Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

INTER SPACE LOCAL BINARY PATTERNS FOR IMAGE INDEXING AND RETRIEVAL

DILKESHWAR PANDEY[1], RAJIVE KUMAR[2]
Department of Mathematics
Deenbandhu Chhotu Ram University of Science & Tech.
Murthal, Haryana, INDIA
E-mail: [1]dilkeshwar@hotmail.com, [2]rajeev_kansal@yahoo.com

ABSTRACT

In this paper, inter space local binary pattern (ISLBP) algorithm for content based image retrieval (CBIR) is proposed. First the image is separated into red(R), green(G), and blue(B) color spaces, and these are used for inter space local binary patterns (ISLBP), which are evaluated by taking into consideration of local difference between the center pixel and its neighbors by changing center pixels of one color space with other color space. Local binary pattern (LBP) extracts the information based on distribution of edges in an image. Finally, inter LBP histograms are constructed between the color spaces for image retrieval. The experimentation has been carried out for proving the worth of our algorithm. It is further mentioned that the databases considered for experiment viz. Corel 1000 and MIT VisTex databases. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to LBP on RGB spaces separately.
Keywords: *Feature Extraction; Local Binary Patterns; Image Retrieval.*

1. INTRODUCTION

A. Motivation

Content-based image retrieval has become a prominent research topic because of the proliferation of video and image data in digital form. Increased bandwidth availability to access the internet in the near future will allow the users to search for and browse through video and image databases located at remote sites. Therefore fast retrieval of images from large databases is an important problem that needs to be addressed.

Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. CBIR is an important alternative and complement to traditional text-based image searching and can greatly enhance the accuracy of the information being returned. It aims to develop an efficient visual-content-based technique to search, browse and retrieve relevant images from large-scale digital image collections. Most proposed CBIR techniques automatically extract low-level features (e.g. color, texture, shapes and layout of objects) to measure the similarities among images by comparing the feature differences. Several methods achieving effective feature extraction have been proposed in the literature [1]–[4].

Swain et al. proposed the concept of color histogram in 1991 and also introduced the histogram intersection distance metric to measure the distance between the histograms of images [5]. Stricker et al. (1995) used the first three central moments called mean, standard deviation and skewness of each color for image retrieval [6]. Pass et al. (1997) split the each histogram bin into two parts called a color coherence vector (CCV) [7]. CCV partitions the each bin into two types, i.e., coherent, if it belongs to a large uniformly colored region or incoherent, if it does not. Huang et al. (1997) used a new color feature called color correlogram [8]. Color correlogram characterizes not only the color distributions of pixels, but also spatial correlation of pair of colors. Lu et al. (2005) proposed color feature based on vector quantized (VQ) index histograms in the DCT domain. They computed 12 histograms, four for each color component from 12 DCT-VQ index sequences [9].

Texture is another salient and indispensable feature for CBIR. Smith et al. used the mean and variance of the wavelet coefficients as texture features for CBIR [10]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [11, 12]. Ahmadian et al. used the wavelet transform for texture classification [13]. Moghaddam et al. introduced new algorithm called

Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

wavelet correlogram (WC) [14]. Saadatmand et al. [15, 16] improved the performance of WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). Birgale et al. [17] and Subrahmanyam et al. [18] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Subrahmanyam et al. proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC+RWC) [19].

B. Related Work

Ojala et al. proposed the local binary pattern (LBP) features for texture description [20] and these LBPs are converted to rotational invariant for texture classification [21]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [22]. Ahonen et al. [23] and Zhao et al [24] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [25]. Huang et al. proposed the extended LBP for shape localization [26]. Heikkila et al. used the LBP for interest region description [27]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [28]. Face recognition under different lighting conditions by the use of local ternary patterns is discussed in [29] where emphasis lays on the issue of robustness of the local patterns.

C. Main Contributions

To improve the retrieval performance in terms of retrieval accuracy, in this paper, we constructed the inter space local binary patterns (ISLBP) histograms between the red (R), green (G), and blue (B) spaces. These histograms are used as the feature vectors for image retrieval. The experimentation has been carried out on Corel and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP histogram on R, G, B spaces separately.

The organization of the paper as follows: In section 1, a brief review of image retrieval and related work is given. Section 2 presents a concise review of local binary patterns. Section 3 presents feature extraction and proposed system framework. Experimental results and discussions are given in section 4. Based on above work conclusions are derived in section 5.

2. LOCAL BINARY PATTERNS

Ojala et al. introduced the LBP [20] for texture description as show in Fig. 1. For given a center pixel in the image, a LBP value is computed by comparing it with those of its neighborhoods:

$$LBP_{P,R} = \sum_{i=0}^{P-1} 2^i \times f(g_i - g_c) \qquad (1)$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (2)$$

where g_c is the gray value of the center pixel, g_i is the gray value of its neighbors, P is the number of neighbors and R is the radius of the neighborhood. Fig. 2 shows the examples of circular neighbor sets for different configurations of (P, R).

