Applied Medical Informatics
Original Research Vol. 35, No. 3 /2014, pp: 1-10

A New Laws Filtered Local Binary Pattern Texture Descriptor for Ultrasound Kidney Images Retrieval

Chelladurai CALLINS CHRISTIYANA[1,*], Vayanaperumal RAJAMANI[2]

[1] Department of Computer Science and Engineering, Sethu Institute of Technology, Madurai, Tamilnadu, India.
[2] Department of Electronics and Communication Engineering, Veltech Multitech Dr. Rangarajan Dr. Sakunthaladevi Engineering College, Chennai, Tamilnadu, India.
E-mails: callinschristiyana_c@yahoo.co.in; rajavmani@gmail.com

* Author to whom correspondence should be addressed; Tel.: +91-99650 90567

Received: 11 June 2014 / Accepted: 15 September 2014 / Published online: 30 September 2014

Abstract

Content Based Image Retrieval (CBIR) is an inevitable technique in medical applications. One of the important tasks in CBIR is the feature extraction process. A new feature extraction procedure called Laws Filtered Local Binary Pattern (LFLBP) for extracting texture features from ultrasound kidney images is proposed in this manuscript. This new texture feature combines the gain of Laws Masks and Local Binary Pattern (LBP). The Laws Masks enhance the discrimination power of LBP by capturing high energy texture points in an image and efficiently characterize the textures. The new descriptor is intended to utilize the local information in an effective manner neither the increase of encoding levels nor the usage of adjacent neighbourhood information. The performance of this new descriptor is compared with the LBP and the Local Ternary Pattern (LTP). The experimental results show that the ultrasound kidney images retrieval system with this new descriptor has good average precision value (77%) as compared to LBP (74%) and LTP (74.3%).

Keywords: Content Based Image Retrieval (CBIR); Texture; Local Patterns; Local Binary Pattern (LBP); Local Ternary Pattern (LTP); Laws Masks; Retrieval efficiency.

Introduction

Medical Images take part a predominant role in various medical applications such as patient diagnosis, medical citation and setting up surgery. More amounts of medical images are generated due to the encroachment in digital imaging modalities on top of the images digitized from conventional devices. The generated medical images are stored in the database. The medical images in the database should be indexed properly for various medical applications. The medical applications look for the similar content images in the database. It is high priced to manually catalogue all the images in medical image database based on their content [1]. The content of medical images is hard to express in words. To solve these difficulties Content Based Image Retrieval (CBIR) technique is used which automatically accesses the similar content images from medical image database [2, 3].

A detailed review is done to analyze the increasing research on CBIR approaches to medical applications [4]. The majority of research is directed towards the representation of the image content, modality, body region, or pathology. This work focuses the symbolization of medical image content in CBIR techniques. Image content is represented by the features such as colour, texture and shape. Depending upon the application, the image content may be represented in terms of either the mixture of features or the individual feature. The feature extraction phase of the CBIR system derives the features from the images. The similar images in the database are retrieved based on their feature similarity. The efficient results of CBIR system mainly depend upon the feature extraction procedure in the system.

Among the various features, Texture plays an important role in the medical image analysis [5], because it interprets the image content as well as delivers the semantic information. There are number of methods such as Grey Level Co-occurrence Matrix (GLCM) [6], Laws filter [7], Gabor filtering [8], wavelet transform [9, 10], wavelet frames [11] and Local Binary Pattern (LBP) [12] are used extensively in texture representations. Texture description approach is fall under statistical and structural methods. Among the various texture representation methods, the LBP facilitates the statistical and structural models of texture analysis [13]. In every 3 x 3 domain of an image, the LBP operator thresholds the 8 possible pixels in the neighborhood with respect to the value of the central pixel. Thus, an image is left with a set of 2^8 possible binary patterns. The LBP is simple to compute and highly discriminative. Even though the benefits are more with LBP, it has some problems also. The LBP loses the local texture information, since it considers the signs of differences of neighboring. The various LBP variants and its extensions were proposed [14, 15] to solve the problems of LBP.

