ISSN 2395-1621

Content based Image Retrieval Using Multichannel Feature Extraction Techniques

#1Pooja P. Patil1, #2Prof. B.H. Thombare

1patilpoojapandit@gmail.com

#1M.E. Student, Computer Engineering Department
#2Professor, Computer Engineering Department

Ramchandra College of Engineering,
Lonikand, Pune.

ABSTRACT

The image retrieval techniques are the important part in the multimedia information retrieval, and its application fields are becoming more widely used, such as web related applications, biomedical applications, earth and space sciences etc. Basically there are two research communities, the first one is text based image retrieval, and the other one is content based image retrieval (CBIR).Text based image retrieval gives less complexity method and they are widely used in image retrieval. But manual annotation is required to assist the text based retrieval process. Due to that, the text based image retrieval is not preferable in case of images. The feature extraction in CBIR is a prominent step whose effectiveness depends upon the method adopted for extracting features from given images. The CBIR utilizes visual contents of an image such as color, texture, shape, faces, spatial layout, etc., to represent and index the image database. These features can be further classified as general features such as color, texture, and shape.

ARTICLE INFO

Article History

Received: 15th November 2016

Received in revised form :

15th November 2016

Accepted: 19th November 2016

Published online :

19th November 2016

Keywords: Image retrieval, local patterns, multichannel, LBP, color, texture.

I. INTRODUCTION

The aim of CBIR is to neglect the use of textual descriptions. So in CBIR, retrieving of image based on similarities in their contents like textures, colors, shapes etc. are lower level features of image. CBIR is the application of computer vision techniques to the image retrieval problem, that is, the problem of finding of images from large databases. In Content based image retrieval the search will identifies the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The interesting images to the user are only a very small portion of the large image database, in which most images remain unlabelled. Much work regards the problem as a strict two class classification problem, with equal treatments on both positive and negative examples. It is reasonable to assume positive examples to cluster in certain way, but negative examples usually do not cluster since they can belong to any class . In CBIR, retrieval of image is based on similarities in their contents, i.e., textures, colors, shapes, etc., which are considered the lower level features of an image. Milestone of CBIR system is low level feature extraction. Feature extraction may be done from region or an entire image. These conventional approaches for image retrieval are based on the computation of the similarity between the users query and images. In CBIR each image stored in the large database and its features are extracted, compared to the features of the query image. Thus, broadly, it involves two processes, viz, feature extraction and feature matching. Although, images of real things normally do not contains regions of uniform intensities. Let us take an example, image of a cloth, that is not uniform but having different intensities which form certain repeated patterns called visual texture. The patterns can be the result of cloth properties such as roughness or oriented strands, or they could be the result of reflectance differences such as the color of cloth. We recognize texture when we see it but it is very difficult to define. This difficulty is demonstrated by the number of different texture definitions attempted by vision researchers.

Image texture, defined as a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. An application of image texture is the recognition of image regions using texture properties.

The aim of Content Based Image Retrieval (CBIR) is to extract the similar images of a given image from huge databases by matching a given query image with the images of the database. Matching of two images is facilitated by the matching of actually its feature descriptors (i.e. image signatures). It means the performance of any image retrieval system heavily depends upon the image feature descriptors being matched. Color, texture, shape, gradient, etc. are the basic type of features to describe the image. Texture based image feature description is very common in the research community. Recently, local pattern based descriptors have been used for the purpose of image feature description. Local binary pattern (LBP) has extensively gained the popularity due to its simplicity and effectiveness in several applications. Inspired from the recognition of LBP, several other LBP variants are introduced basically for gray images, in other words only for one channel and performed well but most of the times in real cases the natural color images are required to be characterize which are having multiple channel. Local binary pattern (LBP) is widely adopted texture based feature descriptor for efficient image feature description and simplicity. To describe the color images, it is required to combine the LBPs from each channel of the image. The traditional way of binary combination is to simply concatenate the LBPs from each channel, but it increases the dimensionality of the pattern.

II. CONTENT-BASED IMAGE RETRIEVAL

Content-based image retrieval (CBIR) is a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape. The architecture of a CBIR system can be understood as a basic set of modules that interact within each other to retrieve the database images according to a given query. In typical content-based image retrieval system (Figure 1), the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. With the development of the Internet, and the availability of image capturing devices such as digital cameras, image scanners, the size of digital image collection is increasing rapidly. Efficient image searching, browsing and retrieval tools are required by users from various domains, including remote sensing, fashion, crime prevention, publishing, medicine, architecture, etc. For this purpose, many general purpose image retrieval systems have been developed.

