Content-Based Image Retrieval Using Multi-Channel Decoded LBP

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Abstract- *Local binary pattern (LBP) is wide adopted for economical image feature description and simplicity. to explain the color photos, it's required to combine the LBPs from each channel of the image. The quality technique of binary combination is to simply concatenate the LBPs from each channel, but it'll increase the dimensionality of the pattern. Thus on deal with this drawback, this paper proposes a unique technique for image description with multichannel decoded LBPs. we tend to introduce adder- and decoder-based two schemas for the mixture of the LBPs from over one channel. Image retrieval experiments area unit performed to observe the effectiveness of the proposed approaches and compared with the present ways in which of multichannel techniques. The experiments square measure performed over twelve benchmark natural scene and color texture image databases, like Corel-1k, MIT-VisTex, USPTex, coloured Brodatz, and so on. It's determined that the introduced multichannel adder- and decoder-based LBPs considerably improve the retrieval performance over every info and outdo the opposite multichannel-based approaches in terms of the average retrieval preciseness and average retrieval rate.*

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

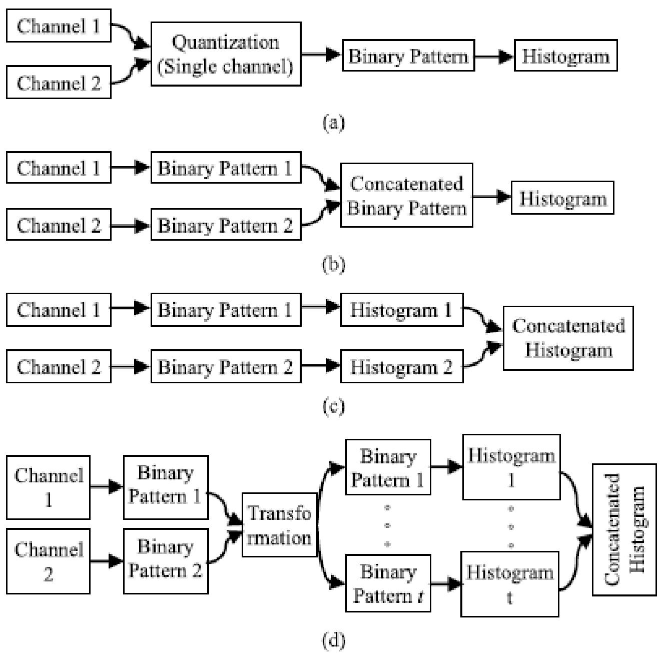
1. INTRODUCTION

IMAGE classification and retrieval is difficult additional and additional attention as a result of its rapid climb in many places. Image retrieval has several applications like in object recognition, biomedical, agriculture, etc. . The aim of Content based Image Retrieval (CBIR) is to extract the similar pictures of a given image from huge databases by matching a given query image with the pictures of the database. Matching of 2 pictures is expedited 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. area unit the basic style of features to explain the image [. Texture based mostly image feature description is incredibly common within the analysis community. Recently, native pattern based mostly descriptors are used for the purpose of image feature description. Local binary pattern (LBP) has extensively gained the popularity as a result of its simplicity and effectiveness in many applications. Inspired from the recognition of LBP, many alternative LBP variants are proposed in the literature. These approaches are introduced basically for grey pictures, in alternative words just for one channel and performed well however most of the days in real cases the natural color pictures are needed to be characterize that are having multiple channel.