The uniform LBP pattern refers to the uniform appearance pattern which has limited discontinuities in the circular binary presentation. In this paper, the pattern which has less than or equal to two discontinuities in the circular binary presentation is considered as the uniform pattern and remaining patterns considered as non-uniform patterns.

Fig. 3 shows all uniform patters for P=8. The distinct values for given query image is $P(P-1)+3$ by using uniform patterns.

After identifying the LBP pattern of each pixel (j, k), the whole image is represented by building a histogram:

$$H_S(l) = \sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f(BLP_{P,R}^{u2}(j,k), l);\ l \in [0, P(P-1)+3] \qquad (3)$$

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & othrwise \end{cases} \qquad (4)$$

where the size of input image is $N_1 \times N_2$.

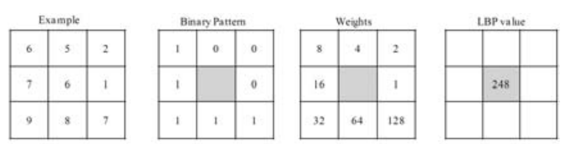


Fig. 1: LBP calculation for 3×3 pattern

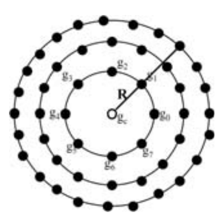


Fig. 2: Circular neighborhood sets for different *(P,R)*

Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

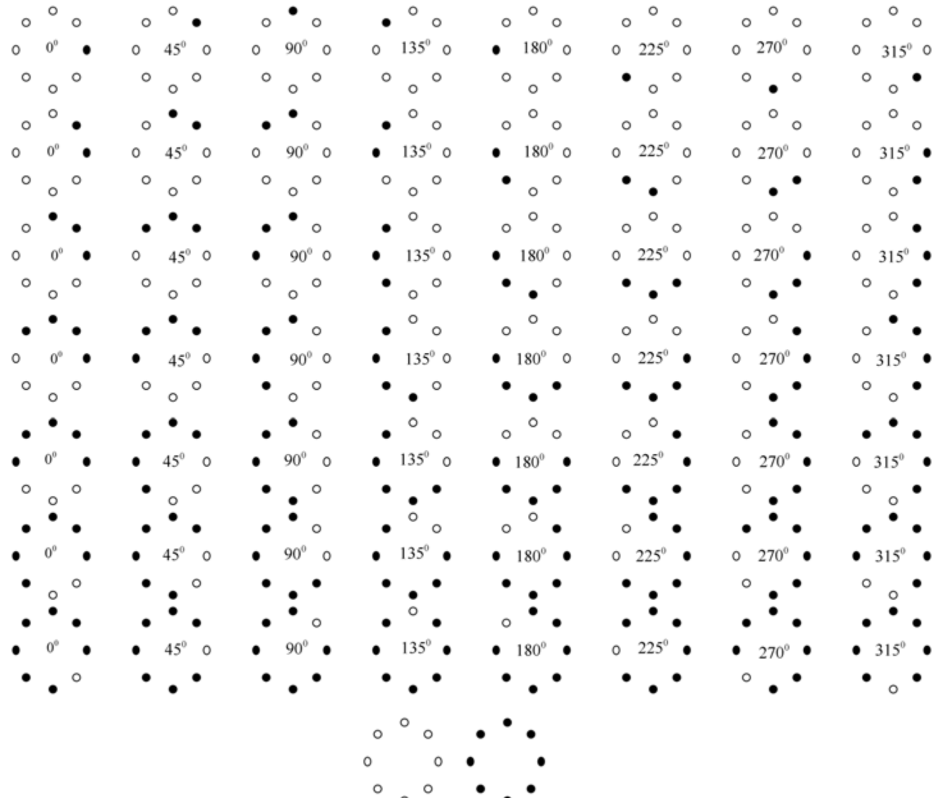


Fig. 3: Uniform patters when P=8. The black and white dots represent the bit values of 1 and 0 in the LBP operator.

