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Center symmetric local binary co-occurrence pattern for texture, face and bio-medical image retrieval ☆

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ABSTRACT

Content based image retrieval is a common problem for a large image database. Many methods have been proposed for image retrieval for some particular type of datasets. In the proposed work, a new image retrieval technique has been introduced. This technique is useful for different kind of dataset. In the proposed method, center symmetric local binary pattern has been extracted from the original image to obtain the local information. Co-occurrence of pixel pairs in local pattern map have been observed in different directions and distances using gray level co-occurrence matrix. Earlier methods have utilized histogram to extract the frequency information of local pattern map but co-occurrence of pixel pairs is more robust than frequency of patterns. The proposed method is tested on three different category of images, i.e., texture, face and medical image database and compared with typical state-of-the-art local patterns.

1. Introduction

1.1. Motivation

Content based image retrieval is a technique for retrieving similar images for a particular query image from a large image dataset. Different kinds of image have different features. Extracting image features according to the user requirement and database images, is a difficult task in the present scenario. Many feature descriptors have been proposed for image retrieval in the past few years. Most of them stick to a particular type of images. A multipurpose image feature descriptor is essential need of present scenario which can be beneficial to the different kind of images. Extensive and comprehensive reviews of content based image retrieval techniques have been given in [1–3].

1.2. Related work

Low level features, e.g., color, shape, texture, are so popular since they are easy to extract, and many methods have been proposed for extracting these low level features. Similar patterns in an image, define the presence of texture. Texture can be found within an image in some blocks or in the whole image. Texture analysis and retrieval can be of interest of plants, clothing, furniture, etc. industries since all of these images carry full of texture. For texture feature analysis, many methods have been used, including discrete wavelet transform [4–6], Gabor filters [7,8], etc. Wavelet transform gives four sub-band images that provide directional information about image and that helps in texture classification. For more direction based information, discrete wavelet transform is modified into rotated wavelet filter [9], rotated complex wavelet filter [10] and dual tree complex wavelet transform [11] for texture features.

Haralick et al. introduced the concept of gray level co-occurrence matrix (GLCM), and extracted statistical features for texture image classification [12]. GLCM works directly with intensity of image and provides the spatial co-relation of pixels in the image and hence, it is helpful in texture feature extraction. GLCM was improvised in generalized co-occurrence matrix that extracts some important spatial properties of distribution of local maxima [13]. GLCM was used for rock texture image retrieval [14]. Instead of the original image, GLCM was extracted from Prewitt edge images, and statistical parameters were calculated from GLCM [15]. Further, GLCM was extended for better feature

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extraction in texture description [16]. Motif co-occurrence matrix (MCM) has been proposed for content based image retrieval that extracts the information using third order neighborhood statistics of image [17]. It is extended to 'modified color motif co-occurrence matrix' (MCMCM) [18], that explains the inter co-relation between red, green and blue channels. Texton histogram is combined with motif co-occurrence matrix for content based image retrieval [19].

Local binary patterns (LBPs) were invented for extracting local information of each pixel using neighboring pixels [20]. Moreover, LBP was converted in uniform and rotation invariant patterns [21]. LBP was used in many image and signal processing applications, e.g., texture classification [20,21], face recognition [22], facial expression recognition [23], object tracking [24], etc. Extensions of LBP were proposed for better quantitative and qualitative performance. Dominant LBP [25], completed LBP [26], Line edge pattern for segmentation and image retrieval (LEPSEG & LEPINV) [27], local ternary pattern (LTP) [28], center symmetric local binary pattern (CSLBP) [29], etc. have been proposed for image feature extraction. The pyramid based local binary pattern (PLBP) [30] has been proposed for texture classification by Qian et al. In this method, multi-resolution images were extracted from the original image using a low pass filter, and LBP features collected from the multi-resolution low pass images. LBP works uniformly for all neighboring pixel irrespective of direction. To overcome this issue, directional local extrema patterns (DLEP) have been proposed that extract the edge information on the basis of four directions in the image [31] and applied for image retrieval. DLEP extracts only directional edge information. Reddy et al. have included magnitude patterns in DLEP and created directional local extrema and magnitude patterns [32]. Murala et al. have proposed local maximum edge binary pattern that based on the magnitude of the local edge for each pixel in the image [33]. After LBP and LTP, Local tetra patterns have been proposed which consider the second order derivation in horizontal and vertical directions [34], that form a tetra pattern, and further converted into binary patterns. Moreover, local tetra patterns were extended into RGB color space and called local oppugnant pattern [35]. A robust local binary pattern (RLBP) has been proposed that contains sign and magnitude local patterns, also it is extended using Gabor wavelets [36]. Local patterns were extended to three dimensional patterns for dynamic images and better feature extraction. Local binary pattern has been extended into three dimensional patterns for dynamic texture recognition [37]. Murala and Wu used Gaussian filters and RGB color space to use to provide a 3D space and extracted LTP from different directions and called spherical symmetric 3D local ternary patterns [38].

