Joint Multi-resolution gray scale LBP Histograms for Content Based Image Retrieval

Mohan V. Bonde, Dr. Dharmpal D. Doye
S.G.G.S. Institute of Engineering & Technology,
Nanded-431606, Maharashtra, India
(E-mail: mohanbonde@yahoo.com, dddoye@sggs.ac.in)

Abstract— In this paper, new algorithm for image indexing and retrieval is proposed which utilizes the texture content of the image. Colour RGB image is first converted to gray scale, then multi-resolution Local Binary Pattern (LBP) are efficiently used. LBP gives the information based on edge distributions in an image. These multi-resolution texture images are figured using Gaussian filter to collect LBPs from these textures. Finally joint histograms are constructed out of these multi-resolution LBPs to form a feature vector. The retrieval results of this proposed algorithm is tested over Corel 1000 image database. After analysis, the results show substantial improvement in terms of precision and recall as equated to LBP.

Keywords— *image retrieval; feature extraction; histogram; local binary patterns;*

I. INTRODUCTION

In the present scenario there is a drastic expansion of digital multimedia databases and image libraries. Hence storage and retrieval from these databases become extremely impractical task. To overcome this difficulty, Content based image retrieval was proposed (CBIR). In these systems some features are extracted from every image and saved as a feature vector for indexing purpose. CBIR uses the visual contents such as colour, shape, texture, faces, spatial layout etc. of an image. Feature extraction is prominent step and the efficiency of a CBIR system depends heavily on method of feature extraction from the raw images. There is no single representation of an image for all perceptual subjectivity, as the user may take the pictures in different conditions. The challenge in CBIR is to develop an algorithm that will increase the retrieval accuracy. Extensive and comprehensive literature survey on CBIR is presented in [1-4].

Texture is another prominent and vital feature for CBIR. J. Smith et al. used the first and second moment in the wavelet domain as texture features for image retrieval [6]. H. Moghaddam et al. introduced the Gabor wavelet correlogram (GWC) for image content representation [7, 8]. H. Moghaddam et al. presented new algorithm called wavelet correlogram (WC) [9]. Using genetic algorithm and by optimizing quantization threshold, the performance of WC technique is then improved by M. Saadatmand et al. [10, 11]. L. Birgale et al. [12] and M. Subrahmanyam et al. [13] integrates the colour (histogram) and texture (wavelet transform) features for CBIR. Texture classification using Wavelet Transform is then proposed by A. Ahmadian et al. [14]. M. Unser used the wavelet frames for texture classification and segmentation [15]. B. Manjunath et al. [16] presented in their paper, the Gabor transform for image retrieval on Bordatz texture database. M. Kokare et al. used the rotated wavelet filters [17], dual tree complex wavelet filters (DT-CWF), and dual tree rotated complex wavelet filters (DT-RCWF) [18], rotational invariant complex wavelet filters [19] for image retrieval. They have calculated the characteristics of image in different directions using rotated complex wavelet filters.

LBP is used for texture description by T. Ojala et al. [20]. These LBPs are then converted for texture classification to rotational invariant [21]. Using feature distributions, M. Pietikainen et al. proposed rotational invariant texture classification [22]. LBP operator was then used by T. Ahonen et al [23] and G. Zhao et al. [24] for facial expression recognition. M. Heikkila et al. used LBP for background modeling and detection [25]. X. Huang et al. proposed for shape localization the extended LBP [26]. M. Heikkila et al. used the LBP for interest region description [27]. M. Li et al. combined the Gabor filter and LBP for texture segmentation [28]. Face recognition using local derivative pattern [29] is proposed by B. Zhang et al. in which they considered LBP as a non-directional first order local pattern.

Rest of the paper is prepared as follows: In section I, a brief introduction, review of image retrieval and related work is given. Section II, gives a concise review of local binary patterns. Section III, presents the proposed methodology and different distance measures used for similarity measurement. Experimental results and discussions are presented in section IV. Based on above work, conclusions are derived in section V.