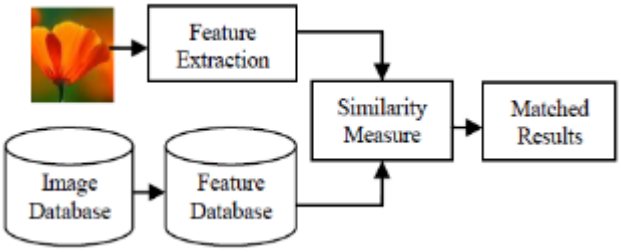

Fig. 1 Content based Image Retrieval System

III. FEATURE EXTRACTION

Visual feature extraction is the basis of any content-based image retrieval technique. In a broad sense, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, etc.). Within the visual feature scope, the features can be further classified as low-level features and high-level features. The selection of the features to represent an image is one of the keys of a CBIR system. Because of perception subjectivity and the complex composition of visual data, there does not exist a single best representation for any given visual feature. Multiple approaches have been introduced for each of these visual features and each of them characterizes the feature from a different perspective.

1. Color

Color is a perception that depends on the response of the human visual system to light and the interaction of light with objects. It is a product of the illuminant, surface spectral reflectance and sensor sensitivity (i.e., of digital sensors or of cones in the human eye). Color is one of the most widely used visual features in content-based image retrieval. It is relatively robust to background complication and independent of image size and orientation. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function. Various studies of color perception and color spaces have been proposed. Each pixel of the image can be represented as a point in a 3D color space. If we want to describe an image by its color features, we have to first determine the color space to use. There exist different space models such as RGB, HSV or opponent color. The best representation depends on the special needs of the application.

2. Gray Level Co-occurrence Matrix

Gray Level Co-occurrence Matrices (GLCM) is a popular representation for the texture in images. They contain a count of the number of times a given feature (e.g., a given gray level) occurs in a particular spatial relation to another given feature. GLCM, one of the most known texture analysis methods, estimate image properties related to second-order statistics.

3. Color Histogram

Color is the most widely used "feature" owing to its intuitiveness compared with other features and most importantly, it is easy to extract from the image. The color histogram depicts color distribution using a set of bins. However, a CBIR system based on color features shows distorted results sometime, because it uses global color feature, It cannot capture color distributions or textures within the image in some cases. To improve the method of the color extraction the color histogram feature can be divided into global and local color extraction. Using Global Color Histogram (GCH), an image will be encoded with its color histogram, and the distance between two images will be determined by the distance between their color histograms. Local color histogram (LCH) can give some sort of spatial information, however the con associated with it is that it uses very large feature vectors. LCH includes information concerning the color distribution of regions. The first step is to segment the image into blocks and then to obtain a color histogram for each block. An image will then be represented by these histograms. When comparing two images, we calculate the distance, using their histograms, between a region in one image and a region in same location in the other image. The distance between the two images will be determined by the sum of all these distances. However, it does not include information concerning the color distribution of the regions, so the distance between images sometimes cannot show the real difference between images. Moreover, in the case of a GCH, it is possible for two different images to have a very short distance between their color histograms. This is their main disadvantage.

4. Geometric Moments

An image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of such moments, normally chosen to have some attractive properties. Image moments are useful to describe objects after segmentation. Simple properties of the image which are found via image moments include area (or total intensity), its centroid, and information about its orientation. This feature use only one value for the feature vector, however, the performance of current implementation isn't well scaled, which means that when the image size becomes relatively large, computation of the feature vector takes a large amount of time. The pros of using this feature combine with other features such co-occurrence, which can provide a better result to user.

5. Color Moments

To overcome the quantization effects of the color histogram, the color moments as feature vectors for image retrieval are used. So color distribution can be characterized by its moments and most information is concentrated on the low moments, only the first moment (mean), the second moment (variance) and the third moment (skewness) are taken as the feature vectors. With a very reasonable size of feature vector, the computation is not expensive. Color Moments are measures that can be differentiate images based on their feature of color, however, the basic concept behind color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. The advantage is that, the degree of asymmetry in the distribution can be measure by its skew-ness.

IV. MULTICHANNEL FEATURE EXTRACTION

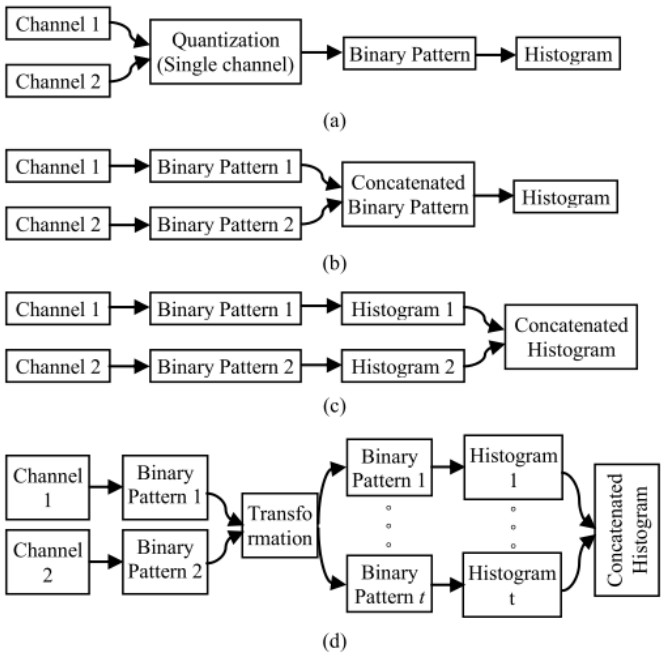

Fig. 2 Illustration of four types of the multichannel feature extraction technique using two input channels

