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Lemp: a Robust Image Feature Descriptor for Retrieval Applications

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Abstract: *line edge magnitude pattern (lemp) is proposed in this paper. Line edge distribution is used to denote local region of an image. Popular texture descriptors such as lbp deal with a comparison of centre pixel with neighbors and thus encode the information. In lemp ,pixel at the centre is replaced by edge values of neighbors. Discriminating information provided by line edges makes this method different from many of the existing methods. Magnitude is also added to the line edge information in order to make the feature descriptor more effective and robust. Performance of lemp method is estimated with corel database. Standard metrics such as recall, precision and average retrieval rate are determined for comparison purpose. Experimental values exhibit a notable improvement in the performance.*

KEY WORDS – Retrieval , Patterns, Magnitude, Edge.

I. INTRODUCTION

A. Motivation

Due to the advancements in Multimedia and digital Electronics field, numerous images are created, shared every moment . Conventional methods such as text annotation fail to provide a mechanism for effective utilization of imagery data. Content based image retrieval, in short CBIR, resolves all problems in traditional annotation methods. It depends on extraction of inherent features of any image and thus provides an effective mechanism to manage the data. Key step in CBIR is extraction of image features. Effectiveness of this system primarily depends on feature extraction method. Key features of any image are color, shape, texture and layout etc. Since the user captures a photograph is various conditions, there exists no single way of image representation. Survey on CBIR is provided in [1]–[5].
There exists any one feature descriptor or a combination of features .Swain et al. devised color histogram [5] and histogram intersection method to calculate distance between histograms. In [12], Pass *et al.* used CCV to create a coherent or incoherent histogram bin. To represent color distribution as well as spatial correlation, Huang [9] introduced a color featured correlogram.
Texture is an indispensable part of CBIR .In [6],Smith computed Mean and Variance values of wavelet coefficients . Concept of ridgelet transform was devised by Gonde et al[7].

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S Murala introduced the correlogram concept to create a feature descriptor [13]. L K Rao proposed the quantized patterns for image retrieval. Researchers introduced many feature descriptors for image retrieval [14]-[19]. All of them are based on the relationship among pixels.

B. Relevant Work

Ojala [23] devised LBP for texture analysis and classification. Guo *et al*.[24] introduced complete LBP scheme for classification. Considering LBP as a point edge, Reddy *et al*. proposed the LEBP [25]. In [25], authors used the sign information to create feature vector.

C. Prime Contributions

Motivated by the pattern described in [20]-[22], We propose a robust and effective feature descriptor. Proposed LEMP extracts more discriminating information.

1. Combination of LEBP and MLEBP is considered for retrieval system.
2. Retrieval efficiency tested on Corel imagery database and precision, recall and avg. retrieval rate (ARR) are computed.

Paper is organized as follows: Brief review of CBIR is provided in section I .Section II covers a review of local patterns, line magnitude patterns. Section III explains framework, similarity measurement. Results of experiments are given in section IV. Section V contains derived observations and conclusions.

II. RELATED LOCAL PATTERNS

A. Local Binary Patterns (LBP)

Ojala *et al.* [21] proposed LBP for image texture classification. LBP is illustrated in fig.1. Derivation of local pattern for a specified region is done as per the equations (1)-(2).

$$LBP_{P,R} = \sum_{i=0}^{P-1} 2^i \times f_1(h_i - h_c) \qquad (1)$$

$$f_1(n) = \begin{cases} 1 & n \geq 0 \\ 0 & else \end{cases} \qquad (2)$$

where h_c is gray level of centre pixel, h_i is gray value of neighbor, P denotes no. of neighbors and R denotes radius of neighborhood.

