International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622
NATIONAL CONFERENCE on Developments, Advances & Trends in Engineering Sciences
(NCDATES- 09th & 10th January 2015)

RESEARCH ARTICLE OPEN ACCESS

Retrieval of Image Using RGB, HSV With Magnitutde

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Abstract:
In this paper, we integrate the concept of local oppugnant color space extrema patterns (LOCSEP) and their magnitude based patterns for content based image indexing and retrieval. 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) However, they are not considering the magnitudes of local extremas. The proposed method integrates these two concepts for better retrieval performance The performance of the proposed method is compared with DLEP, LOCSEP, LBPs by conducting two experiments on benchmark databases, viz. Corel-5K and Corel-10K databases. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to other existing methods on respective databases.

I. Introduction

Retrieval of images from large image databases has been an active area of research for long due to its applications in various fields like satellite imaging, medicine, etc. Content based image retrieval (CBIR) systems extract features from the raw images and calculate an associative 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. Several methods achieving effective feature extraction have been proposed in the literature [1–4]. Texture is the most important feature for CBIR. Smith and Chang used the mean and variance of the wavelet coefficients as texture features for CBIR [5]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [6,7]. Ahmadian and Mostafa used the wavelet transform for texture classification [8]. Moghaddam et al. Introduced new algorithm called wavelet correlogram (WC) [9]. Saadatmand and Moghaddam [7,10] improved the performance of the WC algorithm by opti-mizing the quantization thresholds using genetic algorithm (GA). Birgale et al. [11] and Subrahmanyam et al. [12] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Subrahmanyam et al. proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC + RWC)[13].

Ojala et al. proposed the local binary pattern (LBP) features for texture description [14] and these LBPs are converted to rotational invariant for texture classification [15]. Pietikainen et al. proposed the rotational invariant texture classification using feature distri- butions [16]. Ahonen et al. [17] and Zhao and Pietikainen [18] used the LBP operator facial expression analysis and recognition. Heikkila and Pietikainen proposed the background modeling and detection by using LBP [19]. Huang et al. proposed the extended LBP for shape localization [20]. Heikkila et al. used the LBP for interest region description [21]. Li and Staunton used the combi-nation of Gabor filter and LBP for texture segmentation [22]. Zhanget al. proposed the local derivative pattern for face recognition [23].They have considered LBP as a nondirectional first order local pat-tern, which are the binary results of the first-order derivative in images.

The block-based texture feature which use the LBP texture fea-ture as the source of image description is proposed in [24] for CBIR. The center-symmetric local binary pattern (CS-LBP) which is a modified version of the well-known LBP feature is com-bined with scale invariant feature transform (SIFT) in [25] for description of interest regions. Yao and Chen [26] have pro-posed two types of local edge patterns (LEP) histograms, one is LEPSEG for image segmentation, and the other is LEPINV for image retrieval. The LEPSEG is sensitive to variations in rotation and scale, on the contrary, the LEPINV is resistant to variations in rotation and scale. Subrahmanyam et al. [27] have proposed the DLEP which collects the directional edge information for image retrieval. The above discussed various extensions of LBP features consider only the sign of differences but not magnitudes. The main contributions of this work are summarized as follows: (a) the existing DLEPs are considering only sign of difference between the pixels whereas our method considers the both sign as well as magnitudes and (b) 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 local pattern operators. The proposed system framework and query matching are illustrated in Section 3. Experimental results and discussions are given in Section4. Based on above work, conclusions and future scope are derived in Section 5.

II. Local patterns

2.1. Local binary patterns (LBPs)

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 Eq. (1) and Eq. (2):

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

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

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).

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

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

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.

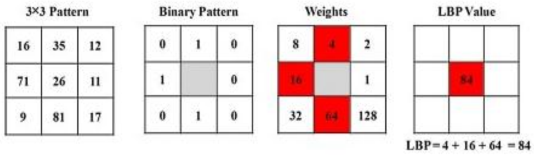

Fig. 1. Calculation of LBP.

