Scientific Journal of Impact Factor(SJIF): 3.134
e-ISSN(O): 2348-4470
p-ISSN(P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 2, Issue 4, April -2015

Combining Color and Wavelet Transform based Statistical Signatures Towards Content Based Image Retrieval

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Abstract —*This paper describes a Content Based Image Retrieval technique based on combined color and texture feature. The color features are extracted in the form of weighted color moments using Hue, Saturation and Value (HSV) color space. The texture information is characterized by exploring the statistical properties of wavelet detail coefficients. Three different types of signatures are extracted: Energy signatures to estimate the distribution of energy at different frequencies and scales, Histogram signatures to describe the shape of histogram for detail coefficients, and Co-occurrence signatures as a measure of gray level distribution. Euclidean distance is used to search relevant images based on each of the above measures. Finally an integrated similarity index is computed to refine the results and retrieve top 30 images relevant to the user's query. The experimental results show the effectiveness of the proposed technique over existing techniques using various other measures to describe texture and shape. The proposed method gives an average accuracy of 71 % on Wang's Image Database.*

Keywords-*Color Moment; Co-occurrence Signatures; Discrete Wavelet Transform; Euclidean distance; Kurtosis; Skewness.*

I. INTRODUCTION

Digital acquisition of information has become one of the popular methods in recent years. Use of digital content necessitates the development of effective ways for management and retrieval of visual information. The traditional methods for image searching rely on comparison of metadata or textual tags associated with the images. A limitation of textual annotations is that they fail to describe images that are generated automatically, for example those in medical and surveillance applications. An alternative to text-based approach is to retrieve the images based on their content. The purpose of Content Based Image Retrieval (CBIR) techniques is to retrieve semantically-relevant images from a large database based on image features [1]-[2]. The term CBIR originated in early 1990's [3]. The CBIR techniques make the use of low-level visual features of an image such as colour, texture and shape for indexing and retrieval. A number of techniques have been proposed in the past based on above features. Work proposed in [4] and [5] used Curvelet transform to extract textural features. Reference [6] presents a novel fusion approach towards Content Based Image Retrieval. The authors have considered both local as well as global properties of image region. Initially the query image is segmented into coherent regions by employing K-Means algorithm. After this colour and texture features are extracted for each of these regions which represent the query image. Reference [7] provides detailed performance evaluation of feature extraction and classification techniques. The authors have analyzed three important feature extraction techniques namely Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and classifiers such as Neural Network (NN) and Support Vector Machines (SVM). The evaluation is done based on Recognition Rate and F-score. At the end they have concluded that combination of PCA and SVM provides good performance.

The rest of the paper is organized as follows. Section II describes the proposed methodology in detail. Section III presents Experiments and Results. Section IV concludes the paper by presenting the scope for future work.

II. METOHODOLOGY

Feature extraction is an important component in any CBIR system. The retrieval accuracy highly depends upon the extent the given feature vector represents an image under test.

2.1 Color Feature Extraction

Colour is one of the widely used and an important attribute for image retrieval. A number of methods exploring colour information have been proposed in the past. These include colour histogram [8], colour-correlogram [9], colour moment [10], colour structure descriptor, colour coherence-vector etc. A number of colour representation schemes (e.g. RGB, HSV, CMY etc) have been discussed in literature. We have used Hue, Saturation and Value (HSV) colour space in our algorithm because it more suitable for human visual perception. As a measure of colour feature we compute colour moments. This is because use of colour moments produces the feature vector with least dimensions compared with all other methods. To obtain these moments first we transform the RGB image to HSV colour space. Then we compute first four moments to represent the colour distribution in H, S and V image components [11]. The first colour moment for i^{th} colour component $i=1,2,3$ is given by

$$M_i^1 = \frac{1}{N}\sum_{j=1}^{N} p_{i,j} \tag{1}$$

where, $p_{i,j}$ represents the colour value of the i^{th} colour component of the j^{th} image pixel and N is the total number of pixels in the image [11]. The r^{th} moment ($r=2,3,4$) of the i^{th} colour component is then defined as

$$M_i^r = \left(\frac{1}{N}\sum_{j=1}^{N}(p_{i,j} - M_i^1)^r\right)^{1/r} \tag{2}$$