To describe the color images using local patterns, several researchers adopted the multichannel feature extraction approaches. These techniques can be classified in four categories. The first category as shown in Fig. 2(a) first quantizes each channel then merges each quantized channel to form a single channel and form the feature vector over it. The major drawback of this category is the loss of information in the process of quantization. The second category simply concatenates the binary patterns of each channel into the single one as depicted in the Fig. 2(b). The dimension of the final descriptor is very high and not suited for the real time computer vision applications. The main problem with these approaches is that the discriminative ability is not much improved because these methods have not utilized the inter channel information of the images very efficiently. In order to overcome the drawback of the third category, the fourth category comes into the picture where some of bits of the binary patterns of two channels are transformed and then the rest of the histogram computation and concatenation takes place over the transformed binary

patterns as portrayed in the Fig. 2(d). In the third category (see Fig. 2(c)), the histograms are computed for each channel independently and finally aggregated to form the feature descriptor. In this method, the problem arises when more than two channels are required to model.

In furtherance of solving the above mentioned problems of multichannel based feature descriptors, we use generalized 4th category of multichannel based descriptors where any number of channels can be used simultaneously for the transformation. In this scheme a transformation function is used to encode the relationship among the local binary patterns of channels. We use two new approaches of this category in this project, where transformation is done on the basis of adder and decoder concepts. The Local Binary Pattern is used in conjunction with the two methods as the feature description over each Red, Green and Blue channel of the image. Consider the case of color LBP, where simply the LBP histogram over each channel are just concatenated, there is no cross-channel co-occurrence information, whereas, if we want to preserve the cross-channel co-occurrence information then the dimension of the final descriptor will be too high. So, in order to capture the cross-channel co-occurrence information to some extent, we use the adder and decoder based method with lower dimensions. Moreover, the joint information of each channel is captured in each of the output channels of adder and decoder before the computation of the histogram.

V. LITERATURE SURVEY

VI.

To describe the color images using local patterns, several researchers adopted the multichannel feature extraction approaches. Heng et al. [1] computed the multiple types of LBP patterns over multiple channels of the image such as Cr, Cb, Gray, Low pass and High pass channels and concatenated the histograms of all LBPs to form the single feature descriptor. To reduce the dimension of the feature descriptor, they selected some features from the histograms of LBPs using shrink boost method. Choi et al. [2] computed the LBP histograms over each channel of a YIQ color image and finally concatenated to from the final features. Zhu et al. [3] have extracted the multiscale LBPs by varying the number of local neighbors and radius of local neighborhood over each channel of the image and concatenated all LBPs to construct the single descriptor. They also concatenated multiple LBPs extracted from each channel of RGB color image [4]. The histograms of multiscale LBPs are also aggregated in [5] but over each channel of multiple color spaces such as RGB, HSV, YCbCr, etc. To reduce the dimension of the descriptor, Principle Component Analysis is employed in [6]. A local color vector binary pattern is defined by Lee et al. for face recognition [6]. They computed the histogram of color norm pattern (i.e. LBP of color norm values) using Y, I and Q channels as well as the histogram of color angular pattern (i.e. LBP of color angle values) using Y and I channels and finally concatenated these histograms to form the descriptor.

VI. RESEARCH DIRECTION

Local binary pattern (LBP) is widely adopted for efficient image feature description and simplicity. To describe the color images, it is required to combine the LBPs from each channel of the image. The traditional way of binary combination is to simply concatenate the LBPs from each channel, but it increases the dimensionality of the pattern. In order to cope with this problem, this paper proposes a novel method for image description with multichannel decoded LBPs. We introduce adder- and decoder-based two schemas for the combination of the LBPs from more than one channel.

1. Feature Extraction based on multichannel adder based local binary pattern (maLBP)

Algorithm:
Input: Color image;
Output: Feature Vector
1. Load the color image.
2. Calculate the binary pattern using LBP operator for each channel in color image.
3. Transform LBP based binary patterns of each channel in color image into other binary patterns using maLBP.
4. Compute histograms of each maLBP based binary patterns.
5. Concatenate these histograms to form a single feature vector i.e., concatenated histogram.
6. Add the feature vector to the feature matrix i.e., feature database.