The LBP variants were proposed based on the idea of either giving different threshold interval in a 3x3 domain itself or extracting the pixel information from adjacent neighborhoods of 3×3 domain. The different threshold interval in 3x3 domain function raises the number of encoding levels. The higher number of encoding levels increases the length of feature vector too. The methods such as Local Ternary Pattern (LTP) [15] and Local Quinary Pattern (LQP) [16] were intended to give different encoding levels in a 3x3 domain. The variant such as Local Derivative Pattern (LDP) [17] was proposed to improve the discriminating power of LBP but it uses the pixels information from adjacent neighborhoods also. The boundary pixels in an image do not get the fullest adjacent neighborhood information. The time taken to derive the pattern is also increased whenever adjacent neighborhood pixels information is used. In some other extensions, the LBP is augmented with some components to improve its power. In Weber Local Binary Pattern (WLBP) [18], the LBP is augmented with differential excitation component. The LBP variance LBPV [19] texture descriptor couples the LBP with variance value.

From the above description, we are motivated to propose a new LBP variant to enhance its discrimination power without increasing the encoding levels and not using the adjacent neighborhood information. This is possible if and only if modifying the pixel information statistics in a local domain with respect to any other texture analysis method. Su et al. have presented structured local binary haar pattern for pixel based graphics retrieval [20]. Four haar masks are used in that method to capture the changes in the grey values along vertical, horizontal and diagonal directions in the local window. Then the changes in the grey values are encoded as the binary pattern. This pattern gave the path to our work. Instead of capturing the gray value changes in the local domain, we are interested to encode the high texture energy points in the local domain as the binary pattern. Laws [7] have presented the novel texture energy approach to texture analysis. In order to describe the local patterns of a 3×3 domain in an effective way, the Laws masks are applied over the domain. The Laws Masks are used to capture high texture energy points in a local window. The magnitude values and the polarity values of the Laws Masks are considered for encoding purpose. The polarity and magnitude relationship are then encoded in to the binary value. The pixel information in the 3×3 domain is characterized by five different ways and yield 5 bit code. The encoded values are mapped into one of the 32 values. Only $32(2^5)$ values are possible since combined five Laws masks are used instead of 9 convolved masks. This factor reduces the histogram length of LBP from 256 to 32. The new pattern is called as Laws Filtered Local binary pattern (LFLBP). Thus the descriptor blends the benefit of Laws Masks and LBP.

This work applies the LFLBP descriptor to represent the content of ultrasound kidney images for the retrieval purpose. The ultrasound kidney images which have the similar LFLBP patterns are retrieved as similar using CBIR system. Antonio et al. [21] have proved that LTP is performed better among the various LBP variants. So the performance of ultrasound kidney image retrieval system with LFLBP descriptor is compared with LBP and LTP based system to show its superiority. There are number of local patterns which are used in the analysis of different medical images. The study of various local pattern based medical image retrieval is given in the Table 1.

Table 1. Related study of medical image analysis using local texture patterns

Study	Feature representation method	Application
Murala et al. [22]	Local Mesh Peak Valley Edge Pattern (LMePVEP)	MRI and CT image retrieval.
Murala et al. [23]	Local Ternary Co-occurrence Pattern (LTCoP)	MRI and CT image retrieval.
Liu et al. [24]	Multi-scale spatial pyramid as global descriptors and dimension-reduced local binary pattern histograms as local descriptors	Analysis of optical coherence tomography (OCT) images.
Bi et al. [25]	H-LBP feature	Edge extraction procedure for blurry digital radiography (DR) images.
Häfner et al. [26]	Multi-scale local color vector. patterns	To classify magnification-endoscopic images.
Gu et al. [27]	Feature Local Binary Patterns (FLBP)	Eye detection and Eye center localization application.
Burçin et al. [28]	Local Binary Pattern (LBP)	To recognize Down syndrome using facial features.
Peng et al. [29]	Uniformity Estimation Method (UEM)	To detect the pathological change in the chest CT images.
M. Muthu Rama Krishnan et al. [30]	Oral Malignancy Index (OMI) using the Higher Order Spectra (HOS), Local Binary Pattern (LBP), and Laws Texture Energy (LTE) features	To diagnose benign or malignant tissues using just one number.
Li et al. [31]	Curvelet transformation and Local Binary Pattern (LBP)	To identify ulcer regions in capsule endoscopy images.

