REVIEW ARTICLE

e-ISSN: 2349-0659 p-ISSN: 2350-0964
doi: 10.21276/apjhs.2018.5.1.29

Local mesh patterns for medical image segmentation

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ABSTRACT

In this paper, local mesh patterns (LMeP) feature extractor is proposed for medical image segmentation. The local region of image is represented by LMeP, which are evaluated by taking into consideration the magnitude of the local difference between the center pixel and its neighbors. First, image split into subblocks and LMeP features are extracted from each subblock. Once the image has been split into blocks of roughly homogeneous texture, we apply an agglomerative procedure to merge similar adjacent regions until one of the two stopping criteria is satis1ed. At each stage, we merge the pair of adjacent regions which have the largest merger importance (MI) value. Based on MI the regions are merged and then form the segmented regions for medical image segmentation application. Experimental results are tested on benchmark magnetic resonance image database for medical image segmentation application. Results after being investigated, proposed method shows a significant improvement for segmentation of images.

Key words: Local binary patterns, medical image segmentation, texture

INTRODUCTION

Motivation

Nowadays, a lot of medical images are available, and this data need to be stored for a particular time period to maintain the medical data about the patient. But with data medical hospitals are not getting any benefit from the storage. The retrieving system adopts feature database for matching so as to reduce the search space which is especially useful in a larger image database. Retrieval images are selected according to the closest similar measures computed by distance. In medical image segmentation, we will segment the certain regions for analysis purpose.

Initially, cluster-based medical segmentation like k-mean, fuzzy c-mans algorithms are proposed for medical image segmentation. In recent years, researchers using the feature based algorithms for medical image segmentation. Based on the literature, we motivated to work in the direction of medical image segmentation using feature descriptors.

Now, a concise review of the related literature available, targeted for development of our algorithms is given here. Local binary pattern (LBP) features have emerged as a silver lining in the field of texture retrieval. Ojala *et al.* proposed LBP[1] which are converted to rotational invariant for texture classification in based on Kullback discrimination of sample and prototype distributions is used. The classification results for single features with one-dimensional feature value distributions and for pairs of complementary features with two-dimensional distributions are presented.[2] Rotational invariant texture classification using feature distributions is proposed in study by Pietikainen *et al*.[3] The combination of Gabor filter and LBP for texture segmentation[4] and rotational invariant texture classification using LBP variance with global matching[5] has also been reported. Liao *et al*. proposed the dominant LBP for texture classification.[6] Guo *et al*. developed the completed LBP scheme for texture classification.[7] LBP operator on facial expression analysis and recognition is successfully reported in Ahonen *et al*., and Zhao *et al*.[8,9] Li *et al*. proposed multiscale heat kernel based face representation, for heat kernels that perform well in characterizing the topological structural information of face appearance. Further, the LBP descriptor is incorporated into the multiscale heat kernel face representation for capturing texture information of face appearance.[10] Face recognition under different lighting conditions by the use of local ternary patterns (LTP) is discussed in Tan and Triggs[11] where emphasis lays on the issue of robustness of the local patterns. The background modeling and detection using LBP extended LBP for shape localization and LBP for interest region description have been reported in Heikkil *et al*., Huang *et al*., and Heikkila *et al*.,[12-14] respectively. Zhao *et al*. proposed the local spatiotemporal descriptors using LBP to represent and recognize spoken isolated phrases based solely on visual input.[15] Spatiotemporal LBPs extracted from mouth regions are used for describing isolated phrase sequences. Unay *et al*. proposed the local structure-based region of interest retrieval in brain magnetic resonance images (MRIs).[16] Yao and Chen proposed the local edge patterns (LEP) for texture retrieval[17] where LEP value is computed using an edge obtained by applying the Sobel edge detector to intensity gray level and then LEP feature is extracted to describe the spatial structure of the local texture according to the organization of the edge pixels in a neighborhood.

Main Contributions

The authors have bestowed the thrust for carrying out the experiments on the following:

1. The local mesh patterns (LMeP) operator is used for medical image segmentation.

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Received: 19-12-2017 **Revised:** 20-01-2018 **Accepted:** 28-02-2018

2. Results are tested on benchmark medical image databases.

The organization of the paper is as follows: In section 1, a brief review of texture features for various applications is given. A concise review of LBPs and LMeP can be visualized in Section 2. Section 3, presents the proposed algorithm for medical image segmentation. Further, experimental results and discussions to support the algorithm can be seen in section 4. Conclusions are derived in Section 5.

LOCAL PATTERNS

LBPs

The LBP operator was introduced by Ojala *et al.*[1] for texture classification. Success in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification,[1-7] face recognition,[8-11] object tracking, biomedical image retrieval, and fingerprint recognition.

Given a center pixel in the 3 × 3 pattern, LBP value is computed by comparing its grayscale value with its neighborhoods based on Equation (1) and Equation (2):

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

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{else} \end{cases} \quad (2)$$

Where $I(g_c)$ enotes the gray value of the center pixel, $I(g_i)$ is the gray value of its neighbors, P stands for the number of neighbors and R, the radius of the neighborhood.

