International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:9, No:6, 2015

Local Mesh Co-Occurrence Pattern for Content Based Image Retrieval

C. Yesubai Rubavathi, R. Ravi

Abstract**—**This paper presents the local mesh co-occurrence patterns (LMCoP) using HSV color space for image retrieval system. HSV color space is used in this method to utilize color, intensity and brightness of images. Local mesh patterns are applied to define the local information of image and gray level co-occurrence is used to obtain the co-occurrence of LMeP pixels. Local mesh co-occurrence pattern extracts the local directional information from local mesh pattern and converts it into a well-mannered feature vector using gray level co-occurrence matrix. The proposed method is tested on three different databases called MIT VisTex, Corel, and STex. Also, this algorithm is compared with existing methods, and results in terms of precision and recall are shown in this paper.

Keywords**—**Content-based image retrieval system, HSV color space, gray level co-occurrence matrix, local mesh pattern.

I. Introduction

CONTENT-BASED image retrieval has become dynamic research area since the 1990's. Typically, image retrieval system is based on two techniques. First technique is based on keyword-based image retrieval system. As manual image annotation is a tiresome process, it is impossible to annotate all images for large database manually. Furthermore, due to the multiple contents of the image and multiple subjectivity of human perception, it is also difficult to make the same annotation to the same image by different users. To overcome these difficulties, content-based image retrieval attempts to mechanize the process of annotating images in the database. The term content in content-based image retrieval may refer to the features such as texture, shape, and spatial layout, etc., Feature extraction plays vital role in CBIR whose efficiency depends on the methods adopted by methods used for the extraction of features.

Color and texture analysis are the key fields in the image retrieval process. The use of joint-color texture in texture feature extraction has been a popular approach in color-texture analysis. Texture feature is based on the local intensity of the image. Hence, statistical features and neighborhood features are discovered for texture pattern. The color feature is represented as a distribution of intensity in various color channels, so that color histogram, color coherence vector, color correlogram, etc., were proposed for color feature descriptors.

C. Yeaubai Rubavathi is with the Anna University, Chennai India (corresponding author, phone: 99407-52988; e-mail: yesubaicharles@gmail.com).

Dr. Ravi Ramraj is with the Francis Xavier Engineering College, Tirunelveli (e-mail: fxcsehod@gmail.com).

II. Related Work

Grey Level Co-occurrence matrix first proposed by Haralick, is well-known method for texture feature extraction. GLCM is a matrix that describes the co-occurrence of the every two pixels in an image. GLCM can be applied to the image for extracting texture features. In [1] correlation between textures of different color channels was calculated and applied for content-based image retrieval system. In [2], GLCM is applied on the multi-scale image obtained from Gaussian smoothing and pyramid representation. [3] Considered three image features for feature extraction. Color co-occurrence matrix (CCM) was adopted and computed the difference between pixels of scan pattern (DSPSP) as feature and color histogram for k mean (CHKM). This method is applied to image retrieval system for large, labeled and unlabelled image databases. [4] applied weight values for a pixel and neighbors and constructed an integrated co-occurrence matrix that is used as a feature in image retrieval process. In [5], joint correlation histograms are constructed between the motif and texon maps in the HSV color space. Local Ternary Pattern (LTP) that compares neighboring pixels and center pixel with a threshold interval was proposed by Tan and Triggs [6]. This assigns a ternary pattern (0,1,-1) then converted into a binary pattern (0,1) and it was applied to the face recognition. Murula et al. proposed a novel algorithm using local extrema pattern and color features. The joint histogram between RGB color channels and LEP patterns has been constructed which is used as a feature vector in object tracking [7]. A novel higher order local pattern descriptor called local derivative pattern was proposed for face recognition by Zhang et al., [8]. Local ternary co-occurrence pattern was proposed [9] for biomedical image retrieval that calculates the co-occurrence of similar ternary edges by using gray values of the center pixel and its neighboring pixels [10]. Murala et al., proposed local maximum edge binary pattern (LMEBP) for object tracking that extract the features based on the magnitude of the local difference between the center pixel and surrounding neighbors. HSV histogram and local maximum edge binary pattern joint histogram were integrated for image retrieval system [11]. Murala et al. proposed the local tetra pattern calculated based on the relationship between the referenced pixels and its neighbors using the first order derivatives in vertical and horizontal directions [12]. Color and local edge features are utilized for color texture retrieval in [13] where distributions of color and local edge patterns [LEPs] are used to retrieve texture images. Center Symmetric Local Binary Pattern (CSLBP) was employed for region descriptor in [14] which combines the power of SIFT and

