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Scene Image Classification Descriptors

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Abstract: This paper mainly focused on scene image classification which is one of the challenging topics in computer vision and which is also important in terms of image search and image retrieval applications. this paper mainly emphasizes on the three approaches, first one is a 3-Dimensional Local Binary Pattern (3DLBP) descriptor is proposed for color image local feature extraction. Second, a new shape descriptor (HaarHOG) is introduced by combining Haar wavelet transformation and Histogram of Oriented Gradients (HOG). Third, these descriptors are fused using an optimal feature representation technique to generate a robust 3-Dimensional LBP-HaarHOG (3DLH) descriptor that can perform well on different scene image categories. This paper describes in detail the three approaches and also shows effect on combining both approaches. Also we explain the different novel image descriptors with their role.

Keywords— Scene classification, HaarHOG descriptor, 3D-LBP descriptor, image search.

I. INTRODUCTION

Classifying scenes (such as mountains, forests, and offices) is not an easy task owing to their variability, ambiguity, and the wide range of illumination and scale conditions that may apply. The ability to analyze and classify accurately and rapidly the scene in which we find ourselves is highly useful in everyday life.

In recent years, use of color as a means to face recognition and object and scene retrieval has gained popularity. Color features can be derived from various color spaces and they exhibit different properties.

Recent work on color based image search appears in [1], [5], [4] that propose several new color spaces and methods for face, object and scene category recognition. It uses an intermediate representation before classifying scenes [9], and has been applied to cases where there are a larger number of scene categories

The 3-Dimensional Local Binary Pattern (3DLBP) descriptor is for color image local feature extraction. Second, a new shape descriptor (HaarHOG) which combines Haar wavelet transformation and Histogram of Oriented Gradients (HOG).

The HOG descriptor is able to represent an image by storing information about its local shape. The generation of the HOG vector is explained in Figure 1. Efficient retrieval requires a robust feature extraction method that has the ability to learn meaningful low dimensional patterns in spaces of very high dimensional it. Low-dimensional representation is also important when one considers the computational aspect.

In this paper, we employ three masks in three perpendicular planes to generate a novel 3D-LBP feature that contains more information than the traditional LBP. We also subject the image to a Haar wavelet transformation and then generate the HOG of the resultant image to create a robust HaarHOG feature vector. We fuse these two feature vectors in the PCA space to form the 3-Dimensional LBP-HaarHOG (3DLH) feature.

Karhunen Loeve transformation to Achieve this. The linear transformation is defined as follows:

$$I1 = (R+G+B)/3$$
$$I2 = (R-B)/2$$
$$I3 = (2G-R-B)/2$$

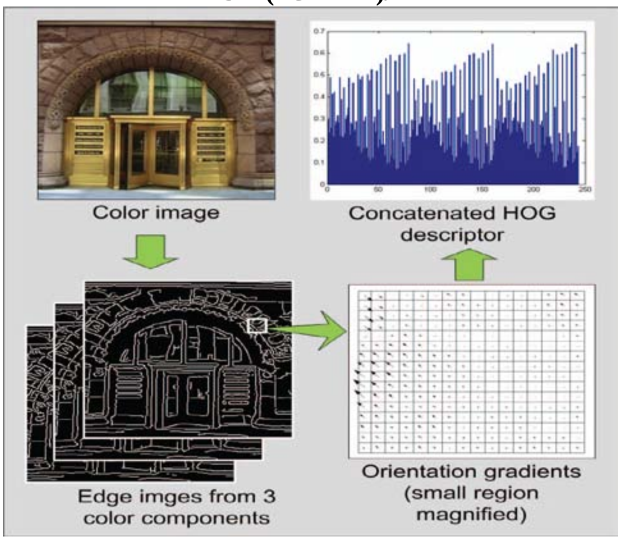

Figure.1 The Histograms of Oriented Gradients (HOG) descriptor.

II. APPROACHES FOR SCENE IMAGE CLASSIFICATION

In this section we study three approaches used for scene image classification namely, 3-Dimensional Local Binary Pattern (DLBP) descriptor, HaarHOG descriptor, 3-Dimensional LBP-HaarHOG (3DLH) descriptor.

A. 3-Dimensional Local Binary Pattern (DLBP) descriptor:

A color image contains three component images, and each pixel of a color image is specified using three values which show varying degrees of correlation. The RGB color space, whose three component images represent the red, green, and blue primary colors, is the common tristimulus space for color image representation. Other color spaces are

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usually calculated from the RGB color space by means of either linear or nonlinear transformations.

To reduce the sensitivity of the RGB images to luminance, surface orientation, and other photographic conditions, the rgb color space is defined by normalizing the R, G, and B components. The HSV color space is motivated by human vision system because humans describe color by means of hue, saturation, and brightness. Hue and saturation define chrominance, while intensity or value specifies luminance [10]. The YCbCr color space is developed for digital video standard and television transmissions. In YCbCr.

