An Effective Combined Feature For Web Based Image Retrieval

H.M.R.B Herath, Y.P.R.D Yapa

Abstract: Technology advances as well as the emergence of large scale multimedia applications and the revolution of the World Wide Web has changed the world into a digital age. Anybody can use their mobile phone to take a photo at any time anywhere and upload that image to ever growing image databases. Development of effective techniques for visual and multimedia retrieval systems is one of the most challenging and important directions of the future research. This paper proposes an effective combined feature for web based image retrieval. Frequently used colour and texture features are explored in order to develop a combined feature for this purpose. Widely used three colour features: Colour moments, Colour coherence vector and Colour Correlogram, and three texture features: Grey Level Co-occurrence matrix, Tamura features and Gabor filter were analyzed for their performance. Precision and Recall were used to evaluate the performance of each of these techniques. By comparing precision and recall values the methods that performed best were taken and combined to form a hybrid feature. The developed combined feature was evaluated by developing a web based CBIR system. A web crawler was used to first crawl through Web sites and images found in those sites are downloaded and the combined feature representation technique was used to extract image features. The test results indicated that this web system can be used to index web images with the combined feature representation schema and to find similar images. Random image retrievals using the web system shows that the combined feature can be used to retrieve images belonging to the general image domain. Accuracy of the retrieval can be noted high for natural images like outdoor scenes, images of flowers etc. Also, images which have a similar colour and texture distribution were retrieved as similar, even though the images were belonging to deferent semantic categories. This can be ideal for an artist who wants to retrieve images which are aesthetically similar and not interested in semantic similarity.

Index Terms: Content Based Image Retrieval, Computer Vision, Image Retrieval, Image Processing, Web Based Image Retrieval

1 INTRODUCTION

Retrieval of images is used in many professional fields such as crime investigation, medicine, journalism, fashion, graphics design, advertising, architectural design, engineering design, historical research, security [32] and so forth [1]. Finding appropriate images effectively and efficiently from large image databases has become increasingly difficult. This is even elevated by increased volumes of digital images produced by scientific, educational, medical, industrial, and other applications available to users by the rapid growth of the World Wide Web and largely available efficient image acquisition equipments such as digital cameras and mobile phones. Therefore, retrieval of digital images has become an important research problem that has stirred up the interest of lot of researches in the past few decades. Traditional text based image retrieval systems require manual annotation of images. Manual annotation is a cumbersome and expensive task for large image databases, and is often subjective, context-sensitive and incomplete. Because of this reason it is difficult for traditional text-based methods to support image queries that arise in unique situations. Limitations in traditional image retrieval techniques have led researches to look for efficient and effective techniques for retrieving images from large and diverse image databases and have introduced concepts like Content Based Image Retrieval (CBIR). Content Based Image Retrieval, widely known as CBIR describes the process of retrieving desired images from a large collection based on the image content such as colour, texture and shape that can be automatically extracted from the images themselves [1]. Features used for retrieval can be either primitive or semantic. However the feature extraction process must be primarily automatic. In a typical CBIR system, the visual contents of the images are extracted and described by multi-dimensional feature vectors. The feature vectors of the images form a feature database. To retrieve an image, a typical user provides the retrieval system with an example image or a sketched figure. Then the System changes these examples into its internal representation of feature vectors. The similarity / distances between the feature vectors of the query example and those of the images in the database are then calculated and retrieval is performed based on the similarity measure [29]. Many of the feature extracting methods used in CBIR are drawn from the field of image processing and computer vision. The image features can be categorized mainly, into three main categories. Colour based features, Texture based features and Shape based features. In colour based features, features like Colour moments, Colour histograms, Colour coherence vector, Colour correlograms, Colour emotions, Dominant colour, and Colour structure are used. As texture based features, features like Gray level co-occurrence matrix, Tamura features, Gabor features, Wavelet transform are used. As shape based features, features like Shape signature feature, Shape scale method, Chain code method, Chain code histogram feature, Edge histogram descriptor are used. This paper explores combined features for indexing and retrieving web images.