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:9, No:6, 2015

LBP. Joint histogram of color and local extrema pattern has been proposed by Murala et al. [15].

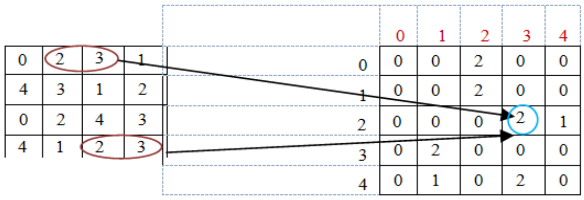

Fig. 1 Original Matrix and GLCM matrix given respectively

A. Main Contribution

A new feature descriptor local mesh co-occurrence pattern (LMCoP) has been proposed for image retrieval system. Color information is extracted from hue and saturation components of HSV color space, and LMCoP is computed for value component. Joint histogram has been built and matching has been done for image retrieval system. The proposed method has been applied on Corel 10k and STex standard texture databases and has been compared with some existing methods. The proposed paper is organized in the following manner: Section I gives a brief introduction. Section II includes a summary of the previous work and major contribution of the presented work. Section III describes the color space, co-occurrence matrix, and local mesh pattern. Proposed approach and similarity measurement are explained in Section IV. Experimental result and discussions are given in Section V. Finally, Section V concludes the paper.

III Color and Texture Descriptor

A. Color Space

HSV color space is most often used in vision and image process applications due to the fact that it separates image intensity information from color information. HSV is the hue, saturation and value in which hue is defined as the angular dimension, saturation represents the brightness and lightness of color components, and value defines the intensity of color. Hue is starting at the red primary at angle 0^o, passing through the green primary at 120° and the blue primary at 240°, and then wrapping back to red at 360°. Saturation and value have the range varies from 0 to 1. In this paper, RGB image is then converted into HSV space.

B. Gray Scale Co-Occurrence Matrix

Gray scale co-occurrence matrix was proposed by Haralick and 24 statistical features are extracted from it. This is a well-known statistical feature for computing image texture feature. It describes how often two pixels occurs together (in a particular direction and distance). Matrix elements correspond to the relative occurrence of pixels of interest and its neighbors. Matrix's size depends on the maximum gray levels in the image. An example of GLCM is shown in Fig. 1. The original matrix is given in Fig. 1 (a) and their corresponding GLCM is given in Fig. 2 (b). For each pair of pixels (0, 0), (0,1),(0,2),(0,3),(0,4),…,(4,4), co-occurrence has been calculated. In matrix (a), a pixel with gray level 2 is occurring two times with pixel 3 in a pair (2, 3) as shown in Fig. 1.

C. Local Mesh Pattern

Subrahmanyam et al. [16] proposed Local Mesh Pattern (LMeP) for biomedical image indexing and retrieval. LMeP defines the local spatial structure of the texture using the relationship between surrounding neighbors for a given center pixel. Local mesh pattern for a 3x3 pattern is obtained by computing differences between two surrounding pixels around the center pixel as shown below:

$$I^1(g_i) = I(g_\alpha) - I(g_i) \qquad (1)$$

where i=1,2,..,8 and α=1+ ((j+P+i-1) mod P).

