CONTENT BASED MEDICAL IMAGE RETRIEVAL USING TEXTURE DESCRIPTOR

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ABSTRACT

In the medical field, images, and especially digital images, are produced in ever increasing quantities and used for diagnostics and therapy. 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. Still only few systems were developed and used in real clinical environment. It rather seems that medical professional define their needs and computer scientists develop system based on data sets they receive with little or no interaction between the two groups. 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 CBMIRs which underline the potential importance of this technique. CBMIRs can be of great use in managing large medical image databases. 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.

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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, shape is selected as a primary feature in indexing the image database. CBIR is more robust and makes it easier for image retrieval. 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.

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. 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. There have been several methods of textural feature extraction, such as gray level co-occurrence matrices and Tamura's textual features. The main objective of the work is to retrieve the images from huge volume of medical databases with high accuracy by performing feature extraction, classification process. So that the retrieved images are used for various medical diagnosis purpose.

The simplest form of visual feature is directly based on pixel values of the image. However, these types of visual features are very sensitive to noise, brightness, hue and saturation changes, and are not invariant to spatial transformations such as translation and rotation. As a result , CBIR systems that are based on pixel values do not generally have satisfactory results Much of the research in this area has placed the emphasis on computing characteristics from image images using image processing and computer vision techniques.

Usually, general purpose features in CBIR have included color, texture, shape and structure. Other features are specific to the application domains and require some special knowledge and consequently put constraints on the database. For example, facial CBIR systems require techniques widely studied in image processing in face recognition.

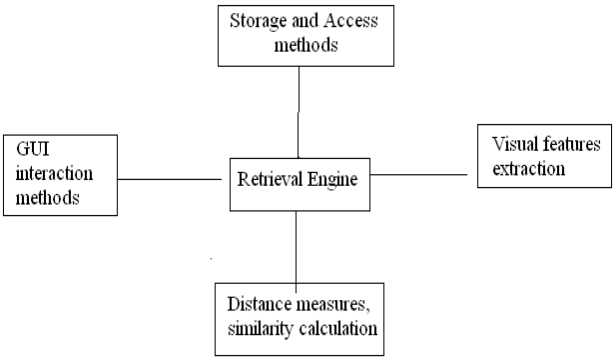


Fig. 1 The principal components of all content-based image retrieval systems.

II. TEXTURE RETRIEVAL

Texture features: In this paper focus is on texture features. This is because texture feature work well in general images. It is very important property of images. Texture is that innate property of all surfaces that describes visual patters, and that contain important information about the structural arrangement of the surface and its relationship to the surrounding environment. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation method can be classified in two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be very effective when applied to textures that are very regular. Statistical methods, including fourier power spectra, co-occurrences matrices, shift-invariant principal component analysis, Markov random field, fractal model and multi-resolution filtering techniques such as gabor and wavelet transform, characterize textures by the statistical distribution of the image intensity. Coarseness, contrast, directionality, line likeness, regularity and roughness. The roles of textures in scene analysis are:

- Texture – innate property of all surfaces
- Clouds, trees, bricks, hair etc…
- Refers to visual patterns of homogeneity
- Texture more robust than color with respect to illumination changes
- Texture can be utilized in different applications, like night vision
- Intensity information is very important for observer

Fig. 2 Examples: brick texture, finger print texture, clouds texture, rocks texture

Global Texture Descriptor There is a model for describing texture properties of images consisting of four parts:

- Fractal dimension: measures the roughness of a surface.
- Coarseness: measures the grain size of the image.
- Entropy: describes the level of unorderedness.
- Spatial grey-level difference statistics: describes the brightness relationship of pixels within neighborhoods.

