

Image Retrieval Using Texture and its Spatial Information

S. Sathiamoorthy

Computer Science and Engineering Wing, DDE, Annamalai University, Annamalainagar, Tamilnadu, India

ABSTRACT: In this paper, novel approach for BDIP (block difference of inverse probabilities) and BVLC (block variation of local correlation coefficients) texture features characterization and discrimination is presented. BDIP captures the global distribution of local spatial correlations between the identical BDIP (block difference of inverse probabilities) values. BVLC captures global distribution of local spatial correlations between the identical BVLC (block variation of local correlation coefficients) values. The Canberra distance measure is used as a measure of similarity. The precision and recall is employed to measure the performance of the proposed novel approach based on BDIP and BVLC values. The exhausted experiments on benchmark database confirm that the proposed approach outperforms the existing one.

KEYWORDS: BDIP, BVLC, Canberra distance, Local spatial correlation.

I. INTRODUCTION

The fast development of multimedia, the availability of huge digital achieves and the speedy emergence of internet has drawn the attention of research efforts towards the techniques for effective retrieval of images. More and more effective image retrieval techniques are central importance in the utilization of day to day raising digital data available on the internet. Over the decade, a growing interest has been seen in the development of effective techniques for searching huge image archive. Nowadays, image databases are much more used in the domains like medicine, entertainment, engineering, advertisement, weather forecasting, etc. However, as the database size grow up day to day, the traditional keyword based techniques to retrieve a image from the huge archive becomes inefficient and undergo some limitations like subjectiveness, requires skilled labour and huge keyword database corresponding to the domain of images, time consuming and it is also more difficult to express the color, texture and shape features in terms of precise keyword.

In order to overcome the aforesaid limitations, content based image retrieval (CBIR) method has come out as a potential choice. CBIR is extremely active and vigorous research topic in recent years. In CBIR, images are retrieved by its own visual contents such as color, texture and shape. The major benefit of CBIR system is its capability to support visual queries. The major challenge in CBIR system is developing a technique that will improve the retrieval accuracy and decreasing the retrieval time. The complete and broad literature survey on CBIR is found in [1]-[3].

In computer vision and pattern recognition, texture features acquires significant role in describing the content of images. Texture feature presents in many real world images like beach, mountain, clouds, leaves, desert, waterfalls, etc. Earlier methods for image retrieval undergo two main drawbacks. That is either they are computationally cost or accuracy is less. This paper concentrates only on the problem of finding a rich texture features for image retrieval system with high accuracy. The contribution of novelty in this paper is instead of simply representing the effective BDIP and BVLC features by using the histogram of 57 bins, we also capture the local spatial information of computed BDIP and BVLC texture features.

II. RELATED WORK

Broadly, there are three types of methods used to describe the texture of an image and they are statistical, structural and spectral [4]. In the literature, statistical features like Tamura textures [5], Laws texture energy approach [6],

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

Markov random field (MRF) model [7], Laws texture energy approach [8], Haralick's gray-level co-occurrence matrix (GLCM) [9], Derin-Elliot model [10] and auto-binomial model [11], local binary pattern (LBP) [12], color edge co-occurrence histogram (CECH) [13], multi-texton histogram (MTH) [14] has been reported. On the other hand, since the development of multi-channel filtering methods, a number of researchers [15, 16, 17, 18, 19, 20, 21] have turned their interest on analysing textures in the frequency domain by using the wavelet transforms like orthogonal, bi-orthogonal, tree-structured, pyramid, Harr, Gabor wavelet transform, etc. In recent years, [19] presented a BDIP and BVLC moments for extracting the edge and valley and texture smoothness characteristics of an image, and they reported that the BDIP and BVLC moments outperform the existing methods. In their approach, the image in RGB color space is converted into HSV color space then they separated the H, S and V components of an image. Later they performed wavelet decomposition on each component image using the Harr wavelet. Consequently, from the H and S components they calculated color autocorrelogram and from V component they computed BDIP and BVLC for each sub bands of all the 2 level of decomposition respectively. Afterwards, from the computed BDIP and BVLC values of each sub band of an image, first order statistics i.e. mean and standard deviation is computed. The BDIP and BVLC moments are combined together with the color autocorrelogram computed for each corresponding sub bands of H and S images to form a single feature vector and it is used for retrieving the images from the database. Minkowski distance is employed in [19] for measuring the similarity between the input and target images.