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2 RELATED WORK

In [30], a combined feature was explored to enhance the retrieval of images. Colour moments can be used to overcome the problems by quantization of the colour histogram. Colour coherent vector provides spatial information which colour histogram method or colour moments method does not have. Combined feature of colour moments and colour coherent vector is explored in this research. First they have separated the coherent and incoherent regions of Red Green and Blue colour channels of the image and then calculated first, second and third order moments of the separated regions. Their experimental results show that the combined method achieves better performance than existing low-level features. Colour histogram has low computational cost and is generally insensitive to small changes in camera position. Wavelet transform is used widely in representing texture features of images. It can be used to characterise textures using statistical properties of the gray levels of pixels. In [31] a combined feature of Colour histogram moments and 2D-DWT is explored. They have calculated histogram colour moments for the wavelet coefficients of colour images after performing three-level discrete wavelet transform. It is shown in their research that the combined feature outperform traditional colour moments as well as 2D-Discrete Wavelet Transform. A comparison of texture features for performance evaluation is carried out in [34]. They have investigated First-order statistics, second-order statistics, Gabor transform and 2D Wavelet transform for texture based image features. However according to their experimental results it was difficult to state that one method is superior to the other. But when the images were homogeneous GLCM matrix have performed better than the other texture based features and generally it was noted that structural texture features was more effective than statistical texture features. Colour is a widely used feature in CBIR research. It is invariant with respect to scaling, translation and rotation of an image. In [33] three of the most widely used colour based image features: Colour histograms, colour moments and colour coherent vector (CCV) are evaluated for performance. They have calculated both GCH (Global Colour Histogram) and LCH (Local Colour Histogram) for performance evaluation. When calculating colour moments they have utilized the already calculated colour histogram of the image which is more efficient. They have also compared combination of these techniques for performance. It is stated that it is hard to say one method is superior to other by the experimental results obtained, as the performance depends on the colour distribution of images. Their test results indicate that colour histogram performs well when images have mostly uniform colour distribution. For images those have widely scattered colours, CCV method had performed well. Compared to individual methods combined features had given better results.

3 MATERIAL AND METHODS

The main objective is to find a combination of techniques from colour and texture based image retrieval methods. Colour moments, Colour coherent vector (CCV), Colour Correlogram, Gray level co-occurrence matrix, Tamura features and Gabor features are analyzed for their performance.

3.1 Materials Used

This section provides a brief account of materials used in this research.

3.1.1 Colour Moments

The first-order (*Mean*), the second (S*tandard deviation*), and the third-order (*Skewness*) colour moments have been proved to be efficient and effective in representing colour distributions of images [22].

$$Mean = \mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \tag{1}$$

$$Variance = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^2\right)^{\frac{1}{2}} \tag{2}$$

$$Skewness = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^3\right)^{\frac{1}{3}} \tag{3}$$

3.1.2 Colour Coherence Vector

One inherit problem with colour histogram is the lack of special information. Colour Coherence Vector captures the special information of the pixel distribution in terms of colour. Colour coherence is defined as the degree to which pixels of a particular colour are members of a large similarly-coloured region [8]. These similar regions are referred to as coherent regions and are very important in characterizing images [7]. The coherence measure classifies pixels as either coherent or incoherent. A colour coherence vector (CCV) represents this classification for each colour in the image. CCVs prevent coherent pixels in one image from matching incoherent pixels in another.

3.1.3 Colour Correlogram

Colour Correlogram extracts the essential information about the special correlation of colour pixels and is both effective and inexpensive for content-based image retrieval [21]. Colour Corelogram is immune to large changes in appearance and shape caused by changes in viewing positions, camera zooms, etc. A colour correlogram of an image is a table indexed by colour pairs, where the k-th entry for <i, j> specifies the probability of finding a pixel of colour j at a distance k from a pixel of colour i in the image.

