Comparison of Computer Graphics identification in Different Color Spaces

Joyal John, Dr. Shyama Das, Anoop A. Jose, Jithin G. Fernando
Department of Computer Science and Engineering
College of Engineering
Chengannur, India

Abstract— **Development of advanced rendering software gave computer graphics a capability to create highly photorealistic images and it has become difficult for people to visually differentiate these images from photographic images. Thus these images questioned the credibility of natural images. So we have to authenticate an image as either photographic or photo realistic computer graphics. In this paper we used a new approach for computer generated graphics identification using image contour information. In addition, we made a comparative study of this algorithm in different color spaces. Specifically, we investigated this in HSV, YCbCr and Lab color spaces. The results of these experiments have shown that Lab demonstrated better performance than the other two.**

Keywords— ***Image Contour Information; Contourlet Transform; Colour Space; Luminance; Chrominance***

I. INTRODUCTION

In the recent times, computer graphics rendering shows a steep growth; new rendering techniques have been developed to visualize data in a realistic manner. These realistic rendering brought new challenges towards the credibility of natural images. We cannot differentiate these images with our visual perception. That's why, there is a need of an automatic system to classify computer generated graphics and natural images. On the one hand this research will defeat the image forgery in the areas of criminal investigation, journalism, intelligence etc. and the other hand it will help to improve the rendering technologies which paves the development of more photorealistic computer graphics to be used in movie industry. The Fig. 1 shows how difficult it is to differentiate these two images with our visual perception.

This paper aims to develop a new method for automatically separating computer graphics from photographic images. In this paper, computer graphics is used to refer images which are created by the modern rendering software and photographic images are the output of imaging acquisition devices. Simply we can say, this is a pattern recognition problem in which we extract some features from the images and classify it into either photographic or photorealistic computer graphics based on the features. Several approaches have been proposed to address this problem and the features used in those approaches can be included in three kinds; statistical features of wavelet coefficients, geometrical features and physics- motivated features introduced from image generation process.

Fig. 1. Example of natural image and photorealistic computer generated image

The first approach of this classification was proposed by Hany Farid in 2003 [1]. He used first and higher order statistics from the wavelet coefficient as features. Later Yun Q. Shi [2] outperformed Farid's work by using HSV color space instead of RGB. In 2007, Cui Xia [3] proposed a new method based on statistical moment of wavelet sub bands histogram in DFT domain and made an accuracy of 94%. Tian- Tsong Ng and Shihu- Fu Chang [4] have completed a lot of work in geometric features to identify computer graphics. The geometric features include differential geometry, fractal geometry and local patch statistics. They also upgraded their research by including Natural Image Statistics (NIS). Other researchers have focused on Physical image generation process. A digital photographic image undergoes Optical lens transformation, gamma correction, white balancing and colour processing, doing these steps image will tinted with quantization noise and sensor fitted pattern noise. These steps give the intrinsic features of photographic images. Andrew C. Gallaghner [5] achieved an accuracy of 98.4% by detecting traces of demosaicing. But this is effective only at distinguishing photographic images at native resolution. Later Memon [6] explored the common properties of the pattern noise introduced by digital cameras which includes traces of demosaicing and chromatic aberration, and he used them to differentiate PRCG from digital camera images.

Above methods have advantages and disadvantages. However wavelet has the property of invariance of image statistics to scaling of image and it have been proved as the right tool to isolate the discontinuities along edge points. But it will not see the smoothness along the contours, so it can capture only limited directional information. Recently Shaojing Fan [7] and his co-researchers have done a research based on image contour information. Contour information can be used to capture the smoothness along the contours and improve the directional information.

Most of the researches are either done in RGB or HSV color space. In this paper, the proposed method construct features in HSV, YCbCr and LAB color spaces and did a comparative study on it. The features we used in this paper are the first order statistical moments of contourlet coefficients. We can extract contour information from the contourlet transform of the image. The paper is organized as follows. In section 2, the proposed features for classification of computer graphics from photographic images and the selection of color models are discussed. We described the implementation and experimental results in section 3 and concluded in section 4.

