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Content based Image Retrieval with Multi-Channel Decoded Local Binary Pattern

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ABSTRACT

CBIR technologies provide a method to find images in large databases. Content Based mage Retrieval (CBIR) is a technique which uses visual features of image such as color, shape, texture, etc. Local binary pattern (LBP) is used 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 is concatenation of the LBP's from each channel, but it increases the dimensionality of the pattern. To resolve this problem a method is proposed for image description with multichannel decoded LBPs. The adder and decoder based two schemes are proposed for the combination of the LBPs from more than one channel.

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

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I. INTRODUCTION

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. 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.1.2 (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. 1.2 (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. 1.2 (d). In the third category (see Fig. 1.2(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.

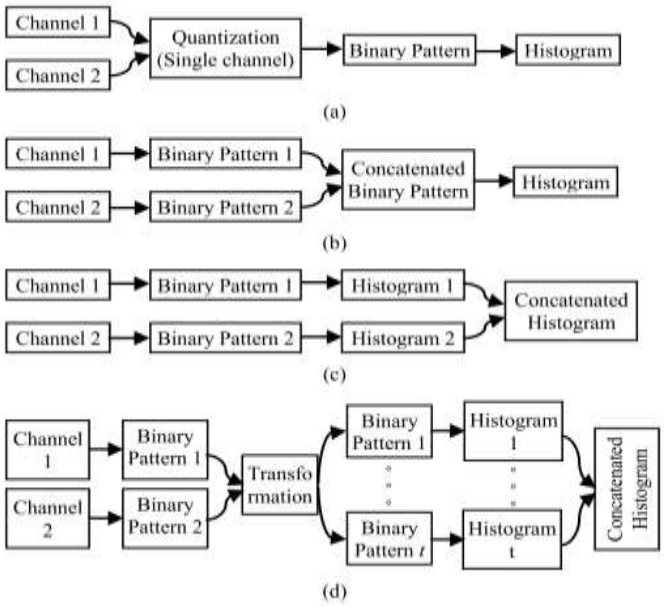


Fig 1 Illustration of four types of the multichannel feature extraction technique using two input channels

The 4th category is generalized on 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. The two new approaches of this category shows transformation is done on the basis of adder and decoder concepts. The Local Binary Pattern is used in conjunction with our 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. 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, adder and decoder based method with lower dimension.

II. RELATED WORK

Cher Keng Heng ,Sumio Yokomitsu, Yuichi Matsumoto, Hajime Tamur "Shrink Boost for Selecting Multi-LBP Histogram Features in Object Detection" proposes a novel "shrink boost" method. It solves a sparse regularization problem with two iterative steps. First, a "boosting" step uses weighted training samples to learn a full high dimensional classifier on all features. This avoids over fitting to few features and improves generalization. Next, a "shrinkage" step shrinks least discriminative classifier dimension to zero to remove the redundant features.

Jae Young Choi, Konstantinos N. Platanioti, Yong Man Ro "USING COLOUR LOCAL BINARY PATTERN FEATURES FOR FACE RECOGNITION" proposes a novel feature representation based on color-based Local Binary Pattern (LBP) texture analysis for face recognition (FR). The proposed method exploits both color and texture discriminative features of a face image for FR purpose. Evaluate the proposed feature using three public face databases: CMU-PIE, Color FERET, and XM2VTSDB. Experimental results show that the results of the proposed feature impressively better than the results of grayscale LBP and color features. In particular, it is shown that the proposed feature is highly robust against severe variations in illumination and spatial resolution.

Chao Zhu, Charles-Edmond Bichot, Liming Chen "Image region description using orthogonal combination of local binary patterns enhanced with color information" propose a new operator called the orthogonal combination of local binary patterns (denoted as OC-LBP) and six new local descriptors based on OC-LBP enhanced with color information for image region description. The aim is to increase both discriminative power and photometric invariance properties of the original LBP operator while keeping its computational efficiency. The experiments in three different applications show that the proposed descriptors outperform the popular SIFT, CS-LBP, HOG and SURF, and achieve comparable or even better performances than the state-of-the-art color SIFT descriptors. Meanwhile, the proposed descriptors provide complementary information to color SIFT, because a fusion of these two kinds of descriptors is found to perform clearly better than either of the two separately. Moreover, the proposed descriptors are about four times faster to compute than colors SIFT.

Sugata Banerji, Abhishek Verma and Chengjun Liu "Novel Color LBP Descriptors for Scene and Image Texture Classification" proposes four novel color Local Binary Pattern (LBP) descriptors are presented in this paper for scene image and image texture classification with applications to image search and retrieval. The oRGB-LBP descriptor is derived by concatenating the LBP features of the component images in the oRGB color space. The Color LBP Fusion (CLF) descriptor is constructed by integrating the LBP descriptors from different color spaces; the Color Grayscale LBP Fusion (CGLF) descriptor is derived by integrating the grayscale-LBP descriptor and the CLF descriptor; and the CGLF+PHOG descriptor is obtained by integrating the Pyramid of Histogram of Orientation Gradients (PHOG) and the CGLF descriptor. Feature extraction applies the Enhanced Fisher Model (EFM) and image classification is based on the nearest neighbor classification rule (EFMNN). The proposed image descriptors and the feature extraction and classification methods are evaluated using three grand challenge databases and are shown to improve upon the classification performance of existing methods.