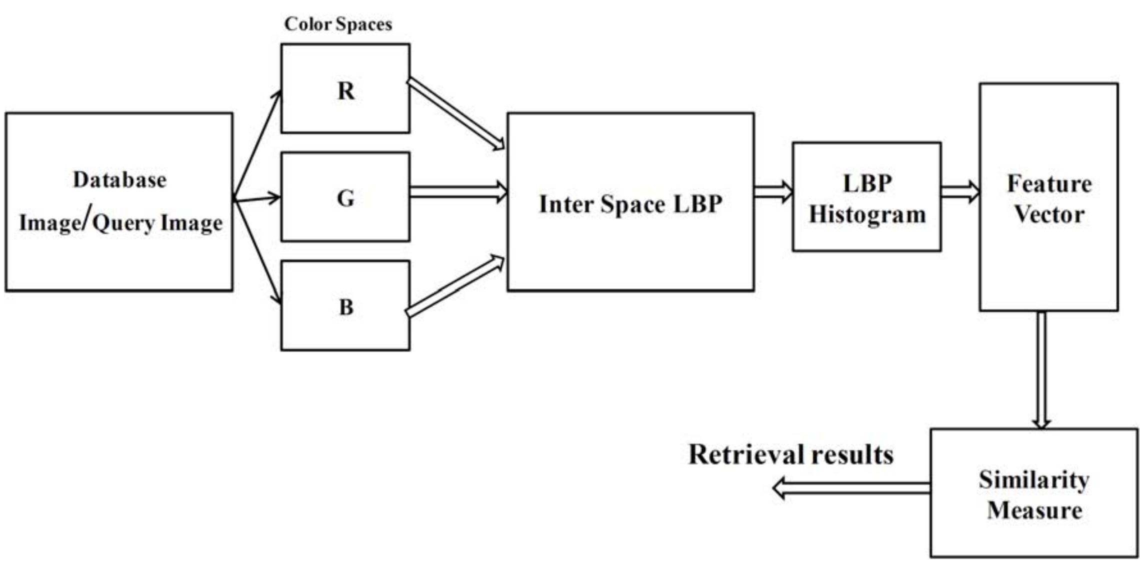


Fig. 4: Proposed image retrieval system framework

3. FEATURE EXTRACTION

In this paper, we proposed the new technique by using color and texture features for image retrieval. First the R, G, and B spaces of RGB image are separated, then the inter space LBPs are calculated by changing the center pixel of one space (R) pattern with the other space patterns (G or B). Finally, feature vector is constructed by concatenating the features collected on RGB spaces

Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(ISLBP histograms) and then these are used for image retrieval.

A. Proposed System Framework (ISLBP)

The flowchart of the proposed system is shown in Fig. 4 and algorithm for the same is given below:

Algorithm:

Input: Image; Output: Retrieval results.

1. Load the input image.
2. Separate the RGB color spaces.
3. Calculate three LBPs on R space by replacing the R pattern center pixel with G and B patter center pixels.
4. Construct the LBPs on G and B spaces also.
5. Construct the inter space LBP histogram between RGB color spaces.
6. Form the feature vector by using LBP histograms.
7. Calculate the best matches using Eq. (5).
8. Retrieve the number of top matches.

B. Similarity Measurement

In the presented work d_1 similarity distance metric is used as shown below:

$$D(Q, I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{I,i} - f_{Q,i}}{1 + f_{I,i} + f_{Q,i}} \right| \quad (5)$$

where Q is query image, Lg is feature vector length, I_1 is image in database; $f_{I,i}$ is i^{th} feature of image I in the database, $f_{Q,i}$ is i^{th} feature of query image Q.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

For the work reported in this paper, retrieval tests are conducted on Corel 1000 and MIT VisTex image databases and results are presented separately.

A. Database DB1

Corel database [30] contains large amount of images of various contents ranging from animals and outdoor sports to natural images. These images are pre-classified into different categories of size 100 by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content. In this paper, we collected the database DB1 contains 1000 images of 10 different categories (groups G). Ten categories are provided in the database namely *Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and food.* Each category has 100 images ($N_G = 100$) and these have either 256×384 or 384×256 sizes. Fig. 5 depicts the sample images of Corel 1000 image database (one image from each category)

The performance of the proposed method is measured in terms of average precision and average recall by Eq. (6) and (7) respectively.

$$Precision(\%) = \frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Images\ Retrieved} \times 100 \quad (6)$$

$$Recall(\%) = \frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Relevant\ Images\ in\ Database} \times 100 \quad (7)$$

Fig. 5: Sample images from Corel 1000 (one image per category)