Later, Sathiamoorthy [20] represented the BDIP and BVLC features using low and higher order statistics i.e., mean standard deviation, skewness and kurtosis and reported that his approach is superior to [19]. Afterward, Sathiamoorthy [21] represented the BDIP and BVLC features using a histogram of 57 bins for each respectively, which is robustness to noise and considerably better than the BDIP and BVLC moments presented in [19,20,21]. However, the method of representing the BDIP and BVLC feature in [21] fails to capture the spatial information of edge and valleys and texture characteristics. As the spatial information plays a notable role in texture analysis, image retrieval and classification, in this paper, a novel scheme for texture feature characterization and discrimination is presented and it captures the global distribution of local spatial correlations between the identical BDIP values as well as for BVLC values also. The Canberra distance measure [21, 22] is used as a measure of similarity. The precision and recall [22] is employed to measure the performance of the proposed novel representation of BDIP and BVLC.

The remainder of the paper is structured as follows. In Section 3, we describe the image feature extraction and representation. In Section 4, the framework for proposed image retrieval is discussed. Section 4.1 and 4.2 discuss about similarity measure and performance assessment. Comprehensive experiments and analysis of results are presented in Sections 5 and Section 6 gives the conclusion.

III. PROPOSED TEXTURE FEATURES

3.1. BDIP

BDIP is an entropy operator and is defined as the difference between the number of pixels in a block and the ratio of the sum of pixel intensities in the block to the maximum in the block, and it uses local probabilities in an image block to measure the local brightness variations. The BDIP captures the both the edges and valleys. In an image, edge pixels represent the local intensity maximum and pixels in the valley represent local intensity minima. Both the edges and valleys play a central role in human visual perception system to recognize an object. Based on the fact, BDIP is suggested in [19] and is computed as follows in equation (1).

$$BDIP^l(l) = \frac{\frac{1}{B_1^d} \sum_{(x,y) \in B_1^d} (\max_{(x,y) \in B_1^d} f(x,y) - f(x,y))}{\max_{(x,y) \in B_1^d} f(x,y)} \quad (1)$$

Where $f(x,y)$ designates the pixel intensity at location (x,y) in the block B_1^k of size $(k+1) \times (k+1)$, l is the place index of the block in an image and k is the maximum distance of pairs of pixels in the block. Therefore, $B_1^k = (k+1)^2$. The

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

maximum intensity variation in a block and the representative value in a block are expressed in the numerator and denominator of equation (1) respectively.

3.2. BVLC

BVLC [19] is the difference between the maximum and minimum of local correlation coefficients according to four orientations ($0^\circ, 90^\circ, 45^\circ, -45^\circ$) in a block. This feature measures the texture smoothness using variations of local correlation coefficients in an image blocks as follows in equation (2).

$$\rho(k, l) = \frac{\frac{1}{M^2} \sum_{(x,y) \in B} f(x, y) f(x+k, y+l) - \mu_{0,0} \mu_{k,l}}{\sigma_{0,0} \sigma_{k,l}} \quad (2)$$

Where B is a block of size $M \times M$ and $\mu_{0,0} \mu_{k,l}$ is the local mean, and $\sigma_{0,0} \sigma_{k,l}$ is the local standard deviation. The (k, l) represents a pair of horizontal shift and vertical shift associated with four orientations ($0^\circ, 90^\circ, 45^\circ, -45^\circ$). After shifting the $M \times M$ windows in each of four directions, compute $p(0, 1)$, $p(1, 0)$, $p(1, 1)$, $p(1, -1)$ then the BVLC is computed as shown in equation (3).

