Imperial Journal of Interdisciplinary Research (IJIR)
Vol-3, Issue-6, 2017
ISSN: 2454-1362, http://www.onlinejournal.in

Image Retrieval System Using Improved Local Binary Patterns and GLCM Matrices

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Abstract: *Medical images produced by different hospitals and health care centers are increasing day by day. Medical images play a vital role in identification of various diseases, clinical diagnosis and prognosis, medical training and surgical planning. Management, indexing and retrieval of such a huge collection of images tend to be very expensive and time consuming when manual methods are employed. A lot of work has been done on generic image retrieval systems using content based information. Many feature descriptors have been proposed for image retrieval in the past few years. Most of them stick to a particular type of images. In this work content based image retrieval system has been proposed which uses both spatial as well as frequency domain texture features of input images and classify them into relevant categories. System has been tested by considering mix databases in which medical datasets of different types has been included along with face image or other object images. Center symmetric Local binary patterns and local phase quantization features has been used as spatial and frequency domain features respectively along with GLCM texture features of the images to extract the features from variety of datasets. Four different types of distance measure metrics i.e. Chi-square, Manhattan, Canbarra and Euclidian has been used for getting the similarity between query and dataset images. Experimental results shows high precision ratio when canbarra distance metrics has been considered.*

Keywords: *biomedical image retreival, GLCM, CSLBP, similarity measure*

1. Introduction

Despite the numerous image retrieval algorithms have made significant achievements [1], medical image retreival is still a challenging and active topic in computer vision research field. It is not perfect and struggles to perform under certain conditions. Some algorithms perform well under relatively controlled environments but tend to be vulnerable from variations in different factors, e.g., shape, illumination etc. are present [2].

The feature description and extraction play the great important roles in image retreival process. Texture which inherently exists in an image is a vital visual cue and feature. Early image texture description methods focused on the statistical analysis [3]. The most representative methods are based on the co-occurrence matrix and filtering techniques which are sensitive to the rotation and time-consuming [4, 5]. Recently, local texture features have gained reputation as powerful texture descriptors because the approach is robust to variations of facial pose, expression, occlusion, etc. Among these methods, Local Binary Pattern (LBP) texture descriptor [6] which was presented by Ojala in 1996 has achieved impressive classification results on representative texture databases and also been adapted to texture recognition.

LBP which was originally aimed to help measuring the local contract is a simple yet efficient and rotation invariant operator to describe local image pattern. On the basis of their early research [7], Ojala extended the IBP to a multidimensional distribution of Signed Gray Level Difference (SGLD) [8] which can be applied to any scaled structure texture. LBP made many good results in early texture classification experiments. However, in some applications, applying the basic LBP method can not get satisfied results. So many research efforts have been made towards improving the LBP in some specific applications, especially in texture analysis [9] and face recognition [4, 10, 11]. Tan and Triggs proposed Local Ternary Pattern (LTP) [12] to quantize the difference between a pixel and its neighbors within three levels which yields a higher discriminative ability and higher tolerance to illumination in homogeneous region than LBP. But this descriptor still has some limits in multiscaled images. Hafiane presented Median Binary Pattern (MBP) [13] to compare the difference between a pixel, its neighbors and the median value. These methods mainly take the difference between the center pixel and its neighbors into account but ignore the more information on interest region.

From the point of view of interest region descriptor, Marko Heikkila combined the strengths of the well-known SIFT (scale-invariant feature transform) descriptor with the LBP texture operator and proposed Center-Symmetric Local Binary Pattern (CS-LBP) [14] descriptor which describes each pixel by the relative gray levels of its neighboring pixels. It can capture better gradient information than the basic LBP and has significant reduction in dimensionality while preserving distinctiveness. However, this operator completely ignores the center pixel information which may affect the discriminative result in some applications. In order to take advantage of more information, Guo presented a Completed Local Binary Pattern (CLBP) [3] from the view of local difference sign-magnitude transform. The CLBP method includes three operators, namely the CLBP-Center, CLBP-Sign and CLBP-Magnitude which can be readily combined to form the final CLBP histogram. The CLBP can achieve much better rotation invariant texture classification results than the conventional LBP based schemes. Yet, it is more complex and sensitive to noise. Due to it limitation which represents missing information similar to the results of a standard LBP, a better texture classification with a high discriminative power needs to be developed.