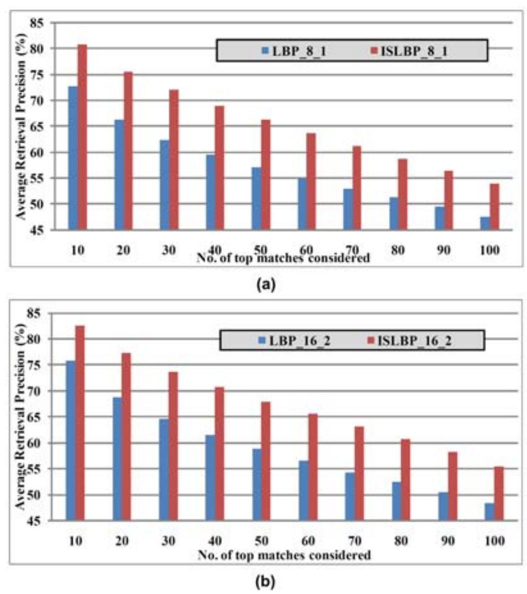


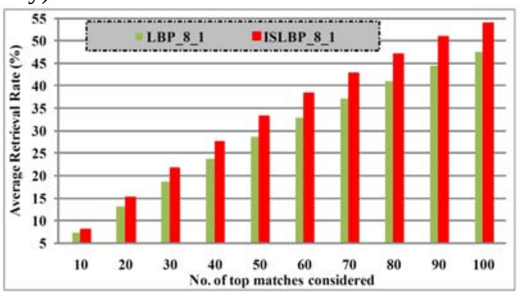
Fig. 6: Comparison of proposed method (ISLBP) with LBP on color spaces separately on DB1 database in terms average retrieval precision: (a) P=8, R=1, (b) P=16, R=2.

Table 1 and 2 summarizes the retrieval results of the proposed method (ISLBP_P_R), LBP_P_R histograms on RGB spaces separately for each group in terms of average retrieval precision and recall respectively. Table 3 and Fig. 6 illustrates the retrieval results of ISLBP and LBP in terms of average retrieval precision (ARP). Fig. 7 illustrates the comparison between ISLBP and LBP in terms of average retrieval rate (ARR). Table 4 and Fig. 8 summarizes the performance of different distance measures on proposed method in terms of ARP and

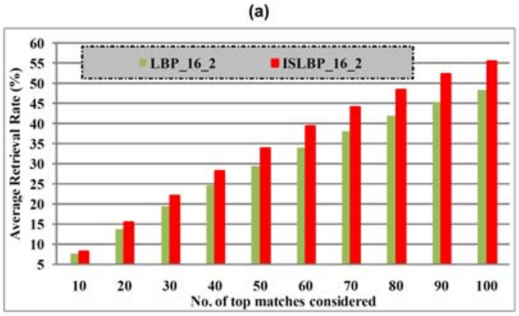
Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

it clears that d_1 distance metric is outperforming the Manhattan, Euclidean, and Canberra distance metrics. From Tables 1–4, and Fig. 6–7, it is clear that the proposed method showing better performance compared to LBP_P_R on RGB spaces separately in terms of all evaluation measures. Fig. 9 illustrates the retrieval results based on the proposed method (top left image is the query).

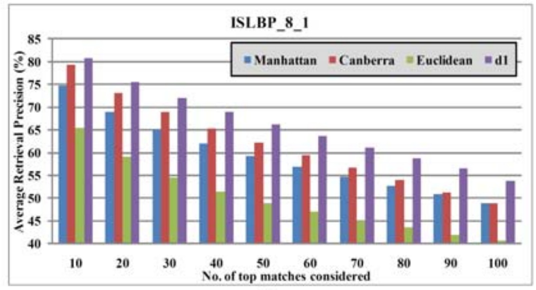


(a)

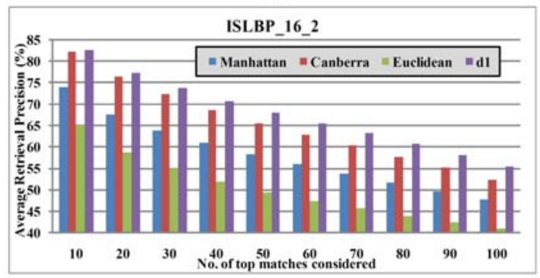


(b)

Fig. 7: Comparison of proposed method (ISLBP) with LBP on color spaces separately on DB1 database in terms average retrieval rate: (a) P=8, R=1, (b) P=16, R=2.



(a)



(b)

Fig. 8: Comparison of proposed method (ISLBP) with different distance measures on DB1 database in terms average retrieval precision: (a) P=8, R=1, (b) P=16, R=2.