II. LOCAL BINARY PATTERN

For texture classification, the LBP operator was proposed by T. Ojala *et al.* [21]. This operator proved its successful use in terms of efficiency and performance in many active research areas like, face recognition, object tracking, texture classification, fingerprint recognition, and bio-medical image retrieval.

LBP operator value is calculated by comparing a canter pixel value in a specified neighborhood with its neighbors. The equations to compute LBP is given by Eq. (1) and Eq. (2):

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

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

Where P and R denotes the number of neighbors and radius of neighborhood respectively, $I(g_c)$ denotes the gray value of canter pixel, and $I(g_i)$ is the gray scale value of its neighbor. A sample computation of a LBP value using a 3x3 neighborhood is shown in Fig. 1 as given below. Fig. 2 shows the examples of circular neighbor sets for different alignments of (P,R).

Fig. 3 shows all uniform patters for *8* neighbors. The distinct values for a given query image is $P(P-1)+3$ by using uniform patterns but deprived of rotational invariant. The rotational invariant LBP patterns $(LBP_{P,R}^{riu2})$ can be built by adding all eight patterns in the each row of Fig. 3 as shown in Fig. 4. The distinct values for a given query image is $P+2$ by using rotational invariant LBP patterns $(LBP_{P,R}^{riu2})$.

Sample Image			Binary Pattern			Weights			LBP value		
9	5	4	1	0	0	8	4	2			
8	6	5	1		1	16		1		249	
7	8	9	1	1	1	32	64	128			

LBP = 1+8+16+32+64+128 = 249

Figure 1. Calculation of LBP

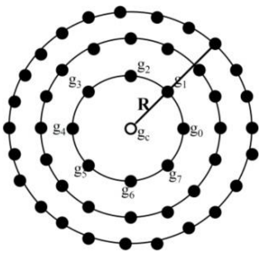

Figure 2. Circular neighborhood sets for different (P,R)

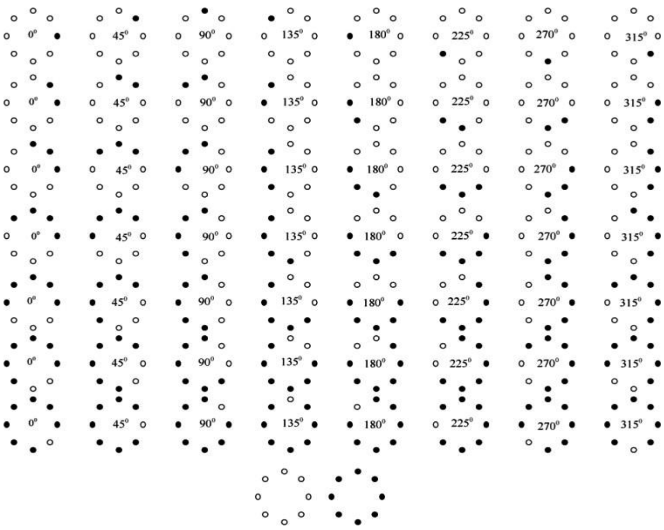

Figure 3. Uniform patterns when P=8. The black and white dots represent the bit values of 1 and 0 in the LBP operator

