ISSN 2320 - 2602
Volume 2, No.5, May 2013
International Journal of Advances in Computer Science and Technology
Available Online at http://warse.org/pdfs/2013/ijacst03252013.pdf

CLINICAL ANATOMY IMAGE RETRIEVAL SYSTEM USING LOCAL TETRA PATTERN

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ABSTRACT

The field of medical sciences is an ever changing and a vast research area. There is a new invention every now and then; be it diagnostics or treatment of various diseases. This instantaneous field needs to maintain and store all the data in its history to dwell in the future. The field of image processing and retrieval is turmoil in diagnostics as well as detection of vivid diseases and disorders. The detection of a particular disease or disorder needs to follow a series of steps in order to identify the actual area of problem. For this particular detection, a large number of images are referred to find out just the initial information and after this the detailed information is acquired through conducting some follow up tests. The contents of images in the database are very carefully evocated so as to get better results. An image basically constitutes of three features - colour, shape and texture. These behave as three basic grounds for extracting various details from an image. The CRIR actually works on the image itself rather than the database. This means that the contents of the image (query image) are matched with those of the database images. This is a fine approach that filters appropriate content by reducing the garbage outputs to a great extent. CBIR provides better extraction from complex image structures. In the earlier methods (i.e. LBP, LDP & LTP) the value is computed by comparing the gray value of the centre pixel with its neighbours. In this thesis work, the Content-Based Medical Retrieval Algorithm is implemented for abstracting the more detailed information of medical image using Local Tetra Patterns. The proposed algorithm encodes the relationship between referenced pixel and its neighbour based on the directions. The directions are calculated using first order derivative in horizontal and vertical direction. The Algorithm describes the spatial structure of the local texture using the direction of the centre gray pixel (also called referenced pixel).The proposed method used the Euclidean distance for similarity measurement between query image and database images

Keywords: Content Based Image Retrieval (CBIR), Distance D, Euclidean Distance (ED) Fourier Descriptor (FD), Local Tetra Pattern (LTrPs)

1. INTRODUCTION AND RELATED WORK

Image has been a source of capturing things, events, people etc for years. A simple click can make your memories alive forever. With the advancement in the modern world, clicking an image just for the sake of remembering memories is no more the sole aim. Today, images add a lot our day to day discoveries and researches. One such area, where image storage and retrieval has saved lives is the field of medical sciences. A large database is to be maintained which contains numerous images of various organs or earlier scanned copies of detected diseases. Hence, such a database becomes more and more complex and therefore requires much of hard work to find out a particular image. This raises a need for a technique that automatically searches the required image from a large database.

CBIR provides better extraction from complex image structures. In the earlier methods (i.e. LBP, LDP & LTP) the value is computed by comparing the gray value of the centre pixel with its neighbours. In this thesis work, the Content-Based Medical Retrieval Algorithm is implemented for abstracting the more detailed information of medical image using Local Tetra Patterns. The proposed algorithm encodes the relationship between referenced pixel and its neighbour based on the directions. The directions are calculated using first order derivative in horizontal and vertical direction. The most promising criteria is the feature extraction in CBIR. This is a turning point in field of image retrieval and its success depends upon the kind of method chosen for extracting features from given images. The Algorithm describes the spatial structure of the local texture using the direction of the centre gray pixel (also called referenced pixel).The proposed method used the distance D and the Euclidean distance for similarity measurement between query image and database images. In Section 4, the detailed description of proposed framework is presented. Section 5 comprises the experimental results along with their discussions. Finally, Section 6 concludes the paper.