A performance evaluating of color descriptors like color SIFT (we have termed mSIFT for color SIFT in this paper), Opponent SIFT, etc. are created for object and scene Recognition in. These descriptors initial notice the regions within the image using region detectors, then figure the descriptor over every region and at last the descriptor is made by using bag-of-words (BoW) model. Researchers are operating to upgrade the BoW model. Another interesting descriptor is GIST, which is largely a holistic illustration of options and has gained wider promotional material due its high discriminative ability. so as to encode the region based mostly descriptors into one descriptor, a vector locally aggregated descriptors (VLAD) has been proposed in the literature . Recently, it's used with deep networks for image retrieval . Fisher kernels are used with deep learning for the classification. terribly recently, a hybrid classification approach is designed by combining the fisher vectors with the neural networks . another recent developments are deep convolutional neural networks for imagenet classification super vector coding discriminative distributed neighbor coding quick coding with neighbor-to-neighbor search, projected transfer distributed committal to writing and implicitly transferred codebooks based mostly visual illustration . These strategies usually higher for the classification downside, whereas we tend to designed the descriptors during this paper for image retrieval. Our strategies don't need any coaching info within the descriptor construction method. Still, we tend to compared the results with SIFT and GIST for image retrieval.

A recent trend of CBIR has been efficient search and retrieval for large-scale datasets using hashing and binary coding techniques. Various methods proposed recently for the large scale image hashing for efficient image search such as Multiview Alignment Hashing (MAH), Neighborhood Discriminant Hashing (NDH) , Evolutionary Compact Embedding (ECE) and Unsupervised Bilinear Local Hashing (UBLH) . These methods can be used with the high discriminative descriptors to improve the efficiency of image search.

To describe the color images using local patterns, several researchers adopted the multichannel feature extraction approaches. These techniques can be classified in five categories. The first category as shown in Fig. 1(a) first quantizes each channel then merges each quantized channel to form a single channel and form the feature vector over it.



Some typical example of this category is Local Color Occurrence Descriptor (LCOD) , Rotation and Scale Invariant Hybrid Descriptor (RSHD) , Color Difference His- togram (CDH) and Color CENTRIST . LCOD basi- cally quantized the Red, Green and Blue channels of the image and formed a single image by pooling the quantized images and finally computed the occurrences of each quantized color locally to form the feature descriptor . Similarly, RSHD computed the occurrences of textural patterns and CDH used the color quantization in its construction process . Chu et al. have quantized the H, S and V channels of the HSV color image into 2, 4 and 32 values respec- tively and represented by 1, 2 and 5 binary bits respectively. They concatenated the 1, 2 and 5 binary bits of quantized H, S and V channels and converted back into the decimal to find the single channel image and finally the features are computed over this image. The major drawback of this category is the loss of information in the process of quanti- zation. The second category simply concatenates the binary. patterns of each channel into the single one as depicted in the Fig. 1(b). The dimension of the final descriptor is very high and not suited for the real time computer vision applications. In the third category (see Fig. 1(c)), the histograms are com- puted for each channel independently and finally aggregated to form the feature descriptor

2. METHODOLOGY

The basic aim of distance measures is to find out the similarity between the feature vectors of two images. Six types of distances used in this paper are as follows:

1) Euclidean distance,
2) L1 or Manhattan distance,
3) Canberra distance,
4) Chi-square (Chisq) or $\chi 2$ distance,
5) Cosine distance, and
6) D1 distance.

B. Evaluation Criteria

In content based image retrieval, the main task is to find most similar images of a query image in the whole database. We used each image of any database as a query image and retrieved *NR* most similar images. We used *Precision* and *Recall* curves to represent the effectiveness of proposed descriptor. For a particular database, the average retrieval precision (ARP) and average retrieval rate (ARR) are given as follows as follows,

$$ARP = \frac{\sum_{i=1}^{\mathbb{C}} AP(i)}{\mathbb{C}} \quad \& \quad ARR = \frac{\sum_{i=1}^{\mathbb{C}} AR(i)}{\mathbb{C}}$$

Where C is the total number of categories in that database, *AP* and *AR* are the average precision and average recall respectively for a particular category of that database and defined as follows for *i th* category,

$$AP(i) = \frac{\sum_{j=1}^{\mathbb{C}_i} Pr(j)}{\mathbb{C}_i} \quad \& \quad AR(i) = \frac{\sum_{j=1}^{\mathbb{C}_i} Re(j)}{C_i} \quad \forall i \in [1, \mathbb{C}]$$