3.1.4 Gray level Co-occurrence Matrix

GLCM is essentially a matrix composed of probability values. Let us define the probability as $P(i,j|d,\theta)$ which is the probability of couple pixel at θ direction and *d* interval. When θ and *d* is determined, $P(i,j|d,\theta)$ is showed by $P_{i,j}$. GLCM matrix elements are computed according to the following equation,

$$M(i,j) = \frac{P(i,j|d,\theta)}{\sum_i \sum_j P(i,j|d,\theta)} \tag{4}$$

Finally it describes the texture properties of the image by means of statistical equations. For our study we considered Energy, Contrast, Correlation, Entropy, and Inverse Different Moment. They are defined as follows.

$$Energy = \sum_x \sum_y P(x,y)^2 \tag{5}$$

$$Contrast = \sum_x \sum_y (x-y)^2 P(x,y) \tag{6}$$

$$Correlation = \sum_x \sum_y (x-\mu)(x-\mu)\frac{P(x,y)}{\sigma^2} \tag{7}$$

Where μ and σ are mean and standard deviation of $P(x,y)$.

$$Entropy = -\sum_x \sum_y P(x,y) log P(x,y) \tag{8}$$

$$Inverse\ Different\ Moment = \sum_x \sum_y \frac{1}{1+(x-y)^2} P(x,y) \tag{9}$$

3.1.5 Tamura Features

Tamura et al in their research defined six textural features namely coarseness, contrast, directionality, line-likeness, regularity and roughness and coarseness. Contrast and directionality have proven to show promising results in their evaluation. These are defined as follows.

Coarseness

To calculate coarseness of an image moving averages $A_k(x,y)$ are computed first using $2^k \times 2^k$ $(k = 1,2,...,5)$ size windows at each pixel(x,y), i.e.,

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} g(i,j)/2^{2k} \tag{10}$$

Where $g(i,j)$ are the pixel intensities at (x,y).

Then, the differences between pairs of non-overlapping moving averages in the horizontal and vertical directions for each pixel are computed, i.e.,

$$E_{k,h}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)| \quad (11)$$

$$E_{k,v}(x,y) = |A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1})| \quad (12)$$

After that, the value of *k* that maximizes *E* in either direction is used to set the best size for each pixel, i.e.,

$$S_{\boldsymbol{best}}(x,y) = 2^k \quad (13)$$

Then the coarseness is then computer by averaging S_{best} over the entire image.

$$F_{crs} = \frac{1}{m \times n}\sum_{i=1}^{m}\sum_{j=1}^{n} S_{\boldsymbol{best}}(i,j) \quad (14)$$

Contrast

$$F_{con} = \frac{\sigma}{\alpha_4^{1/4}} \quad (15)$$

Where the kurtosis $\alpha_4 = \mu_4/\sigma^4$, μ_4 is the fourth moment about the mean, and σ^2 is the variance. This formula can be used for both the entire image and a region of the image.

Directionality

To compute the directionality, image is convoluted with two 3x3 arrays i.e.

$$\begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix} \quad \text{and} \quad \begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}$$

and a gradient vector at pixel is computer.

The magnitude and the angle of this vector are defined as:

$$|\Delta G| = (|\Delta_H| + |\Delta_V|)/2 \quad (16)$$

$$\theta = \tan^{-1}\left(\frac{\Delta_V}{\Delta_H}\right) + \pi/2 \quad (17)$$

Where Δ_H and Δ_V are the horizontal and vertical differences of the convolution.

After that by quantizing θ and counting the pixels with the corresponding magnitude $|\Delta G|$ larger than a threshold, a histogram of θ, denoted as H_D, can be constructed. This histogram will exhibit strong peaks for highly directional images and will be relatively flat for images without strong orientation. The entire histogram is then summarized to obtain an overall directionality measure based on the sharpness of the peaks:

$$F_{dir} = \sum_{p}^{n_p}\sum_{\phi \in w_p}\left(\phi - \phi_p\right)^2 H_D(\phi) \quad (18)$$

In this sum p ranges over n_p peaks; and for each peak p, w_p is the set of bins distributed over it; while ϕ_p is the bin that takes the peak value.