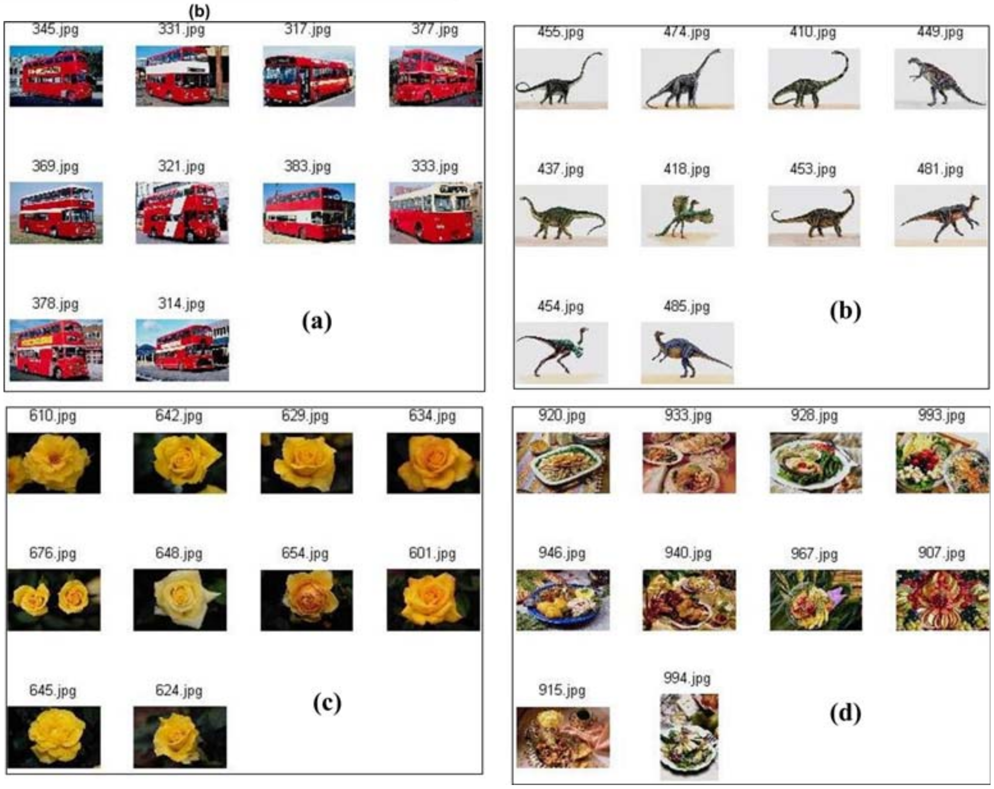


Fig. 9: Examples of retrieval for a given query image number: (a) 345, (b) 455, (c) 610, (d) 920

Journal of Theoretical and Applied Information Technology
31st October 2011. Vol. 32 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TABLE I RESULTS OF ALL TECHNIQUES IN TERMS OF PRECISION ON DB1 DATABASE

Category	LBP_8_1	LBP_16_2	ISLBP_8_1	ISLBP_16_2
Africans	65.0	67.5	76.3	77.7
Beaches	57.6	58.9	59.7	62
Buildings	69.9	73.2	81.5	81.5
Buses	97	97.5	98.1	99.4
Dinosaurs	99	98.7	98.9	99.1
Elephants	51.4	59.3	63.9	67.8
Flowers	91.6	93.4	96.9	96.6
Horses	79.1	83.7	92.9	94.5
Mountains	42.9	47.7	56.6	61
Food	73.1	78.4	82.6	86.3
Total	**72.66**	**75.83**	**80.7**	**82.6**

TABLE II RESULTS OF ALL TECHNIQUES IN TERMS OF RECALL ON DB1 DATABASE

Category	LBP_8_1	LBP_16_2	ISLBP_8_1	ISLBP_16_2
Africans	38.4	38.2	49.3	45.7
Beaches	35.7	33.5	33.3	34.5
Buildings	35.9	37.6	40.7	41.5
Buses	72.2	77.1	74.1	80.9
Dinosaurs	91.3	88.7	89.2	89.2
Elephants	26.8	29.3	32.3	33.5
Flowers	66.3	69.4	70.1	70.1
Horses	42.3	42.2	64.5	65.6
Mountains	26.6	26.0	32.1	37.3
Food	40.0	42.3	53.2	55.9
Total	**47.5**	**48.46**	**53.9**	**55.4**

TABLE III RESULTS OF ALL TECHNIQUES IN TERMS OF AVERAGE RETRIEVAL PRECISION ON DB1 DATABASE

Method	Number top matches considered									
	10	20	30	40	50	60	70	80	90	100
LBP_8_1	72.66	66.24	62.33	59.57	57.15	54.87	53.04	51.27	49.44	47.57
ISLBP_8_1	80.74	75.52	72.02	68.95	66.23	63.67	61.17	58.80	56.48	53.88
LBP_16_2	75.8	68.7	64.64	61.47	58.84	56.51	54.35	52.48	50.5	48.4
ISLBP_16_2	82.59	77.35	73.73	70.73	67.94	65.56	63.21	60.68	58.17	55.44