Where *Ci* is the number of images in the *i th* category of that database, *Pr* and *Re* are the precision and recall for a query image and defined as follows for *j th* image of *i th* category,

$$Pr(j) = \frac{NS}{NR} \quad \& \quad Re(j) = \frac{NS}{ND} \quad \forall j \in [1, \mathbb{C}_i]$$

where *NS* is the number of retrieved similar images, *NR* is the number of retrieved images, and *ND* is the number of similar images in the whole database.

In this section, we proposed 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 $2c$ number of output channels are generated by using multichannel adder and decoder respectively from c number of input channels for $c \geq 2$.Let I_t is the tth channel of any image I of size $u \times v \times c$, where $t \in [1, c]$ and c is the total number of channels. If the N neighbors equally-spaced at radius R of any pixel $I_t (x, y)$ for $x \in [1, u]$ and $y \in [1, v]$ are defined as $I^n_t (x, y)$ also depicted in Fig. 2, where $n \in [1, N]$. Then, according to the definition of the Local Binary Pattern (LBP) [6], a local binary pattern $LBP_t (x, y)$ for a particular pixel (x, y) in tth channel is generated by computing a binary value $LBP^n_t (x, y)$ given by the following equation,

$$LBP_t(x, y) = \sum_{n=1}^{N} LBP_t^n(x, y) \times f^n, \quad \forall t \in [1, c] \qquad (1)$$

where,

$$LBP_t^n(x, y) = \begin{cases} 1, & I_t^n(x, y) \geq I_t(x, y) \\ 0, & otherwise \end{cases} \qquad (2)$$

and f^n is a weighting function defined by the following equation,

$$f^n = (2)^{(n-1)}, \forall n \in [1, N] \qquad (3)$$

We have set of N binary values $LBP^n_t (x, y)$ for a particular pixel (x, y) corresponding to each neighbor $I^n_t (x, y)$ of tth channel. Now we apply the proposed concept of multichannel LBP adder and multichannel LBP decoder by considering $LBP^n_t (x, y)\ |\forall t \in [1, c]$ as the c input channels.

The four multichannel adder local binary patterns (i.e. $maLBP_{t1}$ for $t1 \in [1, 4]$) and eight multichannel decoder local binary patterns (i.e. $mdLBP_{t2}$ for $t2 \in [1, 8]$) of example binary patterns (i.e. $LBP^n_t (x, y)$ for $t \in [1, 3]$ and $n \in [1, 8]$) of Fig. 3(a) are mentioned in the Fig. 3(e) and Fig. Respectively. An illustration of the adder output channels and decoder output channels are presented in the Fig. 4 for an example image. An input image in RGB color space (i.e. $c = 3$) is shown in Fig. 4(a). The corresponding Red (R), Green (G) and Blue (B) channels are extracted in the Fig. 4(b-d) respectively. Three LBPs corresponding to the Fig. 4(b-d) are portrayed in the Fig. 4(e-g) for R, G and B channels respectively. The four output channels of the adder and eight output channels of the decoder are displayed in Fig. 4(h-k) and Fig. 4(l-s) respectively. It can be perceived from the Fig. 4 that the decoder channels are having a better texture differentiation as compared to the adder channels and input channels while adder channels are better differentiated than input channels

