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Features affecting the Classification of images

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***Abstract*— There are numbers of methods prevailing for Image classification. This Paper includes the effect of various features to classify the image into natural & synthetic. The database of 400 JPG images was created including the raw data. Single simple features such as color map, edge map, energy level(e1, e2, e3), & thresholding value are extracted from the raw images data in order to exploit the difference of color pattern and spatial correlation of pixels in natural and synthetic images. Every feature are extracted separately and evaluation was done to identify the class of an image. The class of the image is basically based on the Human Perception of the image. The Machine interpretation of the image is based on the number of colors & pixels, their edge location & mean and wavelet mean of image.**

***Keywords*--Synthetic image, Natural image, Color map, Edge map, Energy Level, Threshold value**

I. INTRODUCTION

Content Based Image Retrieval (CBIR) is a technique which uses visual contents, normally called as features, to classify images. Thinking of what the main differences between natural and synthetic image are, synthetic image are typically generated using a limited number of colors and usually containing only a few areas of uniform colors. Moreover, highly saturated colors are more likely to be used. Sharp edges also are typical feature characterizing synthetic images that can be used by an image classifier. It is possible to easily spot these characteristics in maps, charts , logo and cartoons[1] . On the other hand, very often a natural image depicts real life objects and subjects. These have usually textures, smooth angles, larger variety of colors but less saturated. Because of the way a photograph is acquired and the way a camera works, natural pictures also results in being more noisy. For an human being, distinguishing between a photograph and a graphic is almost always an easy task. It is often just matter of a glance. Unfortunately it is not for a computer Since visual features are automatically extracted from images, lot of human effort can be saved. [5]

The color map of image shown the accuracy rate of 87 percent for synthetic and 90 percent for natural image. Edge map shown the low level of accuracy then color map. The three energy level are calculated from image and combine together to evaluate the class of image which shown the 75% accuracy for natural & 80% for synthetic image.

The input image is broken in two part foreground & background for fore ground value is 1 & background value is 0 then segmentation of image is done, segmented area value & threshold level is calculated this feature achieved the 63% of accuracy level in identifying the class of image.

II. IMAGE DATASET

The choice for creating the database was JPEG images. This chose was made because of a main assumption, since images can be compressed in a different way, the classification algorithm has to be tuned accordingly to each format, multiple factors have to been taken into account such as the reduced/altered palette and the noise added while resizing/compressing. Hence a mixed dataset can not be used with a single classification method. GIF and PNG formats are very popular formats for synthetic images but less used for encoding photographs. For transmissions of true color images over the internet, especially photographic ones, JPEG is almost always a better choice [3]. For this reason, the dataset was created to find the effect of every feature on the classification of image as natural & synthetic. The image is resized into 256*256 a first test has been done using an imbalanced dataset (70 percent natural, 30 percent synthetic). This setup showed a very good accuracy for natural images and a poor accuracy for synthetic images For this reason a balanced dataset is preferred the final dataset is formed by 300 natural and 300 synthetic images.

Image features and their effects

The main step in order to be able to classify an image is to extract numerical features from the raw data, The feature used in classification system are color map, edge map, energy level, threshold. Color map & edge map consider as L1, Energy level (e1,e2,e3) as L2 & Threshold segmentation as L3 features. These single features exhibit promising performance with low computational cost because each classifier has its own weakness and strengths.

L1 feature

Color transitions from pixel to pixel have different models in photographs(Natural image) and graphics (Synthetic image).

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Photographs depict objects of the real world, and in such a context, it is not common to find regions of constant color because objects tend to be shaded and have texture. In addition, during the process of taking a photograph, some noise is added to the subject and that causes neighbor pixels to have different RGB values (even when they are supposed to have the same color). It is possible to exploit these simple features related to colors by extracting and analyzing the features. Photographs often have more color than graphics. This is because synthetic images tend to have large uniform regions with the same color. On the Web in particular, graphics with few color are more popular because they compress better. The number of different colors of an image is extracted but it cannot be directly used as metric since the raw number is also dependent from the size of the image[6]. Therefore a more accurate metric is used: the rate between the number of different colors and the number of total pixels. Color map of input image is plot for black & white image histogram(gray) of image is calculated for color image extended histogram is used .For edge map edges of image is taken and from edge location edge map is created. The fig 1.1a & 1.1b show the color map & edge map of Natural image .The fig 1.2a & 1.2b show the the color map & edge map of synthetic image.