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 0º, 45º, 90º, and 135º directions are obtained by computing local difference between the center pixel and its neighbors as shown below:

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

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

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

$$f_3(I'(g_j), I'(g_{j+4})) = \begin{cases} 1 & I'(g_j) \times I'(g_{j+4}) \geq 0 \\ 0 & else \end{cases} \qquad (7)$$

The DLEP is defined (*α*=0º, 45º, 90º, and 135º) as follows:

$$DLEP(I(g_c))\big|_\alpha = \left\{ \hat{I}_\alpha(g_c); \hat{I}_\alpha(g_1); \hat{I}_\alpha(g_2); \ldots\ldots\ldots \hat{I}_\alpha(g_8) \right\} \qquad (8)$$

Eventually, the given image is converted to DLEP images with values ranging from 0 to 511. After calculation of DLEP, the whole image is represented by building a histogram supported by Eq. (15) [37].

$$H_{DLEP|_\alpha}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(DLEP(j,k)\big|_\alpha, l); \qquad l \in [0, 511] \qquad (9)$$

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

2.3 Local Oppugnant Color Space Extrema Patterns (LOCSEPs)

The operators DLEP [37] and LOCTP [42] are motivated us to propose the LOCSEP operator for natural and texture image retrieval. In the proposed LOCSEP, the local chromatic-texture operator is applied on each RGB color channel separately with the oppugnant color channel of V from HSV space. The color channels are used to collect the oppugnant color patterns in such a way that the center pixel is taken from V color channel and the neighbor pixels are taken from R, G and B color channels.

For a given color image *I*, the RGB and HSV color channels are used for the proposed color-texture feature extraction. The LOCSEP is extracted based on the local difference between two oppugnant color channels c_1 and c_2 as follows.

$$I^1_{c_1c_2}(g_i) = I_{c_1}(g_i) - I_{c_2}(g_c); \forall \begin{bmatrix} i = 1,2,....,8 \\ c_1c_2 = RV, GV, BV \end{bmatrix} \tag{10}$$

The local extremas are obtained by Eq. (11).

$$\hat{I}_{c_1c_2,\alpha}(g_c) = f_3(I^1_{c_1c_2}(g_j), I^1_{c_1c_2}(g_{j+4})); \Big| j = (1+\alpha\big/45); \forall \begin{bmatrix} \alpha = 0°,45°,90°,135° \\ c_1c_2 = RV, GV, BV \end{bmatrix} \tag{11}$$

$$f_3(I^1_{c_1c_2}(g_j), I^1_{c_1c_2}(g_{j+4})) = \begin{cases} 1 & I^1_{c_1c_2}(g_j) \times I^1_{c_1c_2}(g_{j+4}) \geq 0 \\ 0 & else \end{cases} \tag{12}$$

The LOCSEP is defined in $\alpha = 0°, 45°, 90°, 135°$ as follows:

$$LOCSEP(I_{c_1c_2}(g_c))\Big|_\alpha = \left\{\hat{I}_{c_1c_2,\alpha}(g_1), \hat{I}_{c_1c_2,\alpha}(g_2), ..., \hat{I}_{c_1c_2,\alpha}(g_8)\right\} \tag{13}$$

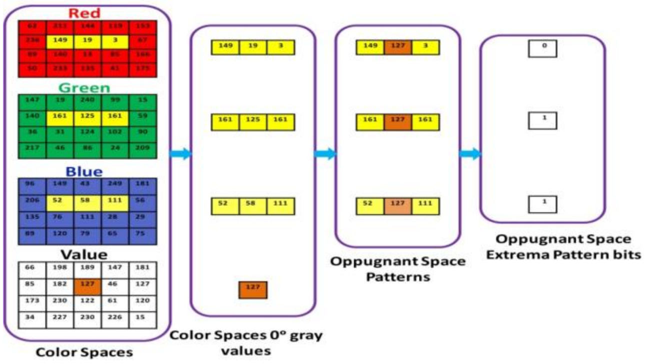

Fig. 2: Calculation of LOCSEP operator in 0®direction.