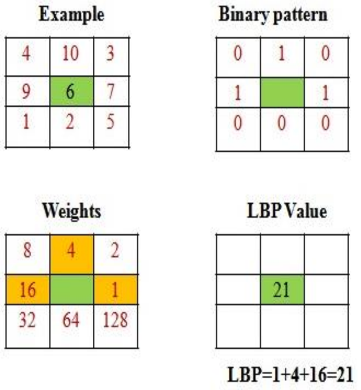


Fig.1 LBP computation for a 3×3 pattern

B. Line Edge Binary Patterns (LEBP)

As mentioned in [21], line edges of a centre pixel are calculated with the help of eight window functions (WF_{β}) as follows:

$$WF_{\beta} = \begin{bmatrix} r & s & t \\ u & v & w \\ x & y & z \end{bmatrix}, \quad \beta = 0^{o}, 45^{o}, ..., 315^{o} \quad (3)$$

Values *a to i* in Eq. (3) are given below:

β	z	y	x	w	v	u	t	s	r
0°	1	-1	0	1	-1	0	1	-1	0
45°	-1	0	0	1	-1	0	1	1	-1
90°	0	0	0	-1	-1	-1	1	1	1
135°	0	0	-1	0	-1	1	-1	1	1
180°	0	-1	1	0	-1	1	0	-1	1
225°	-1	1	1	0	-1	1	0	0	-1
270°	1	1	1	-1	-1	-1	0	0	0
315°	1	1	-1	1	-1	0	-1	0	0

Further, convolution of a pattern and window function results in directional edges (DLE) These are extracted by convolution of a pattern with window function.

$$DLE(\beta) = PTRN(g_c) * WF_{\beta}; \quad \beta = 0° to 315°, 45° steps \quad (4)$$

$PTRN(g_c)$ denotes a 3×3 sized pattern of central pixel g_c, * denotes a convolution.
Line edge pattern, LEBP is computed according to equation below.

$$LEBP = \sum_{p} 2^{(p/45)} \times f_1(LE(p)); \; p = 0^{0}, 45^{0}, ..., 315^{0} \quad (5)$$

Once the patterns for all pixels are obtained, a histogram is built which thus represents an image.

$$H(u) = \sum_{s=1}^{P_1} \sum_{t=1}^{P_2} f_2(LEBP_{P,R}^{u2}(s,t), u); \; u \in [0, 255] \quad (6)$$

$$f_2(q,r) = \begin{cases} 1 & q = r \\ 0 & else \end{cases} \quad (7)$$

where $P1xP2$ denotes the size.

B. Magnitude line edge patternsl

Line edge Magnitude patterns (LEMP) are extracted from line edges. Line edge computation is done according to the equation (4).
In step-1, modulus of *LE* is calculated as follows:

$$Magn(a,\beta) = |LNE(\beta)|, a = 1, 2, ..., (P_1 - 2) \times (P_2 - 2) \quad (8)$$

In next step, obtain mean of all *Magn* as specified in Eq. (9).

$$M_n = mean2(Magn) \quad (9)$$

MLEP is calculated according to Eq. (10).

$$LEMP(a) = \sum_{\theta} 2^{\beta/45} * h_3(Magn(a,\beta)); \beta = 0°, 45°, ..315° \quad (10)$$

$$h_3(b) = \begin{cases} 1 & b \geq M_n \\ 0 & else \end{cases} \quad (11)$$

After LEMP calculation for each pixel, entire image is represented by means of a histogram.

$$Histo(q) = \sum_{z=1}^{(B_1-2)\times(B_2-2)} f_2(MLEP_{P,R}^{u2}(z), q); \; q \in [0, 255] \quad (12)$$

Here, B1xB2 is size of input image

III. PROPOSED SYSTEM

In this work, a method termed as magnitude line edge magnitude binary patterns (LEMP) is introduced. Further, it is integrated with LEBP to achieve improved performance. Flowchart of proposed method is provided in Fig. 2, algorithm is given hereunder.

Algorithm:

1. Get the input and convert into a gray image.
2. Compute line edges in 0º to 315º directions in steps of 45^{0} using Eq. (4).
3. Deive the LEMP using Eq. (10) and build histogram using Eq. (12)
4. Concatenate both LEBP and LEMP histograms
5. Identify the similar images using Eq. (13).
6. Retrieve top level matches

D. Similarity Measurement

d_1^2 distance metric is used for calculating the similarity .

$$Dist(Qu, D_1) = \sum_{i=1}^{Vg} \left| \frac{f_{D1,i} - f_{Qu,i}}{1 + f_{D1,i} + f_{Qu,i}} \right|^2 \quad (13)$$

Here, *Qu* is image query, V*g* is length, I_1 is database image; $f_{D1,b}$ is b^{th} feature of image D1 of database, $f_{Qu,b}$ is b^{th} feature of *Qu*.