TABLE IV RESULTS OF PROPOSED METHOD (ISLBP) WITH DIFFERENT DISTANCE MEASURES
IN TERMS OF AVERAGE RETRIEVAL PRECISION ON DB1 DATABASE

Method	Distance Measure	Number of top matches considered									
		10	20	30	40	50	60	70	80	90	100
ISLBP_8_1	Manhattan	74.85	68.91	65.04	62.07	59.35	56.95	54.79	52.74	50.84	48.91
	Canberra	79.34	73.19	68.98	65.30	62.15	59.39	56.63	53.98	51.33	48.83
	Euclidean	65.39	59.04	54.59	51.37	48.92	46.97	45.11	43.58	42.03	40.59
	d_1	80.74	75.52	72.02	68.95	66.23	63.67	61.17	58.80	56.48	53.88
ISLBP_16_2	Manhattan	73.88	67.64	63.89	60.91	58.37	56.01	53.85	51.68	49.72	47.75
	Canberra	82.22	76.35	72.25	68.66	65.59	62.88	60.30	57.73	55.15	52.40
	Euclidean	65.01	58.76	54.92	51.96	49.45	47.42	45.64	43.98	42.46	40.98
	d_1	82.59	77.35	73.73	70.73	67.94	65.56	63.21	60.68	58.17	55.44

B. Database DB2

The database DB2 used in our experiment consists of 40 different textures [31]. The size of each texture is 512×512. Each 512×512 image is divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 640 (40×16) images. The performance of the proposed method is measured in terms of average retrieval rate (ARR) is given by Eq. (8).

$$ARR = \frac{1}{|DB|} \sum_{i=1}^{|DB|} R(I_i, n) \Bigg|_{n=16} \tag{8}$$

The database DB2 is used to compare the performance of the proposed method (ISLBP_P_R) with LBP_P_R on RGB spaces separately. Fig. 10 and Fig. 11 illustrate the retrieval results of proposed method (ISLBP_P_R) and LBP_P_R on RGB spaces separately on DB2 database in terms of ARR and ARP. From Fig. 10 and Fig. 11, it is evident that the proposed method (ISLBP) is outperforming the LBP in terms of ARR and ARP. Fig. 12 illustrates the performance of proposed method (ISLBP) with different distance measures on DB2 database and it is found that the Manhattan distance is showing better performance at ISLBP_8_1 and d_1 distance is showing better

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

performance at ISLBP_16_2 as compared to other distance metrics.

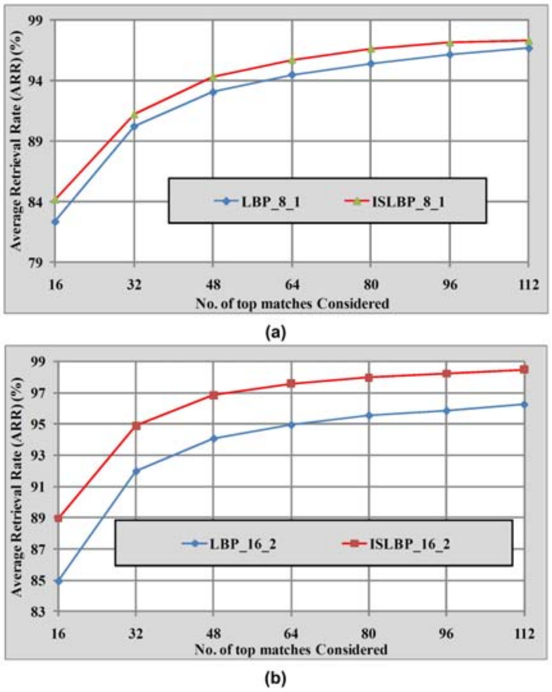


Fig. 10: Comparison of proposed method (ISLBP) with LBP on color spaces separately on DB2 database in terms average retrieval precision: (a) P=8, R=1, (b) P=16, R=2.

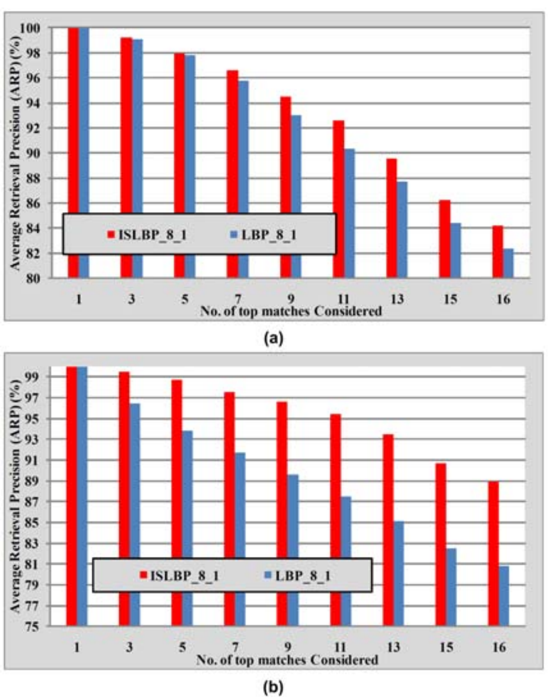


Fig. 11: Comparison of proposed method (ISLBP) with LBP on color spaces separately on DB2 database in terms average retrieval rate: (a) P=8, R=1, (b) P=16, R=2.