$$LMeP^{i}_{P,R} = \sum_{j=1}^{P} 2^{j-1} \times f_1(g_s - g_j) \qquad (2)$$

$$s = 1+ ((j+P+i-1) \bmod P) \text{ and } \quad i=1, 2, 3.$$

where i represent the first three patterns, and s represents the surrounding neighbors around the center pixel. After the calculation of LMeP, the whole image is represented by computing the histogram as in (3):

$$H_{LMeP}(l) = \sum_{j=1}^{N} \sum_{k=1}^{M} f_2(LMep(j,k),l); \qquad (3)$$

$$l \in [0, P(P-1)+2]$$

where N and M are the size of the image.

IV. Proposed Method

A novel image retrieval method has been proposed using color and texture information features. As mentioned before, color and texture both are salient features of the image. The selection od color space and quantization of color space are major issues involved in the use of color histograms for retrieval. Initially, RGB image is converted into HSV color space. HSV color space is used for extraction of information in hue, saturation and value components. Hue represents the chromatic components and it varies from 0 to 360. So as to produce color histogram, color quantization needs to be applied. In this work, three quantization schemes of hue component i.e., 18, 36, and 76 have been used. Saturation is quantized into 10 and 20 bins for color information extraction. All possible combinations of hue and saturation have been used and performance has been observed on different databases. Image retrieval from databases using color histogram has proven its excellence. The histogram is built for the hue and saturation parts.

Value component of HSV color space is similar to the gray scale conversion of the RGB image, value component can be used for texture feature extraction method. Color histogram helps to extract the global information of image constructed from hue and saturation components. As local information of each pixel belongs to the texture of image, it is extracted using local mesh patterns (LMeP). LMeP is applied to the value channel of original image. It gives a LMeP map same as the image size with entries from 0 to P(P-1)+2. Histogram extracts the information about the frequency of intensity from the whole image, which means co-occurrence of every pattern across the whole image, and ignores the information about the co-occurrence of pixels.

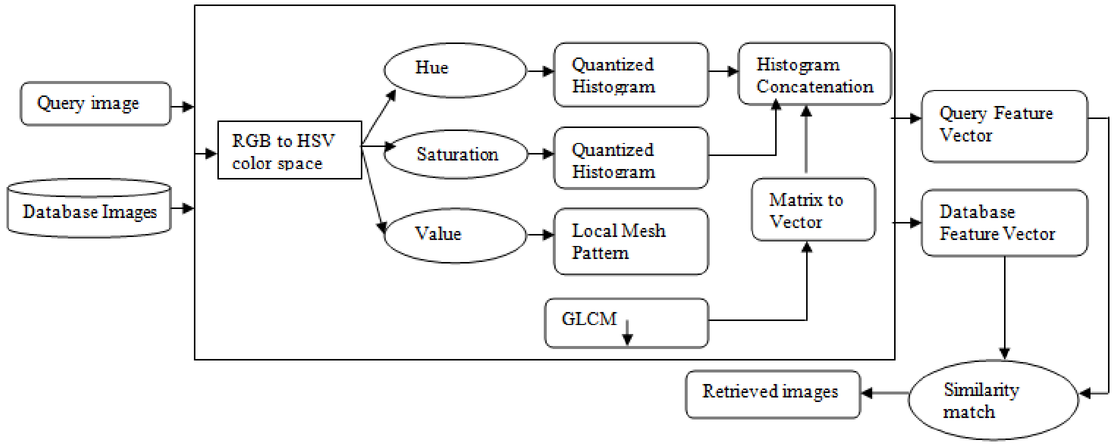

Fig. 2 Flowchart of the proposed approach

Grayscale co-occurrence matrix estimates the relative occurrence of intensity pairs in the image so that the local information of co-occurrence of every pixel pairs in the LMeP map can be extracted in the matrix format. Hence, GLCM is calculated from LMeP map. GLCM in 00 with one distance has been utilized in this proposed approach. In this approach, the size of GLCM is set as 58×58 since values varying in LMeP are 0 to P(P-1)+2. Hence, all possible pairs are 58×58. GLCM is again converted into a single vector, and a combined histogram is constructed from a GLCM single vector, hue and saturation histograms. The total length of the feature vector is based on the quantization number of hue and saturation part.