3.1.6 Gabor Texture

For a given image $I(x,y)$ with size PXQ, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_s \sum_t I(x-s, y-t)\psi_{mn}^*(s,t) \quad (19)$$

Where, *s* and *t* are the filter mask size variables, and ψ_{mn}^* is a complex conjugate of ψ_{mn} which is a class of self similar functions generated from dilation and rotation of the following mother wavelet:

$$\psi_{mn}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \cdot exp(j2\pi Wx) \quad (20)$$

Where *W* is called the modulation frequency and the self similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x,y) = a^{-m}\psi(\bar{x},\bar{y}) \quad (21)$$

Where *m* and *n* specify the scale and orientation of the wavelet respectively, with $m = 0,1,\dots M-1$, $n = 0,1,\dots N-1$, and

$$\bar{x} = a^{-m}(x\cos\theta + y\sin\theta) \quad (22)$$

$$\bar{y} = a^{-m}(-x\sin\theta + y\cos\theta) \quad (23)$$

Where $a > 1$ and $\theta = n\pi/N$

The variables in the above equation are defined as follows:

$$a = (U_h/U_l)^{\frac{1}{M-1}}, \; W_{m,n} = a^m U_l$$

$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2ln2}}{2\pi a^m (a-1)U_l} \quad (24)$$

$$\sigma_{y,m,n} = \frac{1}{2\pi\tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h^2}{2\ln 2} - \left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}} \quad (25)$$

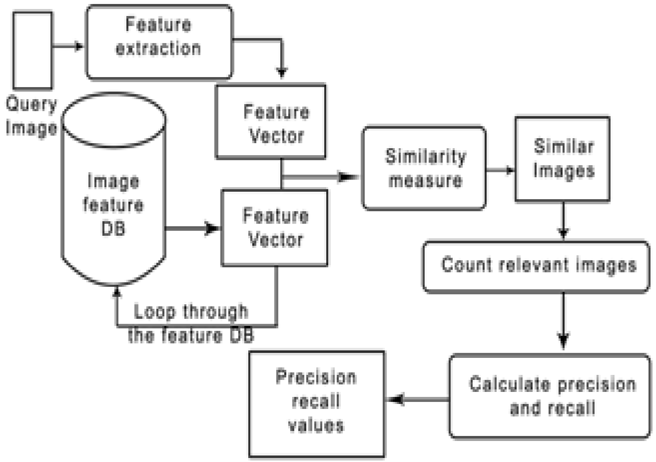
Corel image database consist of 10800 images from the Corel Photo Gallery belonging to 80 different already categorized semantic concept groups such as autumn, aviation, bonsai, castle, cloud, dog, elephant, iceberg, primates, ship, stalactite, steam-engine, tiger, train, waterfall etc. is used as the test image database and al the images are same size 120 by 80 pixels. **Crawler4j** an open source Java web crawler with a simple interface was used to set up the web crawler to crawl a specific website domain and download images. Evaluation of methods is carried out by calculating the ratio of relevant retrieved images to the total number of retrieved images (Precision) and the ratio of retrieved relevant images to the total number of relevant images in the database (Recall).

3.2 Methodology

As the first step, individual methods were implemented and tested for analyzing their performance. Secondly based on the performance of individual features combined features were developed by integrating colour feature and the texture feature methods. Average Precision and average Recall were calculated for all the individual methods. The following combinations were investigated in order to identify good combinations.

1. CCV and Gabor (ccv_gabor)
2. CCV and GLCM (ccv_glcm)
3. CCV and Tamura (ccv_tamura)
4. CCV(HSV colour space) and GLCM (ccvhsv_glcm)
5. Colour moments and Gabor (cm_gabor)
6. Colour moments and GLCM (cm_glcm)
7. Colour moments and Tamura (cm_tamura)
8. Correlogram and Gabor (corr_gabor)
9. Correlogram and GLCM (corr_glcm)
10. Correlogram and Tamura (corr_tamura)
11. CCV, Correlogram and GLCM (ccv_corr_glcm)

For evaluation of these combinations the same procedure used for the individual methods were repeated. After calculating the Precision and Recall values for all the methods a statistical analysis (analysis of variance and multiple comparisons) was carried out to statistically evaluate methods and to find out the statistical significant of their performance.