Content-based image retrieval (CBIR) is one of the commonly adopted and best suited technique for such applications. A pioneering work was published by Chang in 1984, in which the author presented a picture indexing and abstraction approach for pictorial database retrieval [1]. The CBIR basically uses visual contents of an image such as color, texture, shape, spatial layout, etc. The difficulty to find a single best representation of an image for all perceptual subjectivity is due to the fact that the user may take photographs in different conditions such as view angle, illumination changes, etc. Arnold et al.[2] discussed the working conditions of content-based retrieval : patterns of use, types of pictures, the role of semantics, and the sensory gap. The texture feature for image extraction is quiet better and produces finer results. Certain cases, such as face or texture patterns, simple textual descriptions can be ambiguous and often inadequate for database search. Image textures are defined as images of natural textured surfaces and artificially created visual patterns, which approach, within certain limits, these natural objects. Image sensors yield additional geometric and optical transformations of the perceived surfaces, and these transformations should not affect a particular class of textures the surface belongs. These features, which define a spatial arrangement of texture constituents, help to single out the desired texture types, e.g. fine or coarse, close or loose, plain or twilled or ribbed textile fabrics. Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features. Moghaddam *et al.* have introduced the concept of wavelet correlogram [3], [4] and have further shown that the performance improvement can be obtained by optimizing the quantization thresholds using genetic algorithm for CBIR application. Texture retrieval is a branch of texture analysis that has attracted wide attention from industries since this is well suited for the identification of products such as ceramic tiles, marble, parquet slabs, etc. Ahmadian *et al.* have used the discrete wavelet transform (DWT) for texture classification [5]. However, the DWT can extract only three directional (horizontal, vertical, and diagonal) information from an image. Rotational invariant complex wavelet filters [6] have been proposed for texture image retrieval. Texture analysis has a long history and texture analysis algorithms range from using random field models to multiresolution filtering techniques such as the wavelet transform. Several researchers have considered the use of such texture features for pattern retrieval [7], [8].

2. CBIR TECHNIQUES

2.1. LOCAL BINARY PATTERN

LBP operator is first introduced by Ojala et al. [9] to encode the pixel – wise information in the texture images Figure.1 illustrates that each neighbouring pixel corresponding to the centre pixel is assigned with binary label, which can be either “0” or “1”. The basic version of LBP works in 3 × 3 pixel block of an image. The Local binary pattern (LBP) operator is defined as grey scale invariant texture measure, derived from texture definition in the local neighborhood. It based on the assumption that texture has two important aspects, a pattern and its strength. Its basic version works in 3 × 3 pixel block of a image. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models for texture analysis.

Real world application of LBP operator is its variance against monotonic grey level changes. Figure 1 illustrates that, at a centre pixel t_c each neighbouring pixel is assigned with binary label, which can be either “0” or “1” depending upon whether the centre pixel has higher intensity value then the neighbouring pixel. It means that LBP value is

2	2	4	17	29
6	4	45	3	12
10	1	5	2	6
4	7	9	8	25
2	1	1	2	3

0	1	0
0		0
1	1	1

8	4	2
16		1
32	64	128

	228	

Figure 1: Calculation of LBP

calculated by comparing the grey value of centre pixel with its neighbors and it is based on

$$LBP_{P,R} = \sum_{P=1}^{P} 2^{(P-1)} \times f_1(g_p - g_c) \quad (1)$$

$$f(x) = \begin{cases} 1, & x \geq 1 \\ 0, & \text{else} \end{cases} \quad (2)$$

where, g_c is the gray value of the centre pixel, g_p is the gray value of its neighbours, P is the number of neighbors, and R is the radius of the neighbourhood.

2.2. LOCAL TERNARY PATTERN

LBPs have proven to be highly discriminative features for texture classification [11] and are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations. However because they threshold at exactly the value of the central pixel they tend to be sensitive to noise, particularly in near-uniform image regions, and to smooth weak illumination gradients. Many facial regions are relatively uniform and it is legitimate to investigate whether the robustness of the features can be improved in these regions. Tan & Triggs [12] extends LBP to 3-valued codes, LTP, in which gray-levels in a zone of width $\pm t$ around i_c are quantized zero, ones above this are quantized to 1 and ones below it to -1, i.e., the indicator $s(u)$ is replaced with a 3-valued function and the binary LBP code is replaced by a ternary LTP code. Here t is a user-specified threshold—so LTP codes are more resistant to noise, but no longer strictly invariant to gray-level transformations. The illustration of LTP is given in Figure 2., in which grey value in the zone of width $\pm t$ around g_c are quantized to zero, those above $(g_c + t)$ are quantized to +1,those below $(g_c - t)$ are quantized to -1,i.e., indicator $f_1(x)$ is replaced with three valued function(name) and the binary LBP is replaced by ternary LTP code. When using LTP for visual matching, we could use 3^n valued codes, but the uniform pattern argument