$$\text{BVLC}^d(l) = \max_{\Delta(k) \in O_4} [\rho^k(l, \Delta(k))] - \min_{\Delta(k) \in O_4} [\rho^k(l, \Delta(k))] \quad (3)$$

Where $\Delta(k) = (\Delta_x(k), \Delta_y(k))$ stands for shift in one four directions and $O_4 = \{(-k, 0), (0, -k), (0, k), (k, 0)\}$

IV. PROPOSED SYSTEM

4.1. Feature Extraction and Representation

In the proposed system the color images in RGB color space are transformed into HSV color space [19] then the images are separated out into Hue, Saturation and Intensity component images, where Hue and Saturation component images have chromatic information and intensity component image contains achromatic information. In the proposed work, the discussion is limited to texture feature only. Hence, we consider intensity component image only. Wavelet decomposition is performed using wavelet transform [19] on intensity component image. The level of decomposition is set to 2 as in [19]. After that, the BDIP and BVLC features are extracted for each sub band of intensity image. In [19], the moments of BDIP and BVLC is considered for representing the texture feature of an image. In [20], both low and higher order moments of BDIP and BVLC is considered for representing the texture feature of an image and Canberra distance is adopted. In [21], BDIP and BVLC features are represented using a histogram of 57 bins for each. Both, the low and higher order statistics of BDIP and BVLC alone or histogram of 57 bins for BDIP and BVLC will not give an efficient discriminative power for an image and even though it is computed for each sub bands (LL, LH, HL, HH) of intensity image in all the level of decomposition. Thus, in order to increase the efficacy of BDIP and BVLC features, in this paper, a new texture feature representation method is presented. The aim is exploiting the global distribution of local spatial correlation between the identical BDIP edges and valleys as well as to identical BVLC textures also. The changes in correlation are observed with respect to distance. The proposed work suggests that the new representation of BDIP and BVLC has superior discrimination ability.

The identified BDIP textures are defined as a table, which is indexed by $BDIP_{texNum}$ and distance. Each entry in the table specifies the probability of finding a texture of $BDIP_{texNum}$ i at a correlation distance d from a texture of $BDIP_{texNum}$ i . Similarly, the identified BVLC textures are also defined as a table, which is indexed by $BVLC_{texNum}$ and distance. Each entry in the table specifies the probability of finding a texture of $BVLC_{texNum}$ i at a correlation distance d from a texture of $BVLC_{texNum}$ i . In both cases, the proposed method only consider the spatial correlation between the identical BDIP textures as well as BVLC textures and the proposed work fix the correlation distance d to 1

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

because smallest correlation distance gave the detailed local properties of an image. For example, the proposed representation of BDIP and BVLC is depicted in the Table.1.

The proposed system strongly believed that the global distribution of local spatial correlation among the identical BDIP values and spatial correlation among the identical BVLC values play a vital in the image retrieval and experimental results confirm that the proposed novel method significantly superior than the approach reported in [21]. The algorithm for the proposed method is as follows

Algorithm:

Input: QRGB stands for query image in RGB color space and NDB stands for total number of images in the database. L stands for level of quantization.

Output: NR stands for number of retrieved images akin with query image QRGB.