3.2.6 Web based image retrieval system

Each individual method was first implemented in a web based programming environment using java. We used ImageJ image processing library to aid the method implementation. The same programming environment was maintained for the consistency of the evaluation. We calculated CCV for both RGB and HSV colour space. When calculating the CCV the image was slightly blurred using the Gaussian blur to eliminate variations between neighbouring pixels. The colour space was descritized to 64 distinct colours. 4-connected neighbourhood was selected for adjacency. A pixel is considered coherent if the size of its connected component exceeded a fixed value τ; otherwise, the pixel is in-coherent. τ is taken to be 1% of the total image pixels. Due to the reduced complexity we used Auto-correlogram instead of colour correlogram. When calculating the GLCM we took distance d to be 1 pixels and θ $(0°, 90°, 180°, 270°)$ values. For Gabor texture feature we used $U_l = 0.05$, $U_h = 0.4$ and filter mask size to be 4×4 as commonly used in the literature. After implementing the individual methods we implemented the combined methods.

3.2.3 Initial extraction of image features

The first step in our evaluation was to extract image features for each colour and texture based feature extraction methods. The process of initial feature extraction is graphically represented in Fig. 1.

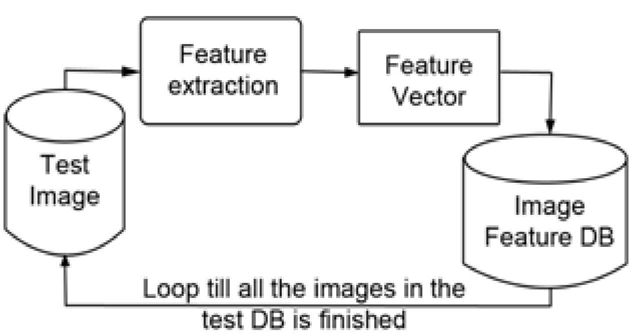


Fig. 1. *Initial feature extraction from the test image database*

3.2.4 Method of Evaluation

After features for each method was extracted, method evaluation process was performed. Following image categories were selected and six carefully selected images from each category were taken as test images. The image categories pl_flower, sc_cloud, sc_forests, sc_rockform, sc_rural, sc_waterfal, wl_horse, art_mural, obj_car, sc_indoor, texture_2, texture_4 and texture_6 were considered. First we calculated the precision and recall values of each individual method and then we calculated the precision and recall values for combined methods. Calculating the precision and recall values was carried out as depicted in Fig. 2.

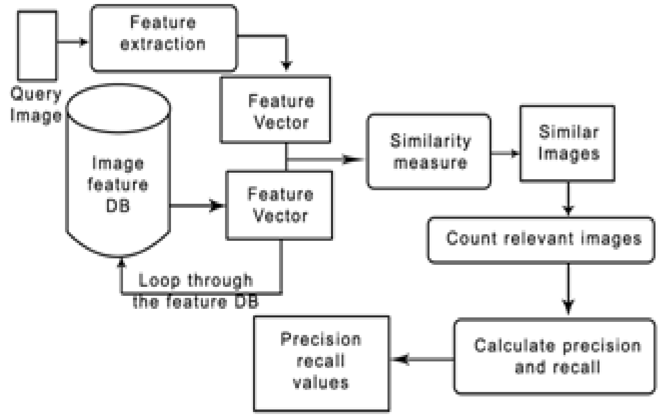


Fig. 2. *Process of calculating Precision and Recall for each method*

The same procedure was repeated for the combined methods. Finally we selected the combined method with the best performance as the combined image retrieval method for our web based image retrieval system.

3.2.5 Statistical Evaluation

When combining methods we did not used any criteria for selecting the combinations, instead we carried out the experiment for all the combinations. Because of this reason we had to make sure whether a difference between two method combinations' averages (average Precision and Average Recall) is unlikely to have occurred because of random chance in method combination selection or there is a significant different in their performance. For this reason and to avoid a false positive we performed an Analysis of Variance (ANOVA) on the data collected. We were also interested to find out whether there is an interaction between image category and image retrieval method so we also performed a two-way ANOVA to find interactions. To identify methods that are significantly different in performance we also performed a multiple comparison analysis using Tukey's method.

3.2.6 Web based image retrieval system.

As final deliverables of this research project, we developed a Web Based Image Retrieval system. The system contains a web crawler which crawl a given URL and download images and extract feature vectors. The feature extraction process happen offline and the obtained information on each crawled image, the name, URL, and feature vector are stored in the feature database. A user can query and find relevant images by doing a query, based on an example image.