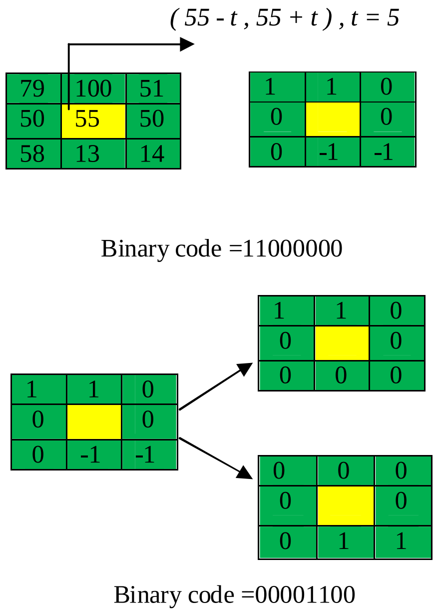


Figure 2. Calculation of LTP

also applies in the ternary case. For simplicity, the experiments below use a coding scheme that splits each ternary pattern into its positive and negative halves subsequently treating these as two separate channels of LBP descriptors for which separate fourier descriptors and similarity metrics are computed, combining the results only at the end of the computation. LTPs bear some similarity to the texture spectrum (TS) technique from the early 1990s [13]. However, TS did not include pre-processing, thresholding, local fourier descriptors, or uniform pattern-based dimensionality reduction and it was not tested on faces.

$$s'(u, i_c, t) = \begin{cases} 1, & u \geq I_c + t \\ 0, & |u - I_c| < t \\ -1, & u \leq I_c - t \end{cases} \qquad (3)$$

2.3. LOCAL DERIVATIVE PATTERN

LBP actually encodes the binary result of the first-order derivative among local neighbors by using a simple threshold function, which is incapable of describing more detailed information. Zhang *et al.* proposed the LDPs for face recognition [14].They considered the LBP as the nondirectional first-order local pattern operator and extended it to higher orders (nth-order) called the LDP. The LDP contains more detailed discriminative features as compared with the LBP. LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) can not obtain from an image. Given an image *I(Z)*, the first-order derivative along 0^o , 45^o , 90^o and 135^o directions are denoted as $I'_\alpha(Z)$ where $\alpha = 0^o$, 45^o , 90^o and 135^o.Let Z_0 be a point in *I(Z)*, and Z_i , $i = 1,\ldots\ldots,8$ be the neighboring point around Z_0.The four first-order derivatives at $Z = Z_0$ can be written as

$$\begin{aligned} I'_{0^o}(Z_0) &= I(Z_0) - I(Z_4) \\ I'_{45^o}(Z_0) &= I(Z_0) - I(Z_3) \\ I'_{90^o}(Z_0) &= I(Z_0) - I(Z_2) \\ I'_{135^o}(Z_0) &= I(Z_0) - I(Z_1) \end{aligned} \qquad (4)$$

The second –order directional LDP,$LDP^2_\alpha(Z_0)$, in α direction at $Z = Z_0$ is defined as

$$LDP^2_\alpha(Z_0) = \{ f(I'_\alpha(Z_0), I'_\alpha(Z_1)), f(I'_\alpha(Z_0), I'_\alpha(Z_2)) \text{----------}, f(I'_\alpha(Z_0), I'_\alpha(Z_8)) \} \qquad (5)$$

Where f(·,·) is a binary coding function determining the types of local pattern transitions.It encodes the co-occurance of two derivative directions at different neighboring pixel. Finally, the second-order Local Derivative Pattern,$LDP^2(Z)$ is defined as the concatenation of four 8-bit directional LDP'S

$$LDP^2(Z) = \{ LDP^2_\alpha(Z) | \alpha = 0^0, 45^0, 90^0, 135^0 \} . \qquad (6)$$

It can be seen from the above equations that the proposed LDP operator labels the pixels of an image by comparing two derivative directions at two neighbouring pixels and concatenating the results as a 32-bit binary sequence. To calculate the third-order Local Derivative Pattern, we first compute the second-order derivatives along 0^0 , 45^0 , 90^0 and 135^0 directions, denoted as $I^{IJ}_\alpha(Z)$ where $\alpha = 0^0$, 45^0 , 90^0 and 135^0.