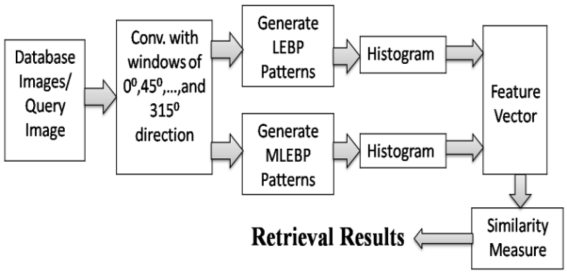


Fig. 2. Schematic of LEMP system

IV. EXPERIMENTS AND DISCUSSIONS

Retrieval efficacy is tested with corel database (1000 (DB1) and 5000 (DB2)) . A comparision is made among the LBP,LEBP and Proposed method.
Recall,Precision and avg. retrieval rate are calculated as per Eq. (14)–(16).

$$Precision(Pr) = \frac{relevant\ images\ retrieved}{Total\ \ retrieved} \quad (14)$$

$$Recall(Re) = \frac{Relevant\ images\ retrieved}{Total\ relevant\ images} \quad (15)$$

$$Avg.Retr.Rate = \frac{1}{X_1}\sum_{b=1}^{\Gamma_1} GRe \quad (16)$$

Here, X_1 is number of categories.

A.Corel-1000 Database

In this paper, we use corel database[25], consisting of different categories. In the first phase, 1000 images in group of 100 in 10 different categories (X_1 =10) are used for evaluation. Table I and II depict retrieval results from three methods . From Table I, we noticed that precision of LEMP method (75.41%) is higher than other two approaches. From Table II, it is evident that devised method outperforms the other two approaches. Fig.3 provides a graphical comparison of all methods.

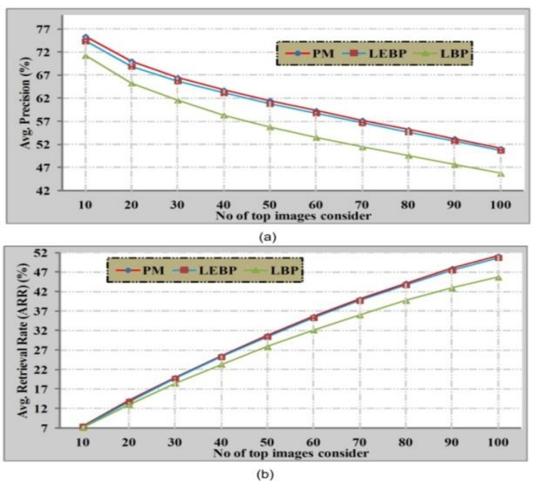


Fig. 3. Graphical comparison (a) avg. precision (b) avg. retr. rate (ARR) on DB1

TABLE I RESULTS OF PRECISION ON DB1

Class	PM	LEBP	LBP
Beaches	58.1	57.1	54.8
Buildings	75.0	73.8	63.8
Buses	98.7	98.1	95.5
Elephants	57.5	55.1	45.8
Flowers	92.0	92.1	91.8
Horses	81.0	80.8	74.3
Dinosaurs	98.6	97.9	98.3
Mountains	44.4	43.6	47.6
Food	87.7	86.7	80.9
Africans	61.1	58.7	59.5
Total	**75.41**	**74.39**	**71.23**

TABLE II RECALL VALUES ON DB1

Class	PM	LEBP	LBP
Beaches	38.97	38.87	32.95
Buildings	38.56	37.7	33.67
Buses	73.3	73.36	57.65
Dinosaurs	87.67	86.05	83.59
Elephants	31.15	30.29	27.32
Flowers	73.65	73.04	72.96
Horses	44.88	45.6	42.57
Mountains	29.97	30.01	27.56
Food	56.97	56.46	46.02
Africans	35.95	35.76	32.77
Total	51.17	50.71	45.71