Figure 1 shows an example of obtaining an LBP from a given 3 × 3 pattern. The histograms of these patterns extract the distribution of edges in an image.[1]

LTP

Tan and Triggs[11] extended the LBP to three-valued code called LTP, in which gray values in the zone of width ± t around g_c are quantized to zero, those above (g_c + t) are quantized to +1, and those below (g_c – t) are quantized to-1, i.e., the indicator f (x) is replaced with 3-valued function Equation (3) and binary LBP code is replaced by a ternary LTP code as shown in Figure 1.

$$\vec{f}(x,g_c,t)=\begin{cases} +1, & x \geq g_c + t \\ 0, & |x-g_c| + t \\ -1, & x \leq g_c - t \end{cases}\Bigg|_{x=(g_p-g_c)} \quad (3)$$

LTP can be found in An image feature named Local Triplet Pattern (LTP) is proposed for image retrieval applications. The LTP feature of an image is a histogram which contains spatial information among neighboring pixels in the image. An LTP level is extracted from each 3×3 pixel block. The color levels of the eight surrounding pixels are compared with the color level of the center pixel. The comparison returns one of the triplet codes: 0, 1, or 2 to represent the three conditions: the color level of a neighboring pixel is smaller than, equal to, or larger than the color level of the center pixel. The eight triplet codes from the eight surrounding pixels are then transformed to an LTP level. We also consider extracting the LTP from a quantized color space and at different pattern length according to the application needs. Experimental results show that our proposed LTP histogram consistently outperforms other histograms with spatial information on both the texture and generic image datasets.[17]

After computing the LP (LBP or LTP) for each pixel (j,k), the whole image is represented by building a histogram as shown in Equation (4).

$$H_{LP}(l) = \sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f(LP(J,k),l); l \in [0,(2^P-1)] \quad (4)$$

$$f(x,y)=\begin{cases} 1 & x=y \\ 0 & \text{else} \end{cases} \quad (5)$$

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

LMeP

The idea of the LBP has been motivated us to propose the LMeP for biomedical image retrieval. The LMeP value is computed based on the relationship among the surrounding neighbors for a given center pixel in an image Equation (3). Figure 1 illustrates the LMeP values calculation for a given 3 × 3 pattern.[18]

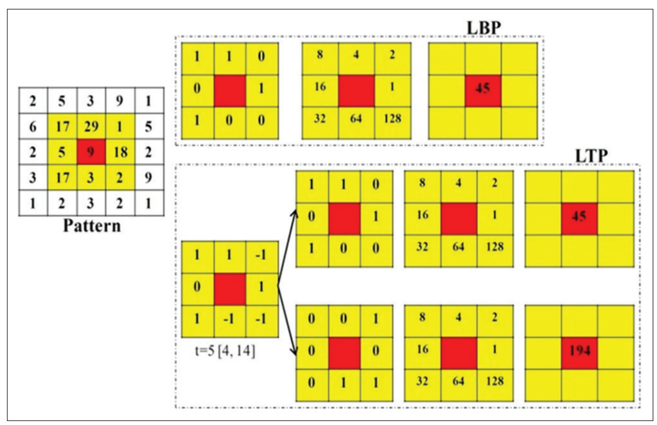

Figure 1: Example of obtaining local binary pattern and local ternary patterns for the 3 × 3 pattern

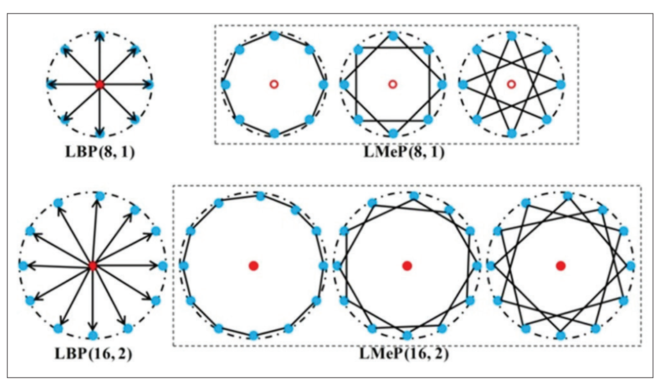

Figure 2: The local binary pattern and the first three local mesh patterns calculations for a given (P, R)

$$LMeP^{j}_{P,R} = \sum_{i=1}^{P} 2(i-1) \times f_1(g_\alpha|_R - g_i|_R);\alpha = 1 + \mathrm{mod}((I + P + j - 1), P); \forall j = 1,2,..,(P/2) \quad (6)$$

Where, j represents the LMeP index and mod (*x*, *y*) returns the reminder for *x*/*y* operation.

From Equation 6 it can be observed that the possible LMeP patterns for P neighbors are P/2. In this paper, we consider only first three LMeP patterns (j=1, 2, 3 in Equation (6)) for experimentation as shown in Figures 1 and 2. Figure 2 illustrates the LBP and the first three LMeP calculations for a given (P, R). In this paper, (8.1) (16.2) and (24.3) combinations are considered for experimentation.