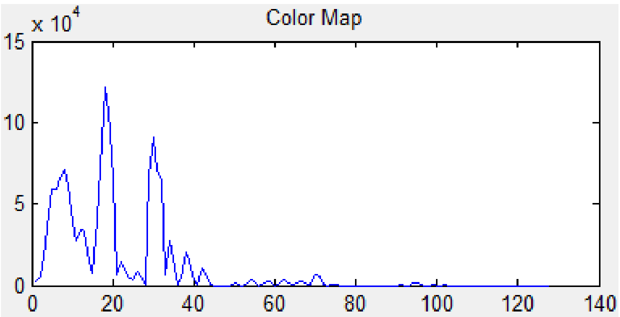

Fig 1.1a

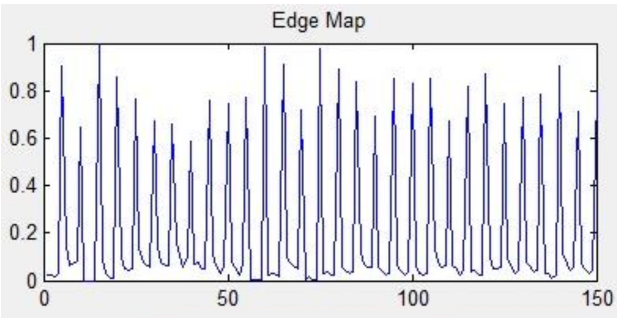

Fig 1.1b

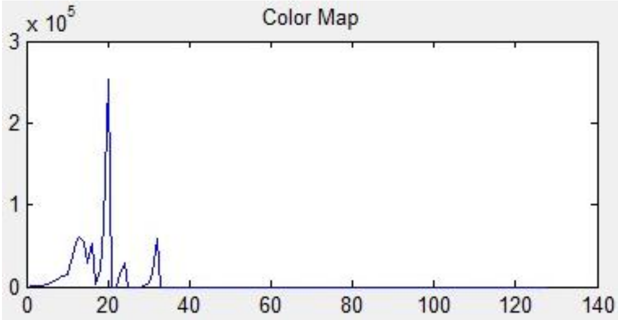

Fig 1.2a

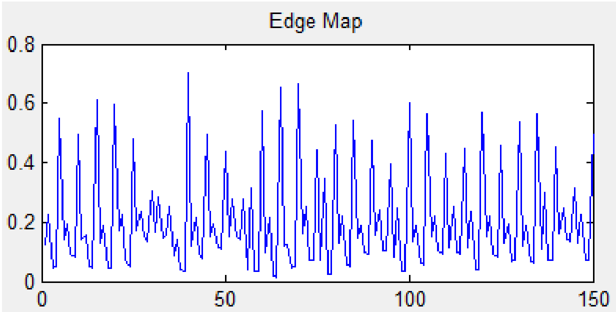

Fig 1.2b

L1 feature, color map & edge map is taken to achieve the high level of accuracy. Analysis of color map & edge map of 300 image is done separately for natural & synthetic image. If the value of color map is in the range 0 to 30 image is classify as synthetic & as the value extend this rang image is classify as natural image. Edge map show small different in value for natural & synthetic image. The spike found in natural image is lower then the synthetic image. By combining this two feature the performance of classification system is boosted & 90% of accuracy is achieved.

L2 Feature Energy level

The evaluation of energy level start form converting the image into gray scale. For texture analysis rangfilt function is used which returns the array of image, where each output pixel contains the range value (maximum value − minimum value) of the 3-by-3 neighborhood around the corresponding pixel in the input image . The image can have any dimension. The output image is the same size as the input image . First the total energy is calculated using DWT. Then the precision of image is double to calculate Single-level discrete 2-D wavelet transform. Which performs a single-level 2-D wavelet decomposition with respect to particular wavelet .DWT2 computes the approximation coefficients matrix and details coefficients matrices (horizontal, vertical, diagonal) obtained by a wavelet decomposition of the input matrix of image.

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In this work only one set of DWT derived features is considered. It is a vector, which contains energies of wavelet coefficients calculated in subbands at successive scales. [14] &[15] To compute the wavelet features Harr wavelet is calculated for whole Image it transfer the image into 4 subband image at its scale.

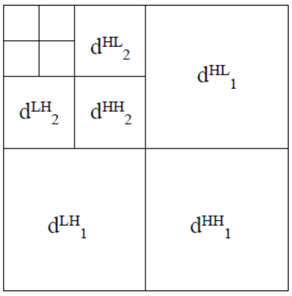

Fig 3 Subband Image

Subband image aLL is used only for DWT calculation at the next scale for the given image, the maximum of 8 scales can be calculated. The Harr wavelet is calculated only if output subbands have dimensions at least 8 by 8 points. In the next step, energy (3) of dLH, dHL and dHH is calculated at any considered sale in marked ROIs. ROIs are reduced in successive scales in order to correspond to subband image dimensions. In a given scale the energy is calculated only if ROI at this scalecontains at least 4 points. Output of this procedure is a vector of features containing energies of wavelet coefficients calculated in subbands at successive scales. The three energy level e1,e2 ,e3 of various natural & synthetic image is calculated. The natural images that are directly capture from digital camera chosen for analysis, energy level found for natural image are e1=54.36, e2=108.71,

& e3 = 217.43. As synthetic image belonging to one of the following categories: Logos, Maps, Chart, Drawing, & Windows Application Screen shoot. The energy belong to each categories is shown below in table.