1. Image QRGB in RGB color space is converted into HSV color space and is denoted by QHSV
2. QHSV is separated into H component, S component and V component images and are denoted by QH, QS, QV respectively.
3. Harr wavelet is used to perform 2 level decomposition on QH, QS, QV images.
4. for i=1 to L
 - a. Compute BDIP values for each sub-bands
 - b. Compute BVLC values for each sub-bands
 - c. Compute the spatial correlation among the identical BDIP values
 - d. Compute spatial correlation among the identical BVLC values
 - e. Combine the extracted feature vectors into a single one.
 - f. Normalize the combined feature vector and is stored in feature database.end
5. [Assume that the feature vector is computed as mentioned in step 4 for all the images in the experimental database]
6. int D[NDB];
7. For i=1 to NDB
 - for i=1 to Number of images to be retrieved
 - i. Measure the similarity between the QV and TV and is assigned to Dv.
 - ii. $D[i] = D[i] + Dv;$End
 - $D[i] = D[i] / \text{Number of images to be retrieved}$end
8. Sorting is performed on D[NDB].
9. Return the similar images in ascending order of similarity.

4.2. Similarity Measure

Measuring the distance between the query and target images using the derived feature vectors is an indispensable module of any image retrieval system. Different distance measures from computational geometry, statistics and information theory are described for image retrieval systems. In the proposed work, Canberra distance [22] measure is

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

used because of its significance performance in image retrieval. The computational cost of Canberra distance is also less. The Canberra distance is a weighted version of L1 distance and it is computed as follows in equation (4).

$$S(Q, T) = \sum_{i=1}^n \frac{|Q_i - T_i|}{|Q_i| + |T_i|} \tag{4}$$

Where Q and T stand for the query and target image feature vectors respectively and n is the number of features in each feature vector. The features are placed in increasing order that the value in the top most gives high similarity.

BDIP or BVLC texture value	Distance=1
0	0.0098
1	0.09
2	0.0002
3	0.03
.	.
.	.
.	.
n	0.0001

Table 1. Representation of BDIP and BVLC

4.3. Performance Assessment

The performance of the proposed system is measured using the most widely used precision (percentage of retrieved images that are also relevant) and recall (percentage of relevant images that are retrieved) methods [23] and is defined as follows in equation (5) and (6)

$$\text{Precision} = \frac{R_i}{T_i} \tag{5}$$

$$\text{Recall} = \frac{R_i}{T} \tag{6}$$

Where R_i is the total number of relevant images retrieved, T is the total number of relevant images in the image database, and T_i is the total number of all retrieved images. The effectiveness of the proposed system is also measured in terms of average recognition rate (ARR), which is defined as the percentage of retrieved images in top matches.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

V. EXPERIMENTAL RESULTS

To verify the efficiency of proposed method, two different image databases has been used in the experiments and results are shown separately.

Database 1:

Texture images from Brodatz texture photographic album [24] is considered in our experiment and size of each texture image is 512 x 512. We also considered the 40 real- world texture images from VisTex database [25]. Few sample images from the database 1 is depicted in Fig.1a.

Database 2:

The images from Wang's image database [26] are also considered in our experiments. It consists of 1000 images of different category like beach, Africans, seashore, clouds, buildings, flowers, elephants, buses, etc. Few sample images from the database 2 is depicted in Fig.1b.

In both databases the images are in JPEG format. In this paper, two different set of experiments using two different databases have been performed to test the retrieval performance of the proposed novel representation of BDIP and BVLC features. The results of the proposed method are compared with existing method [21]. The precision versus recall of the proposed and existing approach is shown in Fig.2 and Fig.3 for database 1 and database 2 respectively. In the proposed work, the performance is also measured in terms of average retrieval rate. From Fig.2 and Fig.3, it is very clear that the new approach for BDIP and BVLC feature characterization and discrimination is superior to existing one in the case of database 1. When the experiments are conducted on image database 2, the proposed approach also outperforms the existing one.