The high-order local patterns provide a stronger discriminative capability in describing detailed texture information than the first-order local pattern as used in LBP. This can alleviate the noise sensitivity problem in the high-order LDP representation, making it more robust and stable in binary encoding identity patterns in human faces

2.4. LOCAL TETRA PATTERN(LTrP)

Subrahmanyam Murala et al[16] proposed a novel image indexing and retrieval algorithm using local tetra patterns (LTrPs) for content-based image retrieval (CBIR).

The proposed method encodes the relationship between the referenced pixel and its neighbour pixels, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. In addition, we propose a generic strategy to compute n^{th}-order LTrP using (n – 1)th order horizontal and vertical derivatives. In this method the first order derivative at center pixel *c g* can be defined as:

$$I^1_{0^o}(g_c) = I(g_h) - I(g_c) \qquad (7)$$

$$I^1_{90^o}(g_c) = I(g_v) - I(g_c) \qquad (8)$$

And the corresponding value of the centre pixel is derived as:

$$I^1_{Dir.}(gc) = \begin{cases} 1, & I^1_{0^o}(gc) \ge 0 \text{ and } I^1_{90^o}(gc) \ge 0 \\ 2, & I^1_{0^o}(gc) < 0 \text{ and } I^1_{90^o}(gc) \ge 0 \\ 3, & I^1_{0^o}(gc) < 0 \text{ and } I^1_{90^o}(gc) < 0 \\ 4, & I^1_{0^o}(gc) \ge 0 \text{ and } I^1_{90^o}(gc) < 0 \end{cases} \quad (9)$$

This shows that the image is evaluated in four directions revolving around the centre pixel and therefore the image is converted into four values.

The second order derivative is evaluated as:

$$LTrP^2 \,|_{Direction = 2,3,4} = \sum_{p=1}^{P} 2^{(p-1)} \times f_4(LTrP^2(g_c)) \,|_{Direction = 2,3,4} \quad (10)$$

$$f_4(LTrP^2(g_c)) \,|_{Direction = \phi} = \begin{cases} 1, & \text{if } LTrP^2(g_c) = \phi \\ 0, & \text{else} \end{cases}$$

where ϕ = 2,3,4 (11)

From (10) and (11), 8 bit pattern is extracted for each centre pixel. Thus 12 (4 X 3) binary patterns are obtained. After these binary patters, a 13th binary pattern is proposed by using the magnitudes of horizontal and vertical first-order derivatives using

$$M_{I^1(g_p)} = \sqrt{(I^1_{0^o}(g_p))^2 + (I^1_{0^o}(g_p))^2} \quad (12)$$

$$LP = \sum_{P=1}^{P} 2^{(P-1)} \times f_1(M_{I^1(g_p)} - M_{I^1(g_p)}) \,|_{p=8} \quad (13)$$

Once the 13 bit binary pattern is formed, histogram is applied on the query image and compared to all the images in the database. While processing, all the images (x_1,x_2.........x_n) are compared and analysed. The most similar images are hence displayed as result. The experimentation proves that LTrP provides far better results as compared to LBP, LTP and LDP.

3. PROPOSED WORK

The proposed method encodes the relationship between the referenced pixel and its neighbors, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. The proposed system selects the best images from clinical anatomy database that resemble best to the query image.

Figure 3 illustrates the flowchart of the proposed image retrieval system using Local Tetra Pattern given below.