In the proposed system, databases considered for the experiment, are standard databases, so the size of images in databases is same for certain databases. The feature vector can be normalized to a factor 'n' based on the database images. If the size of images is different, then normalization factor 'n' can vary. We choose factor n=100 for database1 and 2.

A. Similarity Measurement

Similarity measurement has been done between query image and images from the database. Different similarity measures will have an impact on retrieval performance of the CBIR system significantly. The following distance measures have been used in the proposed approach.

1. d1 Distance

$$\text{Dis}(DB_i,Q)=\sum_{n=1}^{l}\left|\frac{f_{DB_i}(n)-f_Q(n)}{1+f_{DB_i}(n)-f_Q(n)}\right| \quad (4)$$

2. Canberra Distance

$$\text{Dis}(DB_i,Q)=\sum_{n=1}^{l}\left|\frac{f_{DB_i}(n)-f_Q(n)}{f_{DB_i}(n)+f_Q(n)}\right| \quad (5)$$

3. Manhattan Distance

$$\text{Dis}(DB_i,Q)=\sum_{n=1}^{l}\left|f_{DB_i}(n)-f_Q(n)\right| \quad (6)$$

4. Euclidean Distance

$$\text{Dis}(DB_i,Q)=\left(\sum_{n=1}^{l}\left|\left(f_{DB_i}(n)-f_Q(n)\right)^2\right|\right)^{1/2} \quad (7)$$

where (DB_i,Q) compares the distance between i^{th} database image and query image. Length of the feature vector is denoted by l. f_{DBi} *and* f_Q are the feature vector of i^{th} images in the database and query image respectively.

B. Proposed System Framework

Flow chart of the proposed system is presented in Fig. 2. Algorithm of the proposed approach is given below.

1. Load the input image
2. Convert it to HSV color space.
3. Quantize the hue and saturation part into 18-36-72 and 10-20 bins respectively and histograms for both.
4. Apply LMeP on the value component of HSV color space and construct LMeP map.
5. Construct GLCM of LMeP map and convert it to vector form.
6. Construct the feature vector by combining all histograms of hue and saturation part of HSV space with GLCM of LMeP map.
7. Compare the database images with query image by using distance measure.
8. Retrieve the best match images as final results.

V. Experimental Results

Two benchmark databases corel-10k and STex have been used for the performance analysis of the proposed method.

Corel-10 k consists of a huge number of images of various contents from animals to outdoors to natural images. An existing method associated with color and texture have been compared with the proposed method. Fig. 1 shows the result of a query on corel-10 k database. Some of the sample images of STex database is given in Fig. 2. Average precision rate of the presented method with other methods on the corel-10k database have been shown in Fig. 5. Average retrieval recall of the proposed approach with existing methods has been shown in Fig.6. From Figs. 5 and 6, it is evident that proposed method outperforms the existing methods. The proposed method has been increased from CS-LBP [14], LEPSEG [13], LEPINV [13], Joint LEP CH [15] up to 9.17%, 17.67%,12%,9.1% in terms of average precision rate on corel-10k. Figs. 7 and 8 show the retrieval performance of the proposed method in terms of APR and ARR respectively on STex database. From Fig. 7, it is clear that proposed method APR on STex has been significantly improved from CS-LBP [14], LEPSEG [13], LEPINV [13], Joint LEP CH [15] up to 21.67%, 28.63%, 26.88%, 15.08%. Table 1 illustrates the retrieval performance of proposed approach using various distance measures on benchmark databases corel-10k and STex. From the Table I, it is evident that proposed method d1 distance measure offers a considerable improvement over other distance measures.