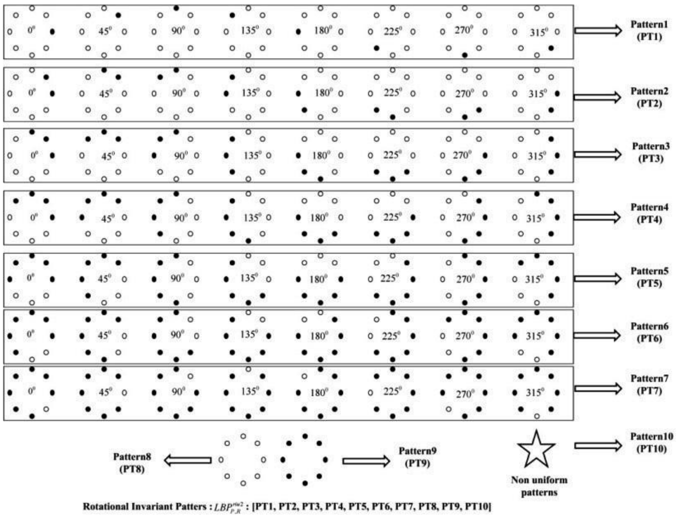

Figure 4. Rotational variant LBP patterns are converted into rotational invariant LBP patterns

III. JOINT LBP HISTOGRAM

We proposed, in this paper, new technique by calculating joint multi-resolution gray scale LBP histogram for image retrieval. The algorithm for the proposed image retrieval system is as given below:

Algorithm:
Input: Query Image *Output: Image Retrieval results*
Steps:

1. Input the query image.
2. Covert RGB query image to gray scale for texture feature extraction.
3. Gather multi-resolution texture images by using Gaussian filter.
4. Calculate LBP patterns for each texture images.
5. Build the joint histogram of these LBPs.
6. Generate the feature vector by means of LBP joint histogram.
7. Find the best matches using (5).
8. Retrieve number of top matches using different distance measures.

A. Similarity Measurement

Four types of similarity distance measures are used in the presented work as given below:

Manhattan Distance [5]

Manhattan distance is less expensive in computation because it considers only absolute differences from each feature. This distance is also known as L_1 or city-block distance and expressed as

$$D(Q,T) = \sum_i \left| f_i(Q) - f_j(T) \right| \qquad (3)$$

Euclidean Distance [5]

For $P=2$ in (3) give the Euclidean distance and defined as:

$$D(Q,T)=\left(\sum_i \left| f_i(Q)-f_j(T)\right|^2\right)^{1/2} \quad (4)$$

Euclidian distance computation is the most expensive as it requires to find square root value.

D_1 Distance [5]

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

Canberra Distance [5]

$$D(Q,T)=\sum_{i=1}^{L_g}\left|\frac{f_{T,i}-f_{Q,i}}{f_{T,i}+f_{Q,i}}\right| \quad (6)$$

Where Q and T are the query image and image in database respectively, Lg denotes feature vector length; $f_{I,i}$ is i^{th} feature of image I in the database, $f_{Q,i}$ is i^{th} feature of query image Q.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Retrieval tests are conducted on Corel 1000 image database and results are presented in the following subsections.

B. Corel 1000 Database

Corel 10000 image database [30] contains huge amount of images of different contents ranging from outdoors and animals to nature and human face. Domain experts pre-classified these images into various categories of size 100. In this paper, we used Corel 1000 image database [30] which contains 1000 images of 10 different categories (groups G). Total 10 categories are present in this database namely Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, food and mountains. Each category contains 100 images ($N_G=100$) and all these images have either 384×256 or 256×384 sizes. Fig. 5 shows the sample images (one from every category) from Corel 1000 image database.

Figure 5. Sample images (one per category) from Corel 1000 database

The performance of the proposed method is measured in terms of average retrieval precision and recall by (7) and (8) respectively.

$$Precision\left[P(I_q,n)\right]=\frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Images\ Retrieved} \quad (7)$$

$$Recall\left[R(I_q,n)\right]=\frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Relevant\ Images\ in\ Database} \quad (8)$$

where I_q is query image and n is considered as number of top matches.

Retrieval results, using a query image, of proposed method is shown in Fig. 6. Retrieval results of LBP and proposed method (Joint_LBP), in terms of average retrieval precision and recall, are summarized in Table I. It is clear that, from Fig. 7, proposed method shows better performance as equated to LBP. The results of LBP and proposed algorithm, in terms of average retrieval precision and recall respectively to number of top matches, is shown in Table II, Fig. 7 and Fig. 8. It is observed that, proposed method outperforms LBP histogram algorithm. The performance of proposed method in terms of average retrieval precision to number of top matches using various distance measures is given in Table III and Fig. 9. Also it is very much evident from Table III that d_1 distance outperform the other distance measures.