Taking first four moments of each colour component (i.e. H, S and V) in the image a vector CF, representing the colour feature is formed

$$CF = [\alpha_1 M_1^1, \alpha_1 M_1^2, .., \alpha_1 M_1^4, \alpha_2 M_2^1, ...\alpha_2 M_2^4 ..., \alpha_3 M_3^4]$$

Here $\alpha_1, \alpha_2,$ and α_3 represent the weights assigned to H, S and V colour components respectively. The dimensions of the above vector will be 1×12.

2.2 Texture Feature Extraction

As a measure of texture feature we have combined statistical and multi-scale views on texture. To describe these statistical properties we employ a combination of two types of wavelet signatures. Wavelets provide a convenient way to obtain a multi-resolution representation [12]-[13], from which texture features are easily extracted. The 2-D discrete wavelet transform is computed by applying a separable filter bank to the image [12] as follows:

$$L_n(b_i, b_j) = [H_x * [H_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \tag{3}$$

$$D_{n1}(b_i, b_j) = [H_x * [G_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \tag{4}$$

$$D_{n2}(b_i, b_j) = [G_x * [H_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \tag{5}$$

$$D_{n3}(b_i, b_j) = [G_x * [G_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \tag{6}$$

where, * denotes convolution operator, $\downarrow 2,1$ $(\downarrow 1,2)$ denotes sub-sampling along the rows (columns), and $L_0 = I(\vec{x})$ is the original image. H and G represent low pass and band pass filters respectively. L_n is obtained by low-pass filtering and is therefore referred to as low resolution image at scale n. The detail images D_{ni} are obtained by band-pass filtering in specific direction. Hence these images contain directional detail information at a given scale n. Thus the original image I can be represented by a set of sub-images at several scales: $\{L_d, D_{ni}\}_{i=1,2,3/n=1....d}$, which serves as a multi-scale representation of image I at a depth d. Having obtained the multi-scale representation of the original image the wavelet signatures are extracted from the detailed matrices as explained below:

2.2.1 Wavelet Energy Signatures:

The so-called energy signatures have proven to be very powerful for texture analysis [14]. The normalized energy of a detail image D_{ni} having N coefficients is given by

$$E_{ni} = \frac{1}{N}\sum_{j,k}(D_{ni}(b_j, b_k))^2 \tag{7}$$

These wavelet energy signatures $\{E_{ni}\}_{n=1......d/i=1,2,3}$ provide the distribution of energy along the frequency axis over at different scales and orientations and have proven to be very useful for gray-level texture characterization [14].

2.2.2 Wavelet Histogram Signatures:

The histogram signatures are computed based on the shape parameters of the frequency distribution. The two measures that are used to describe the shape of wavelet histograms are Skewness and Kurtosis. Skewness provides information about asymmetry of the histogram, while Kurtosis quantifies the width of the histogram for each particular neighbourhood. For a data $(x_1, x_2, ..., x_n)$, the Skewness and Kurtosis are given by (8) and (9) respectively [15].

$$Skewness = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \overline{x}}{\sigma}\right]^3 \tag{8}$$

$$Kurtosis = \left\{\frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \overline{x}}{\sigma}\right]^4\right\} - 3 \tag{9}$$

Here, $\overline{x}$ and σ represent the mean and standard deviation for the data sample respectively.

2.2.3 Co-occurrence Signatures:

In addition to first order signatures, second order signatures are computed to improve the retrieval process. We have already extracted the first order statistical information using Histogram signatures hence we obtain second order statistics with the help of Co-occurrence signatures. The Co-occurrence signatures are computed for each of the decomposed wavelet bands. The element (i, j) of the co-occurrence matrix $C_{ni}^{\delta\theta}$ is defined as the joint probability that the wavelet coefficient $D_{ni} = i$ occurs with the coefficient $D_{ni} = j$ at a distance δ in a direction θ [16]. Andrea et al. proved in [17] that out of fourteen features proposed in [16] only six are considered to be most relevant. The equations governing these six co-occurrence features are listed in Table 1. Here N_g specifies the number of distinct gray levels in the transformed image, i and j represent the matrix indices and $g(i, j)$ represents the gray level values at index (i, j). Also μ and σ indicate mean and standard deviation respectively. As these features are extracted from the detail images, these are termed as wavelet co-occurrence signatures.