Fig. 3 Query results of the PM on corel-10k database

Fig. 4 STex image samples

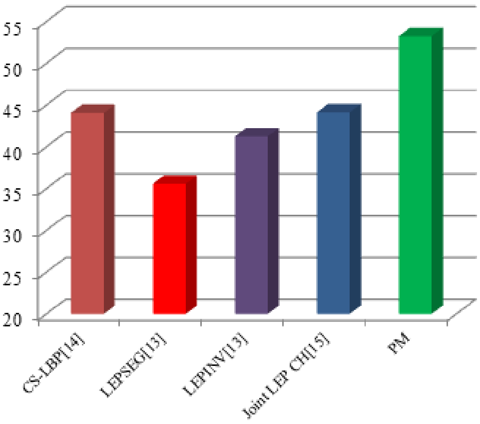

Fig. 5 Average precision rate (APR) of PM on corel-10 k database

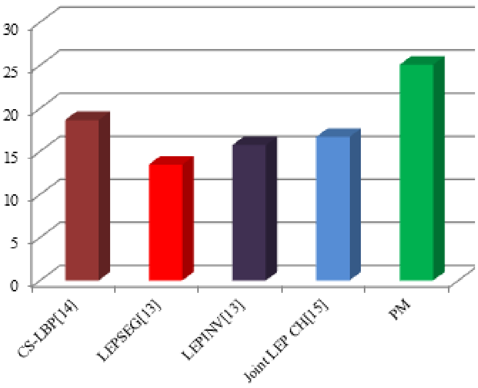

Fig. 6 Average retrieval recall (ARR) of PM on corel -10k database

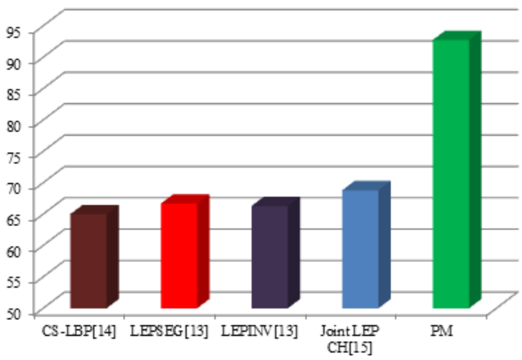

Fig. 7 Average precision rate of PM on STex database

TABLE I
RETRIEVAL PERFORMANCE OF PM ON VARIOUS DISTANCE MEASURE

Distance	Corel - 10K		STex	
	APR	ARR	APR	ARR
d1	53.25	25.06	75.65	92.76
Canberra	50.5	22.78	71.28	88.65
Manhattan	44.34	20.01	66.3	85.46
Euclidean	40.5	18.3	56.75	76.34

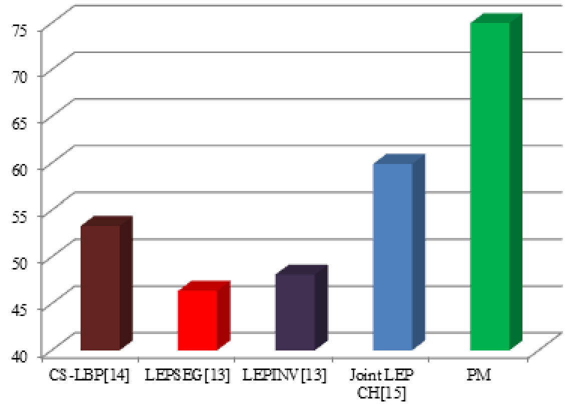

Fig. 8 Average retrieval recall of PM on STex database

VI. CONCLUSION

A novel feature descriptor LMCoP is proposed for color and texture feature extraction. The proposed method uses the properties of local pattern and co-occurrence matrix in HSV color space. This method extracts the local directional information by using GLCM of LMeP. In this work, HSV color space has been used for the color feature in which hue and saturation are used for histogram quantization, the value part of HSV space is applied on LMeP map. Co-occurrence of LMeP map is extracted using GLCM and combined feature vector is used for similarity measures which retrieve the top most matches as the query result. In future, GLCM with other direction and distance can be used for feature extraction. Instead of LMeP, other local patterns with less histogram values may be used.