The total possible LOCSEP operators for a given image is given as follows.

$$\Gamma_L = \begin{Bmatrix} Pattern_{RV,0°}, Pattern_{RV,45°}, Pattern_{RV,90°}, Pattern_{RV,135°} \\ Pattern_{GV,0°}, Pattern_{GV,45°}, Pattern_{GV,90°}, Pattern_{GV,135°} \\ Pattern_{BV,0°}, Pattern_{BV,45°}, Pattern_{BV,90°}, Pattern_{BV,135°} \end{Bmatrix} \tag{14}$$

Eventually, the given image is converted to LOCSEP images with values ranging from 0 to 255. After calculation of LOCSEP, the whole image is represented by building a histogram supported by Eq. (15).

$$H_{LOCSEP^{c_1c_2}_\alpha}(l) = \sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f_2(LOCSEP(j,k)\big|^{c_1c_2}_\alpha, l); l \in [0,255]; \forall \begin{bmatrix} c_1c_2 = RV, GV, BV \\ \alpha = 0°,45°,90°,135° \end{bmatrix}$$

15)

Fig. 2 illustrates the detailed representation of LOCSEP in 0° direction. Let three pixels are selected in 0° direction from Red (149,19,3), Green (161,125,161) and Blue (52,58,111) channels and corresponding one pixel is selected in the Value (127) channel. The oppugnant space/channel patterns are collected by replacing the center pixel of Red, Green and Blue by Value pixel value, the resultant patterns are (149,127,3), (161,127,161) and (52,127,111) respectively. Finally, the oppugnant extrema bits are coded based on the relationship between the center pixel and its neighbors as "0", "1" and "1" respectively.

2.4 *Magnitude* Local Oppugnant Color Space Extrema Patterns (MLOCSEPs)

The existing DLEP [27] considers only the sign of local extrema values which are calculated between the given center pixel and its surrounding neighbors. From the above observation it can be analyze that there is a possible to increase the performance of the system by considering the magnitude of local extremas. The magnitude patterns for local extremas are calculated follows.

$$\hat{I}^M_\alpha(g_c) = f_4(I'(g_j), I'(g_{j+4}));\quad j = \frac{1+\alpha}{45}\ \forall\alpha = 0°,\ 45°,\ 90°,\ \text{and } 135° \tag{16}$$

$$f_4(I'(g_j), I'(g_{j+4})) = \begin{cases} 1 & \text{abs}(I'(g_j)) + \text{abs}(I'(g_{j+4})) \geq Th \\ 0 & \text{else} \end{cases} \tag{17}$$

$$Th = \frac{1}{N_1 \times N_2}\sum_{i=1}^{N_1}\sum_{k=1}^{N_2}(\text{abs}(I'(g_j)\big|_{(i,k)}) + \text{abs}(I'(g_{j+4})\big|_{(i,k)})) \tag{18}$$

The *MLOCSEPs defined as (α*=0º, 45º, 90º, and 135º) as follows:

MLOCSEP **is**

$$(I(g_c))\Big|_\alpha = \{\hat{I}^M_\alpha(g_c); \hat{I}^M_\alpha(g_1); \hat{I}^M_\alpha(g_2); \ldots.\hat{I}^M_\alpha(g_8)\} \tag{19}$$

After calculation *MLOCSEP* of, the whole image is represented by building a histogram supported by Eq (15).

III. Proposed system framework

3.1. Image retrieval system

In this paper, we integrate the features of LOCSEP and magnitude LOCSEP for image retrieval. First, the image is loaded and converted into gray scale if it is RGB. Secondly, the LOCSEPs and magnitude LOCSEPs,(MLOCSEP s) are collected and then go for the histograms calculation. Finally, the feature vector is generated by concatenating the histograms of LOCSEP and MLOCSEP. Fig. 2 depicts the flow chart of the proposed technique and algorithm for the same is presented here:

Algorithm:
Input: Image; Output: Retrieval result

1. Load the image and converted into RGB and HSV channels.
2. Collect the oppugnant channels of RV, GV and BV.
3. Calculate the LOCSEP in α direction.
4. Compute the MLOCSEP patterns in 0◦, 45◦, 90◦ , and 135◦ directions.
5. Construct the histograms LOCSEP for and MLOCSEP patterns in 0◦, 45◦, 90◦, and 135◦ directions.
6. Construct the feature vector by concatenating all histograms.
7. Compare the query image with the image in the database using Eq. (23).
8. Retrieve the images based on the best matches.