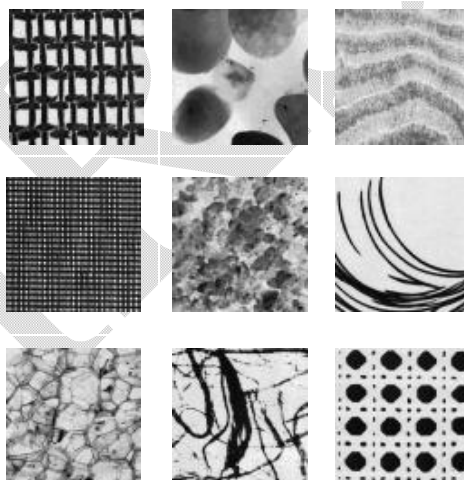


Fig.1a. Sample images from database 1



International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

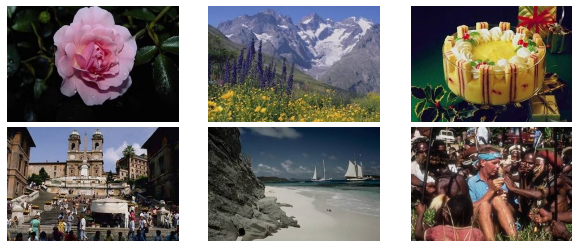


Fig.1b. Sample images from database 2

In Fig. 3a and Fig. 3b the retrieved top 4 images for a given query is shown for both existing [21] and proposed approaches. The global distribution of local spatial correlations between the identical BDIP feature and the global distribution of local spatial correlations between the identical BVLC features play a central role in the discrimination of BDIP and BVLC features and it leads to better results in image retrieval system. Query images chosen randomly from the database1 as well as from database 2 also. After extracting the feature vector of query image, it is compared with the feature vectors in the feature database using the Canberra distance measure. The images having less distance with the query image is retrieved first. Few images in the benchmark databases are duplicated and few of them are rotated through different angle and few of them are scaled up and scaled down to different sizes in order to measure the robustness of the proposed system against rotation and scaling.

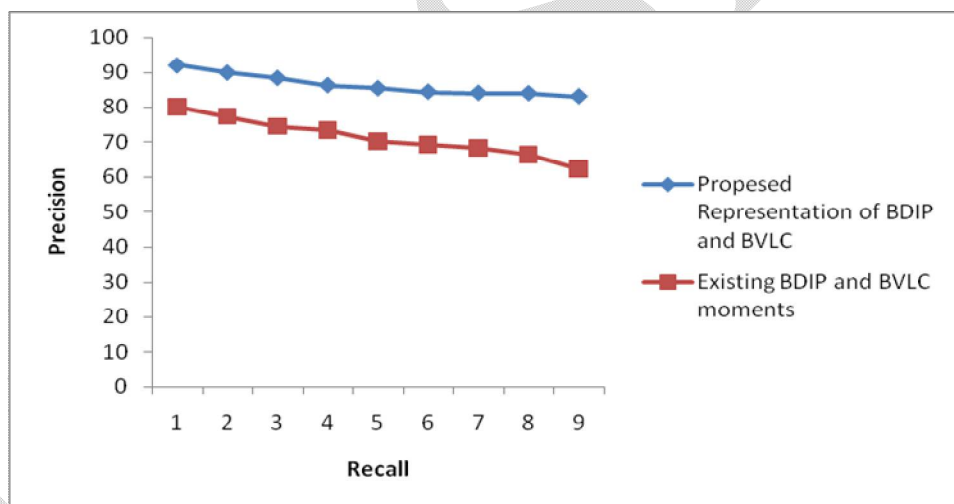


Fig.2. The precision Vs recall of the proposed and existing BDIP and BVLC feature characterization for database 1

