Information Retrieval on Image Processing

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Abstract—The Local binary pattern (LBP) is used for efficient image feature description. LBP is a simplest method that is widely used. It is required to combine the LBPs from each channel of the image to describe color images. The traditional way is to concatenate LBPs from each channel. It increases dimensionality of the pattern. To overcome this problem, here proposes a method for image description with multichannel decoded LBPs. The adder based and decoder based schemas introduced for the combination of the LBPs from multiple channels. The multichannel LBP is used along with Structured Similarity Index Method (SSIM). SSIM is used for deciding the uniformity between two images. Image retrieval experiments are performed to heed the strong point of the expected approaches and compared by the whole of the critical methods of multichannel approaches. The analogy experiments are performed completely twelve benchmark impulsive scene and enlarge texture conception databases one as Corel-1k, MIT-VisTex, USPTex, Colored Brodatz, etc. It is observed that the approved multichannel adder and decoder based local twin patterns significantly improves the retrieval performance completely each database and outperforms the distinctive multichannel based techniques in skepticism of the decent retrieval un ambiguity and fair retrieval rate.

Keywords—Local Binary Pattern, Multichannel LBP, CBIR, SSIM.

I. INTRODUCTION

The scan in Content-based image retrieval today is a lively discipline, expanding in breadth. It happens around the maturation behavior of many a discipline, abaft early successes in more or less applications, research instantly concentrates on deeper problems, challenging the hard problems at the crunch of the comeuppance from which it was born: computer vision, databases, and information retrieval [2]. Image retrieval demands greater attention merit to its hot growth in antithetical areas. The image retrieval is having applications such as in object recognition, biomedical, agriculture, etc. [1]. The aim of Content Based Image Retrieval (CBIR) is to extract the similar images of a given image from huge databases by matching the given query image with the images of the database. Matching of the two images is facilitated by the matching of actually its feature descriptors. Feature descriptor means the image signatures. The performance of any image retrieval system heavily depends upon the image feature descriptors being matched [2]. Color, gradient, shape, texture etc. are the basic type of features to describe the image [2, 3, 4].

The texture based image feature description is common in the research field. Recently, local pattern based descriptors have been used for the purpose of image feature description. Local binary pattern (LBP) [5, 6] has extensively gained the popularity due to its simplicity and effectiveness in several applications [7]. The recent trend of CBIR has been efficient search and retrieval of image for a large-scale datasets using hashing and binary coding techniques. A performance evaluating of color descriptors such as color SIFT (termed as mSIFT for color SIFT), Opponent SIFT, etc. are made for object and scene Recognition in. These descriptors first find the regions in the image using region detectors, then compute the descriptor over each region and finally the descriptor is formed by using bag-of-words (BoW) model. Researchers are also working to upgrade the BoW model. Another interesting descriptor is GIST which is basically a holistic representation of features and has gained wider publicity due its high discriminative ability.

Low-level image feature extraction is the basis of CBIR systems. To performance CBIR, image features can be either extracted from the entire image or from regions. As it has been found that users are usually more interested in specific regions rather than the entire image, most current CBIR systems are region-based. Global feature based retrieval is comparatively simpler. Representation of images at region level is proved to be more close to human perception system [3]. Research in content-based image retrieval (CBIR) in the past has been focused on image processing, low-level feature extraction, etc. Extensive experiments on CBIR systems demonstrate that low-level image features cannot always describe high-level semantic concepts in the users' mind. It is believed that CBIR systems should provide maximum support in bridging the 'semantic gap' between low-level visual features and the richness of human semantics.

Shrink boost method [7] computed the multiple types of LBP patterns over more than one 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. Here [7] computed the LBP histograms over each channel of a YIQ color image and finally concatenated to from the final features. Shrink boost method [7] extracted the multi-scale LBPs by varying the number of local neighbours and radius of local neighbourhood 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. The histograms of multi-scale LBPs are also aggregated in 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. A local color vector binary pattern is defined here [7] for face recognition. 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. 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. In mCENTRIST method, the problem arises when more than two channels are required to model, then the author suggested to apply the same mechanism over each combination of two channels which in turn increases the computational cost of the descriptor.

II. PROPOSED SYSTEM

To rejuvenate the farther mentioned problems of multichannel based feature descriptors, we generalized the proposed category of multichannel based descriptors where any number of channels can be used mutually for the transformation. In this approach a conversion function is used to encode the relationship among the local binary patterns of channels. Here considered two new approaches of this type, where transformation is done on basis of adder and decoder concepts. The Local Binary Pattern is used in conjunction with our schemas as the feature description around each Red, Green and Blue channel of the image. The Structured Similarity Index Method is used along with the two approaches that is the adder based and decoder based concepts.

A. Multichannel Decoded Local Binary Patterns

In this section, we considered two multichannel decoded local binary pattern methods namely the multichannel adder based local binary pattern ($maLBP$) and the 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 $c\geq2$. Here we can say that by applying the adder and decoder transformation the inter channel de-correlated information among the adder and decoder channels increases as compared to the same among the input channels.

The process of computation of $maLBP$ and $mdLBP$ feature descriptor of an image is illustrated in Fig. 1 with the help of a schematic diagram. In this diagram, Red, Green and Blue channels of the image are considered as the three input channels. Thus, four and eight output channels are produced by the adder and decoder respectively.