The aim of the research presented in this manuscript was to present a new feature extraction procedure named Laws Filtered Local Binary Pattern (LFLBP) for extracting texture features from ultrasound kidney images.

Material and Methods

Proposed LFLBP Texture Descriptor Formation

This section presents the illustration of forming LFLBP texture descriptor from the images. The LFLBP pattern extends the LBP with Laws masks. These masks capture the high texture energy points in the image. The sign and magnitude information in Laws masks are encoded as a binary value as in LBP. The Laws masks are described in the Figure 1.

The Figure 1(a) shows the basic 1×3 Laws masks. The initial letters of these masks such as L, E and S indicate Local averaging, Edge detection and spot detection respectively. The basic masks are convolved together and derive nine 3×3 Laws masks. These are shown in the Figure 1(b).

From the nine masks described in the Figure 1, we can eliminate the masks whose components do not average to zero because those masks consider the image intensity than the texture and they are less useful in the texture analysis. According to this, the mask L3L3 is eliminated. For Rotational invariance some of the masks are combined. The Figure 2 shows the combined masks.

After the elimination of L3L3, the 8 masks are reduced into 5 distinct masks such as E3L3T, S3L3T, S3E3T, E3E3 and S3S3. These masks are applied over the 3×3 neighborhood of the entire image to find the new value for the center pixel. The center pixel is replaced by 5 bit binary number. Each bit is influenced by one of the 5 masks. The Table 2 describes the bits value influenced by the laws mask and the weight assigned to them.

$$L3 = [\,1 \;\; 2 \;\; 1\,]$$
$$E3 = [\,-1 \;\; 0 \;\; 1\,]$$
$$S3 = [\,-1 \;\; 2 \;\; -1\,]$$

(a)

$$L3L3 = \begin{matrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{matrix} \quad L3E3 = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix} \quad L3S3 = \begin{matrix} -1 & 2 & -1 \\ -2 & 4 & -2 \\ -1 & 2 & -1 \end{matrix}$$

$$E3L3 = \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix} \quad E3E3 = \begin{matrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{matrix} \quad E3S3 = \begin{matrix} 1 & -2 & 1 \\ 0 & 0 & 0 \\ -1 & 2 & -1 \end{matrix}$$

$$S3L3 = \begin{matrix} -1 & -2 & -1 \\ 2 & 4 & 2 \\ -1 & -2 & -1 \end{matrix} \quad S3E3 = \begin{matrix} 1 & 0 & -1 \\ -2 & 0 & 2 \\ 1 & 0 & -1 \end{matrix} \quad S3S3 = \begin{matrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{matrix}$$

(b)

Figure 1. Laws Masks. (a). Basic 1×3 Masks. (b) 3×3 Masks

E3L3T = E3L3 + L3E3
S3L3T = S3L3 + L3S3
S3E3T = S3E3 + E3S3

Figure 2. The Combined 3×3 Laws Masks

Table 2. Laws masks influencing Binary value of the center pixel

Bit Number	Bit5	Bit4	Bit3	Bit2	Bit1
Mask	S3E3T	S3L3T	E3L3T	S3S3	E3E3
Weight	2^4	2^3	2^2	2^1	2^0

The LFLBP value for the center pixel (a,b) in a local 3×3 domain f(a,b) is calculated using the Equation 1.

$$\mathrm{LFLBP}(a,b) = \sum_{i=1}^{5} \mathrm{TH}(\mathrm{LF}_i \otimes f(a,b)) x 2^{i-1} \tag{1}$$

