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Second Order Statistical Texture Features from a New CSLBPGLCM for Ultrasound Kidney Images Retrieval

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Abstract
This work proposes a new method called Center Symmetric Local Binary Pattern Grey Level Co-occurrence Matrix (CSLBPGLCM) for the purpose of extracting second order statistical texture features in ultrasound kidney images. These features are then feed into ultrasound kidney images retrieval system for the point of medical applications. This new GLCM matrix combines the benefit of CSLBP and conventional GLCM. The main intention of this CSLBPGLCM is to reduce the number of grey levels in an image by not simply accumulating the grey levels but incorporating another statistical texture feature in it. The proposed approach is cautiously evaluated in ultrasound kidney images retrieval system and has been compared with conventional GLCM. It is experimentally proved that the proposed method increases the retrieval efficiency, accuracy and reduces the time complexity of ultrasound kidney images retrieval system by means of second order statistical texture features.

Keywords: CBIR; Texture; Second order statistics; GLCM; CSLBPGLCM; Ultrasound kidney images; Recall; Precision.

Introduction

There is a vast development in the field of imaging technology producing medical images. The more number of medical images are produced in clinical laboratories across all over the world. These medical images are used for various medical applications such as assisting diagnosis, education and for surgery purpose. These images should be carefully analyzed and grouped based on their visual similarities. If the medical images are grouped by their content then the similar images are retrieved for various medical applications. It is the complicate task to describe the content of the medical images manually [1]. It is very difficult to state the content of the medical images in words. The Content Based Image Retrieval (CBIR) technique can be used for above mentioned purpose. This provides the way to retrieve the images from medical image databases based on its content [2, 3]. The resulting system is called as Content Based Medical Image Retrieval System (CBMIR).

There are numerous amount of research is going on the approaches of CBIR to medical applications [4]. The direction of research differs in terms of representation of image content, modality, and the region of body or pathology. In medical applications, the CBIR has to find the similar images from the medical database with respect to the query image or input image. The similar images have equivalent content. Color, texture and shape are the features to represent the content of an image. The image content may be represented using individual feature or mixture of features depending upon the application.

Among the various image features, color plays an important role to investigate many pathological characteristics [5]. Color feature poses many problems [6] which is not suited for medical applications. Most of the medical images are grey in color. The grey values in the medical images offer limited amount of information about the color. For this reason, medical image retrieval system uses color as the auxiliary feature for representing the medical image content.

Texture feature in CBIR system is important for medical image analysis. The texture can be able to automatically interpret the content of an image and delivers the semantic information. In addition to that, texture feature provides information about scenic depth, the spatial distribution of tonal variations and surface orientation. Texture feature can be represented by two approaches such as statistical approach and structural approach. In statistical approach, the texture is represented by the statistical distribution of image intensity. The statistical approach uses the following methods to symbolize the texture such as Gray Level Co-occurrence Matrix(GLCM), fractal model, Tamura feature, world decomposition and so on [3]. The major statistical methods which are used in texture analysis based on the definition of joint probability distribution of pair of pixels. The structural approach describes the texture by identifying a set of primitive texels in some regular or repeated pattern.

The method of computing texture feature for CBMIR is related to the kind of medical image database to be used. This work applies the concept of CBMIR in Ultrasound Kidney images. There are number of works have been done on in the retrieval of ultrasound medical images. In Content-Based Retrieval and Classification of Ultrasound Medical Images of Ovarian Cysts system, the authors extract histogram moments and GLCM based texture features [7] for representing the image content. Then the features are used for retrieving and classifying ultrasound images. Landeweerd and Gelsema [8] extracted various first-order statistics (such as mean grey level in a region) as well as second-order statistics (such as grey level co-occurrence matrices) to differentiate different types of white blood cells. Insana et al. [9] used textural features in ultrasound images to estimate tissue scattering parameters. They made significant use of the knowledge about the physics of the ultrasound imaging process and tissue characteristics to design the texture model. Chen et al. [10] used fractal texture features to classify ultrasound images of livers, and used the fractal texture features to do edge enhancement in chest X-rays. The previous work of ultrasound kidney image retrieval developed by Manikandan et al. [11,12] derived second order statistical feature from GLCM as a texture feature to retrieve similar images. The work described by Callins et al. [13] uses statistical texture features derived from grey level difference histogram for retrieving similar images from ultrasound kidney image database.