RGB images is to décor relate the RGB components [2]. The $\mathbf{I_1I_2I_3}$ color space proposed by C. Zhu, C. Bichot, and L. Chen et al. [12] applies a

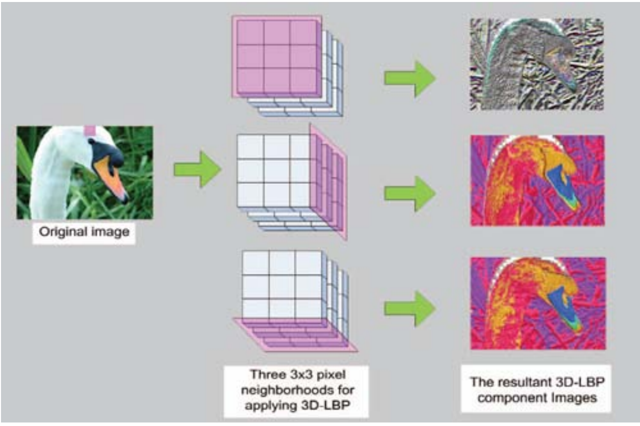

Figure.2 A 3×3×3 pixel region of the original image is magnified to show the 3D-LBP neighborhoods and the resulting LBP images

The LBP descriptor assigns an intensity value to each pixel of an image based on the intensity values of the eight neighboring pixels using a 3×3 mask. Since a color image is represented by a three dimensional matrix, this concept is extended to assign an intensity value to each pixel based on its neighboring pixels not only on the same color plane but on other planes as well. This method as explained in [5] is shown in Fig.2 For doing this operation, replicate the first and third image planes on opposite sides of the three existing planes to create a five-plane matrix. After the 3D-LBP operation, only the three middle planes are retained. The 3D-LBP method produces three images. Concatenate the dense histograms of these three images to obtain the 3D-LBP feature vector.

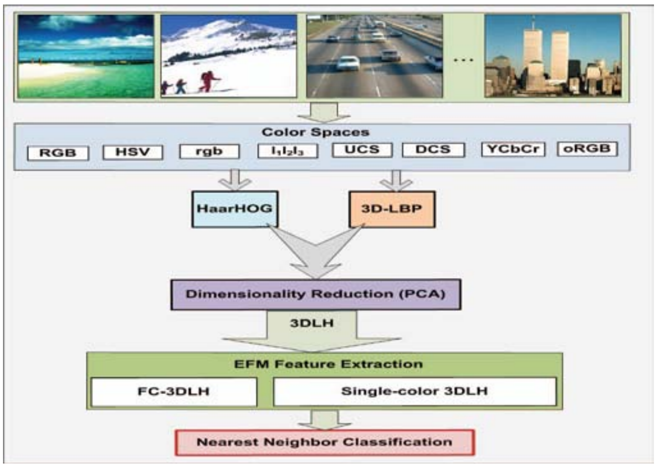

Figure.3 An overview of multiple features fusion methodology, the EFM feature extraction method, and the classification stages.

B. *HaarHOG descriptor :*

To form the HaarHOG feature vector, apply the Haar wavelet transformation to each component of the original image to divide each component image into four distinct regions that separate the local features of each image. Then generate the HOG descriptor for each of these regions and then concatenate them for all the components to get our final HaarHOG feature vector. This process as shown in Fig.4 .

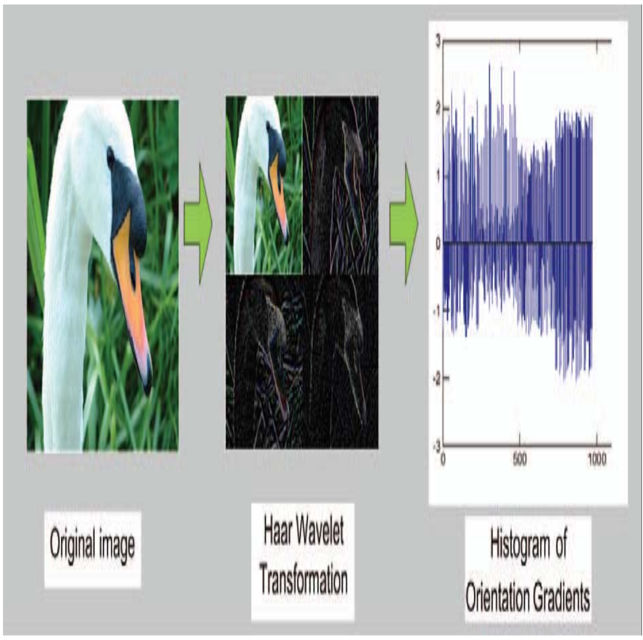

Figure.4 The original image undergoes Haar Wavelet Transformation and then HOG is generated for each component of the resulting image and concatenated.

C. *3-Dimensional LBP-HaarHOG (3DLH) descriptor:*

It should be noted that the generation time for both the 3DLBP and HaarHOG descriptors is linear with respect to the number of pixels. Finally, extract the most expressive features from both these vectors and fuse them in the PCA space to form the 3DLH feature vector which outperforms both 3D-LBP and HaarHOG based classification

III. EXPERIMENTAL RESULTS

The Caltech 256 dataset holds 30,607 images divided into 256 object categories and a clutter class. We have selected 25 scene image categories from this dataset to form the Caltech25 scene dataset.