Content based image retrieval might be beneficial in medical imaging for handling large image database. It can be very useful for medical students and interns to learn disease by retrieving similar images corresponding to a particular image. Medical image retrieval has been performed using an open source system (GNU Image Finding Tool) with some improvement using histogram and Gabor filters [39]. Discrete sine transform is used for feature extraction and 'Boosting' method is applied for increasing the accuracy of the system [40]. Image retrieval has been performed using wavelet transform with Daubuchies, Haar and Gabor wavelets, and statistical features have been extracted for magnetic resonance image retrieval [41]. The directional binary wavelet pattern has been proposed for face and biomedical image retrieval using binary wavelet and local binary pattern [42]. Felipe et al. proposed medical image retrieval using gray level co-occurrence matrix in $0^\circ, 45^\circ, 90^\circ$ and 135° directions, and 1, 2, 3, 4 and 5 distances [43]. Further, feature vector has been obtained from GLCM. Murala et al. proposed local mesh pattern (LMeP) for biomedical image retrieval and indexing. It creates a local pattern using the mesh of neighboring pixels [44]. Peak valley edge patterns were proposed for medical image retrieval that extracts directional edge information using first order derivative [45]. Local mesh patterns and peak valley edge patterns were combined into local mesh peak valley edge patterns and proposed for MRI and CT image indexing and retrieval [46].

1.3. Main contributions

A content based image retrieval system has been proposed in this paper. Main contributions of the paper are as follows:

1. A multi purpose image retrieval method named as center symmetric co-occurrence local binary pattern (CSCoLBP) has been proposed for different kinds of images.
2. Co-occurrence of local patterns has been obtained for image features using center symmetric local binary pattern and GLCM.
3. The proposed method has been tested on texture, face and MRI image database, and compared with some existing local patterns for effectiveness.

This paper is organized in the following manner: In Section 1, introduction has been presented which includes, motivation, literature survey and main contribution of the proposed work. Brief review of existing methods has been given in Section 2. Proposed method has been explained in Section 3. In Section 4, framework of proposed method has been demonstrated. Section 5 is experimental section. Finally, conclusion has been drawn in Section 6.

2. Local patterns and GLCM

2.1. Local patterns

2.1.1. Local binary pattern

LBP is created by the difference of local pixels. Each pixel is considered as a center pixel at a time, and the comparisons of center pixel with local surrounding pixels are obtained. On the basis of the comparison, a binary value is assigned to each surrounding pixel and these binary values multiplied by specific weights and summed up. This summation value is called binary pattern value for that center pixel. For each pixel of the image, a binary pattern value is obtained and all pattern value together called the local binary map of the image. For feature vector, histogram of this local binary map is created. Mathematically, LBP has been defined as follows:

$$\mathrm{LBP}_{P,R} = \sum_{s=0}^{P-1} 2^s \times T_1(I_s - I_c) \tag{1}$$

$$T_1(a) = \begin{cases} 1 & a \geqslant 0 \\ 0 & \text{else} \end{cases}$$

$$H(L)|_{\mathrm{LBP}} = \sum_{x_1=1}^{m} \sum_{x_2=1}^{n} T_2(\mathrm{LBP}(x_1, x_2), L); L \in [0, (2^P - 1)] \tag{2}$$

$$T_2(a_1, b_1) = \begin{cases} 1 & a_1 = b_1 \\ 0 & \text{else} \end{cases} \tag{3}$$

where P and R denote the number of neighboring pixels and radius for neighboring pixels. Center pixel and surrounding pixels are denoted as I_c and I_s. Final histogram of pattern map is computed by Eq. (2). A sample window of LBP calculation is shown in Fig. 1.

2.1.2. Center symmetric local binary pattern

It is a modified form of local binary pattern. It extracts a local pattern for every pixel of the input image region. In center