Seung Ho Lee, Jae Young Choi, Yong Man Ro, and Konstantinos N. Plataniotis "Local Color Vector Binary Patterns From Multichannel Face Images for Face Recognition" proposes a novel face descriptor based on color information, i.e., so-called local color vector binary patterns (LCVBPs), for face recognition (FR). The proposed LCVBP consists of two discriminative patterns: color norm patterns and color angular patterns. In particular, designed a method for extracting color angular patterns, which enables to encode the discriminating texture patterns derived from spatial interactions among different spectral-band images. In order to perform FR tasks, the proposed LCVBP feature is generated by combining multiple features extracted from both color norm patterns and color angular patterns. Extensive and comparative experiments have been conducted to evaluate the proposed LCVBP feature on five public databases. Experimental results show that the proposed LCVBP feature is able to yield excellent FR performance for challenging face images. In addition, the effectiveness of the proposed LCVBP feature has successfully been tested by comparing other state-of-the-art face descriptors.

Shiv Ram Dubey, Satish Kumar Singh, and Rajat Kumar Singh "Multichannel Decoded Local Binary Patterns for Content-Based Image Retrieval" proposes a novel method for image description with multichannel decoded LBPs. Introduce adder- and decoder-based two schemas for the combination of the LBPs from more than one channel. Image retrieval experiments are performed to observe the effectiveness of the proposed approaches and compared with the existing ways of multichannel techniques. The experiments are performed over 12 benchmark natural scene and color texture image databases, such as Corel-1k, MIT-

VisTex, USPTex, Colored Brodatz, and so on. It is observed that the introduced multichannel adder- and decoder-based LBPs significantly improve the retrieval performance over each database and outperform the other multichannel-based approaches in terms of the average retrieval precision and average retrieval rate. 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.

III. IMPLEMENTATION

There are two multichannel decoded local binary pattern approaches namely multichannel adder based local binary pattern (maLBP) and multichannel decoder based local binary pattern (mdLBP) to utilize the local binary pattern information of multiple channels in efficient manners. Total c+1 and 2^c number of output channels are generated by using multichannel adder and decoder respectively from c number of input channels for c ≥ 2.

Table 1 Truth table for adder and decoder map

$LBP_1^n(x,y)$	$LBP_2^n(x,y)$	$LBP_3^n(x,y)$	$maM^n(x,y)$	$mdM^n(x,y)$
0	0	0	0	0
0	0	1	1	1
0	1	0	1	2
0	1	1	2	3
1	0	0	1	4
1	0	1	2	5
1	1	0	2	6
1	1	1	3	7

Let, the multichannel adder based local binary patterns $maLBP_{t1}^n$ (x, y) and multichannel decoder based local binary and multichannel decoder based local binary $mdLBP_{t2}^n$ (x, y) are the outputs of the multichannel LBP adder and multichannel LBP decoder respectively, where t1∈ [1, c + 1] and t2 ∈[1, 2^c]. Note that the values of LBP_t^n (x, y) are in the binary form. Thus the values of $maLBP_{t1}^n$ (x, y) and $mdLBP_{t2}^n$ (x, y) are also in the binary form generated from multi-channel adder and multi-channel decoder map. The truth map of multi-channel adder and multi-channel decoder map are shown in table 1.

$maLBP_{t1}^n$ (x, y) is calculated as below

$$maLBP_{t_1}^n(x,y) = \begin{cases} 1, & if\ maM^n(x,y) = (t_1 - 1) \\ 0, & otherwise \end{cases} \quad 1)$$

Where

$$maM^n(x,y) = \sum_{t=1}^{c} LBP_t^n(x,y) \quad 2)$$

Similarly $mdLBP_{t2}^n$ (x, y) is calculated as below

$$mdLBP_{t_2}^n(x,y) = \begin{cases} 1, & if\ mdM^n(x,y) = (t_2 - 1) \\ 0, & otherwise \end{cases} \quad 3)$$

Where

$$mdM^n(x,y) = \sum_{t=1}^{c} 2^{(c-t)} \times LBP_t^n(x,y) \quad 4)$$

The multichannel adder based binary pattern for the center pixel (x, y) is calculated as below

$$maLBP_{t1}(x,y) = \sum_{n=1}^{N} maLBP_{t_1}^n(x,y) \times f^n \quad 5)$$

Where fn is weighing function.

