Int. J. Electron. Commun. (AEÜ) 69 (2015) 290–298

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

Local oppugnant color space extrema patterns for content based natural and texture image retrieval

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ARTICLE INFO

Article history:
Received 21 April 2014
Accepted 22 September 2014

Keywords:
Local oppugnant patterns
Local extrema
Local binary patterns (LBP)
Color-texture
Databases

ABSTRACT

This paper proposes a novel feature descriptor called local oppugnant color space extrema patterns (LOCSEP) for image indexing retrieval. The existing directional local extrema pattern (DLEP) extracts the directional edge information based on local extrema in 0°, 45°, 90°, and 135° directions in an image. The proposed method integrates the concepts of color and texture features. First, the color image is converted into RGB (red, green and blue) and HSV (hue, saturation and value) color spaces. Then oppugnant color spaces, RV, GV, BV are used for the extract of oppugnant DLEP features (LOCSEP). The performance of the proposed method is tested by conducting two experiments on benchmark databases viz. Corel-1K and MIT VisTex databases. The performance of the proposed method is compared with the state-of-the-art methods for image retrieval and face recognition applications in terms of average retrieval precision (ARP) and average retrieval rate (ARR). The results after being investigated show a significant improvement in terms of their evaluation measures as compared to state-of-the-art methods on respective databases.

1. Introduction

Retrieval of specific images from a large size image database is a challenging task. In the early years, text based retrieval is used to retrieve the images from database. But text based image retrieval is suffering with two major problems: image annotation and human perception. To address these two problems, content based image retrieval (CBIR) is introduced. CBIR extracts the visual features from the raw images and calculate an associated measure (similarity or dissimilarity) between a query image and database images based on these features. Hence the feature extraction is a very important step and the effectiveness of a CBIR system depends typically on the method of extraction of features from raw images. The extensive literature on CBIR is presented in [1–5].

In literature many color features are available, including the color histogram (CH) [6] like HSV color histogram [7,8] and the color correlogram (CC) [9–11]. Some more comprehensive and extensive literature survey on color based CBIR is presented in [11–15]. However, their retrieval performance is usually limited, especially on large databases due to lack of discrimination power of such color descriptors.

Texture analysis has been an eye catcher due to its potential values for computer vision and pattern recognition applications. Smith et al. have used the mean and variance of the wavelet coefficients as texture features for CBIR [16]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [17,18]. Ahmadian et al. used the wavelet transform for texture classification [19]. Moghaddam et al. introduced a new algorithm called wavelet correlogram (WC) [20]. Saadatmand et al. [21,22] improved the performance of the WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). The integration of color and texture features are proposed in [9,23,24]. Jhanwar et al. [23] have proposed the motif co-occurrence matrix (MCM) for content based image retrieval. The MCM is derived from the motif transformed image which is calculated by dividing the whole image into non-overlapping 2×2 pixel patterns. Lin et al. [24] combined the color feature, k-mean color histogram (CHKM) and texture features, motif co-occurrence matrix (MCM) and difference between the pixels of a scan pattern (DBPSP). Vadivel et al. [9] proposed the integrated color and intensity co-occurrence matrix (ICICM) for image retrieval application. First they analyzed the properties of the HSV color space and then suitable weight functions have been suggested for estimating relative contribution of color and gray levels of an image pixel. The suggested weight values for a

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http://dx.doi.org/10.1016/j.aeue.2014.09.015
1434-8411/

pixel and its neighbor are used to construct an ICICM. Subrahmanyam et al. [25] integrated the concepts of wavelet tree and color vocabulary tree for natural and texture image retrieval. The characteristics (vector points) of image are computed using color (color histogram) and SOT (spatial orientation tree). The SOT defines the spatial parent–child relationship among wavelet coefficients in multi-resolution wavelet sub-bands.