The ability to retrieve images on the basis of texture similarity may not seem very useful. But the ability to match on texture similarity can often be useful in distinguishing between areas of images with similar color (such as sky and sea, or leaves and grass). A variety of techniques has been used for measuring texture similarity; the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture

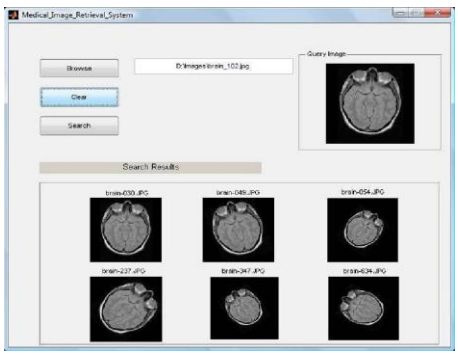


Fig. 3 Retrieved Images (N=6) with the top right image as the query

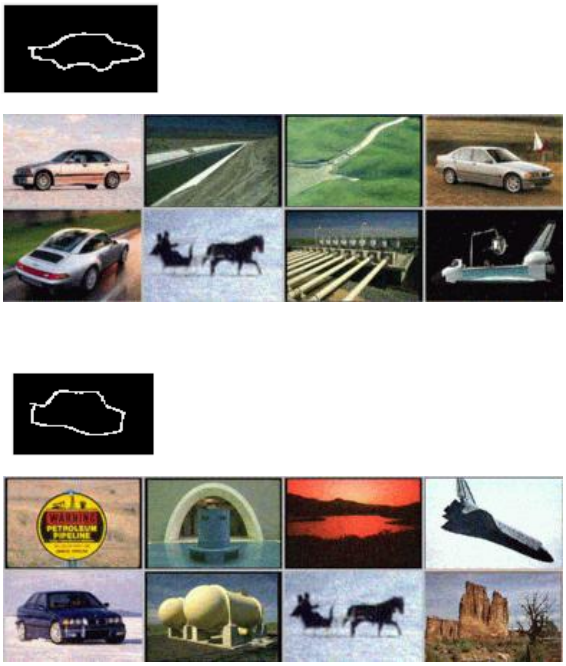


Fig. 4 Retrieved image using Query by sketch

- A user-sketch query paradigm or query-by-sketch (QBS) is very similar to the QBE, namely, the retrieval of images that look like that sketch. Both the paradigms involve usually low-level features such as color, texture, and so on, rather than the meaning (semantics: objects, events, etc.). But it should be noted that users are generally interested in semantics. Generally, the goal and paradigms of the CBIR are application-dependent. For example, it makes no sense to search for pictures of George W. Bush, using texture, whereas in many instances of medical imaging the textual (metadata) search is not nearly as powerful as QBE. The QBE-based retrieval of visual information complements the text-based querying, rather than tends to replace it.

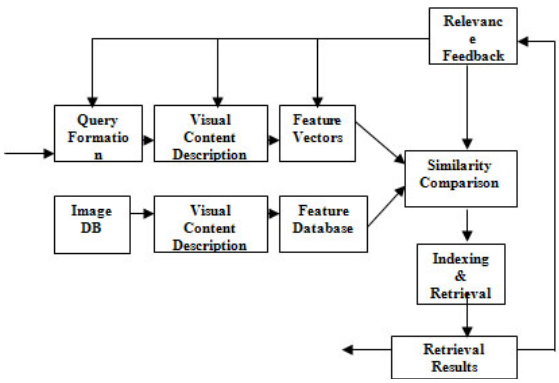


Fig. 5 Diagram of content based image retrieval system

III. PRACTICAL APPLICATIONS OF CBIR

A wide range of possible applications for CBIR technology has been identified. Potentially fruitful areas include:

- Crime prevention
- The military
- Intellectual property
- Architectural and engineering design
- Fashion and interior design
- Journalism and advertising
- Medical diagnosis
- Geographical information and remote sensing systems
- Cultural heritage
- Education and training

IV. PROBLEM FORMULATION

Problem Motivation

Image databases and collections can be enormous in size, containing hundreds, thousands or even millions of images. The conventional method of image retrieval is searching for a keyword that would match the descriptive keyword assigned to the image by a human categorizer. Currently under development, even though several systems exist, is the retrieval of images based on their content, called **Content Based Image Retrieval**, **CBIR**. While computationally expensive, the results are far more accurate than conventional image indexing. Hence, there exists a tradeoff between accuracy and computational cost. This tradeoff decreases as more efficient algorithms are utilized and increased computational power becomes inexpensive.