Similarly multichannel decoder based binary pattern for the center pixel (x, y) is calculated as below

$$mdLBP_{t2}(x,y) = \sum_{n=1}^{N} mdLBP_{t_2}^n(x,y) \times f^n \quad 6)$$

IV. IMPLEMENTATION MODULES

System consists of following main modules:

1. Image enhancement Module

After the input image entered by user it will first come to Image enhancement Module. If the input image is blur then image enhancement is performed. Edges of blur images are sharpened using Sobel operator. Then the images is passed to second module.

2. Computation of feature vectors using maLBP module

The color image is passed to maLBP module. First the binary pattern for each channel in color image are calculated using LBP operator. LBP based binary patterns of each channel in color image are transformed into other binary patterns using maLBP. Histograms for each maLBP patterns are calculated. These histograms are concatenated to form a single feature vector i.e., concatenated histogram. This feature vector is added to the feature matrix i.e., feature database.

3. Computation of matching similarities using maLBP module

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.

4. Computation of feature vectors using mdLBP module

The color image is passed to mdLBP module. First the binary pattern for each channel in color image are calculated using LBP operator. LBP based binary patterns of each channel in color image are transformed into other binary patterns using mdLBP. Histograms for each mdLBP patterns are calculated. These histograms are concatenated to form a single feature vector i.e., concatenated histogram. This feature vector is added to the feature matrix i.e., feature database.

5. Computation of matching similarities using mdLBP module

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.

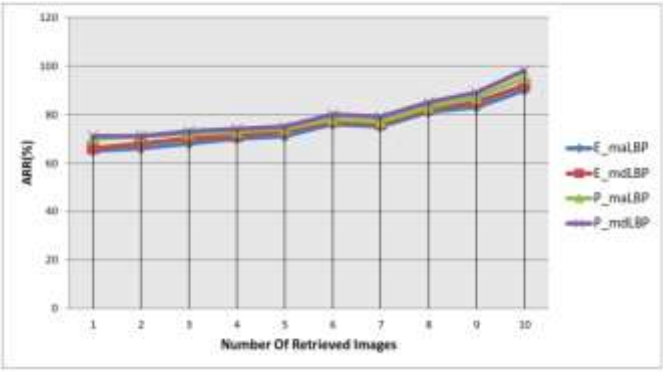
V. EXPERIMENTAL ANALYSIS AND RESULTS

Dataset Description

We use Corel-1k database consists of 1000 images.

- Images are from 10 different categories.
- The categories are 'Buildings', 'Buses', 'Dinosaurs', 'Elephants', 'Flowers', 'Food', 'Horses', 'Africans',' Beaches' and 'Mountains' having 100 images each.

We compared the performance of image retrieval in terms of Average Retrieval Precision rate (ARP) in percentage

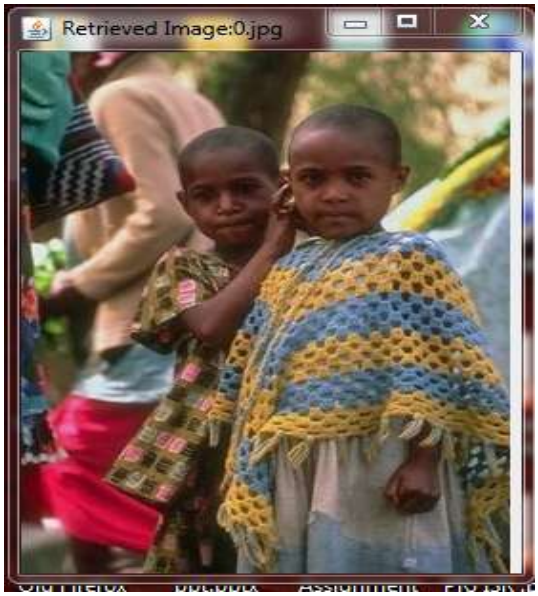


Selection of Input Image

Selected "Search Image"

Retrieved Similar Images

1.

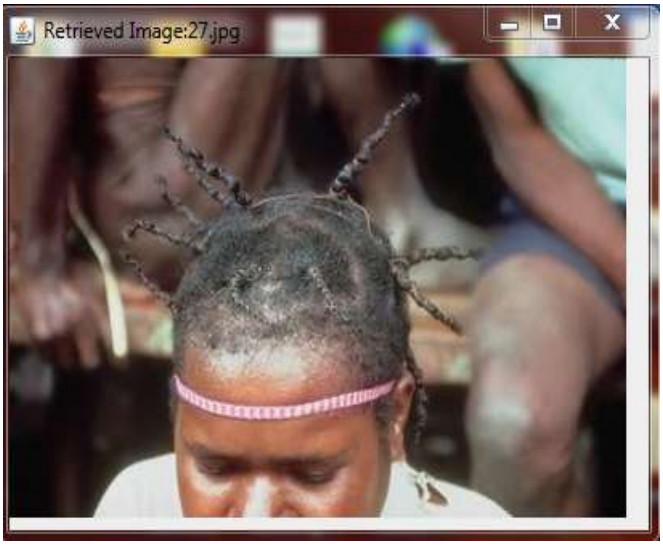


2.

3.

4.

5.



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