In the Equation 1, LF_i indicates one of the 5 laws masks indicated in Table 1. The filter LF_1= E3E3, LF_2=S3S3, LF_3=E3L3T, LF_4=S3L3T, LF_5=S3E3T. The threshold function TH in the Equation 1 is defined in the Equation 2.

$$\mathrm{TH}(x) = \left\{ \begin{matrix} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{matrix} \right\} \tag{2}$$

The histogram of these LFLBP labels such as 2^5=32 can be used as a texture descriptor for an image. The example calculation of the LFLBP for the given 3×3 window is depicted in the Figure 3.

20	40	25
10	30	35
40	15	30

Sample window

Bit1 = 20-25-40+30 = -15 = 0
Bit2 = 20-80+25-20+120-70+40-30+30 = 35 =1
Bit3 = -20-40-10+35+15+30 = 10 =1
Bit4 = -20-25-40-30+120 = 5 = 1
Bit5 = 20-40-10+35+15-30 = -10 =0

LFLBP value = $0x2^0 + 1x2^1 + 1x2^2 + 1x2^3 + 1x2^4 = 14$

Figure 3. Sample LFLBP Calculation for a 3×3 domain

Similarity Measurement

The results of Content Based Medical Image Retrieval (CBMIR) system can be used for the variety of medical applications. The immediate clarification about the particular case is done by verifying the past records. The result efficiency of CBMIR system is depended on the two factors such as feature descriptor for the image content and the similarity measure applied to retrieve the similar images. In this work the new LFLBP texture descriptor represents the image content. There are number of distance metrics used for the similarity assessment in CBIR. The similarity metric that is chosen for an image retrieval system should be compliant with the feature descriptor and modality of the images. The Euclidean distance measure is the efficient similarity metric for the same modality images [32]. This work represents the entire image by means of LFLBP histogram. The chi square distance metric is more appropriate for the histogram based feature [33] since the histogram contains many zeros. The chi square distance metric is used as the similarity metric in this work which is given in the Equation 3.

$$\chi^2(x,y) = \sum_i \frac{(x_i - y_i)^2}{x_i^{\,2} + y_i^{\,2}} \tag{3}$$

The terms x and y in the Equation 3 represents the LFLBP histogram of the query image and the database image respectively. The proposed CBMIR for this work is shown in the Figure 5.

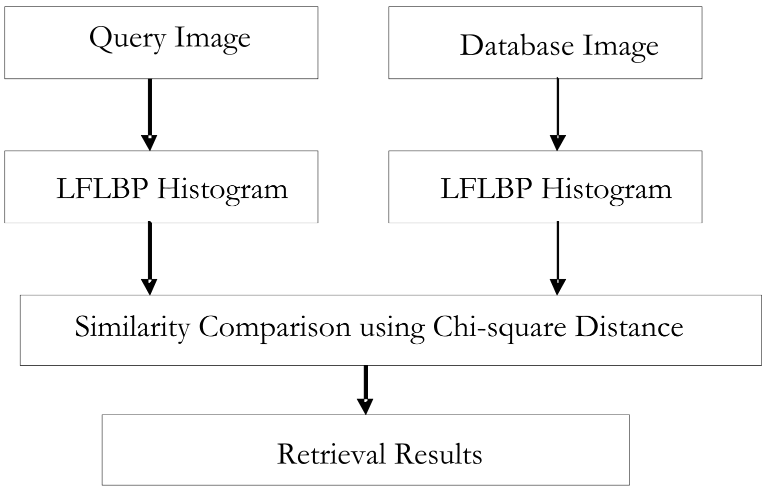


Figure 5. The Proposed CBMIR system using LFLBP Descriptor

Performance Analysis

The efficiency of the CBMIR system is measured by two familiar measures such as precision and recall

[34] which is defined in the Equation 4 and the Equation 5.