From the state of art described above, it is observed that statistical texture features play an important role in representing the content of ultrasound medical images. According to the fact from the medical images, the two medical images are never distinguished if they obey in their second order statistical features. The second order statistical features are normally extracted from GLCM matrix. The GLCM matrix is formed in four directions such as 0°, 45°, 90° and 135° from an image. To determine texture features, the selected statistics are derived from each GLCM by iterating the entire matrix. The GLCM contains relatively few non-zero entries, so it leads to many unnecessary calculations and increasing the computational cost.

The computational efficiency is an important factor in medical applications. The main intention of this work is to derive the second order statistical texture features from computationally efficient GLCM for the retrieval of ultrasound kidney images. The computational efficiency is achieved by forming GLCM from minimum amount of grey levels in an image. The reduction of grey levels in an image is not happened by not simply combining grey levels but it is done based on fit in another texture feature. In this work, the reduction of grey levels are based on the another efficient texture operator called Local Binary Pattern (LBP). LBP is a local texture operator [14], which has a low computational complexity and a low sensitivity to changes in illumination. This feature is very much desirable in medical image analysis. The LBP operator combines the statistical and structural approaches for representing texture features. The LBP has been experimented in various applications such as, in texture classification [14], face recognition [15], smart gun [16], fingerprint identification [17] and automated cell phenotype image classification [18].

The simple LBP method is extended in order to improve its strength and discriminative power. The variants such as center–symmetric LBP (CSLBP) [19], Elongated Quinary Patterns [20] and Elongated Ternary Patterns [21] are used in medical Image Analysis. The LBP variants are varied in terms of formation of histogram bin and length of histogram. The CSLBP has the shortest histogram length of 16 among the other LBP variants. The CSLBP is suitable for grey level reduction. This work uses the CSLBP operator to filter an ultrasound kidney image and then an image is converted to histogram of 16 grey levels. The CSLBP operator reduces the number of grey levels in turn it reduces the computational complexity while forming the GLCM matrix. The central theme of this paper is customizing GLCM Matrix in all four directions such as 0°, 45°, 90°, 135° from CSLBP textured image. The resultant GLCM is called as Center Symmetric Local Binary Pattern Grey Level Co-occurrence Matrix (CSLBPGLCM). Then the second order statistical features are derived from the proposed CSLBPGLCM. This work blends the best practices from GLCM and CSLBP for the application of ultrasound kidney images retrieval.

Second Order Statistical Texture Features from Proposed CSLBPGLCM for Ultrasound Kidney Images Retrieval

The basic LBP operator is modified to make it suitable for different applications. Heikkila.M, et al [19] recommended the Center-Symmetric Local Binary Patterns (CSLBP), in which the opposing pixels are considered with respect to the center pixel. Only 4 comparisons in a local window produce 4 bit binary code. The 16 combinations of values are possible since $2^4=16$. The computation of CSLBP of the center pixel (a,b) of the local neighborhood f(a,b) is given in equation 1. The value n in the equation 1 denotes the number of neighboring pixels and f(a,b) is the intensity of neighboring pixels.

$$CS-LBP(a\ ,b)_{n,d}=\sum_{p=0}^{(n/2)-1}V(f(a_p,b_p)-f(a_{p+n/2},b_{p+n/2}))2^p \tag{1}$$

The value of V(x) in equation 1 is computed using equation 2. The Figure 1 shows computation of CSLBP computation of center pixel of a sample window based on the equation 1.

$$V(x)=\begin{cases}1 \text{ if } x\geq 0\\ 0 \text{ if } x<0\end{cases} \tag{2}$$

20	40	25
10	30	35
40	15	30

a. Sample window before CSLBP Calculation

*	*	*
*	11	*
*	*	*

b. Sample window after CSLBP Calculation

* - Defined based on its neighborhood

Figure 1. Sample CSLBP Calculation of center pixel

The new CSLBPGLCM Matrix is meant to lower the computational cost of forming the GLCM Matrix. This can be accomplished by reducing the number of grey levels in the image. The proposed work reduces the number of grey levels in the image from 256 to 16 by passing an image into the CSLBP operator. The CSLBP calculation explained in figure 1 is done on the entire image. Then the image is transformed into the collection of grey values ranging from 0 to 16. The GLCM calculation is then carried out on this CSLBP transformed image. The entries of GLCM are the frequency of pair of pixels which are separated by a fixed distance at specified angle. The GLCM P_d for a distance d is computed in four directions which are 0°, 45°, 90°, 135°. The value d=1 is assigned in this work. The normalized GLCM is formed using the equation 3.

