texture spectrum image(Fig.2b) through replacing the pixels' gray level value by the values of corresponding texture units. It is shown that texture spectrum image takes on visual character of original image too. The image texture can be represented by the 256-bin LBP histogram for the frequency of the value of texture units.



Threshold value=54
Binary Pattern=11010011
DecimalValue=1+2+0+0+16+0+64+128=211

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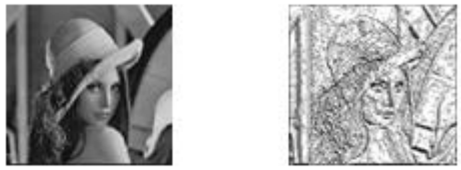
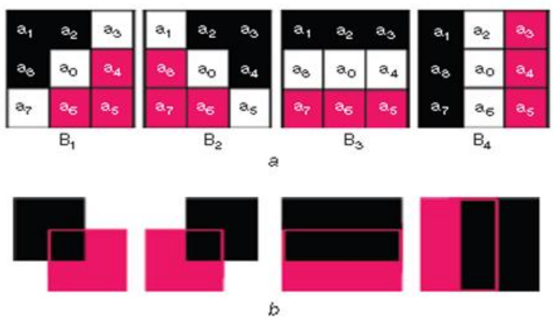


Fig. 1 (a) Image ***(b) Texture spectrum image***

C. Haar Feature

A simple rectangular Haar-like feature can be defined as the difference of the sum of pixels of areas inside the rectangle, which can be at any position and scale within the original image. This modified feature set is called *2-rectangle feature*. Viola and Jones [18] adapted the idea of using Haar wavelets and developed the so called Haar-like features. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in these regions and calculates the difference between them. This difference is then used to categorize subsections of an image. The values indicate certain characteristics of a particular area of the image. Each feature type can indicate the existence (or absence) of certain characteristics in the image, such as edges or changes in texture. Viola and Jones also defined 3-rectangle features and 4-rectangle features.

The algorithm works in following stages:
1.Firstly convert all RGB images in grayscale.
2.Calculate four types of Haar features, which capture the changes of grey values along the horizontal, the vertical and the diagonal directions as shown in Fig.



20	40	25
10	30	35
40	15	30

c

Fig.2 (a) Four Haar features (b) Corresponding Haar features with over-lapping (c) An example to compute SLBHP values.[1]

$$B_1 = |a_1 + a_2 + a_8 - a_4 - a_5 - a_6| = 10 < T$$
$$B_1 = 0$$
$$B_2 = |a_2 + a_3 + a_4 - a_6 - a_7 - a_8| = 35 > T$$
$$B_2 = 1$$
$$B_3 = |a_1 + a_2 + a_3 - a_5 - a_6 - a_7| = 0 < T$$
$$B_3 = 0$$
$$B_4 = |a_1 + a_7 + a_8 - a_3 - a_4 - a_5| = 20 > T$$
$$B_4 = 1$$

1. *After computing Haar features* $(\boldsymbol{B_1},\boldsymbol{B_2},\boldsymbol{B_3},\boldsymbol{B_4})$ *, by combining their values it will become a binary number. i.e*$(\mathbf{1010})_{\mathbf{2}}$*. Then this binary value will be converted into decimal number that become the new value of center pixel.*

$$SLBHP = (B_4B_3B_2B_1)_2 = (1010)_2 = 10$$

Let a_i, i = 0, 1, . . . , 8 denote the corresponding grey values for a 3 × 3 window with a_0 at the centre pixel (x, y) as shown in Fig. 14a. The value of the SLBHP code for the pixel (x, y) is given by the following equation:

$$SLBHP(x,y) = \sum_{P-1}^{4} B(H_P \otimes N(x,y)) \times 2^{P-1}$$

$$where\ N(x,y) = \begin{bmatrix} a1 & a2 & a3 \\ a8 & a0 & a4 \\ a7 & a6 & a5 \end{bmatrix}$$

$$H1 = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{bmatrix}, H2 = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix},$$

$$H3 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}, H4 = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$B(x) = \begin{cases} 1 & if\ |x| > T \\ 0 & otherwise \end{cases} \quad whereT\ as\ a\ threshold$$