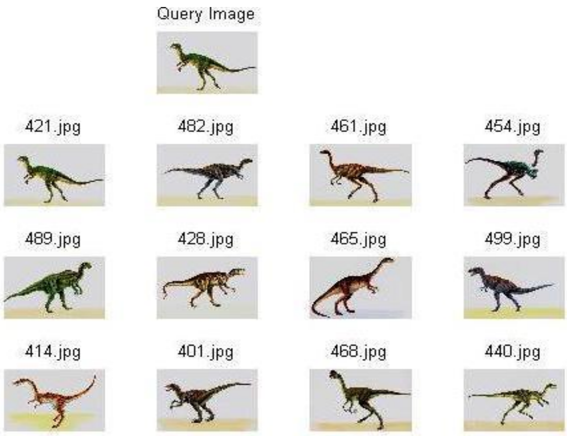

Figure 6. Retrieval results of joint LBP method for a given query image.

TABLE I RESULTS OF LBP AND JOINT-LBP IN TERMS OF PRECISION AND RECALL

Category	Precision (%)		Recall (%)	
	LBP	*Joint LBP*	*LBP*	*Joint LBP*
Africans	58.2	62.4	33.69	30.15
Beaches	43.7	44.6	29.12	29.19
Buildings	62.1	66.4	29.83	33.96
Buses	92.2	94.5	64.74	71.11
Dinosaurs	96.3	98.5	79.99	78.83
Elephants	39.5	57.8	22.44	31.71
Flowers	86.8	90	61.61	69.41
Horses	68.7	79.7	40.73	54.15
Mountains	42.8	48.7	27.79	27.74
Food	64.9	71.4	38.55	42.06
Average	**65.52**	**71.4**	**42.84**	**46.86**

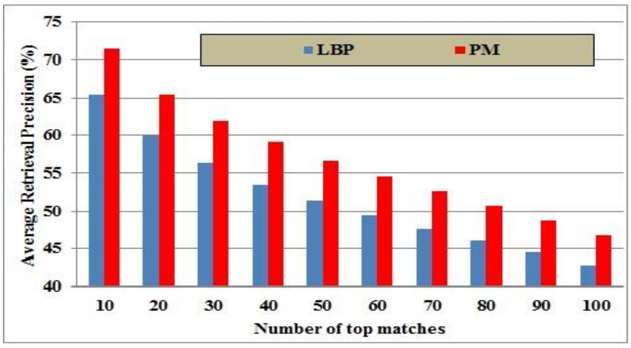

Figure 7. Comparison of Joint_LBP method with LBP in terms of Average retrieval precision

TABLE II RESULTS OF LBP AND JOINT_ LBP IN TERMS OF AVERAGE RETRIEVAL PRECISION AND RECALL

No. of top matches	Precision (%)		Recall (%)	
	LBP	*Joint_ LBP*	*LBP*	*Joint_ LBP*
10	65.52	71.40	6.55	7.14
20	59.90	65.48	11.98	13.18
30	56.43	67.87	16.93	18.56
40	53.48	59.05	21.39	23.62
50	51.31	56.71	25.65	28.35
60	49.47	54.67	29.68	32.80
70	47.73	52.68	33.41	36.88
80	46.06	50.79	36.85	40.63
90	44.49	48.87	40.04	43.98
100	42.85	46.83	42.84	46.83