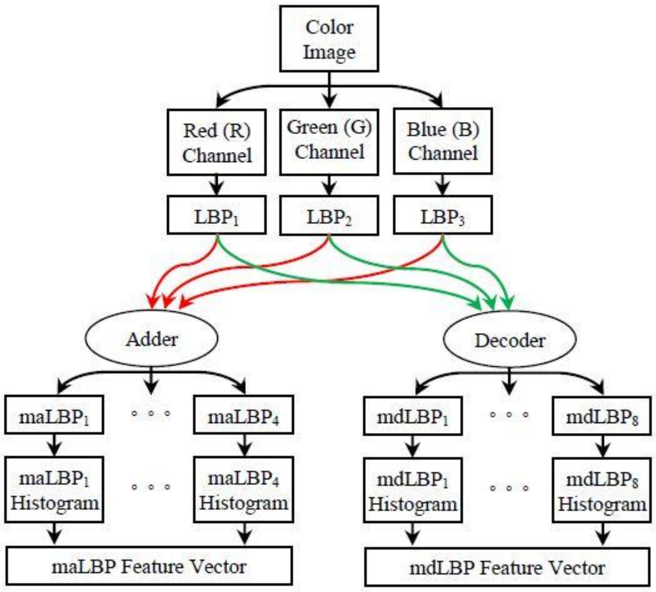

Fig. 1. The flowchart of computation of multichannel adder based local binary pattern feature vector (i.e. *maLBP*) and multichannel decoder based local binary pattern feature vector (i.e. *mdLBP*) of an image from its Red (R), Green (G) and Blue (B) channels.

B. Distance Measure

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) L_1 or Manhattan distance, 3) Canberra distance, 4) Chi-square (Chisq) or χ_2 distance, 5) Cosine distance, and 6) D_1 distance.

C. Stuctured Similarity Index Method

The multichannel LBP is used along with Structured Similarity Index Method. Structured Similarity Index Method is used for deciding the uniformity between two images. The Structured Similarity Index Method index is a entire reference metric; in distinctive words, the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. Structured Similarity Index Method is designed to improve on traditional methods such as peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human visual perception. The SSIM index is calculated on different windows of an image. The measure between two windows x and y of common size N×N is:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

With:

- μ_x the average of x;
- μ_y the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y;

The SSIM index satisfies the condition of symmetry:SSIM (x, y) = SSIM (y, x). The SSIM formula is based on three comparison measurements between the samples of x and y: luminance (l), contrast (c) and structure (s). The individual comparison functions are:

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$

To consider the image quality, this formula is constantly applied only on luma, where luma represents the brightness in an image, during it may also be applied on color (e.g., RGB) values or chromatic (e.g. YCbCr) values. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two equivalent sets of data. Typically it is proposed on window sizes of 8×8. The window can be disjointed pixel-by-pixel on the image, but here it uses only a subgroup of the feasible windows to minimize the difficulty of the calculation.

III. EXPERIMENTS AND RESULTS

Experiments are conducted in Content based image retrieval over databases containing the color images of natural scenes, textures, etc. The results show more accurate images of the query image. The similarity between each image is also distinguished with the similarity index value that is the SSIM index value. On the experiments performed on different images it shows that more similar images have more index value. Experiments also suggested that this approach is generalized and can be applied over any LBP based descriptor. The performances of different descriptors are investigated using average precision, average recall. To demonstrate the effectiveness of the proposed approach, the results of Multichannel Adder and Decoder Local Binary Pattern (i.e. maLBP & mdLBP) compared with existing methods such as Local Binary Pattern (LBP) [8], Color Local Binary Pattern (cLBP) [7], Multi-Scale Color Local Binary Pattern (mscLBP) [7], and mCENTRIST [7].

A. Comparison with Existing systems

The existing system has performed extensive image retrieval experiments over ten databases of varying number of categories as well as varying number of images per category to report the improved performance of proposed multichannel decoded local binary patterns. Proposed method have reported the results using average retrieval precision (ARP), average retrieval rate (ARR), average precision per category (AP) and average recall per category (AR) as the function of number of retrieved images (NR). It is shown by the experiments that proposed mdLBP method outperforms other methods because mdLBP encodes each combination of the red, green and blue channels locally from its LBP binary values. The color in images is depicted by three values but most of methods process these values separately which loss the cross channel information. Whereas, mdLBP takes all the combinations of LBP binary value computed over each channel using a decoder based methodology.

IV. CONCLUSION

Here used two multichannel decoded local binary patterns multichannel adder local binary pattern (maLBP) and multichannel decoder local binary pattern (mdLBP). Along with that here used Structured Similarity Index Method (SSIM) that is integrated with the multichannel decoded local binary patterns. Both the maLBP and mdLBP used the local information of preferably more than one channels on the essence of the adder and the decoder concepts. The proposed techniques are evaluated using image retrieval experiments over the databases having images of natural scene and color textures. By using SSIM along with multichannel decoded LBP the proposed work makes the descriptors noise robust up to the maximum. The results of which are computed in terms of average precision rate and average retrieval rate and improved performance is examined when compared with the results of the existing multichannel based methods over the image database. From the experiments and its results, it can be concluded that the maLBP descriptor is not showing the best performance in most cases while mdLBP descriptor shows the existing futuristic multichannel based descriptors. It is also deduced that Chi-square distance measure is better suited with the proposed image descriptors. The performance of the proposed descriptors is much improved for three input channels and also in the RGB color space. The performance of mdLBP is superior when used with SSIM than alone and non-LBP descriptors. It can also point out that mdLBP with SSIM defeats the futuristic descriptors over large databases. The increased dimension of the decoder based descriptor slows down the retrieval time which is the future direction of this research. It can use noise robust binary patterns over each channel. One of the other future aspects includes integrating other binary pattern methods with this approach.

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