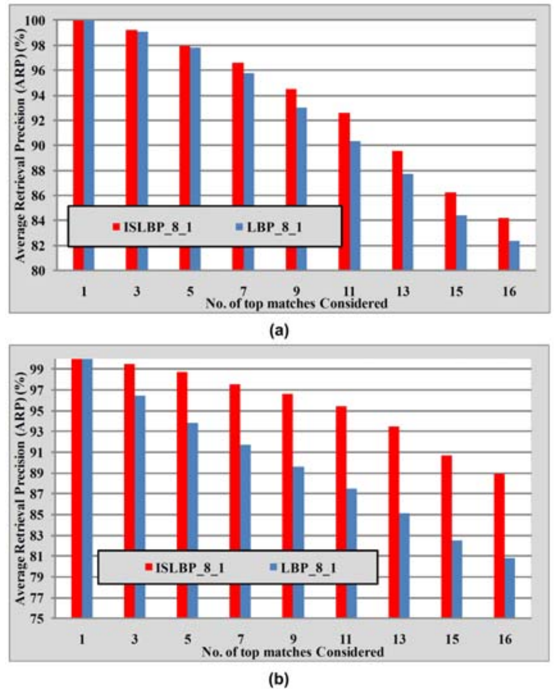


Fig. 11: Comparison of proposed method (ISLBP) with LBP on color spaces separately on DB2 database in terms average retrieval rate: (a) P=8, R=1, (b) P=16, R=2.

5. CONCLUSIONS

A new image indexing and retrieval algorithm is proposed in this paper by constructing the LBP histogram between inter RGB color spaces. The experimentations have been carried out on Corel and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP histogram on each color spaces separately.

REFRENCES:

[1] Y. Rui and T. S. Huang, Image retrieval: Current techniques, promising directions and open issues, *J.. Vis. Commun. Image Represent.*, 10 (1999) 39–62.

[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.*, 22 (12) 1349–1380, 2000.

[3] M. Kokare, B. N. Chatterji, P. K. Biswas, A survey on current content based image retrieval methods, *IETE J. Res.*, 48 (3&4) 261–271, 2002.

[4] Ying Liu, Dengsheng Zhang, Guojun Lu, Wei-Ying Ma, Asurvey of content-based image retrieval with high-level semantics,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Elsevier J. Pattern Recognition, 40, 262-282, 2007.

[5] M. J. Swain and D. H. Ballar, Indexing via color histograms, *Proc. 3rd Int. Conf. Computer Vision*, Rochester Univ., NY, (1991) 11–32.

[6] M. Stricker and M. Oreng, Similarity of color images, *Proc. SPIE, Storage and Retrieval for Image and Video Databases*, (1995) 381–392.

[7] G. Pass, R. Zabih, and J. Miller, Comparing images using color coherence vectors, *Proc. 4th ACM Multimedia Conf., Boston, Massachusetts*, US, (1997) 65–73.

[8] J. Huang, S. R. Kumar, and M. Mitra, Combining supervised learning with color correlograms for content-based image retrieval, *Proc. 5th ACM Multimedia Conf.*, (1997) 325–334.

[9] Z. M. Lu and H. Burkhardt, Colour image retrieval based on DCT domain vector quantization index histograms, *J. Electron. Lett.*, 41 (17) (2005) 29–30.

[10] J. R. Smith and S. F. Chang, Automated binary texture feature sets for image retrieval, *Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing*, Columbia Univ., New York, (1996) 2239–2242.

[11] H. A. Moghaddam, T. T. Khajoie, A. H Rouhi and M. Saadatmand T., Wavelet Correlogram: A new approach for image indexing and retrieval, *Elsevier J. Pattern Recognition*, 38 (2005) 2506-2518.

[12] H. A. Moghaddam and M. Saadatmand T., Gabor wavelet Correlogram Algorithm for Image Indexing and Retrieval, *18th Int. Conf. Pattern Recognition*, K.N. Toosi Univ. of Technol., Tehran, Iran, (2006) 925-928.

[13] A. Ahmadian, A. Mostafa, An Efficient Texture Classification Algorithm using Gabor wavelet, *25th Annual international conf. of the IEEE EMBS*, Cancun, Mexico, (2003) 930-933.