Problem Statement

The problem involves entering an image as a query into a software application that is designed to employ CBIR techniques in extracting visual properties, and matching them. This is done to retrieve images in the database that are visually similar to the query image.

V. PROPOSED SOLUTION & ALGORITHM USED

The solution initially proposed was to extract the primitive features of a query image and compare them to those of database images. The image features under consideration is texture. Thus, 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.

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.

Texture properties include:

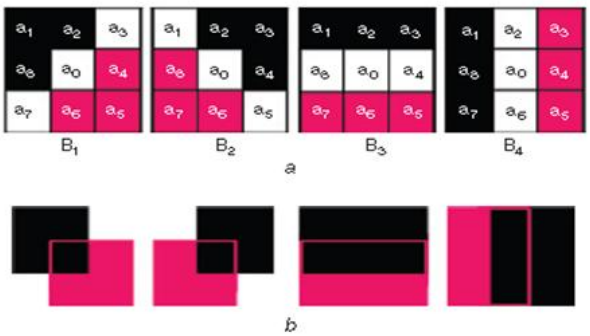
- Coarseness
- Contrast
- Directionality
- Line-likeness
- Regularity
- Roughness

Texture is one of the most important defining features of an image. It is characterized by the spatial distribution of gray levels in a neighborhood. In order to capture the spatial dependence of gray-level values, which contribute to the perception of texture, a two-dimensional dependence texture analysis matrix is taken into consideration. This two-dimensional matrix is obtained by decoding the image file; jpeg, bmp, etc.

VI. IMPLEMENTED ALGORITHM'S

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. 6 (a) Four Haar features

3. After computing Haar features **(B_1,B_2,B_3,B_4)** , by combining their values it will become a binary number. i.e. $(1010)_2$. Then this binary value will be converted into decimal number that becomes the new value of center pixel.

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

4. 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:

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

$$where\ N(x,y) = \begin{bmatrix} a1 & a2 & a3 \\ a8 & a0 & a4 \\ a7 & a6 & a5 \end{bmatrix}, H1 = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{bmatrix}$$

$$H2 = \begin{bmatrix} 0 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & -1 & 0 \end{bmatrix}, H3 = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

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

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

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. 14a. Unlike a traditional Haar feature, here the squares are overlapped with one pixel, as shown in Fig. 14b. 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

5. 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.

6. 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:

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

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

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.

Euclidean Distance

Euclidean Distance Algorithm:

i. Decompose query image.

ii. Get the energies of the first dominant **k** channels.

iii. For image **i** in the database obtain the **k** energies.

iv. Calculate the Euclidean distance between the two sets of energies, using [2]:

v. $$D_i = \sum_{k=1}^{k} (x_k - y_{i,k})^2$$

vi. Increment **i**. Repeat from step 3.

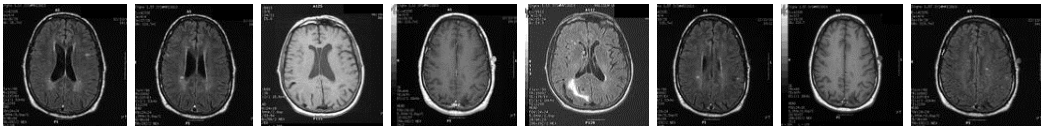
7. Using the above algorithm, the query image is searched for in the image database. The Euclidean distance is calculated between the query image and every image in the database. This process is repeated until all the images in the database have been compared with the query image. Upon completion of the Euclidean distance algorithm, we have an array of Euclidean distances, which is then sorted. The five topmost images are then displayed as a result of the texture search.