II. DESCRIPTION OF FEATURES

A. Selection of Colour Model

Today there are various color models using in image processing researches. Each color model has its own specific application fields. The RGB color models are mostly used in hardware oriented application. Although Human eye is strongly perceptive to red, green and blue colors (component of RGB), RGB representation is not well suited for describing color image for human perception point of view. Human visual system characterizes by the brightness and chromaticity of the viewing object. Brightness is the subjective measure of intensity. Chromaticity is defined by Hue and Saturation. That's why, we used HSV color space and the components of HSV color space are Hue, Saturation and Value. Hue is the color attribute and it shows dominant color. Saturation expresses relative purity or degree to which a pure color is diluted by white light. The HSV model is motivated by human visual system and it is defined as follows:

$$H = \begin{cases} 60\left(\dfrac{G-B}{\delta}\right) & if\ MAX = R \\ 60\left(\dfrac{B-R}{\delta}+2\right) & if\ MAX = G \\ 60\left(\dfrac{R-G}{\delta}+4\right) & if\ MAX = B \\ not\ defined & if\ MAX = 0 \end{cases} \quad (1)$$

$$S = \begin{cases} \frac{\delta}{MAX} & if\ MAX \neq 0 \\ 0 & if\ MAX = 0 \end{cases}$$

$$V = MAX$$

YCbCr is an encoded nonlinear RGB signal commonly used by European television studios for image compression works. The luminance component (Y) of this color space is computed as a weighted sum of the RGB values and two chrominance components (Cb and Cr) are formed by subtracting Y from red and blue channels of RGB.

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ Cr &= R - Y \\ Cb &= B - Y \end{aligned} \quad (2)$$

The transformation simplicity and explicit separation of luminance and chrominance components make this color space attractive for classification.

HSV color space is criticized for not adequately separating color-making attributes, or for their lack of perceptual uniformity. Other more computationally intensive color space like LAB is said to better achieve these goals. LAB color space is a color opponent space with dimension L for lightness and 'a' and 'b' for the color-opponent dimensions, based on nonlinearly compressed CIE XYZ color space coordinates. In this model the color difference which you perceived corresponds to distances when measured colorimetrically. From Fig. 2, the 'a' axis extends from green (-a) to red (+a) and the b axis from blue (-b) to yellow (+b). The brightness (L) increases from bottom to the top of 3D model.

This color space is better suited to many digital image manipulations than RGB and HSV color space. For example, LAB space is useful for sharpening images and removing artifacts in jpeg images.

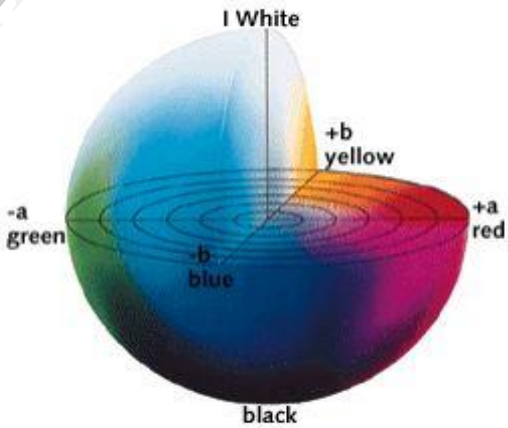

Fig. 2. Model of Lab color space

Intuitively features extracted from Lab color space can capture the distinct characteristics of computer graphics. Fewer colors are contained in computer graphics and in texture areas computer graphics are more color smooth than photographic. These differences are best described by decoupling intensity from chromatic information. We extracted features from HSV, YCbCr and Lab color spaces, compared it and studied. As shown in the next section, Lab features have better performance than YCbCr and HSV.

B. Preprocessing of Image

We extracted the features from the prediction-error image. The prediction error image is the difference between the test and its predicted version. This would help to eliminate the similar factors on image. The prediction algorithm used here is given by

$$\hat{x} = \begin{cases} \max(a,b) & c \le \min(a,b) \\ \min(a,b) & c \ge \max(a,b) \\ a+b-c & otherwise \end{cases} \quad (3)$$

Where a, b, c are the context of pixel x under consideration. $\hat{x}$ is the prediction value of x. The location of a, b, c are illustrated in Fig. 3.

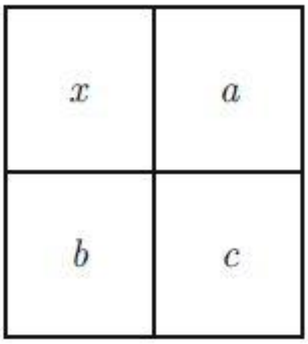

Fig. 3. Context in prediction value

C. Moments of Contourlet Coefficients

To classify computer graphics from photographic images, determination of distinguishing feature is a critical step. The proposed system used contour information for classification. The contourlet transform is a way to capture contour information, which has the ability to see the smoothness along contours.