REFERENCES

[1] Christoph Palm, "Color texture classification by integrative Co-occurrence matrices," *Pattern Recognition*, vol.37 pp. 965-976(2004)

[2] Fernando Roberti de Siqueira, William Robson Schwartz, and Helio Pedrini, "Multi-Scale Gray Level Co-Occurrence Matrices for Texture Description," *Neurocomputing*, vol.120 pp. 336-345,2013

[3] Chuen-Horng Lin, Rong-Tai Chen, and Yung-Kuan Chan, "A smart content-based image retrieval system based on color and texture feature", *Image and Vision Computing*, 2009, 27, 658-665.

[4] A. Vadivel, Shamik Sural, and A.K. Majumdar, "An Integrated Color and Intensity Co-occurrence Matrix", *Pattern Recognition Letters*, vol.28, pp.974-983, 2007.

[5] Santosh Kumar Vipparthi and Shyam Krishna Nagar, "Multi-joint histogram based modeling for image indexing and retrieval", *Computers and Electrical Engineering*, vol.8 pp. 163-173, 2014.

[6] Xiaoyang Tan and Bill Triggs, "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions", *In: Analysis and Modeling of faces and gestures*, 168-182, 2007.

[7] Subrahmanyam Murala, Q.M. Jonathan Wu, R. Balasubramanian ; R.P. Maheshwari, "Joint histogram between color and local extrema patterns for object tracking", *Proc. SPIE* 8663Video Surveillance and Transportation Imaging Applications, 2013.

[8] Baochang Zhang, Yongsheng Gao, Sanqiang Zhao, Jianzhuang Liu, Local derivative pattern versus local binary pattern: Face recognition with higher-order local pattern descriptor, *IEEE Transactions on image processing*, vol.19 pp.533-544, 2010.

[9] Subrahmanyam Murala, Q.M. Jonathan Wu, Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval, Neurocomputing, vol.119 pp.399-412,2013.

[10] Subrahmanyam Murala, R. P. Maheshwari, R. Balasubramanian , Local maximum edge binary patterns: A new descriptor for image retrieval and object tracking, Signal Processing, vol.92 pp.1467-1479,2012.

[11] K.P.Jasmine and P.Rajesh Kumar, Integration of HSV Color Histogram and LMEBP Joint Histogram for Multimedia Image Retrieval, Advances in Intelligent Systems and Computing, vol.243 pp. 753-762, 2014.
[12] Subrahmanyam Murala, R.P. Maheshwari, R. Balasubramanian , Local Tetra Patterns: A New Feature Descriptor for Content-Based Image Retrieval, IEEE Transactions on Image Processing, vol. 21 pp. 2874-2886, 2012.
[13] Cheng-Hao Yao, Shu-Yuan Chen, "Retrieval of translated, rotated and scaled color textures", Pattern Recongition, vol.36 pp.913-929, 2003.
[14] Marko Heikkil¨, Matti Pietik¨ainen, Cordelia Schmid, Description of Interest Regions with Local Binary Patterns, in Computer Vision, Graphics and Image Processing, pp.58-69, 2006.
[15] Subrahmanyam Murala , Q.M. Jonathan Wu; R. Balasubramanian; R.P. Maheshwari, "Joint histogram between color and local extrema patterns for object tracking", *Proc. SPIE* Video Surveillance and Transportation Imaging Applications, pp.86630T, 2013.
[16] Subramaniam Murala, Q. M. Jonathan Wu, "Local Mesh Patterns Versus Local Binary Patterns: Biomedical image indexing and retrieval" IEEE J. Bio. Health. Trans, vol.18 pp.2014, 929-938.