Table1.
Energy Levels

Energy	Logo	Maps	Drawing	Win App Screen Shot
E1	10.33	22.11	23.26	22.89
E2	20.65	44.22	45.14	45.78
E3	91.57	88.45	90.02	91.57

From above analysis if energy level is higher the image is classified as natural otherwise image is classified as synthetic image.

Level 3 Threshold

Threshold of the image is calculated using the OTSU method.

The intensity of a gray level image be expressed in L gray level [1, 2, ……..L]. The number of point with gray level at I is denoted by x_i and the entire number of point can be expressed as $X = x_1 + x_2 + \cdots + x_L$ The histogram of this gray level image is regarded as a occurrence distribution of probability. [16]

$$p(i) = \frac{x_i}{X}, \quad x_i \geq 0, \quad \sum_{i=1}^{L} x_i = 1$$

The image pixel are divided into two parts C_0 and C_1 i.e Foreground and background by a threshold t. Where C_0 Represent pixels with levels [t + 1, …….L]. The occurrence probabilities of this class and average can be expressed as

$$\omega_0 = \omega(t) = \sum_{i=1}^{t} p(i).$$

$$\omega_1 = 1 - \omega(t) = \sum_{i=t+1}^{L} p(i).$$

$$\mu_0 = \sum_{i=1}^{t} \frac{i \cdot p(i)}{\omega_0} = \frac{1}{\omega(t)} \sum_{i=1}^{t} i \cdot p(i).$$

$$\mu_1 = \sum_{i=t+1}^{L} \frac{i \cdot p(i)}{\omega_1} = \frac{1}{1-\omega(t)} \sum_{i=t+1}^{L} i \cdot p(i).$$

Total mean can be writeen as

$$\mu_T = \sum_{i=1}^{L} i \cdot p(i)$$

We can find that

$$\mu_T = \omega_0 \mu_0 + \omega_1 \mu_1$$

Where ω_0 and ω_1 denote probabilities of foreground parts and background parts. Beside μ_0, μ_1 and μ_T refer to the mean in gray level of the foreground of the gray image, the background of gray image. And the entire gray level image.

The between-class variance σ_B^2 of the two classes C_0 & C_1 variance is given by.

$$\sigma_B^2 = \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2$$

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The separate degree η of the class , in discrimination analysis is

$$\eta = \max \sigma_B^2$$

Finally, maximizing σ_B^2 to chose the optimal threshold t.

$$t^* = \arg\max \sigma_B^2$$

Props function is used if the distribution of class C_k (K = o, or 1) is skew or heavy-tailed. It is well known that the mean value is very robust estimate value compared with average gray level. We find that the mid value replace of the average may obtained optimal threshold that is very accurate to the presence of heavy-tailed distribution for C_k compare with this threshold chosen by OTSU method.

So we can replace the total mean μ_T with the total medium level m_T of all the point in the entire gray level image Similarly to the whole image mean value μ_T. the mean value μ_0 & μ_1 can be replace by medium gray level. m_0 and m_1 for foreground part C_0 and the background part C_1 respectively.

The between-class variance σ_B^2 of the two classes C_0 & C_1 Can be rewritten as.

$$\sigma_B^2 = \omega_0 (m_0 - m_T)^2 + \omega_1 (m_1 - m_T)^2$$

And the threshold t^* is chosen by maximizing σ_B^2

$$t^* = \arg\max \sigma_B^2$$

Threshold calculated by OTSU method shown the good performance in classification of image. Threshold of 400 natural image 500 synthetic image was calculated. If the value is between 0.0001 to 0.0002 image is classified as synthetic image & if the value is between 0.0005 to 0.0006 the image is classified as natural image. This feature shown the error rate of 37%.

III. Conclusion

Features chosen to find the effect on image classification system, thinking of what the main differences between natural and synthetic image are. Synthetic image are typically generated using a limited number of colors and usually containing only a few areas of uniform colors. Sometime natural image also have limited number of color and few area of uniform color. Results show that, color map & edge map provides 87% of accuracy. The Level 2 energy level e1, e2 , e3 shown the good performance in identification of natural image & synthetic image.

This method provides the error of 20%. Moreover synthetic image has Sharp edges, as compare with natural image. To spot this characteristic edge map is used to achieve high level of accuracy. Otsu's method is used to automatically perform clustering-based image thresholding, or, the reduction of a gray level image to a binary image. The algorithm assumes that the image to be thresholded contains two classes of pixels or bi-modal histogram (e.g. foreground and background) then calculates the optimum threshold separating those two classes. This method given the error rate of 37% the maximum error accurse in identification of synthetic image. So it is concluded that when these features are taken individually the error rate increases to a considerable amount. But if we combine these features to develop an algorithm, the new combined classificatory provides accurate results and the error rate reduces drastically to 10%.

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