[14] H. A. Moghaddam, T. T. Khajoie and A. H. Rouhi, A New Algorithm for Image Indexing and Retrieval Using Wavelet Correlogram, *Int. Conf. Image Processing*, K.N. Toosi Univ. of Technol., Tehran, Iran, 2 (2003) 497-500.

[15] M. Saadatmand T. and H. A. Moghaddam, Enhanced Wavelet Correlogram Methods for Image Indexing and Retrieval, *IEEE Int. Conf. Image Processing*, K.N. Toosi Univ. of Technol., Tehran, Iran, (2005) 541-544.

[16] M. Saadatmand T. and H. A. Moghaddam, A Novel Evolutionary Approach for Optimizing Content Based Image Retrieval, *IEEE Trans. Systems, Man, and Cybernetics*, 37 (1) (2007) 139-153.

[17] L. Birgale, M. Kokare, D. Doye, Color and Texture Features for Content Based Image Retrieval, *International Conf. Computer Grafics, Image and Visualisation*, Washington, DC, USA, (2006) 146 – 149.

[18] M. Subrahmanyam, A. B. Gonde and R. P. Maheshwari, Color and Texture Features for Image Indexing and Retrieval, *IEEE Int. Advance Computing Conf.*, Patial, India, (2009) 1411-1416.

[19] Subrahmanyam Murala, R. P. Maheshwari, R. Balasubramanian, A Correlogram Algorithm for Image Indexing and Retrieval Using Wavelet and Rotated Wavelet Filters, *Int. J. Signal and Imaging Systems Engineering*.

[20] T. Ojala, M. Pietikainen, D. Harwood, A comparative sudy of texture measures with classification based on feature distributions, *Elsevier J. Pattern Recognition*, 29 (1): 51-59, 1996.

[21] T. Ojala, M. Pietikainen, T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, *IEEE Trans. Pattern Anal. Mach. Intell.*, 24 (7): 971-987, 2002.

[22] M. Pietikainen, T. Ojala, T. Scruggs, K. W. Bowyer, C. Jin, K. Hoffman, J. Marques, M. Jacsik, W. Worek, Overview of the face recognition using feature distributions, *Elsevier J. Pattern Recognition*, 33 (1): 43-52, 2000.

[23] T. Ahonen, A. Hadid, M. Pietikainen, Face description with local binary patterns: Applications to face recognition, *IEEE Trans. Pattern Anal. Mach. Intell.*, 28 (12): 2037-2041, 2006.

[24] G. Zhao, M. Pietikainen, Dynamic texture recognition using local binary patterns with an application to facial expressions, *IEEE Trans. Pattern Anal. Mach. Intell.*, 29 (6): 915-928, 2007.

[25] M. Heikkil;a, M. Pietikainen, A texture based method for modeling the background and detecting moving objects, *IEEE Trans. Pattern Anal. Mach. Intell.*, 28 (4): 657-662, 2006.

[26] X. Huang, S. Z. Li, Y. Wang, Shape localization based on statistical method using extended local binary patterns, *Proc. Inter. Conf. Image and Graphics*, 184-187, 2004.

[27] M. Heikkila, M. Pietikainen, C. Schmid, Description of interest regions with local binary patterns, *Elsevie J. Pattern recognition*, 42: 425-436, 2009.

[28] M. Li, R. C. Staunton, Optimum Gabor filter design and local binary patterns for texture segmentation, *Elsevie J. Pattern recognition*, 29: 664-672, 2008.

[29] X. Tan and B. Triggs, Enhanced local texture feature sets for face recognition under difficult lighting conditions, *IEEE Tans. Image Proc.*, 19(6): 1635-1650, 2010.

[30] Corel 1000 and Corel 10000 image database. [Online]. Available: http://wang.ist.psu.edu/docs/related.shtml.

[31] MIT Vision and Modeling Group, Vision Texture. [Online]. Available: http://vismod.www.media.mit.edu.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AUTOHR PROFILES:

Dilkeshwar Pandey did his B.E. in Civil Engineering in the year 1986-1990 from BITS, Ranchi University, Jharkhand, India and M.E. in Computer Science from Delhi College of Engg., University of Delhi, India. Presently he is working as professor & In-charge of Principal in Satyam College of engineering, Ghaziabd.

Dr. Rajive Kumar did his doctorate from I.I.T., Delhi in the year 1990 in the field of Numerical Methods. He has published and presented number of research articles in various Journals of repute and International conferences in the fields of Numerical Methods, Software Engineering and Computer Vision. Presently he is working as a Professor in the Department of Mathematics, D C R University of Science & Technology, Murthal (Haryana) India.