The UIUC sports events dataset [28] contains 8 sports event categories color descriptor at 83.3% followed by DCS-3DLH, YCbCr-3DLH and oRGB-3DLH respectively. The combined descriptor FC-3DLH gives a mean average performance of 84.9%.

The MIT Scene dataset [3] has 2,688 images classified as eight categories All of the images are in color JPEG format. There is a large variation in light and angles, along with a high intra-class variation. From each class, we use 250 images for training and the rest of the images for testing the performance, and we do five-fold cross-validation. Here YCbCr-3DLH is the best Single-color descriptor at 88.4% followed closely by HSV- 3DLH and oRGB-3DLH. The combined descriptor FC-3DLH gives a mean average performance of 90.4%.

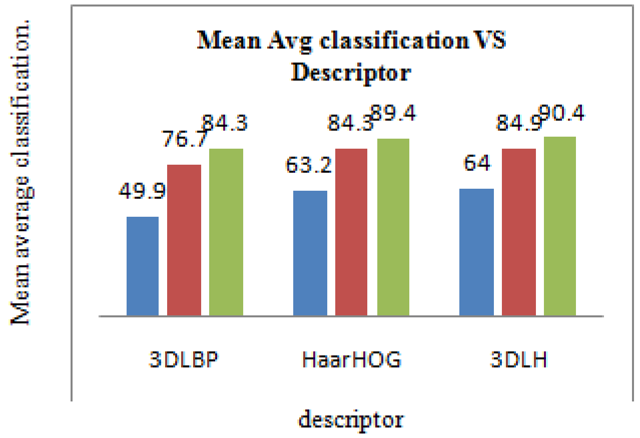

Figure. 5 The comparative mean average classification performance of the FC-3DLBP, FC-HaarHOG and FC-3DLH descriptors on the Caltech scene 25,UIUC Sports Event and MIT Scene datasets

IV. CONCLUSION

We have proposed a new LBP-based color and texture feature extraction method for images and combined it with Haar wavelet features and HOG features to generate several new descriptors for color scene images: the RGB-3DLH descriptor, the oRGB-3DLH descriptor, the YCbCr-3DLH descriptor, theDCS-3DLH descriptor, the HSV-3DLH descriptor and the FC-3DLH descriptor for scene image classification. Results of the experiments using three challenging datasets show that our oRGB-3DLH, HSV-3DLH, DCS-3DLH and YCbCr-3DLHdescriptors improve recognition performance over conventional Color and grayscale LBP descriptors. Different color spaces perform differently for different image sets, and further, the fusion of multiple color 3DLH descriptors (FC-3DLH) shows improvement in the classification performance, which indicates that various color 3DLH descriptors are not fully redundant for image classification tasks.

V. REFERENCES

[1]. C. Liu and J. Yang, "ICA color space for pattern recognition," IEEE Transactions on Neural Networks, vol. 20, no. 2, pp. 248–257, 2009.

[2]. T. Ojala, M. Pietikainen, and D. Harwood, "Performance evaluation of texture measures with classification based on Kullback discrimination of distributions," in International Conference on Pattern Recognition, Jerusalem, Israel, 1994, pp. 582–585.

[3]. S. Banerji, A. Verma, and C. Liu, "Novel color LBP descriptors for scene and image texture classification," in 15th International Conference on Image Processing, Computer Vision, and Pattern Recognition, Las Vegas, Nevada, July 18-21 2011.

[4]. A. Verma, S. Banerji, and C. Liu, "A new color SIFT descriptor and methods for image category classification," in International Congress on Computer Applications and Computational Science, Singapore, December4-6 2010, pp. 819–822.

[5]. H. Stokman and T. Gevers, "Selection and fusion of color models for image feature detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 3, pp. 371–381, 2007.

[6]. G. Burghouts and J.-M. Geusebroek, "Performance evaluation of local color invariants," Computer Vision and Image Understanding, vol. 113, pp. 48–62, 2009.

[7]. A. Bosch, A. Zisserman, and X. Munoz, "Scene classification using a hybrid generative/discriminative approach," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 4, pp. 712–727,2008.

[8]. C. Liu, "Learning the uncorrelated, independent, and discriminating color spaces for face recognition," IEEE Transactions on Information Forensics and Security, vol. 3, no. 2, pp. 213–222, 2008.

[9]. J. Yang and C. Liu, "Color image discriminant models and algorithms for face recognition," IEEE Transactions on Neural Networks, vol. 19, no. 12, pp. 2088–2098, 2008.

[10]. R. Datta, D. Joshi, J. Li, and J. Wang, "Image retrieval: Ideas, influences, and trends of the new age," ACM Computing Surveys, vol. 40, no. 2, pp. 509–522, 2008.

[11]. P. Shih and C. Liu, "Comparative assessment of content-based face image retrieval in different color spaces," International Journal of Pattern Recognition and Artificial Intelligence, vol. 19, no. 7, 2005.

[12]. C. Zhu, C. Bichot, and L. Chen, "Multi-scale color local binary patterns for visual object classes recognition," in International Conference on Pattern Recognition, Istanbul, Turkey, August 23-26 2010, pp. 3065– 3068.