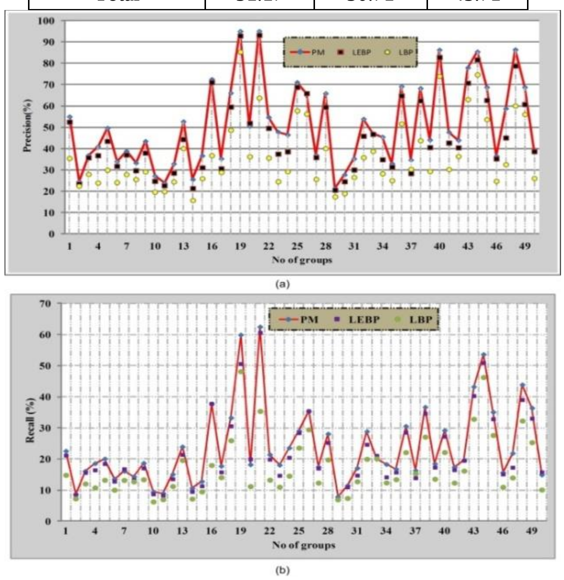
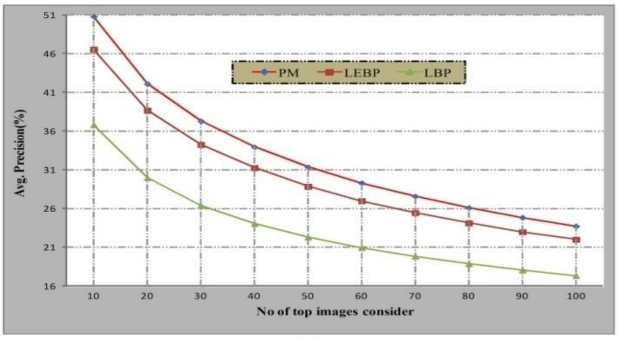
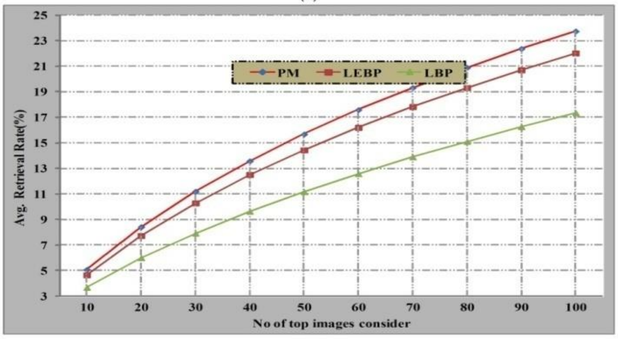


Fig. 4. Graphical comparison of proposed method with other methods (a) category wise precision (b) category wise recall on DB2



(a)



(b)

Fig.5. Comparison (a) average precision and (b) avg. retr. rate (ARR) on DB2

E. Corel 5000 Database (DB2)

In the second phase, a subset of Corel database is used for evaluation purpose. A total of 5000 images (DB2) with 50 categories are considered (X_1 =50). Category wise precision and recall values are shown in figure 4, while average precision and recall are provided in figure 5. From the two figures, it is evident that the proposed method outperforms the other methods. Query results are shown in figure 6. In all these retrieval results, top left image is query and the remaining are similar images.

V. CONCLUSIONS

A Novel feature descriptor named Line magnitude edge pattern (LEMP) is devised for image retrieval. Combination of LEBP and LEMP is also introduced. Performance is tested on Corel–1000 and Corel–5000 databases. Experimental results indicate that the LEMP method outperforms other methods. There exists 2-3% of improvement in precision and recall values

Fig. 6. Retrieved results (a)- (b) DB1 and (c)- (d) DB2

REFERENCES

1. M. Kokare, B. N. Chatterji and P. K. Biswas, “A survey on current content based image retrieval methods”, IETE J. Res., vol. 48 (3&4), pp. 261–271, 2002.
2. 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.
3. 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 (12), pp. 1349–1380, 2000.
4. Ying Liu, Dengsheng Zhang, Guojun Lu and Wei-Ying Ma, “A survey of content-based image retrieval with high-level semantics”, Elsevier J. Pattern Recognition, vol. 40, pp. 262-282, 2007.
5. M. J. Swain and D. H. Ballar, “Indexing via color histograms”, Proc. 3rd Int. Conf. Computer Vision, Rochester Univ., NY, pp. 11–32, 1991.
6. 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, pp. 2239–2242, 1996.
7. A. B. Gonde, R. P. Maheshwari, R. Balasubramanian, “Complex Wavelet Transform with Vocabulary Tree for content based image retrieval”, Proc. Seventh Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP’10), Chennai, pp. 359-366, Dec 2010.