Recently, local features called local binary patterns (LBP) [26] are used for image retrieval. Initially, LBP is proposed by Ojala et al. for texture description [27] and these LBPs are converted to rotational invariant for texture classification [28]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [29]. Ahonen et al. [30] and Zhao et al. [31] used the LBP operator facial expression analysis and recognition. Li et al. used the combination of Gabor filter and LBP for texture segmentation [32]. Zhang et al. proposed the local derivative pattern for face recognition [33]. They have considered LBP as a nondirectional first order local pattern, which are the binary results of the first-order derivative in images. The versions of the LBP and the LDP in the open literature cannot adequately deal with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc. In order to address this problem, the local ternary pattern (LTP) [34] has been introduced for face recognition under different lighting conditions. Subrahmanyam et al. have proposed the various pattern based features, local maximum edge patterns (LMEBP) [35], local tetra patterns (LTrP) [36] and directional local extrema patterns (DLEP) [37] for natural/texture image retrieval and directional binary wavelet patterns (DBWP) [38], local mesh patterns (LMeP) [39] and local ternary co-occurrence patterns (LTCoP) [40] for biomedical image retrieval. Reddy et al. [41] have extended the DLEP features by adding the magnitude information of the local gray values of an image. Jacob et al. [42] have proposed the local oppugnant color texture pattern (LOCTP) for image retrieval.

The main contributions of the presented work are summarized as follows. (a) The existing features in literature collect the color-texture information from individual color spaces like RGB, HSV, LAB, etc. Whereas our operator (LOCSEP) is obtained by computing the texture pattern over R, G and B channels with the oppugnant color space of V from HSV color space. It is developed as a joint space color-texture operator for color-texture features. (b) The joint color-DLEP features are extracted from the oppugnant color space of RV, GV and BV. (c) The performance of the proposed method is tested on benchmark image databases.

The paper is summarized as follows: In Section 1, a brief review of content based image retrieval and related work is given. Section 2, presents a concise review of existing local pattern operators. The proposed local operator, proposed system framework and query matching are illustrated in Section 3. Experimental results and discussions are given in Section 4. Based on the above work, conclusions and future scope are derived in Section 5.

2. Review of existing local patterns

2.1. Local binary patterns (LBP)

Ojala et al. [27] have proposed the LBP for texture classification. Success in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification [27–29], face recognition [30,31], object tracking [35], bio-medical image retrieval [38–40] and fingerprint recognition. Given a center pixel in the 3×3 pattern, LBP value is computed by comparing its gray scale value with its neighborhoods based on Eqs. (1) and (2):

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

$$f_1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \tag{2}$$

where $I(g_c)$ denotes the gray value of the center pixel, $I(g_p)$ represents the gray value of its neighbors, P stands for the number of neighbors and R, the radius of the neighborhood.

After computing the LBP pattern for each pixel (j, k), the whole image is represented by building a histogram as shown in Eq. (3).

$$H_{LBP}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(LBP(j,k), l); \quad l \in [0, (2^P - 1)] \tag{3}$$

$$f_2(x, y) = \begin{cases} 1 & x = y \\ 0 & else \end{cases} \tag{4}$$

where the size of input image is $N_1 \times N_2$.

Fig. 1 shows an example of obtaining an LBP from a given 3×3 pattern. The histograms of these patterns contain the information on the distribution of edges in an image.

2.2. Directional local extrema patterns (DLEP)

Subrahmanyam et al. [37] directional local extrema patterns (DLEP) for CBIR. DLEP describes the spatial structure of the local texture using the local extrema of center gray pixel g_c.

In proposed DLEP for a given image the local extrema in 0°, 45°, 90°, and 135° directions are obtained by computing local difference between the center pixel and its neighbors as shown below:

$$I'(g_i) = I(g_c) - I(g_i); \quad i = 1, 2, \ldots, 8 \tag{5}$$

The local extremas are obtained by Eq. (7).

$$\hat{I}_\alpha(g_c) = f_3(I'(g_j), I'(g_{j+4})); \quad j = (1 + \alpha/45) \ \ \forall \alpha = 0°, 45°, 90°, 135° \tag{6}$$

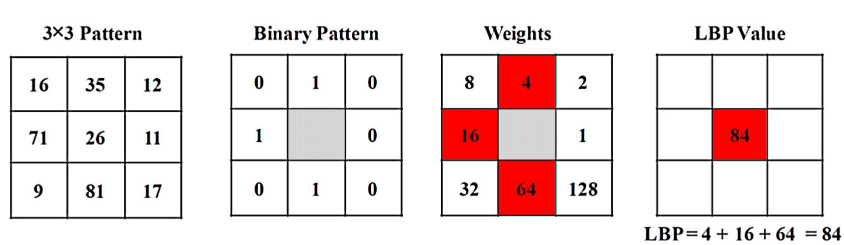

Fig. 1. Calculation of LBP.