Due to its high tolerance to illumination changes, and computational efficiency, the CS-LBP shows good performances in texture classification [15] and face recognition under certain conditions, especially for images with severe illumination variations. The CS-LBP which completely ignores the center pixel information may not generate satisfied results in some applications. In fact, the intensity value of the center pixel itself can also contribute useful information to discriminative result. In order to take advantage of more useful information, this paper fuses the center pixel information into the CS-LBP, namely CS-LBP. Thus, a local region is represented by its center pixel and CS-LBP. The center pixel represents the image gray level and the CS-LBP represents the gradient information of the interest region. In biomedical image retrieval , the input image is first divided into small blocks from which CS-LBP histograms are extracted, respectively. It can be expected that some of the blocks contain more useful information than others in terms of distinguishing. To take it into account, weights are set for blocks based on the image entropy. Finally, all the weighted histograms are connected serially to create a final texture descriptor. The experimental results in medical datasets show that a higher recognition accuracy can be obtained by employing the proposed method with nearest neighbor classification.

2. Center-symmetric local binary pattern

The Center-Symmetric Local Binary Pattern(CS-LBP) [14]is another modified version of LBP. It is originally proposed to alleviate some drawbacks of the standard LBP. For example, the original LBP has not been used for describing interest regions, the original LBP histogram yields a long feature vector (256 dimension) and the original LBP feature is not robust on flat images. Inspired by the gradient magnitude and orientation used by the SIFT, the CS-LBP descriptor combines the strengths of the SIFT descriptor [16] with the LBP operator. Instead of comparing the gray level of each pixel with the center pixel, the centersymmetric pairs of pixels are compared in CS-LBP. CS-LBP can be computed by (6):

$$\mathbf{C}S - LBP_{N,P,T} = \sum_{i=1}^{P/2-1} s(\mathrm{g}_i - \mathrm{g}_{i+(\mathrm{p}/2)}).2^i$$

$$s(\mathrm{x}) = \begin{cases} 1, \text{if } x \geq T \\ 0, \text{otherwise} \end{cases}$$

Here, gi and gi+(P /2) correspond to the gray level of center symmetric pairs of pixels of P equally spaced pixels on a circle of radius R. Moreover, T is a small value used to threshold the gray level difference so as to increase the robustness of the CS-LBP feature on flat image regions. Since the region data lies between 0 and 1, T is set to 0.01. The radius is always set to 1 and the size of the neighborhood is 8 [14]. From the computation of CS-LBP, we can see that the CS-LBP is closely related to the gradient operator, because like some gradient operators, it considers gray level differences between pairs of opposite pixels in a neighborhood. In this way, the CS-LBP feature takes advantage of the properties of both the LBP and gradient based features. Moreover, we can see that for 8 neighbors, CS-LBP only produces 16 different binary patterns which is much less than the LBP. Similar to LBP, the final texture feature employed in texture analysis is the histogram of the operator outputs. The center pixel information reflects the gray level of the region in certain way and the CS-LBP represents the gradient information of the interest region. So the CS-LBP includes more information than original LBP. Texture feature is a measure method concerned with relationship among the pixels in local area. Similarly, the histogram of CS-LBP is regarded as the texture descriptor. The histogram contains information about the distribution of the local micropatterns such as edges, spots, and flat areas over the whole image. According to the definition, the histogram of CS-LBP contains the main gradient information distribution of the image.

3. Local phase quantization

The local phase quantization (LPQ) method is based on the blur invariance property of the Fourier phase spectrum. It uses the local phase information extracted using the 2-D DFT or, more precisely, a short-term Fourier transform (STFT) computed over a rectangular M-by-M neighborhood Nx at each pixel position x of the image f(x) defined by

$$F(\mathbf{u},\mathbf{x}) = \sum_{\mathbf{y}\in N_{\mathbf{x}}} f(\mathbf{x}-\mathbf{y})e^{-j2\pi\mathbf{u}^T\mathbf{y}} = \mathbf{w}_{\mathbf{u}}^T\mathbf{f}_{\mathbf{x}} \; ,$$

So both CS-LBP and LPQ features are combined to get final features.

4. System module

The system design for the medical image retrieval Using Chi-square distance based classification is shown in Fig 1