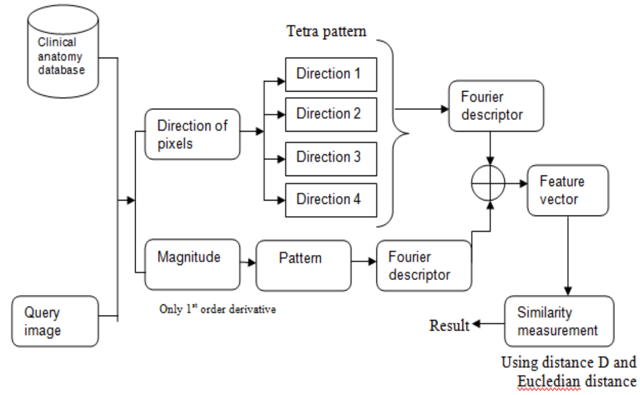


Figure 3: Proposed System Architecture

For each query, the system collects n database images X = (X_1, X_2,.......X_n) with the shortest image matching distance computed. If the retrieved image X_i = (1.2.3........,n) belongs to same category as that of the query image, then we say that the system has appropriately identified the expected image, or else, the system has failed to find the expected image. For better results two types of similarity distances are used and compared finally. The most usual method for comparing two images is using an image distance measure. Various types of distance metrics are used to measure the similarity between the query and the images in the database. Smaller the distance, more similar the pattern to the query. Distance of 0 signifies an exact match with the query, with respect to the dimensions that were considered. In this proposed work two types of similarity measurement distance is used:

1. Distance D[16] :

$$D(Q,DB) = \sum_{i=1}^{Lg} \left| \frac{fDBji - fQi}{1 + fDBji + fQi} \right| \quad (14)$$

2. Euclidean [18] :

$$Di = \sum_{K=1}^{K} (x\,k - y\,i,k)^2 \quad (15)$$

Below mentioned is the proposed algorithm:

1. Load the medical image of 64*64 size.
2. Convert it in to grey scale.
3. Calculate the direction of every pixel (for one direction there is one tetra pattern which will be further divided in to 3 binary patterns). So therefore, for four directions there will be 12 binary patterns.
4. Apply Fourier Descriptor
5. Calculate the magnitude from first order derivative for 13^{th} binary bit and apply fourier descriptor.
6. Construct the feature vector.

7. Compare the query image with Clinical Anatomy Database.

8. For similarity measurement use Distance D and Euclidean Distance and will be compared for better result.

9. Retrieve the best found matches.

Fourier Descriptor:

Consider the N contour points of an image component as a discrete function x (n) = (x_1 (n), x_2 (n)).Using this function, we can define a discrete complex function u (n) as

$$u(n) = x_1(n) + jx_2(n) \qquad (16)$$

u(n) can be transform in to the frequency domain by the Discrete Fourier Transformation(DFT).Fourier transform is used to generate the feature vectors based on the mean values of real and imaginary parts of complex numbers of polar coordinates in the frequency domain. DFT is defined as

$$a(k) = \frac{1}{N} \sum_{n=0}^{n-1} u(n) e e^{-j2\pi kn/N}$$

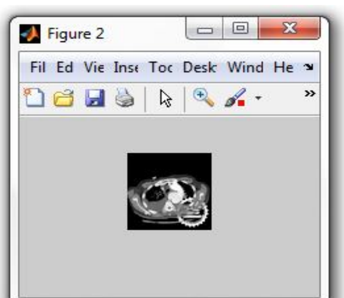
$$K = -N/2, \ldots\ldots N/2 - 1 \qquad (17)$$

The coefficients a(k) are called Fourier descriptors[17]. They represent the discrete contour of a shape in frequency domain. The result can be transformed back in to spatial domain via the Inverse Discrete Fourier Transformation.