$$P(i,j) = \frac{P_d(i,j)}{\sum_{i,j=0}^{15} P_d(i,j)} \tag{3}$$

This resultant GLCM matrix is called as CSLBPGLCM. The normalized CSLBPGLCM P(i,j) is calculated from four directions which are 0˚, 45˚, 90˚, 135˚. There are totally 14 second order statistical features [22] may be derived from each matrix. In this work the most applicable six features [23] are taken into consideration instead of 14 features to avoid the redundancy. They are energy, contrast, variance, correlation, entropy and inverse difference moment (IDM). The statistical features from all the normalized CSLBPGLCM matrices are computed using the equation from 4 to 9. The features computed are then used to form a feature vector.

$$\text{Energy} = \sum_{i=0}^{15}\sum_{j=0}^{15} P^2(i,j) \tag{4}$$

$$\text{Contrast} = \sum_{i=0}^{15}\sum_{j=0}^{15} P(i,j)\,(i-j)^2 \tag{5}$$

$$\text{Variance} = \sum_{i=0}^{15}\sum_{j=0}^{15} (i-\mu)^2 P(i,j) \tag{6}$$

$$\text{Correlation} = \sum_{i=0}^{15}\sum_{j=0}^{15} \frac{(i-\mu)(j-\mu)P(i,j)}{\sigma^2} \tag{7}$$

$$\text{Entropy} = -\sum_{i=0}^{15}\sum_{j=0}^{15} P(i,j)\log P(i,j) \tag{8}$$

$$\text{IDM} = \sum_{i=0}^{15}\sum_{j=0}^{15} \frac{P(i,j)}{1+(i-j)^2} \tag{9}$$

The value μ and σ is used in equation from 4 to 9 are defined as follows.

$$\mu = \sum_{i=0}^{15}\sum_{j=0}^{15} P(i,j) \tag{10}$$

$$\sigma^2 = \sum_{i=0}^{15} (i-\mu)^2 \sum_{j=0}^{15} P(i,j) \tag{11}$$

The feature vector formed using the equations from 4 to 9 in four directions such as 0°, 45°, 90°, 135° are then used in ultrasound kidney images retrieval application.

Similarity Matching

The CBMIR system retrieves similar images from database by comparing the visual similarities between a query image and images in a database. In this work, the visual feature of an image is represented by second order statistics extracted from new CSLBPGLCM. The similarity measure is applied between the feature vectors of two images to find the visual similarity. There are number of distance metrics used for similarity assessment in CBIR. The performance of an image retrieval system is depended on the similarity measure also. The Euclidean distance measure is best suited for similar category of images [24, 25]. The database considered for this work is same modality of ultrasound kidney images, and then the Euclidean distance measure is taken for similarity matching. The Euclidean distance between the query image and the images of the database is computed using equation 12.

$$\sqrt{(p_1-q_1)^2+(p_2-q_2)^2+\ldots\ldots+(p_n-q_n)^2} = \sqrt{\sum_{i=1}^{n}(p_i-q_i)^2} \tag{12}$$

In equation 12, n is the length of feature vector for an image.

Experimental Results

Database consists of different classes of ultrasound kidney images like Normal kidneys, cortical cysts (CC), medical renal diseases (MRD) are taken for performance analysis. The performance of ultrasound kidney image retrieval system using CSLBPGLCM method is compared with conventional GLCM. The retrieval efficiency of the CBIR system is evaluated by two familiar measures such as precision and recall [26-28] which are defined in equation 13 and equation 14.

$$\text{Precision} = \frac{\text{No of Relevant Images Retrieved}}{\text{Total No of images Retrieved}} \tag{13}$$

$$\text{Recall} = \frac{\text{No of Relevant Images Retrived}}{\text{Total no of Relevantimages in Database}} \tag{14}$$

The efficiency of the system is checked on different category of images (Normal, CC, MRD) separately. The average recall and precision values of two systems on the three classes of ultrasound kidney images are listed in Table 1 which shows the retrieval efficiency.

Table 1. Average Recall and Precision values of CSLBPGLCM and GLCM for ultrasound Kidney images retrieval system

Method	Recall			Precision		
	Normal	CC	MRD	Normal	CC	MRD
CSLBPGLCM	0.88	0.8	0.83	0.94	0.9	0.89
GLCM	0.84	0.75	0.63	0.89	0.85	0.76

From the Precision and Recall values listed in Table 1, it is understood that CSLBPGLCM based ultrasound kidney image retrieval system is competent with Conventional GLCM based method.