8. Z. M. Lu and H. Burkhardt, "Colour image retrieval based on DCT domain vector quantization index histograms", J. Electron. Lett., vol. 41 (17), pp. 29–30, 2005.
9. J. Huang, S. R. Kumar, and M. Mitra, "Combining supervised learning with color correlograms for content-based image retrieval", Proc. 5th ACM Multimedia Conf., pp. 325–334, 1997.
10. Z. M. Lu and H. Burkhardt, "Colour image retrieval based on DCT domain vector quantization index histograms", J. Electron. Lett., vol. 41 (17), pp. 29–30, 2005.
11. M. Stricker and M. Oreng, "Similarity of color images", Proc. SPIE, Storage and Retrieval for Image and Video Databases, pp. 381–392, 1995.
12. G. Pass, R. Zabih, and J. Miller, "Comparing images using color coherence vectors", Proc. 4th ACM Multimedia Conf., Boston, Massachusetts, US, pp. 65–73, 1997.
13. 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, pp. 2239–2242, 1996.
14. A. B. Gonde, R. P. Maheshwari, R. Balasubramanian, "Complex Wavelet Transform with Vocabulary Tree for content based image retrieval", Proc. Seventh Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP'10), Chennai, pp. 359-366, Dec 2010.
15. Subrahmanyam M, R. P. Maheshwari, and R Balasubramanian, "A Correlogram algorithm for image indexing and retrieval using wavelet and rotated wavelet filters", Int. J. of Signal and Imaging Systems Engineering, vol. 4(1), pp. 27-34, 2011.
16. M. Kokare, "Texture image retrieval using rotated Complex Wavelet Filters," IEEE Transactions on systems, man and cybernetics, Part B(Cybrnetics),12/2005
17. L K Rao et. al., Local color Oppugnant quantized Extrema Patterns for Content Based Natural and Texture Image Retrieval, Multidimensional sytems and signal Processing, Springer,2018
18. L. K Rao, D. V Rao, " Local quantized extrema patterns for content-based natural and texture image retrieval," Human-centric Computing and Information Sciences, DOI: 10.1186/s13673-015-0044-z, 2015.
19. L K Rao, P Rohini, Multiple color channel local extrema patterns for image retrieval, ICECE 2018
20. S Mathur,M Chaudhury,H Verma,M Mandal,S K Vipparthi,S Murala,Multi channel distributed local pattern for CBIR, 2017,14th IEEE conferece (INDICON),2017
21. L K Rao, D Venkata Rao,L Pratap Reddy, Color based multi directional Local Motif XOR patterns for Image retrieval,ICATCCT 2015
22. S Samantha,R P Maheswari,M Tripathy,Directional lined edge binary pattern for texture image indexing and retrieval",Proceedings of the international conference on advances in computing,communications and Informatics,ICACCI'12,2012
23. S K Vipparthi,S K Nagar,"Integration of color and local derivative pattern features for content basd indexing and retrieval,Journal of the institution of Engineers
24. L K Rao, D Venkata Rao, P Rohini, Improved Directional Local Extrema Patterns as a feature vector for CBIR, ICSC 2013(IEEE Xplore)
25. T. Ojala, M. Pietikainen and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns", IEEE Trans. Pattern Anal. Mach. Intell., vol. 24 (7), pp. 971-987, 2002.
26. Zhenhua Guo, Lei Zhang, and David Zhang, "A Completed modeling of Local Binary Pattern operator for Texture Classification", IEEE Tans. Image Proc., vol. 19 (6), pp. 1657–1663, 2010.
27. P.V.N Reddy. and K.S Prasad. (2012), "Line Edge Binary Patterns for content-based image retrieval", Int. J. Signal and Imaging Systems Engineering.
28. Corel 1000 and Corel 10000 image database. [Online]. Available: http://wang.ist.psu.edu/docs/related.shtml