Contourlet Transform is an advanced version of Wavelet Transform. Wavelet transform cannot capture directional information in two dimensional space. This limitation give rise to the development of many multidirectional Transform. Do and Vetterli [8] introduced the multidirectional multiscale contourlet transform. This transform is of double filter bank structure; the Laplacian pyramid [9] is first used to capture the point discontinuities and then followed by a directional filter bank to link the point discontinuities in to linear structures. The LP decomposition is an efficient approach for multi resolution image analysis. DFB can capture the directional information and it is constructed from two building blocks. First is a two channel quincunx filter bank fan filter that divides a 2D- spectrum into horizontal and vertical directions. The second block is a shearing operator which records the image samples. DFB creates a 2^l sub-bands with wedge shaped frequency partitioning in each scale 'l'. From each counterlet sub bands we collect first for order statistics- mean, variance, skewness and kurtosis as features.

D. Feature Extraction

For image decomposition, we used a four-level Contourlet transform in which level 0 equals normal wavelet. Coefficients are like C{j}{l}(k1, k2), in which j stands for scale and l means direction. (k, k2) is the position in the matrix of the direction l in scale 2^j. The structure of four-level coefficients is shown in Table 1.

Table 1. Contourlet Transform

Level	**Scale**	**No: of Directions**	**Matrix type**
Coarse	C{0}	1	16*16
Detail	C{1}	2	16*16
Detail	C{2}	4	32*32
Detail	C{3}	8	32*64
Fine	C{4}	16	32*128

From the above table, there are 31 directions in all sub bands. The selection of relevant features from the coefficients of contourlet sub band is important. We selected the statistical moments of the sub band coefficients as the features. The characteristic function (CF) in the context is defined as the Fourier transform of the image (or its Contourlet sub bands) histogram. The statistical moments of the CFs of the contourlet sub bands are selected as features. Denote the CF by $H(f_j)$, the statistical moment is defined as follows.

$$M_n = \sum_{j=1}^{(N/2)} f_j^n |H(f_j)| \Big/ \sum_{j=1}^{(N/2)} |H(f_j)| \quad (4)$$

where $H(f_j)$ is the CF component at frequency f_j, n is the moment order, and N is the total number of points in the horizontal axis of the histogram.

We extract first four statistical moments (the average value, variance, skewness and kurtosis) of the 31 direction coefficient in three channels of the color spaces. Finally we get a 372(31*4*3) dimension feature vector.

E. Feature selection and Caliberation

SVM classifier with RBF kernel is difficult to use with a high dimensional feature vector and also extracting a 372 dimensional feature vector is time consuming. So we need to reduce the dimension of the feature vector. From [7], it is experimentally proved that by reducing some feature wouldn't affect the performance of the proposed system. Following are some steps to reduce the features:

- Chromatic components are difficult to be simulated in computer graphics. So we have taken only chromatic components of the color space for these experiments and at a time, we took one channel to reduce the dimension of the feature vector from 372 to 124.
- Image texture is usually described by the high frequency components. This high frequency component is represented by the finest level of contourlet transform, which is the fourth sub band of the contourlet transform. Thus, we reduced the feature vector again to 64.
- Use only the average value instead of the entire four statistical coefficients wouldn't reduce the efficiency to a great extends. Finally, the feature vector reduced to 16.

The large differences in coefficient values may reduce the classification performance. So we have to adjust the values to a suitable scope. For normalizing the feature vector, we used the feature calibration step and it is described as follows:

The 16 dimensional feature vectors are first stored in a matrix $M[i,j]$. Row $i \in [1,k]$ is correlated to each independent image, where k stands for the number of test images. Column $j \in [1,16]$ is the number of features. The calibrating vector v is calculated through following equation:

$$v_j = 10exp\left(1 - \left[log_{10}\left|\frac{1}{k}\sum_{i=1}^{k} M[i,j]\right|\right]\right) \quad (5)$$

For j from 1 to 16, we get a 16 dimensional feature vector v. The normalized feature vector $\widehat{M}$ is got by calculating the inner product of M and v.