$$\text{Precision} = \frac{\text{No of relevant images retrieved}}{\text{Total no of images retrieved}} \quad (4)$$

$$\text{Recall} = \frac{\text{No of relevant images retrived}}{\text{Total nov of relevant images in database}} \quad (5)$$

Results and Discussions

The front end of our ultrasound kidney image retrieval system is designed in IDL 6.3. The system can be easily used by physicians and radiologists without any technical guidance. The efficiency of the system is proved by analyzing the results of the system which are derived from the database. The Database consists of same modality of ultrasound kidney images like Normal, Cortical Cysts (CC), Medical Renal Diseases (MRD) are considered in the performance evaluation of the LFLBP based CBMIR. The total number of 365 images with three categories (Normal, CC and MRD) is taken for analysis. The intention of this work is to prove the competence of the LFLBP texture descriptor.

The average Recall and Precision values are calculated from the results of Top 10 images retrieved to Top 100 images retrieved in the interval of 10. The efficiency of the system is evaluated on different category of images (Normal, CC and MRD) separately. The average recall and precision values are recorded for above mentioned 10 intervals. The performance of the system is compared in terms of the average precision values. The Figure 6 to Figure 8 shows the graphical comparison of average precision values between LFLBP, LTP and LBP based ultrasound kidney images retrieval system.

From the graphical comparison it is observed that the performance of the ultrasound kidney images retrieval system with LFLBP descriptor is better than LBP and LTP. Especially in the Top 10 images analysis, the performance of the LFLBP based system is outstanding. Actually, the top similar images are retrieved in the Top 10 interval. The overall retrieval efficiency comparison of three texture descriptors in three ultrasound image databases is given in the Table 3. For overall comparison, the average values of precision in Top 10 images retrieval is taken into consideration. The 95% confidence interval range is also furnished for average precision value for all the methods.

From the Table 3, it is observed that the LFLBP based ultrasound kidney images retrieval system is superior compared to LTP and LBP based system in terms of retrieval efficiency. The precision value tells how much amount of similar class of query image is retrieved about the total images retrieved. Among the various retrieval intervals, the top 10 interval retrieves the most similar images with respect to the query. The length of the feature vector is also an important parameter for comparison since it decides the quantum of time required to get the results (Table 4).