By this binary operation, the feature becomes more robust to global lighting changes. It is noted that H_p denotes a Haar-like basis function and $H_p \otimes N$ (x, y) denotes the difference between the accumulated grey values of the non-white squares as shown in Fig. 1a. Unlike a traditional Haar feature, here the squares are overlapped with one pixel, as shown in Fig. 1b. Inspired by LBP and the fact that a single binary Haar feature might not have enough discriminative power, we combine these binary features just like

4.In the same manner compute this encoding pattern for each pixel in the Image. It is noted that the number of encoding patterns has been reduced from 256 for LBP to 16 for the SLBHP.

5.SLBHP for graphics retrieval: After the SLBHP values are computed, the histogram of the SLBHP for a region R is computed by the following equation:

$$H(i) = \sum\nolimits_{(x,y)\in R} I\{SLBHP(x,y) = i\}$$

$$where\ I(P) = \begin{cases} 1 & if\ P\ is\ true \\ 0 & if\ P\ is\ false \end{cases}$$

The histogram H contains information about the distribution of the local patterns, such as edges, spots and flat areas, over the region R. To make the SLBHP robust to slight translation, a graphics photo is divided into several small spatial regions (‘block’), for each of which a SLBHP histogram is computed.

III. MAIN RESULTS

Experimental results: 470 medical images are collected from internet to construct a database for retrieval experiments. An image database for the medical images consisting of following images:

- 470 , 32 by 32 images
- 470, 16 by 16 images
- 470, 8 by 8 images.

The performance of graphics retrieval is measured by retrieval accuracy. The retrieval accuracy is computed as the ratio of the number of graphics correctly retrieved to the number of total queries. Only the retrieval accuracy with respect to the best one are concerned in our experiments. In our experiments, image retrieval is carried out based on the calculation of similarity using the Euclidean Distance Function for histogram-based matching. The retrieval accuracy may be defined by the following tables:

I. Retrieval Accuracy of Medical Images without noise.
II. Retrieval Accuracy of Medical Images with change in Resolution.
III. Retrieval Accuracy of Medical Images with Salt and Pepper Noise
IV. Retrieval Accuracy of Medical Images with Gaussian noise.
V. Retrieval Accuracy of Medical Images with Poisson noise.

The accuracy can be determined by the following tables:

TABLE I.

Image size	**SLBHP Accuracy (in %age)**
32 * 32	100
16 * 16	100
8 * 8	97.44

Fig. 3. Retrieval Accuracy of Medical Images without noise.

TABLE II.

Image Size	**SLBHP Accuracy (in %age)**
32 * 32	100
16 * 16	99.36
8 * 8	96.38

Fig. 4. Retrieval Accuracy of Medical Images with change in Resolution.

TABLE III.

Image Size	**SLBHP Accuracy (in %age)**
32 * 32	70.85
16 * 16	91.91
8 * 8	82.97

Fig. 5. Retrieval Accuracy of Medical Images with Salt and Pepper Noise.

TABLE IV.

Image Size	SLBHP Accuracy (in %age)
32 * 32	11.06
16 * 16	16
8 * 8	33.40

Fig. 6. Retrieval Accuracy of Medical Images with Gaussian noise.

TABLE V.

Image Size	SLBHP Accuracy (in %age)
32 * 32	71.91
16 * 16	77.02
8 * 8	70.85

Fig.7. Retrieval Accuracy of Medical Images with Poisson noise.

IV. CONCLUSIONS

Success of a particular technology is often due to the confluence of available, supporting technologies at the time of critical need. Content-Based Image Retrieval of medical images has achieved a degree of maturity, albeit at a research level, at a time of significant need. However, the field has yet to make noticeable inroads into mainstream clinical practice, medical research, or training.

Now in the system we have applied the query image and have retrieved similar images by comparing the Euclidean distance between the query image and the database image.

In this experiment, we have found that Retrieval accuracy for the retrieved images got good results even in noisy condition.

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