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

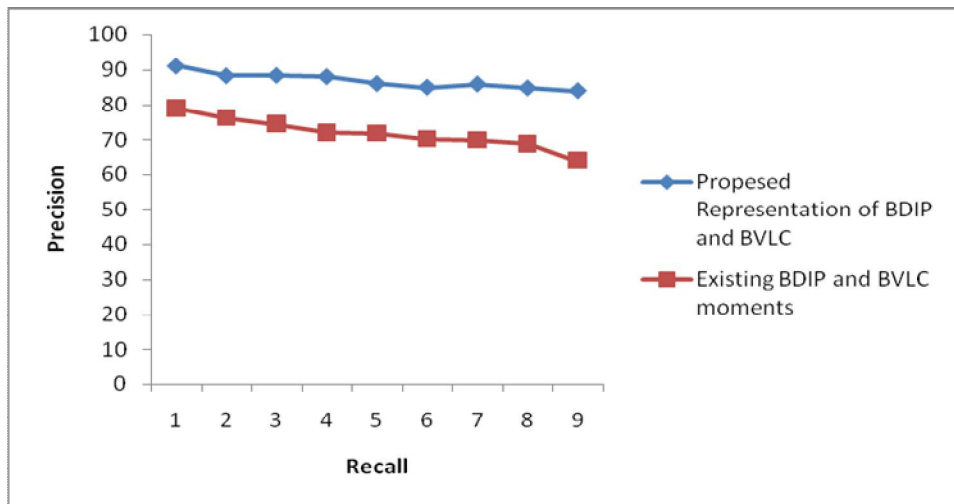


Fig.3.The precision Vs recall of the proposed and existing BDIP and BVLC feature characterization for database2

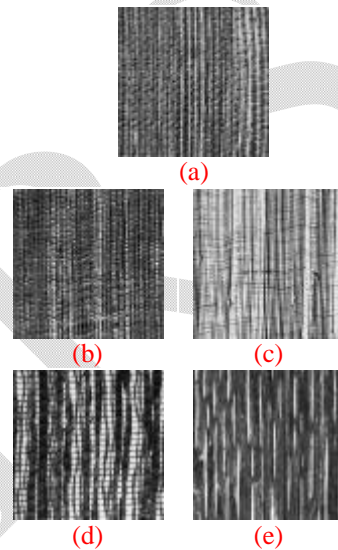
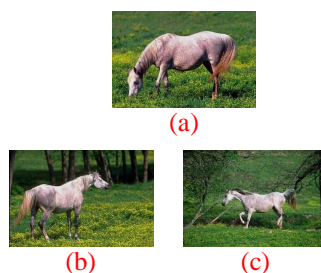


Fig.4a.The 4 top most output (b)-(e) of the proposed system for the query image (a) in database 1



International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

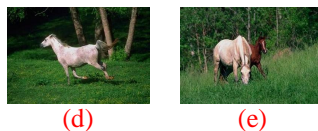


Fig.4b.The 4 top most output (b)-(e) of the proposed system for the query image (a) in database 2

The average retrieval rates of proposed and existing system[21] for database 1 and database 2 are 87.45%, 69.23% and 75.31%, 68.02% respectively. The obtained results confirm that the proposed method achieved improved results than the existing one [21].

VI. CONCLUSION

The proposed work suggested global distribution of local spatial correlations between the identical BDIP values and global distribution of local spatial correlations between the identical BVLC values for image retrieval. In the existing system, the histogram of 57 bins is computed for BDIP and BVLC and is used for image retrieval. The Canberra distance measure is employed to find the similarity based on the new characterization and discrimination of BDIP and BVLC. The result of the proposed system is superior to existing one for both the texture image databases and Wang's database. The proposed system will be more helpful for the student and researchers working in various domain connected with multimedia.