III. EXPERIMENT

For performance evaluation, we used Columbia Image Dataset [10] and this Dataset is a universally accepted dataset for CG and natural image classification. From the dataset, 800 photographic images and 500 photorealistic computer graphic images are used for experiments. In order to better test our method and compare it with the predecessors, we insist using Columbia image dataset without adding any photographic image at native resolution.

We used Support Vector Machine (SVM) with Radial Basis Function (RBF) as classifier. To train the classifier, we randomly select 250 images from each class and the remaining images are used for the testing process. To choose the penalty parameter C and kernel parameter gamma, we use 10- fold cross-validation. The classification performances of each channel of each color space are listed in Table 2 where TPR (true positive rate) represents the detection rate of computer graphics, TNR (true negative rate) represents the detection rate of photographic images.

Table 2. Experimental Result

Color Channels	TPR (%)	TNR (%)	Accuracy (%)
H (HSV)	86	91	89
Cb (YCbCr)	88.5	95	93
Cr (YCbCr)	90.5	94	93
a (Lab)	91	95	93.7
b (Lab)	86	94	91.8

From Table. 2, it is clear that the proposed algorithm in ‘a’ channel of Lab color space have the highest accuracy. It outperforms Cb and Cr channels of Lab color space by 0.7%, and Hue channel of HSV color space by 4.7%. Also the Chromatic channels (Cb and Cr) of YCbCr color space outperforms Hue channel of HSV color space by 4%. Here the length of the feature vector is only 16, so this algorithm has higher efficiency than any other previous methods.

IV. CONCLUSION

This is a new approach of implementing a classification algorithm in a color space other than RGB and HSV. Results show that Lab and YCbCr color space have much advantage than HSV and RGB color spaces.

The proposed algorithm shows that the real world texture has low contrast level and low energy values, while computer generated graphics has a low local correlation with neighboring pixel and contain unwanted patterns. These texture features are usually described by the high frequency components of the image. The proper selection of features also played a key role in this higher detection rate; we choose only the features from the chromatic channels of the color space.

We plan to implement more previous approaches about the computer graphics identification in Lab and YCbCr color space and evaluate its detection performance.

REFERENCES

[1] Hany Farid and Siwei Lyu, “Higher-order wavelet statistics and their application to digital forensics,” IEEE Workshop on Statistical Analysis in Computer Vision, Madison Wisconsin,2003.

[2] Wen Chen, Yun Q. Shi and Guorong Xuan, “Identifying computer graphics using HSV color model and statistical moments of characteristic functions, ” Proceedings of the 2007 IEEE International Conference on Multimedia and Expo, ICME 2007, 1123- 1126.

[3] Cui Xia and Xuefeng Tong, “Discrimination between photo images and computer graphics based on statistical moments in the frequency domain of histogram,” Proceedings of CIHW 2007, 276- 279.

[4] T. T. Ng, S. F. Chang, J. Hsu, L. Xie and M. P. Tsui, “Physics motivated features for distingushing photographic images and computer graphics,” Proceedings of the 13th Annual ACM International Conference on Multimedia, Singapore, November 2005.

[5] Andrew C. Gallagher and Tsuhan Chen, “Image authentication by detecting traces of demosaicing,” IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2008, 51- 62 .

[6] S. Dehnie, H. T. Sencar and N. Memon, “Digital image forensic for identifying computer generated and digital camera images,” in Proc. Of IEEE ICIP, 2006, 2313- 2316.

[7] S. Fan, R. Wang, Y. Zhang and K. Guo, “Clasifying computer generated graphics and natural images based on image contour information,” Journal of Information and Computational Science 9: 10, 2012, 2877- 2895.

[8] M. N. Do and M. Vetterli, “The Contourlet transform: An efficient multidirectional multiresolution image representation,” IEEE Trans. Image Process., Vol. 14, No. 12, Dec. 2005, 2091- 2106.

[9] P. J. Burt and E. H. Adelson, “The Laplacian pyramid as a compact image code,” IEEE Trans. Commun., Vol. COM-31, No. 4, Apr. 1983,532- 540.

[10] T. T. Ng, S. F. Chang, J. Hsu and M. Pepeljugoski, “Columbia Photographic Images and Photorealistic Computer Graphics Dataset,” ADVENT Technical Report, Columbia University, Feb. 2005.