4. Results and Discussion

The Fig. 3. below summarizes the average precision and recall values obtained for all the methods.

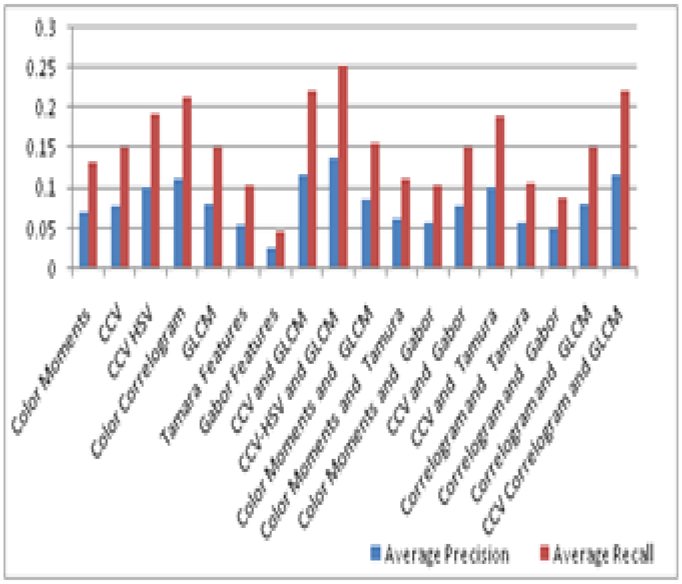


Fig. 3. *Average precision and recall value graph of all methods*
To further evaluate each combined method on performance average execution time was also calculated in milliseconds for each combined method. The Fig. 4. describes the average execution time for each method.

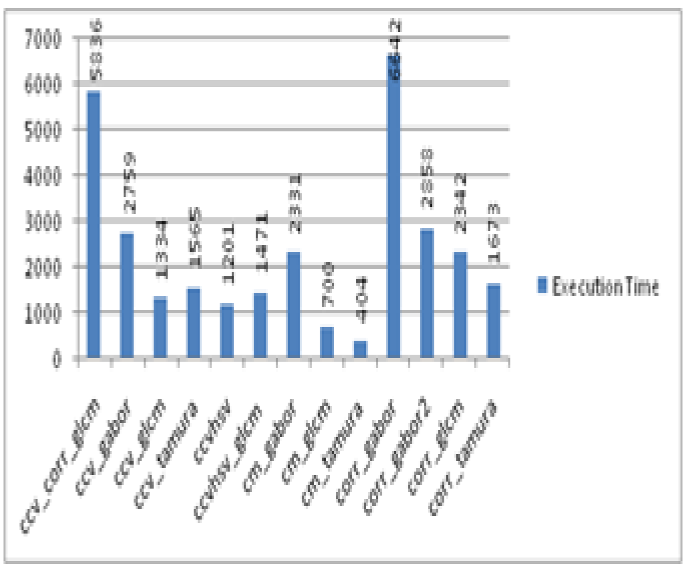


Fig. 4. *Execution Time in Milliseconds for Combined Image Retrieval Methods.*

4.1 Comparison of Methods

ANOVA analysis was performed on average Precision and average Recall of all the methods to further evaluate the methods. The result suggests that there is a significant difference in mean Precision and Recall values, so we performed a multiple comparison analysis on the data set and the result is depicted in Table 1.

TABLE 1
MULTIPLY COMPARISON RESULT OF ALL METHODS

Method name	Multiple Comparison Groupings (* ones in red are for Recall)							
ccvhsv_glcm	A A*							
ccv_corr_glcm	A*	B B*						
ccv_glcm	A*	B B*						
Color Correlogram		B B*						
CCV HSV		B B*	C					
ccv_tamura		B B*	C C*					
cm_glcm			C C*	D D*				
corr_glcm				D D*	E			
GLCM				D D*	E			
ccv_gabor				D D*	E			
CCV				D D*	E	F		
Colour Moments				D D*	E E*	F	G	
cm_tamura					E E*	F F*	G	
corr_tamura					E*	F F*	G	
cm_gabor					E*	F*	G	
Tamura Features					E*	F*	G	
corr_gabor						F*	G	
Gabor Features							G*	H