Table 1. *Equations Governing Six Wavelet Co-occurrence Signatures*

Wavelet Co-occurrence Signatures	
Energy	$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} g^2(i, j)$
Contrast	$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-j)^2 g(i, j)$
Variance	$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-\mu)^2 \bullet g(i, j)$
Correlation	$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \frac{(i-\mu)(j-\mu)g(i, j)}{\sigma^2}$
Entropy	$-\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} g(i, j).\log(g(i, j))$
Inverse Difference Moment	$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} [\frac{1}{(1+(i-j)^2)}]g(i, j)$

Thus in general the steps used to obtain the Wavelet based signatures are:

1. Decompose the image at depth 4 using a bi-orthogonal spline wavelet of order 2 [18].
2. Compute Energy signatures for each detailed matrices. (Total: 12 features).
3. Compute Histogram Signatures for each detailed matrices. (Total: 24 features).
4. Compute Co-occurrence Signatures for each detailed matrices. (Total: 72 features).

2.3 Similarity Matching

The similarity is measured by computing the distance between the two vectors element wise. The metrics used for similarity matching in our algorithm is *Euclidean distance* [19]. Let the query image and the database image be represented by a feature vectors $F_{query} = \{q_1, q_2, ..., q_N\}$ and $F_{database} = \{d_1, d_2, ..., d_N\}$ respectively. Here N represents the dimensions of image feature. Then the Euclidean distance between these two vectors is given by (10).

$$ED = \sqrt{\left\{ \sum_{i=1}^{N} (q_i - d_i)^2 \right\}} \tag{10}$$

After computing the relative distance the database images are stored in increasing order of their distance from the query image. The images having similar features to that of query will have smaller value for distance measure. Let S_{cm} represent the similarity between query and database image based on Colour Moments, S_{wehs} represent the similarity based on wavelet energy and histogram signatures, and let S_{wcs} denote the similarity based on wavelet co-occurrence signatures. The overall combined weighted similarity function is given by

$$S_T = \frac{S_{cm}.w_{cm} + S_{wehs}.w_{wehs} + S_{wcs}.w_{wcs}}{w_{cm} + w_{wehs} + w_{wcs}} \tag{11}$$

Here w_{cm}, w_{wehs} and w_{wcs} are weights assigned to colour, histogram and co-occurrence based similarities respectively. The weight parameters are decided experimentally. We have used $w_{cm} = 3$, $w_{wehs} = 2$ and $w_{wcs} = 3$ in our algorithm giving more importance to colour and co-occurrence based similarities. Based on total similarity S_T, top 30 images are returned to the user as relevant to the query.

III. EXPERIMENTS AND RESULTS

The Database used for testing the performance of our algorithms is *Wang's Database* [20]. This database consists of 1000 images belonging to 10 different classes. Thus there are 100 images from each category. The images are of size 384 × 256 or 256 × 384 pixels. Out of these 100 images from each class, 20 images are used as query, while rest 80 images serve as database from which the similar images will be retrieved. Thus in all 80 images from each class are tested against 20 different queries and the performance of the algorithm is analysed.