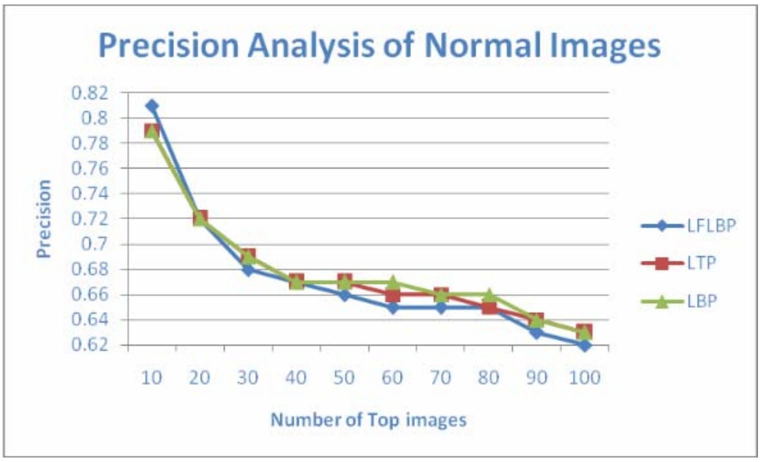


Figure 6. Precision value comparison of normal images

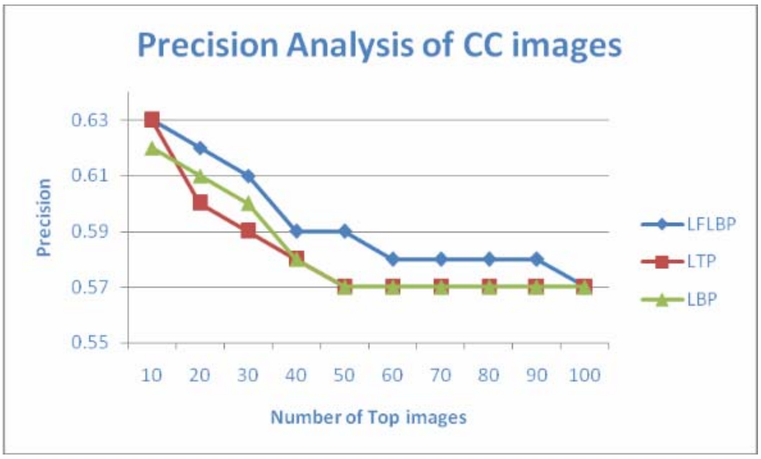


Figure 7. Precision value comparison of CC images

Figure 8. Precision value comparison of MRD images

Table 3. The Retrieval Efficiency comparison of LFLBP, LTP and LBP based ultrasound kidney images retrieval system for Top 10 images

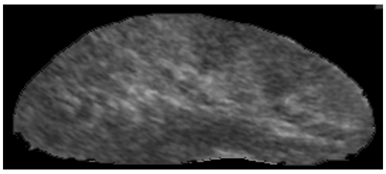
Method	Average Precision for Top 10 Images			A 95% confidence Interval for Average Precision	Average Recall for Top 100 Images		
	Normal	CC	MRD		Normal	CC	MRD
LFLBP	0.81	0.63	0.86	[0.7559; 0.7841]	0.45	0.53	0.54
LTP	0.79	0.63	0.81	[0.7290; 0.7570]	0.45	0.52	0.53
LBP	0.79	0.62	0.81	[0.7284; 0.7575]	0.45	0.52	0.53

Table 4. The feature vector length comparison of LFLBP, LTP and LBP

Method	Number of bits in the Encoded Pattern	Length of the feature vector
LFLBP	5	$32(2^5)$
LBP	8	$256(2^8)$
LTP	2*8	$2*256(2*2^8)$

The Top 5 retrieval results of LFLBP based ultrasound kidney image retrieval system for a given query image is shown in the Figure 9.

QUERY IMAGE



TOP 5 RETRIEVAL RESULTS OF LFLBP BASED IMAGE RETRIEVAL SYSTEM

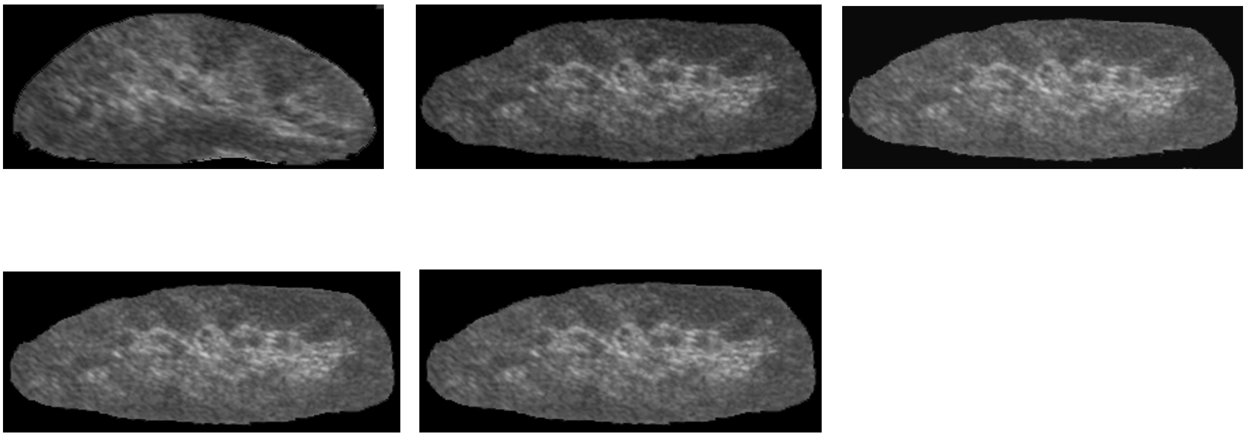


Figure 9. Top 5 Retrieval Results of LFLBP based ultrasound kidney images retrieval system