2 Feature Matching using similarity measurement and Image Retrieval based on maLBP

The maLBP based feature vector for query image is obtained from feature extraction. Similarly each image in the database is represented with feature vector based on maLBP.The goal is to select the n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between feature vector of query image and feature vectors of images in the database. In order to match the images, we can use different similarity measures.

3 Feature Extraction based on multichannel decoder based local binary pattern (mdLBP)

Algorithm:
Input: Color image;
Output: Feature Vector.
1. Load the color image.
2. Calculate the binary pattern using LBP operator for each channel in color image.

3. Transform LBP based binary patterns of each channel in color image into other binary patterns using mdLBP.
4. Compute histograms of each mdLBP based binary patterns.
5. Concatenate these histograms to form a single feature vector i.e., concatenated histogram.
6. Add the feature vector to the feature matrix i.e., feature database.

4 Feature Matching using similarity measurement and Image Retrieval based on mdLBP

The mdLBP based feature vector for query image is obtained from feature extraction. Similarly each image in the database is represented with feature vector based on mdLBP.The goal is to select the n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between feature vector of query image and feature vectors of images in the database. In order to match the images, we can use different similarity measures.

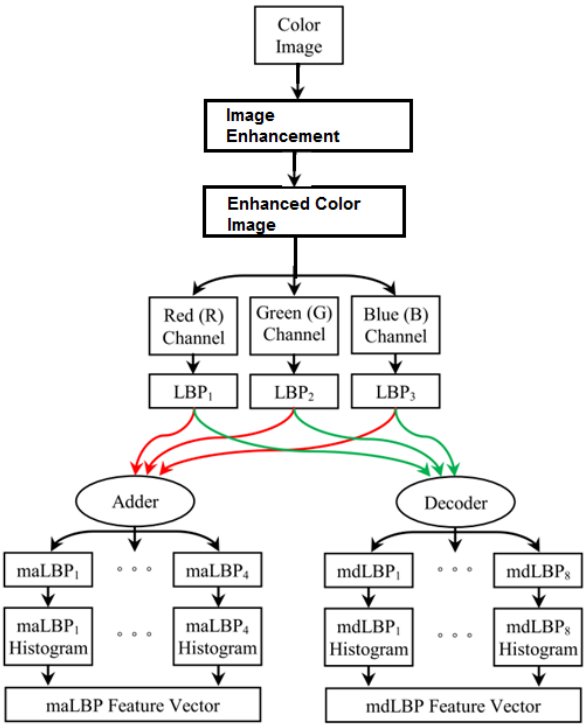

Fig. 3 Proposed texture feature extraction methods for CBIR

VII.CONCLUSION

Content based image retrieval is one of the utmost standard and growing research areas of the DIP (Digital Image Processing). Most of the offered image search tools, for instance Google Images and Yahoo! Image search, are centered on textual annotation of images. The objective of CBIR is to excerpt visual content of an image inevitably, like color, shape or texture. The CBIR tools can be utilized in numerous applications such as digital libraries, photo sharing sites and crime prevention.

REFERENCES

[1] C. K. Heng, S. Yokomitsu, Y. Matsumoto, and H. Tamura, “Shrink boost for selecting multi-LBP histogram features in object detection,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2012, pp. 3250–3257.

[2] J. Y. Choi, K. N. Plataniotis, and Y. M. Ro, “Using colour local binary pattern features for face recognition,” in Proc. 17th IEEE Int. Conf. Image Process. (ICIP), Sep. 2010, pp. 4541–4544.

[3] C. Zhu, C. E. Bichot, and L. Chen, “Multi-scale color local binary patterns for visual object classes recognition,” in Proc. IEEE Int. Conf. Pattern Recognit., Aug. 2010, pp. 3065–3068.

[4] C. Zhu, C.-E. Bichot, and L. Chen, “Image region description using orthogonal combination of local binary patterns enhanced with color information,” Pattern Recognit., vol. 46, no. 7, pp. 1949–1963, Jul. 2013.

[5] S. Banerji, A. Verma, and C. Liu, “Novel color LBP descriptors for scene and image texture classification,” in Proc. 15th Int. Conf. Image Process., Comput. Vis., Pattern Recognit., Las Vegas, NV, USA, 2011, pp. 537–543.

[6] S. H. Lee, J. Y. Choi, Y. M. Ro, and K. N. Plataniotis, “Local color vector binary patterns from multichannel face images for face recognition,” IEEE Trans. Image Process., vol. 21, no. 4, pp. 2347–2353, Apr. 2012.

[7] Shiv Ram Dubey, Satish Kumar Singh, and Rajat Kumar Singh, “Multichannel Decoded Local Binary Patterns for Content-Based Image Retrieval”, IEEE Trans. on Image Processing,vol. 25, no.9, Sept. 2016.