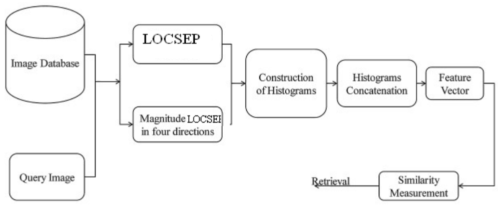

Fig. 2. Proposed image retrieval system framework.

3.2 Query Matching

Feature vector for query image Q is represented as $f_Q = (f_{Q_1}, f_{Q_2}, \ldots\ldots f_{Q_{Lg}})$ obtained after the feature extraction. Similarly each image in the database is represented with feature vector $f_{DB_j} = (f_{DB_{j1}}, f_{DB_{j2}}, \ldots\ldots f_{DB_{jLg}}); j = 1, 2, \ldots\ldots, |DB|$. The goal is to select n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between query image and image in the database $|DB|$. In order to match the images we use four different similarity distance metrics as follows.

Manhattan distance measure:

$$D(Q, I_1) = \sum_{i=1}^{Lg} \left| f_{DB_{ji}} - f_{Q,i} \right| \tag{20}$$

Euclidean distance measure:

$$D(Q, I_1) = \left(\sum_{i=1}^{Lg} (f_{DB_{ji}} - f_{Q,i})^2 \right)^{1/2} \tag{21}$$

Canberra distance measure:

$$D(Q, I_1) = \sum_{i=1}^{Lg} \frac{\left| f_{DB_{ji}} - f_{Q,i} \right|}{\left| f_{DB_{ji}} \right| + \left| f_{Q,i} \right|} \tag{22}$$

d_1 distance measure:

$$D(Q, I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{ji}} - f_{Q,i}}{1 + f_{DB_{ji}} + f_{Q,i}} \right| \tag{23}$$

where $f_{DB_{ji}}$ is i^{th} feature of j^{th} image in the database $|DB|$.

IV. Experiments

The effectiveness of the proposed method is analyzed by conducting two experiments on benchmark databases. Further, it ismentioned that the databases used are Corel-5K. In experiments #1, images from Corel database [30] have been used. This database consists of large number of images of various contents ranging from animals to outdoor sports to natural images. These images have been pre-classified into different categories each of size 100 by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, due its large size and heterogeneous content.

In all experiments, each image in the database is used as the query image. For each query, the system collects n database images X = (x1 , x2 , . . ., xn) with the shortest image matching distance computed using Eq. (15). If the retrieved image xi = 1, 2, . . ., n belongs to same category as that of the query image then we say the system has appropriately identified the expected image else the system fails to find the expected image.

The performance of the proposed method is measured in terms of average precision/average retrieval precision (ARP), average recall/average retrieval rate (ARR) as shown below: For the query image Iq , the precision is defined as follows:

$$Precision - P(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ images\ retrieved} \tag{24}$$

$$Average\ Precision - ARP = \frac{1}{|DB|}\sum_{i=1}^{|DB|} P(I_i)\Bigg| \tag{25}$$

$$Recall - R(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database} \tag{26}$$

$$Average\ Recall - ARR = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R(I_i)\Bigg| \tag{27}$$

a. Corel-5K database

Corel-5K database consists of 5000 images which are collected from 50 different domains have 100 images per domain. The performance of the proposed method is measured in terms of ARP and ARR as shown in Eqs. (24) – (27).