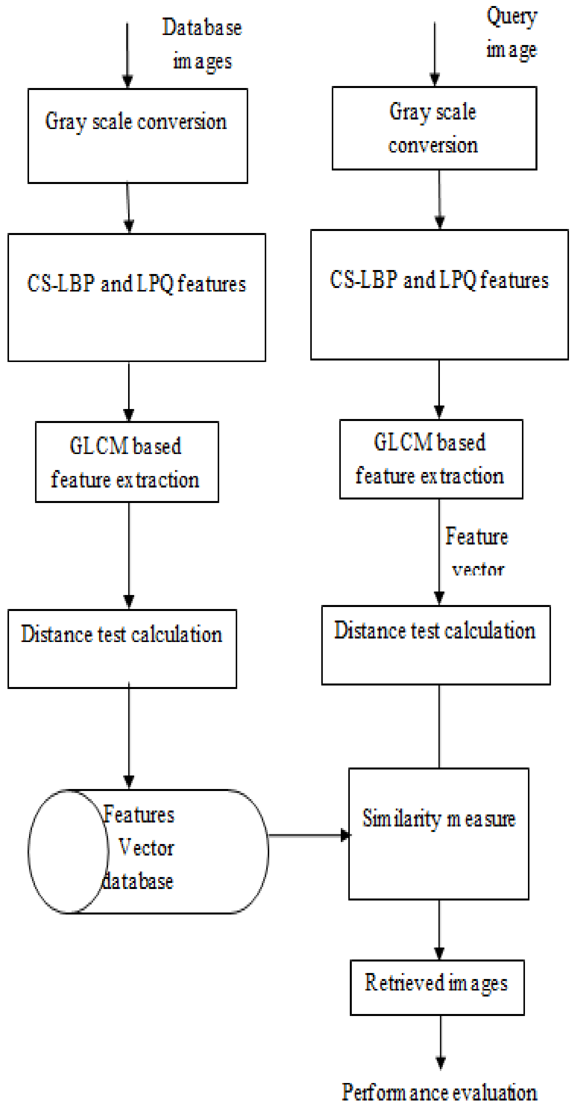

Figure 1: Block Diagram for the System Design

The basic steps in the algorithm are written as below

1. Extract the features of query image using proposed algorithm.

2. Compute similarity index between query image feature vector and every database image feature vector.

3. Sort the similarity index.

4. Retrieve images as final results which correspond to shorter distance.

5. Evaluation measure

5. Results and discussions

In this work, we have used four similarity measures to retrieve images, and Euclidian distance measure shows poor results. It also has been found that when we use canbarra similarity index, it gives best precision values which are almost close to 1 or 100%. The results have been visualized by bar graphs in the figures below.

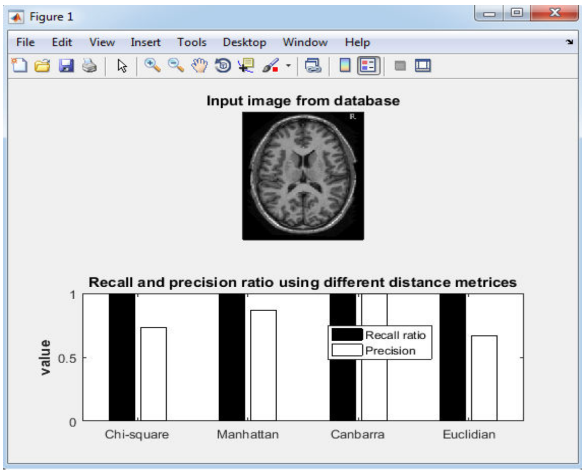

Figure 2: Recall and precision ratio using different distance metrics for image one

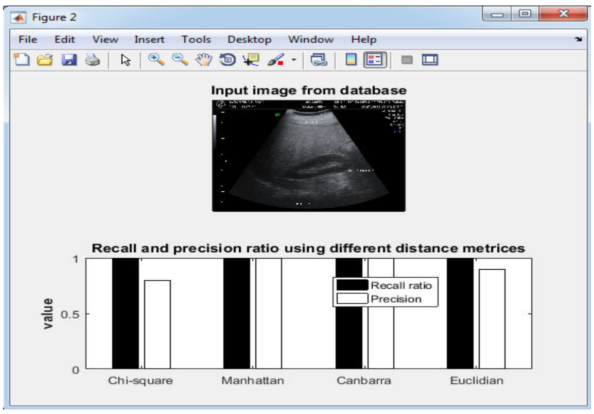

Figure 3: Recall and precision ratio using different distance metrics for image two

6. Conclusion

Medical imaging plays a significantly important role in the fields of computer assisted diagnosis and medical analysis. Among different types of medical data, the images are regarded as a source for the diagnosis aid because they are able to directly capture the patient pathology. Consequently, a huge number of medical images are collected every day in hospitals and medical institutions. To fully apply these medical images, many techniques have been developed to handle the obtained images from different aspects, such as data representation, storage, segmentation, and reconstruction. In this work, local binary patterns and its variants has been explored to extract the spatial domain texture features. For extraction of frequency domain features, local phase quantization has been used (LPQ). LPQ features are similar to LBP in which four STFT transformed pixels from neighborhood are selected and their real and imaginary values are considered to match with center pixel. Along with these GLCM texture features are also included. Similarity has been found by using four different distance measure metrics, in which Canbarra and Manhattan gives higher precision and recall than Euclidian as well as Chi-square test. Proposed method would assist clinical practitioners to retrieve relevant medical image to a query image provided to the system.

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