Conclusions

The LFLBP descriptor combines the best features of Laws Masks and LBP. The Laws Masks improve the discrimination power of LBP by capturing the texture energy in an image. The LFLBP descriptor is encoded by make use of all the pixel information in the 3×3 domain in 5 different ways. The LFLBP pattern does not increase the encoding levels and does not extent the neighborhood range during its computation. The length of the binary code of LFLBP seems to be reduced by this computation. This new descriptor is then used to represent the content of ultrasound kidney images for medical images retrieval applications. The efficiency of the ultrasound kidney images retrieval system with this LFLBP descriptor is compared with the retrieval system using LTP and LBP descriptors. The experimental analysis in the section 4 reports that the LFLBP based ultrasound kidney image retrieval system has the highest retrieval efficiency in terms of minimum feature vector length when it is compared to LTP and LBP based ultrasound kidney images retrieval system. From the various reporting, this work concludes that the LFLBP is the suitable local descriptor for representing texture features for the application of ultrasound kidney images retrieval. Further, this texture descriptor may be applied to any other kind of image retrieval applications, pattern recognition application and etc.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

1. Wei CH, Li CT. Design of content-based multimedia retrieval. In M.Pagani (Ed.) Encyclopedia of multimedia technology and networking. Hershey: PA Idea Group Reference; 2005.
2. Eakins JP. Towards in intelligent image retrieval. Pattern Recognition 2002;35(1):3-14.

3. Feng D, Siu WC, Zhang HJ. Multimedia information retrieval and management-Technological fundamentals and applications. Berlin, Springer; 2003.
4. Muller H, Michoux N, Bandon D, Geissbuhler A. A review of content based image retrieval systems in medical applications-Clinical benefits and future directions. International Journal of Medical Informatics 2004;73(1):1-23.
5. Tuceryan M, Jain AK. Texture analysis, in: Chen CH, Pau LF, Wang PSP (Eds.). Handbook of Pattern Recognition and Computer Vision. Singapore: World Scientific Publishing; 1993.
6. Haralik RM, Shanmugam K, Dinstein I. Texture features for image classification. IEEE Transactions on Systems, Man, and Cybernetics 1973;3(6):610-621.
   Laws KI. Rapid texture identification. Proc SPIE 1980;238:376-380.
7. Manjunath BS, Ma WY. Texture features for browsing and retrieval of image data. IEEE Transactions on Pattern Analysis and Machine Intelligence 1996;18(8):837-842.
8. Chang T, Kuo CCJ. Texture analysis and classification with tree-structured wavelet transform. IEEE Transactions on Image Processing 1993;2(4):429-441.
9. Laine A, Fan J. Texture classification by wavelet packet signatures. IEEE Transactions on Pattern Analysis and Machine Intelligence 1993;15(11):1186-1191.
10. Unser M. Texture classification and segmentation using wavelet frames. IEEE Transactions on Image Processing 1995;4(11):1549-1560.
11. Ojala T, Pietik¨ainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary pattern. IEEE Transactions on Pattern Analysis and Machine Intelligence 2002;24(7):971-987.
12. Mäenpää T, Pietikäinen M. Texture analysis with local binary patterns. In: Chen CH, Wang PSP (eds.). Handbook of Pattern Recognition and Computer Vision, 3rd edn. Singapore, World Scientific; 2005:197-216.
13. Nanni L, Brahnam S, Lumini A. Survey on LBP based texture descriptors for image classification. Expert Systems with Applications 2012;39(3):3634-3641.
14. Nanni L, Lumini A, Brahnam S. Local binary patterns variants as texture descriptors for medical image analysis. Artif Intell Med 2010;49(2):117-125.
15. Tan X, Triggs B. Enhanced local texture feature sets for face recognition under difficult lighting conditions. In Analysis and Modelling of Faces and Gestures. Lecture Notes in Computer Science 2007;4778:168-182.
16. Zhang B,Gao Y, Zhao S, Liu J. Local derivative pattern versus local binary pattern: face recognition with higher-order local pattern descriptor. IEEE Trans Image Process 2010;19(2):533-544.
17. Liu F, Tang Z, Tang J. WLBP: Weber local binary pattern for local image description. Neuro Computing 2013;120:325-335.
18. Guo Z, Zhang L, Zhang D. Rotation invariant texture classification using LBP Variance (LBPV) with global matching. Pattern Recognition 2010;43(3):706-719.
19. Su S-Z, Chen S-Y, Li S-Z, Li S-A, Duh D-J. Structured Local Binary Haar Pattern for pixel-based graphics retrieval. Electronics Letters 2010;46(14):996.
20. Fernandez A, Alvarez MX, Bianconi F. Texture description through histograms of equivalent patterns. Journal of Mathematical Imaging and Vision 2013;45:76-102.
21. Murala S, Wu JQM. MRI and CT image indexing and retrieval using local mesh peak valley edge patterns. Signal Processing: Image Communication 2014;29(3):400-409.
22. Murala S, Wu JQM. Local ternary co-occurrence patterns: A new feature descriptor for MRI and CT image retrieval. Neurocomputing 2013;119:399-412.
23. Liu Y-Y, Chen M, Ishikawa H, Wollstein G, Schuman JS, Rehg JM. Automated macular pathology diagnosis in retinal OCT images using multi-scale spatial pyramid and local binary patterns in texture and shape encoding. Medical Image Analysis 2011:15(5):748-759.
24. Bi B, L Zeng, Kuan Shen, Haina Jian. An effective edge extraction method using improved local binary pattern for blurry digital radiography images. NDT & E International 2013;53:26-30.
25. Häfner M, Liedlgruber M, Uhl A, Vécsei A, Wrba F. Color treatment in endoscopic image classification using multi-scale local color vector patterns. Medical Image Analysis 2012;16(1):75-86.
26. Jiayu Gu, Chengjun Liu. Feature local binary patterns with application to eye detection. Neuro computing 2013;113:138-152.