4.2 Discussion

According to the comparison results the best overall performance is reported by the combined method CCV-HSV / GLCM. Colour Correlogram method is the best performing individual method which was statistically similar in performance with CCV-HSV method. Specialty of both of these methods is they include special colour information. In this sense Colour Correlogram method can describe the global distribution of local spatial correlation of colours in an image which proves to be important for a general domain image database. Also CCV-HSV method performed better than CCV-RGB method. The reason for this may be HSV colour space is insensitive to variations of illumination in an image while RGB colour space is sensitive to it. Among the texture based methods, GLCM method performed the best. GLCM Energy measures textural uniformity, meaning it could detect uniform texture areas. This feature proves to be important in detecting homogeneous texture areas like calm body of water, cloud, smooth surfaces etc. This could be one of the reasons that GLCM method performed the best. Contrast can detect the sharpness of the image while correlation can detect relationship between grey tone values within the image and helps to identify texture patterns in an image. Entropy measures the texture randomness and general domain images frequently have random texture images. Most of the naturally occurring textures in nature have this property. So this could be another reason why GLCM performed better among other texture based methods we consider. Test results for combined method CCV-HSV / GLCM are shown below in Fig. 5 to Fig. 8 The first image of these images is the query images.

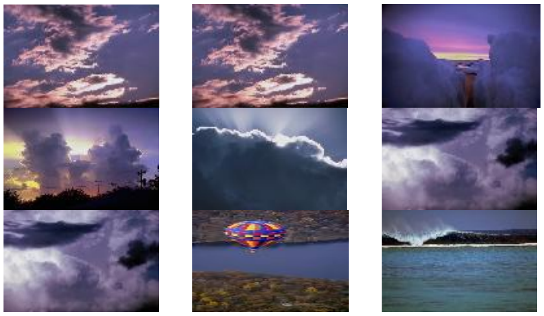


Fig. 5 *Test Image Category sc_clouds*

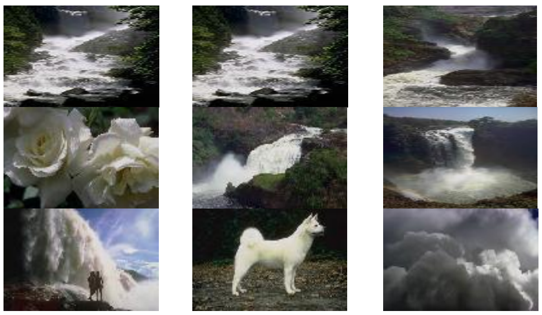


Fig. 6 *Test Image Category sc_waterfall*

Fig. 7 *Test Image Category sc_indoor*

Fig. 8 *Test Image Category texture_2*

5. Conclusions

In this research, we set out to explore the colour based and texture based image retrieval domain in the hope of finding a combined method that would be effective and efficient in retrieving images in the general image domain. Even though CCV (HSV) and GLCM combine method performed the best in our initial evaluation, from the statistical evaluation we found that statistically, methods can be grouped according to their performance and methods in the same group could be interchanged. As we also did a statistical evaluation based on each image category we found that for some image categories using a specific method does not give any statistical advntage as all methods performed uniformly well for that image category, so any method could be used when retrieving images belonging to that image category. Image categories texture_4, sc_indoor, sc_forests, pl_flower, art_mural proved to be such image categories. Other image categories resulted in up to 4 groups of methods with different performance levels. Also considering the execution time groupings and the category wise statistical analysis we saw that the combine method Colour Moments and Tamura Features (cm_tamura) resulted in the best overall performance except for certain image categories like rs_rockform where cm_glcm and ccv_glcm combine methods prove to work best, sc_rural where cm_glcm worked better than other methods, texture_2 where ccv_glcm and cm_glcm worked better and finally for texture_6 cm_glcm worked better. It seems that higher the texture content in the image it's better to combine Grey Level Co-occurrence Matrix method with a colour based image retrieval method and for colour based retrieval methods, Colour moments and Colour Coherent Vector proved to be the best performing methods.

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