3. IMPLEMENTATION

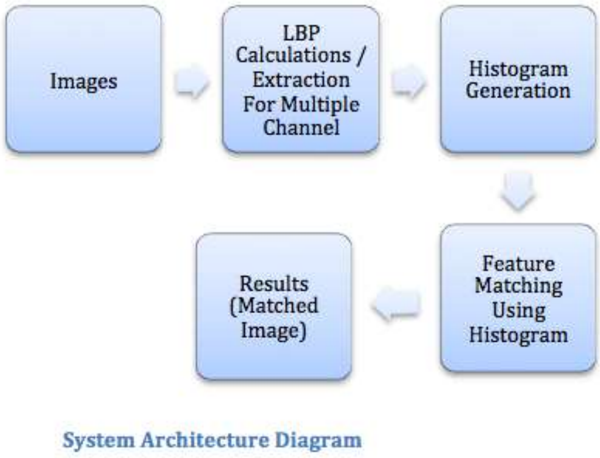


Fig 1:SystemArchitecture

A. LBP Calculations / Extraction For Multiple Channel

The local binary pattern (LBP) texture analysis operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. The current form of the LBP operator is quite different from its basic version: the original definition is extended to arbitrary circular neighbourhoods, and a number of extensions have been developed. The basic idea is however the same: a binary code that describes the local texture pattern is built by thresholding a neighbourhood by the gray value of its center. The operator is related to many well-known texture analysis methods.

B. Histogram Generation

Mage editors typically have provisions to create a histogram of the image being edited. The histogram plots the number of pixels in the image (vertical axis) with a particular brightness value (horizontal axis). Algorithms in the digital editor allow the user to visually adjust the brightness value of each pixel and to dynamically display the results as adjustments are made.Improvements in picture brightness and contrast can thus be obtained.

Image histograms are present on many modern digital cameras. Photographers can use them as an aid to show the distribution of tones captured, and whether image detail has been lost to blown-out highlights or blacked-out shadows.[2] This is less useful when using a raw image format, as the dynamic range of the displayed image may only be an approximation to that in the raw file.

C. Feature Matching Using Histogram

Exact histogram matching is the problem of finding a transformation for a discrete image so that its histogram *exactly* matches the specified histogram.[3] Several techniques have been proposed for this. One simplistic approach converts the discrete-valued image into a continuous-valued image and adds small random values to each pixel so their values can be ranked without ties. However, this introduces noise to the output image.

The histogram-matching algorithm can be extended to find a monotonic mapping between two sets of histograms. Given two sets of histograms $P = \{p_i\}_{i=1}^{k}$ and $Q = \{q_i\}_{i=1}^{k}$ the optimal monotonic color mapping $\min_{M} \sum_{k} d(M(p_k), q_k)$ where $d(\cdot,\cdot)$ is calculated to minimize the distance between the two sets simultaneously, namely where is a distance metric between two histograms. The optimal solution is calculated using dynamic programming.

4. CONCLISION

In this paper, two multichannel decoded local binary pat- terns are introduced specifically multichannel adder local binary pattern (maLBP) and multichannel decoder local binary pattern (mdLBP). primarily both maLBP and mdLBP have utilized the local data of multiple channels on the idea of the adder and decoder ideas. The proposed methods are evaluated using image retrieval experiments over 10 databases having pictures of natural scene and color textures. The results are computed in terms of the average precision rate and aver- age retrieval rate and improved performance is observed compared with the results of the existing multichannel based approaches over every information. From the experimental results, it's concluded that the maLBP descriptor isn't showing the most effective performance in most of the cases whereas mdLBP descriptor outperforms the prevailing progressive multichannel based mostly descriptors. it's also deduced that Chi-square distance measure is better suited with the planned image descriptors. The performance of the proposed descriptors is much improved for 3 input channels and additionally within the RGB color house. The performance of mdLBP is additionally superior to non-LBP descriptors. it's also found out that mdLBP outperforms the state-of-the-art descriptors over large databases. Experiments also suggested that the introduced approach is generalized and can be applied over any LBP based mostly descriptor. The increased dimension of the decoder based descriptor slows down the retrieval time that is the future direction of this analysis. One future aspect of this analysis is to make the descriptors noise robust which can be achieved by using the noise robust binary patterns over every channel because the input to the adder/decoder.

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