3.1 Performance Evaluation

To evaluate the retrieval performance Precision and Recall [21] are computed. Precision is a measure of ability of CBIR algorithm to retrieve only relevant images, while Recall decides the ability of CBIR algorithm to retrieve all relevant images as defined by (12) and (13) respectively.

$$P = \frac{No.of\ relevant\ images\ retrieved}{Total\ number\ of\ images\ retrieved} \tag{12}$$

$$R = \frac{No.of\ relevant\ images\ retrieved}{No.of\ relevant\ images\ in\ the\ database} \tag{13}$$

Table 2 shows the values of average precision for all the ten image classes. The precision is computed for three different retrieval relates. Class of Dinosaurs and Bus contain less complex textures, hence high precision values are obtained for these classes. The proposed approach is compared with three different existing techniques which have been evaluated on the same database. These methods are S. Liapis et al's approach [22] (Based on Wavelet frames and Chromaticity Histograms), J Ahmed et al's approach [23] (Based on colour moments and Ranklet Co-occurrence signatures), and Zhi-Chun Huang et al's approach [24] (Based on Gabor features and colour moment) respectively. The comparison details are listed in Table 3. It is clearly visible that the proposed approach gives higher an improved retrieval performance compared to above three existing techniques.

Table 2. *Average Precision at Different Retrieval Rates*

Average Precision			
Image Class	**No. of Retrieved Images**		
	R_10	***R_20***	***R_30***
Africans	0.76	0.72	0.63
Sea	0.84	0.74	0.69
Building	0.72	0.70	0.62
Bus	1	0.96	0.94
Dinosaur	1	1	0.98
Elephant	0.8	0.77	0.62
Flower	1	0.97	0.93
Horse	0.77	0.73	0.67
Mountain	0.73	0.65	0.52
Food	0.61	0.55	0.50

Table 3. *Comparison of Proposed Method with Existing Techniques*

Average Precision in %				
Image Class	**Method Used**			
	S. Liapis et al's	***J. Ahmed et al's***	***Zhi-Chun Huang et al's***	***Proposed Approach***
Africans	60	60	54	63
Sea	34	70	42	69
Building	32	80	16	62
Bus	92	70	67	94
Dinosaur	88	70	99	98
Elephant	28	50	40	62
Flower	86	70	97	93
Horse	80	50	96	67
Mountain	24	50	46	52
Food	33	40	79	50
Average	**55.7**	**61**	**63.6**	**71**

Figure. 1 and Figure. 3 show retrieval results for two different queries along with their corresponding Euclidean distances from the query image. The images used as query in these results are “248.jpg” from the class of Building and “602.jpg” from the class of Flower respectively. Figure. 2 and Figure. 4 show the relative distance between the query image and other images in the database. The point on the graph with red mark indicates the image number with least distance from the query image. Fig. 5 shows a plot of average precision vs. recall for all the image classes.