REFERENCES

1. Y. Rui and T. S. Huang, "Image retrieval: Current techniques, promising directions and open issues," *J. Vis. Commun. Image Represent.*, vol. 10, pp. 39–62, 1999.
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 Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 12, pp. 1349–1380, Dec. 2000.
3. M. Kokare, B. N. Chatterji, and P. K. Biswas, "A survey on current content based image retrieval methods," *IETE J. Res.*, vol. 48, no. 3&4, pp.261–271, May–Aug. 2002.
4. Gonzalez, R.C., Woods, R.E., 2007. Digital Image Processing, third ed., Prentice Hall.
5. Tamura, H., Mori, S., and Yamawaki, T., 1978. Texture features corresponding to visual perception, *IEEE Trans. on Sys.,Man. and Cyb.* SMC-8(6).
6. Tuceryan, M. and A. K. Jain, 1990. Texture Segmentation Using Voronoi Polygons, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-12, pp. 211-216.
7. Laws, K.I., November 1979, Texture energy measures. *In Proc. Image Understanding Workshop*, pages 47–51.
8. Haralick, R., Sternberg, S., Zhuang, X., 1987. Image analysis using mathematical morphology. *IEEE Trans. Pattern Anal. Machine Intell.* 9 (44), 532–550.
9. Derin, H., Elliott, H., 1987. Modelling and segmentation of noisy and textured images using Gibbs random fields, *IEEE Transaction on Pattern Recognition and Machine Intelligence.* (9): 39–55.
10. Cross, G., and Jain, A.K., 1983. Markov random field texture models, *IEEE Trans. Pattern Anal. Machine Intell.* (5): 25-39.
11. Ojala, T., Pietikainen, M., Maenpaa, T., 2002. Multi-resolution gray-scale and rotation invariant texture classification with local binary patterns, *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 24 (7): 971–987.
12. Luo, J., Crandall, D., 2006. Color object detection using spatial-color joint probability functions, *IEEE Transactions on Image Processing.* 15 (6): 1443–1453.
13. Liu G, Zhang L, Hou Y, Li Z, Yang J., 2010. Image retrieval based on multi-texton histogram. *J. Pattern Recognit.* 43: 2380–2389.
14. Do, M.N., Vetterli, M., 2002. Wavelet-based texture retrieval using general- ized Gaussian density and Kullback–Leibler distance, *IEEE Transactions on Image Processing.* 11 (2): 146–158.
15. Manjunath, B.S., Salembier, P., Sikora, T., 2002. Introduction to MPEG-7: Multimedia Content Description Interface, *John Wiley & Sons Ltd.*
16. Vogel, J., Schiele, B., 2006. Performance evaluation and optimization for content-based image retrieval, *Pattern Recognition.* 39 (5): 897–909.
17. He, Z., You, X., Yuan, Y., 2009. Texture image retrieval based on non-tensor product wavelet filter banks, *Signal Processing.* 89:1501–1510.
18. Subrahmanyam M, Maheshwari R.P, 2011. A correlogram algorithm for image indexing and retrieval using wavelet and rotated wavelet filters. *Int J Signal Imaging Syst Eng.* 4:27–34.
19. Chun, Y.D., Kim, N.C. and Jang, I.H., 2008. Content-Based Image Retrieval using Multiresolution Color and Texture Features, *IEEE Transactions on Multimedia.* 10(6):1073-1084.
20. Sathiamoorthy.S, Kamarasan.M, 2014, Content Based Image Retrieval Using the Low and Higher Order Moments of BDIP and BVLC, *International Journal of Innovative Research in Science, Engineering and Technology.* 3(1):8936-8941.
21. Sathiamoorthy.S, 2014, A Novel Approach for Image Retrieval using BDIP and BVLC, *International Journal of Innovative Research in Computer and Communication Engineering.* 2(9):5897-5902.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

22. Fazal Malik, Baharum Baharudin, 2013. Analysis of distance metrics in content-based image retrieval using statistical quantized histogram texture features in the DCT domain, *Journal of King Saud University – Computer and Information Sciences*, 25, 207–218.
23. Mahmudur Rahman, Md., Prabir Bhattacharya, and Bipin C. Desai, 2007. A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback. *IEEE trans on infor technology in biomedicine*. 11(1), 58-69.
24. P. Brodatz, *Textures: A Photographic Album for Artists and Designers*. New York: Dover, 1966.
25. MIT Vision and Modeling Group. Vision Texture. [Online]. Available:<http://vismod.www.media.mit.edu>.
26. [Http://wang.ist.psu.edu/docs/related](http://wang.ist.psu.edu/docs/related)

IJRSET