The accuracy of proposed CBIR system is evaluated on the basis of how much similar category of images is retrieved with respect to the query image. The three data sets such as Normal, CC and MRD are considered into a single dataset for retrieval accuracy calculation. The classes of retrieval result of query image are analyzed. The score value is assigned to each of the resultant image with respect to the query image. The score 1 is assigned for same class of images with respect to query, otherwise score 0 is assigned. The retrieval accuracy is computed based on equation 15 using score value of resultant images.

$$\text{Retrieval Accuracy} = \frac{\sum_{j=1}^{n} s_j}{n} \tag{15}$$

The value of n in equation 15 is the number of resultant images which are considered. The value s_j indicates that the score of the resultant image j to the query image. The Top 5 retrieval results of GLCM and CSLBPGLCM method is shown in Figure 2. The average retrieval accuracy of GLCM and CSLBPGLCM methods are listed in Table2.

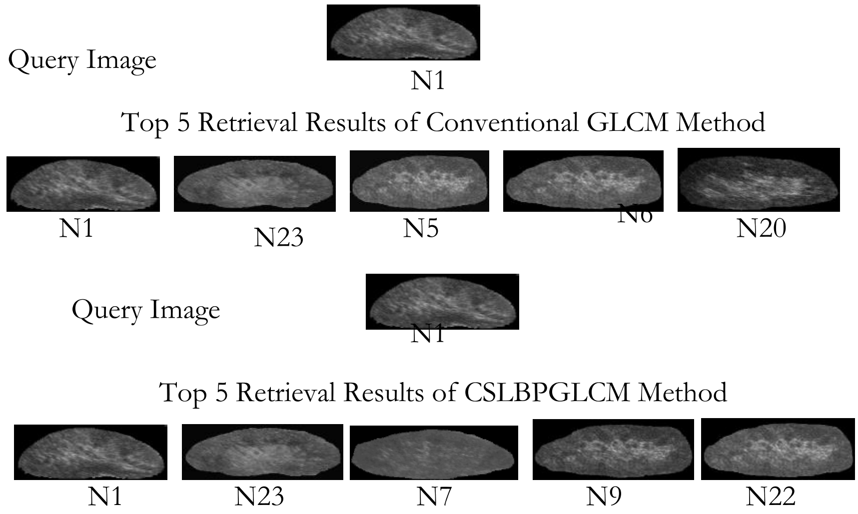

Figure 2. Top 5 Retrieval Results of GLCM and CSLBPGLCM

Table 2. Comparative Retrieval Accuracy

Method	Retrieval Accuracy (%)
CSLBPGLCM	90.2
GLCM	86.6

The next parameter for comparison of retrieval system considered in this work is time complexity [29]. Though the results of medical image retrieval system assisting diagnosis process practically, the quicker diagnosis without sacrificing accuracy of the medical image retrieval system is very much needful. The quicker retrieval result depends on how fast the image retrieval system converts an image into feature vector. In our work, the second order statistical features are used to represent an image. The time complexity of deriving second order statistical features from an image is depended on the customization of GLCM matrix from an image. The size of the conventional GLCM matrix is 256×256, because it considers all the 256 grey values. The size of CSLBPGLCM matrix is 16×16, because the grey values in an image is labeled by CSLBP of 0 to 15. The time complexity comparison of ultrasound kidney image retrieval system is based on CSLBPGLCM and conventional GLCM is shown in Table 3.

Table 3. Time Complexity Comparison of CSLBPGLCM and Basic GLCM

Method	Dimension / No of entries	Time complexity (n=256)
CSLBPGLCM	2 / 256	O(n)
GLCM	2 / 65536	O(n^2)

Conclusion

This work proposes a new method of customizing GLCM matrix from CSLBP textured image. The second order statistical texture features extracted from this new CSLBPGLCM matrix is used to form a feature vector of ultrasound kidney images retrieval system. The retrieval efficiency and accuracy and time complexity of the ultrasound kidney image retrieval system based on this new CSLBPGLCM is excellent and proved in section 4. Besides, the performance of the proposed method is compared with conventional GLCM. The experimental analysis in section 4 reports that the CSLBPGLCM method outruns the conventional GLCM method in terms of retrieval efficiency, accuracy and time complexity. From this work, it is observed that CSLBPGLCM is the best method of extracting second order statistical texture features from an image for the application of ultrasound kidney images retrieval.

Conflict of Interest

The authors declare that they have no conflict of interest

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