27. Kurt Burçin, Nabiyev V. Vasif. Down syndrome recognition using local binary patterns and statistical evaluation of the system. Expert Systems with Applications 2011;38(7):8690-8695.
28. Shao-Hu Peng, Deok-Hwan Kim, Seok-Lyong Lee, Myung-Kwan Lim. Texture feature extraction based on a uniformity estimation method for local brightness and structure in chest CT images. Computers in Biology and Medicine 2010;40(11-12):931-942.
29. Muthu Rama Krishnan M, Vikram Venkatraghavan U, Rajendra Acharya, Mousumi Pal, Ranjan Rashmi Paul, Lim Choo Min, Ajoy Kumar Ray, Jyotirmoy Chatterjee, Chandan Chakraborty. Automated oral cancer identification using histopathological images: A hybrid feature extraction paradigm. Micron 2012;43(2-3):352-364.
30. Baopu Li, Max Q, Meng H. Texture analysis for ulcer detection in capsule endoscopy images. Image and Vision Computing 2009;27(9):1336-1342.
31. Hyun-chong Cho, a-Lubomir Hadjiiski, Berkman Sahiner, b-Heang-Ping Chan, Mark Helvie, Chintana Paramagul, Alexis V. Nees. Similarity evaluation in a CBIR CADx system for characterization of breast masses on ultrasound. Images Med Phys 2011;38(4):1820-1831.
32. Ahonen T, Hadid A, Pietikäinen M. Face recognition with local binary patterns. In: Proc.European Conference on Computer Vision, Springer, Berlin, 2004;469-481.
33. Carson C, Belongie S, Greenspan H, Malik J. Blobworld: Image segmentation using expectation maximization and its applications to image querying. IEEE Trans. on Pattern Analysis and Machine Intelligence 2002;24(8):1026-1038.