Query Image

ED=0.83824

ED=01.144

ED=1.246

ED=1.3837

ED=1.466

ED=1.5025

ED=1.5486

ED=1.5524

ED=1.6976

Figure 1. Query Image from Class of Building and top 9 Retrieved Images

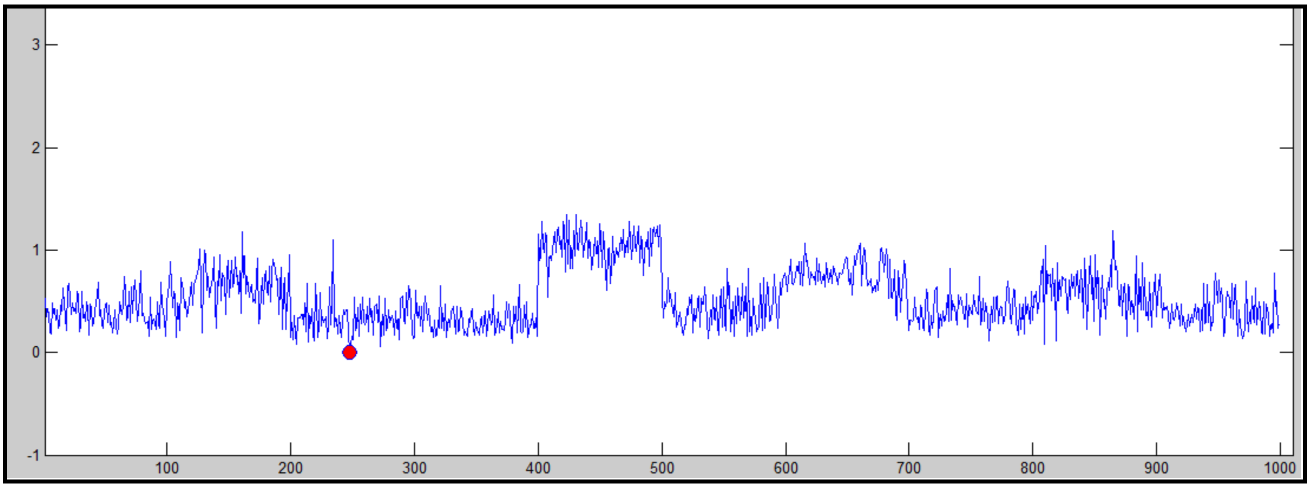

Figure 2. Distance comparison for query image from the class of Building (248.jpg) and remaining images in the database. Red mark indicates the least distance.

Query Image

ED=0.83824

ED=01.144

ED=1.246

ED=1.3837

ED=1.466

ED=1.5025

ED=1.5486

ED=1.5524

ED=1.6976

Figure 3. Query Image from Class of Flower and top 9 Retrieved Images

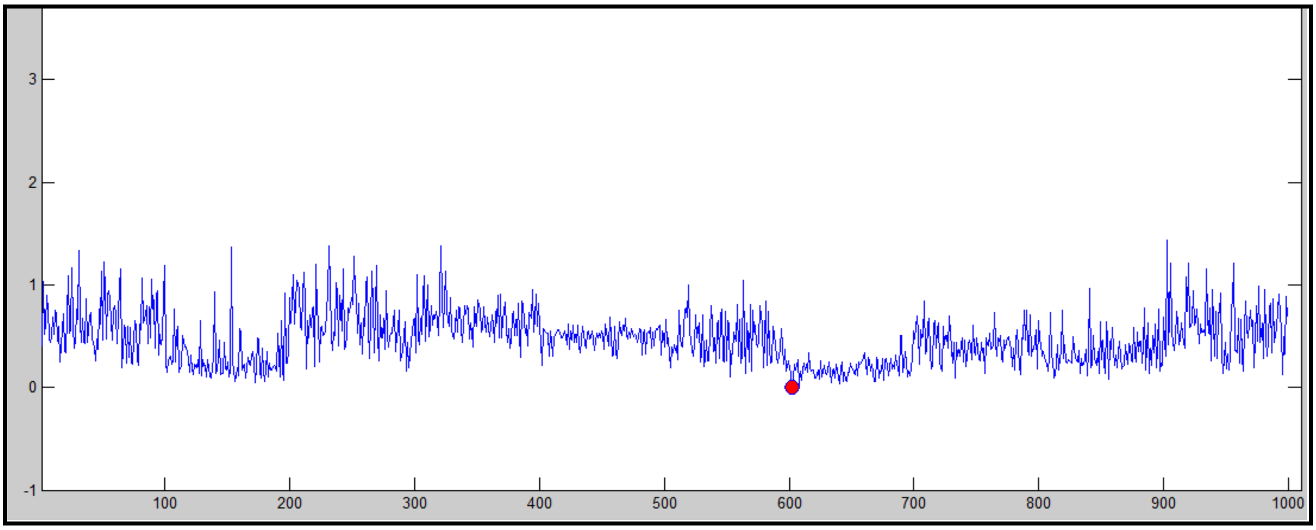

Figure 4. Distance comparison between query image from class of Flower (602.jpg) and remaining images in the database. Red mark indicates the least distance.