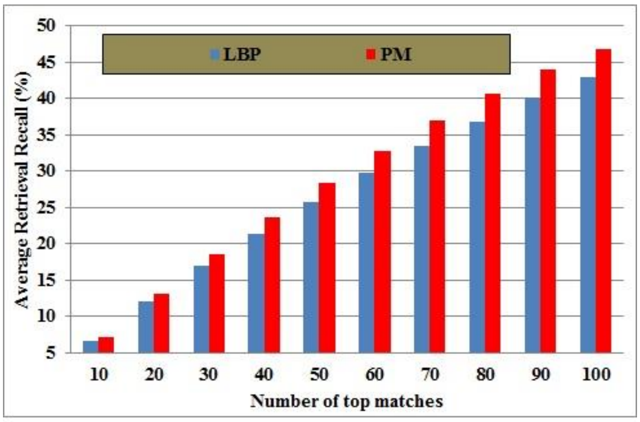

Figure 8. Comparison of Joint_LBP method with LBP in terms of Average retrieval recall

TABLE III RESULTS OF JOINT_LBP WITH DIFFERENT DISTANCE MEASURES IN TERMS OF AVERAGE RETRIEVAL PRECISION

No. of top matches	Distance measures			
	Manhattan	*Canberra*	*Euclidean*	d_1
10	72.15	69.14	66.74	71.40
20	66.41	63.61	60.35	65.48
30	62.48	60.25	55.96	61.87
40	59.23	57.70	52.49	59.05
50	56.31	55.37	49.38	56.71
60	53.66	53.42	46.91	54.67
70	51.15	51.65	44.70	52.68
80	48.78	49.83	42.45	50.79
90	46.53	47.93	40.49	48.87
100	44.40	46.07	38.65	46.83

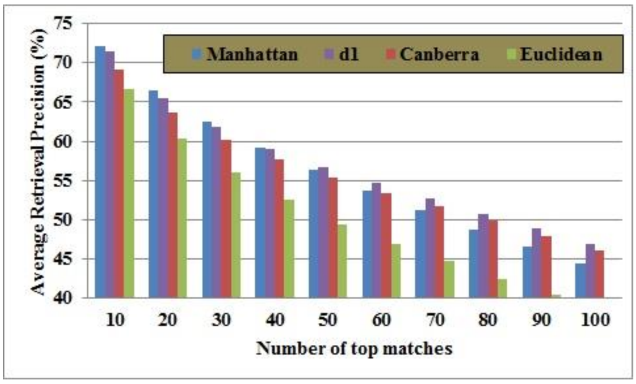

Figure 9. Comparison of Joint_LBP method with LBP in terms of Average retrieval precision to No. of top matches

V. CONCLUSIONS

A new algorithm for image indexing and retrieval is presented in this paper by constructing joint multi-resolution gray scale LBP histogram of images. These multi-resolution images are computed using Gaussian filter bank. The experimentation has been performed on Corel 1000 image database to prove the worth of our algorithm. Results of the proposed algorithm, Joint-LBP, show significant improvement as compared to LBP histogram technique in terms of their performance evaluation. Also it is observed that d_1 distance outperforms amongst various distance measures.

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Author Profile:

M. V. Bonde has obtained Bachelor of Engineering degree in Computer Science & Engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India in 1997. He completed Master of Engineering in Computer Engineering from Mumbai University, Mumbai, Maharashtra, India in 2003. Currently he is a research scholar in CSE Department at SGGSIE&T (Autonomous), Nanded, Maharashtra, India. His areas of interest include signal and image processing, information security. He has nearly 17 years of teaching and 2 years of industry experience.

Dr. D. D. Doye has obtained Bachelor of Engineering degree in Electronics from Marathwada University, Aurangabad, Maharashtra, India in 1988. He completed Master of Engineering in Electronics in 1993 from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, Maharashtra, India. He completed his Ph.D. in 2004 from SGGSIE&T, Nanded, Maharashtra, India. He is currently working as Professor in Electronics and Telecommunication Engineering Department at SGGSIE&T (Autonomous), Nanded, Maharashtra, India since 2003. He has published many research papers in reputed National and International Journals. His areas of interest include speech processing, Image Processing, Pattern Recognition and Fuzzy Neural Networks. He has more than 29 years of teaching experience.