VII. EXPERIMENTAL RESULTS

Experimental results: 95 medical images are collected from internet to construct a database for retrieval experiments. Test images are comprised of medical image graphics photos taken by a digital camera and then noises added to obtain noisy test 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. Moreover, not only the retrieval accuracy with respect to the best one, but also the second and third best ones, is concerned in our experiments. The retrieval accuracy may be defined by the following tables:

- Retrieval Accuracy of Medical Images without noise
- Retrieval Accuracy of Medical Images with Salt and Pepper Noise
- Retrieval Accuracy of Medical Images with Gaussian noise.

a) Query Image



b) Retrieved Images

Note: - We have applied a query image of Brain and have retrieved 8 images similar to the query image.

Fig. 7 An example of Query image, Retrieved images basis on implemented algorithm.

The accuracy can be determined by the following tables:

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

Table 1. Retrieval Accuracy of Medical Images without noise

	SLBHP Accuracy(in %age)
32 * 32	77.89
16 * 16	86.31
8 * 8	89.47

Table 2. Retrieval Accuracy of Medical Images with Salt and Pepper Noise

	SLBHP Accuracy (in %age)
32 * 32	66.31
16 * 16	71.56
8 * 8	75.83

Table 3. Retrieval Accuracy of Medical Images with Gaussian Noise

VIII. CONCLUSION

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.

We maintained an image database for the medical images consisting of following images:

- 95 , 32 by 32 images
- 95, 16 by 16 images
- 95, 8 by 8 images.

Now in the system we have applied the query image of brain and have retrieved 8 similar images by comparing the Euclidean distance between the query image and the database image.

Also we have found the Retrieval accuracy for the retrieved images and have got good results.

IX. REFERENCES

1. Zhiping Shi, Fei Ye, Qing He, Zhongzhi Shi"Symmetrical Invariant LBP Texture Descriptor and Application for Image Retrieval".
2. S.-Z. Su, S.-Y. Chen, S.-Z. Li, S.-A. Li and D.-J. Duh "Structured local binary Haar pattern for pixel-based graphics retrieval".
3. Muller, H., N.Michoux, D.Bandon and A.Geissbuhler, "A review of content based image retrieval systems in medical applications-clinical benefits and future directions", International Journal of Medical Information., pp: 73:13, 2004.
4. Thies C, Guld MO, Fischer B, Lehmann TM, "Content- based queries on the CasImage database with in the IRMA framework", Lec Notes in Comp Sci 2005; 3491:781-92.
5. Antani S, Long LR, Thoma GR, "Content-based Image retrieval for large biomedical image archives. In: Proc 11th World Cong Medical Informatics: 2004. p. 829-33.
6. Long LR, Antani SK, Thoma GR, "Image Informatics at a national research center, CompMed Imaging &graphics 2005; 29:171-93.
7. Chi-Ren Shyu, Carla E. Brodley, Avinash C. Kak, Akio Kosaka,"ASSERT: A Physician-in-the-Loop Content-Based Retrieval System for HRCT Image Databases", Computer Vision and Image Understanding, Vol. 75, Nos. 1/2, July/August, pp. 111-132, 1999.

8. V.S.V.S. Murthy, E.Vamsidhar, J.N.V.R. Swarup Kumar, P.Sankara Rao, "Content Based Image Retrieval using Hierarchical and K-Means Clustering Techniques", International Journal of Engineering Science and Technology, Vol 2(3), pp. 209-212, 2010.
9. G. D. Tourassi, "Journey toward computer-aided diagnosis: role of image texture analysis," *Radiology*, **213**(2), pp. 317-320, 1999.
10. R. M. Haralick, "Statistical and structural approaches to texture," *Proceedings of the IEEE*, **67**(5), pp. 786-304, 1979.