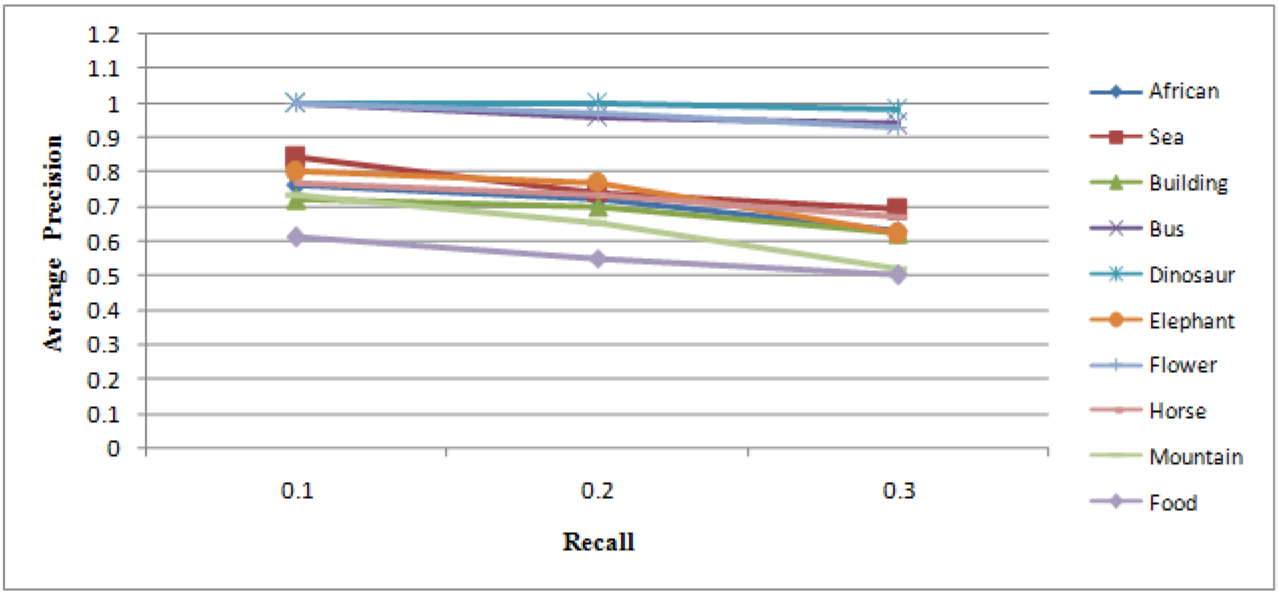

Figure 5. Precision vs. Recall Plot

IV. CONCLUSIONS AND FUTURE WORK

A unique combination of Color Moment and Wavelet Statistics based technique is presented. Both query and database images are represented using multiple features for effective retrieval. The strengths of Color moment and Wavelet based signatures have been utilized to represent minute texture details. Experimental results show that the proposed method has better retrieval accuracy when compared to three other methods employing Gabor Features, Ranklet transform and Multi-resolution analysis for feature extraction. The method gives an average accuracy of 71% on Wang's Image Database.

As a part of future work and to further improve the retrieval accuracy we look forward to introduce techniques to automatically adjust the weights used during integration of similarities. In addition we will try to analyze the performance of our algorithm with different wavelet families.he Database used for testing the performance

REFERENCES

[1] P. Aigrain, H. Zhang, and D. Petkovic, " Content-Based Representation and Retrieval of Visual Media: A State of the Art Review", Multimedia Tools and Applications, Vol. 3, pp.179-202, 1996.

[2] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain,"Content-based image retrieval at the end of the early years," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, pp. 1349–1380, Dec-2000.

[3] F. Long, H. Zhang and D. D. Feng, "Fundamentals of Content-Based Image Retrieval", in Multimedia Information Retrieval and Management Signals and Communication Technology, Springer, pp. 1-26, 2003.

[4] L. Ni and H. C. Leng, "Curvelet Transform and Its Application in Image Retrieval", 3rd International Symposium on Multispectral Image Processing and Pattern Recogntion, Proceedings of SPIE, Vol. 5286, 2003.

[5] I. J. Sumana, M. M. Islam, D. Zhang, G. Lu, "Content Based Image Retrieval Using Curvelet Transform", IEEE 10th Workshop on Multimedia Signal Processing, pp. 11-16, 2008.

[6] Xiaojun Qi, Yutao Han, "A Novel Fusion Approach to Content-Based Image Retrieval", Pattern Recognition, Vol. 38, No. 12, pp. 2449-2465, 2005.