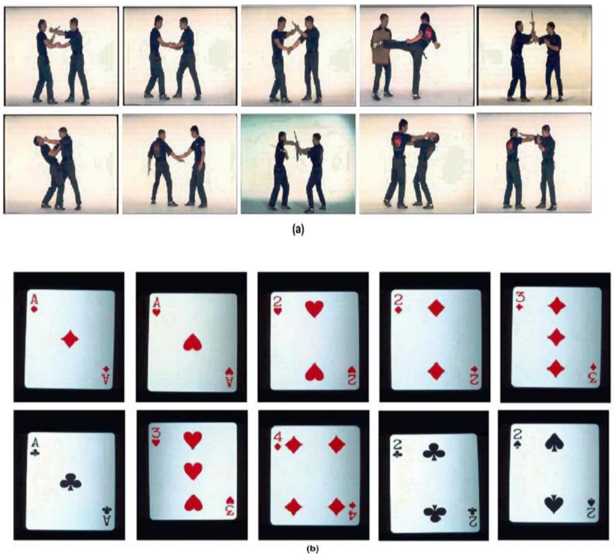

Fig. 3. Two examples of image retrieval by proposed method (MLOCSEP) on Corel-5K database.

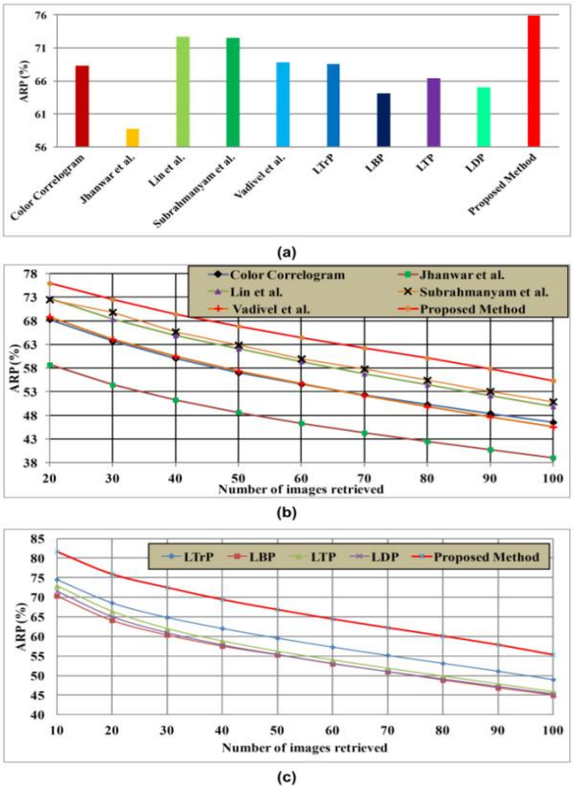

Fig. 4: Comparison of proposed method with other existing methods in terms of ARP on Corel-1K database.

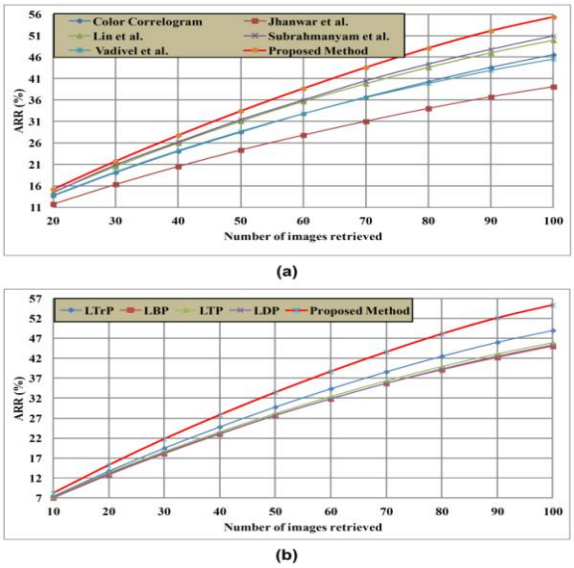

Fig. 5: Comparison of proposed method with other existing methods in terms of ARR on Corel-1K database.

V. Conclusions

A new approach which integrates the LOCSEP and MLOCSEP features for content based image retrieval is presented in this paper. The proposed MLOCSEP differs from the existing LOCSEP in a manner that it extracts the directional edge information based on the magnitudes of local extrema in 0◦ , 45◦ , 90◦ , and 135◦ directions in an image. Performance of the proposed method is tested by conducting experiments on benchmark image databases and retrieval results show a significant improvement in terms of their evaluation measures as compared to other existing methods on respective databases.

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