4. EXPERIMENT

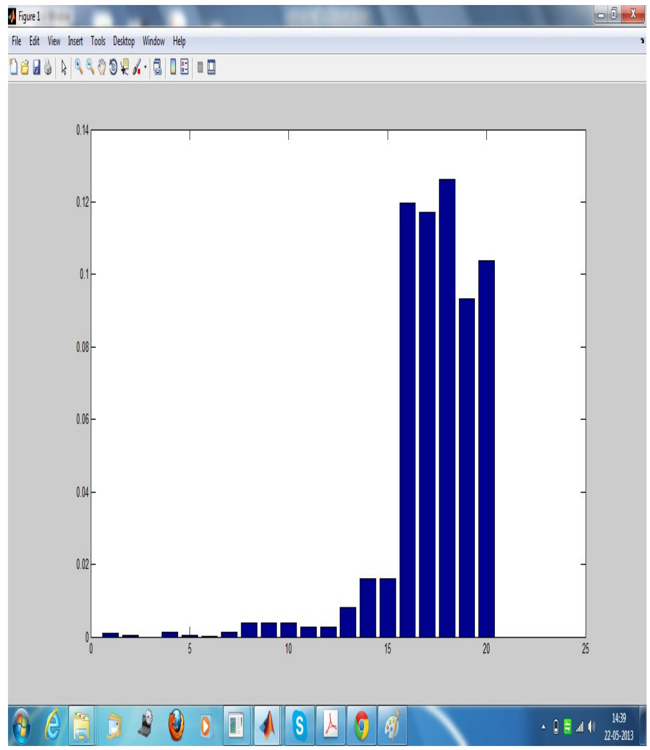
The most usual method for comparing two images is using an image distance measure. Various types of distance metrics are used to measure the similarity between the query and the images in the database. Smaller the distance, more similar the pattern to the query. Distance of 0 signifies an exact match with the query, with respect to the dimensions that were considered. In this proposed work two types of similarity measurement distance is used:

1. Using distance D



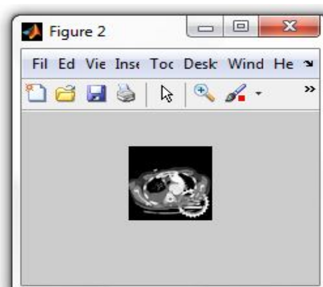
Query image

Resultant images



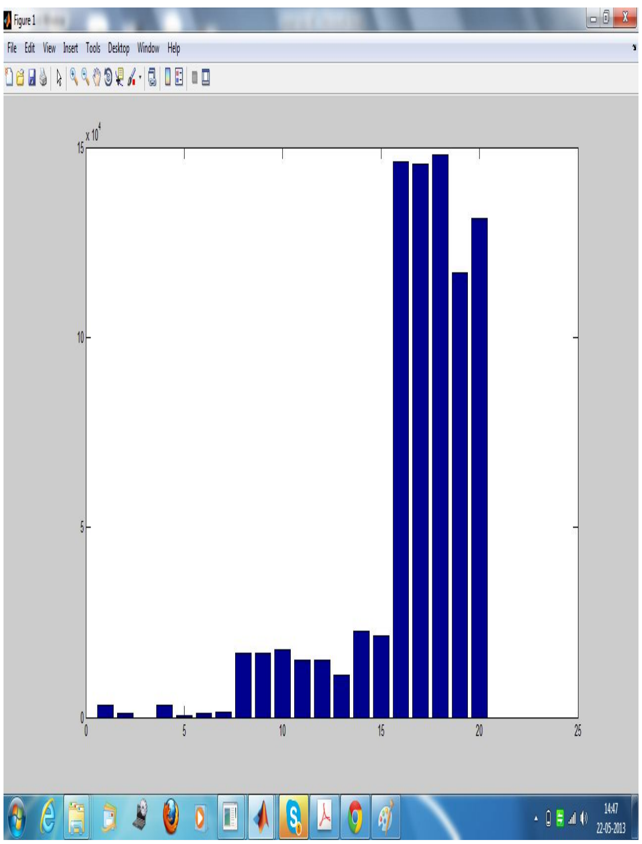
Bar representation of results

2. Using EU Distance



Query image

Resultant images



Bar representation of results

5. CONCLUSION

Table 1: Comparison of the Results

S. NO.	POSITION NO	DISTANCE D	EUCLEDIAN DISTANCE
1	1	0.0011	0.0317
2	2	0.0003	0.0094
3	3	0	0
4	4	0.0011	0.0318
5	5	0.0004	0.0057
6	6	0.0001	0.0096
7	7	0.0012	0.0134

As shown in Table1, after the detailed study of these techniques, we come upon to the theory that distance D calculates much better and promising results as it can provide more precise description of the image by coding the higher order derivative direction variations.
The respective resultants in both the cases (distance D and Eucledian distance) provide a clear picture on how near the distance values lie to the query image respective to the fact that the same query image has been used for both the cases.

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