[7] D. Jeyabharathi, A. Suruliandi, "Performance Analysis of Feature Extraction and Classification Techniques in CBIR", IEEE International Conference on Circuit, Power and Computing Technologies, pp. 1211-1214, 2013.

[8] R. Brunelli and O. Mich, "Histograms Analysis for Image Retrieval," Pattern Recognition, Vol. 34, No. 8, pp. 1625-1637, 2001.

[9] J. Huang, S. R. Kumar, M. Mitra, W. J. Zhu, and R. Zabih, "Image indexing using color correlograms," IEEE International Conference on Computer Vision and Pattern Recognition, San Juan, Puerto Rico, pp. 762–768, June-1997.

[10] A. Del Bimbo, M. Mugnaini, P. Pala, and F. Turco.Picasso, "Visual querying by color perceptive regions", In Proceedings of the 2nd International Conference on Visual Information Systems, San Diego, pp. 125-131, December-1997.

[11] J. L Shih, L. H Chen, "Colour Image Retrieval Based on Primitives of Colour Moments", in the Proceeding of IEE Journal of Visual Image and signal Processing, Vol. 149, No. 6, pp. 370-376, December-2002.

[12] S. Mallat, A theory for multiresolution signal decomposition: the wavelet representation, IEEE Transactions on Pattern Analysis and Machine Intelligence Vol. 11, No. 7, pp.674-693, 1989.

[13] T. Chang, C.-C.J. Kuo, Texture analysis and classification with tree-structured wavelet transform, IEEE Transactions on Image Processing, Vol. 2, No. 4, pp. 429-441, 1993.

[14] G. Van de Wouwer, P. Scheunders, Van Dyck, "Statistical Texture Characterization from Discrete Wavelet Representations", IEEE Transactions on Image Processing, Vol. 8, No. 4, pp. 592-598, April-1999.

[15] A. Fdez-Sarria, L. Ruiz, and J. Recio, "Study of methos based on wavelets for texture classification of high resolution images," in Procs of 25th EARSeL Symposium. Global Developments in Environmental Earth Observation from Space, 2005, pp. 19-25.

[16] R. M. Haralick, K. Shanmugam, I. Dinstein, "Textural Features for Image Classification", IEEE Transactions on Systems, Man, and Cybernetics, pp. 610-621, 1973.

[17] Andrea Baraldi, Flavio Parmiggiani, "An Investigation of the Textural Charactersitics Associated with Gray Level Cooccurence Matrix Statistical Parameters", IEEE Transactions on Geoscience and Remote Sensing, Vol. 33, No. 2, pp.293-304, March-1995.

[18] M. Unser, A. Aldroubi, M. Eden, "A family of polynomial spline wavelet transforms," Signal Processing, Vol. 30, pp. 141-162, 1993.

[19] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, Pearson Education, Third Edition, Copyright © 2008.

[20] J. Z. Wang, "Wang Database," [Online], Available at: http://wang.ist.psu.edu/. Last accessed Jannuary 28, 2014.

[21] Hennig Muller, Wolfgang Muller, David McG. Squire, Stephane Marchand-Maillet, Thierry Pun, "Performance Evaluation in Content Based Image Retrieval: Overview and Proposals", Image/Video Indexing and Retrieval (Elsevier), Vol. 22, No. 5, pp. 593-601, April-2001.

[22] S. Liapis and G. Tziritas, "Color and texture image retrieval using chromaticity histograms and wavelet frames," IEEE Transactions on . Multimedia, Vol. 6, pp. 676–686, October -2004.

[23] Ahmed J. Afifi, Wesam M. Ashour, "Content-Based Image Retrieval Using Invariant Color and Texture Features", International Conference on Digital Image Computing Techniques and Applications, pp.1-6, December-2012.

[24] Zhi-Chun Huang, Patrick P.K. Chan, Wing W. Y. NG, Daniel S. Yeung, "Content-Based Image Retrieval using ColorMoment and Gabor Texture Feature", Ninth International Conferene on Machine Learning and Cybernetics, pp. 719-724, July-2010.