For the local pattern with P neighboring pixels, there are 2^P $(0–2^P–1)$ possible values for both LBP and LMeP, resulting in a feature vector of length 2^P. A high computational cost is involved in extracting such a feature vector. Thus, uniform patterns[19] are considered to reduce the computational cost. A uniform pattern refers to a circular binary representation having limited discontinuities. In this paper, patterns with two or less discontinuities in the circular binary representation are termed as uniform while rest of the patterns are termed as non-uniform. Thus, the distinct uniform patterns for a given query image would be P(P−1)+2. The possible uniform patterns for P = 8 can be seen in Figure 2.[19]

After identifying the local pattern, PTN (the LBP or the first three LMePs) the whole image is represented by building a histogram using Equation (4).

$$H_s(l)=\frac{1}{N_1 \times N_2}\sum_{j-1}^{N_1}\sum_{k-1}^{N_2} f_2(PTN(j,k),l);l \in [0,P(P-1)+2] \quad (7)$$

$$f_2(x,y)=\begin{cases}1 & \text{if } x=y\\ 0 & \text{else}\end{cases} \quad (8)$$

Where, $N_1 \times N_2$ represents the size of input image.

Figure 2 illustrates the feature maps obtained by applying the LBP and the first three LMePs operators on referenced MR image.

The experimental results demonstrate that the proposed LMeP shows better performance as compared to LBP, indicating that it can capture more edge information than LBP for biomedical image retrieval.

PROPOSED SEGMENTATION ALGORITHM

Proposed System Framework

Algorithm:

Input: Image; Output: Retrieval result:

1. Load the grayscale image.
2. Calculate the LMeP features from an image.
3. Divide the LMeP map into subblocks.
4. Apply the similarity between the subblocks.
5. Based on the similarity merge the subblocks.
6. Form the regions (segments) for final segmentation.

Block Matching

Feature vector for block-1, Q is represented as $f_Q = (f_{Q1}, f_Q.....f_{Q_{Lg}})$ $f_Q = (f_{Q1}, f_{Q1},.....f_{Q_{Lg}})$ obtained after the feature extraction. Similarly, block-2 feature vector $f_{DB_i} = (f_{DB_{i1}}, f_{DB_{i1}},.....f_{DB_{iLg}})$; i=1,2,.....|DB|. The goal is to select *n* best blocks that resemble the same region.

To match the subblocks, we used d_1 similarity distance metric computed by Equation (9).

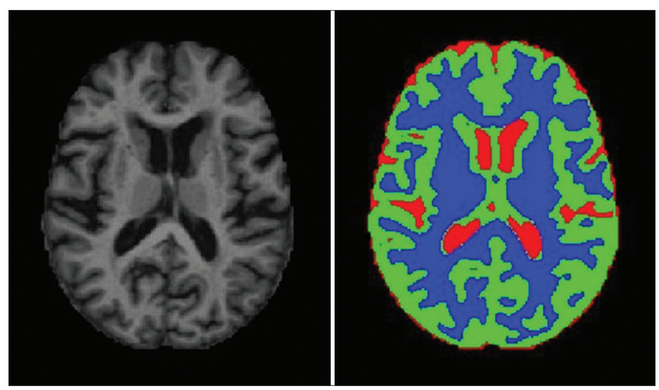

Figure 3: Segmentation results of proposed method

Table 1: Comparison of various techniques in terms of score on image (a) at different Gaussian noise

Method	Gaussian noise (%)											
	5			10			15			20		
	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3
LBP	0.66	0.79	0.86	0.58	0.72	0.81	0.53	0.69	0.80	0.49	0.65	0.78
LMeP	0.68	0.82	0.88	0.59	0.74	0.84	0.56	0.72	0.82	0.53	0.68	0.81

Cl: Cluster, LBP: Local binary patterns, LMeP: Local mesh patterns

Table 2: Comparison of various techniques in terms of score on image (b) at different Gaussian noise

Method	Gaussian noise (%)											
	5			10			15			20		
	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3
LBP	0.73	0.80	0.87	0.58	0.66	0.80	0.54	0.69	0.80	0.51	0.66	0.78
LMeP	0.78	0.84	0.89	0.59	0.68	0.82	0.58	0.74	0.83	0.54	0.67	0.80

Cl: Cluster, LBP: Local binary patterns, LMeP: Local mesh patterns

Table 3: Comparison of various techniques in terms of score on image (a) at different salt-pepper noise

Method	Salt-pepper noise (%)											
	5			10			15			20		
	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3
LBP	0.72	0.76	0.82	0.62	0.69	0.74	0.56	0.66	0.77	0.54	0.68	0.74
LMeP	0.76	0.79	0.84	0.64	0.73	0.77	0.58	0.69	0.79	0.57	0.69	0.76

Cl: Cluster, LBP: Local binary patterns, LMeP: Local mesh patterns

Table 4: Comparison of various techniques in terms of score on image (b) at different salt-pepper noise

Method	Salt-pepper noise (%)											
	5			10			15			20		
	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3
LBP	0.76	0.79	0.85	0.56	0.66	0.77	0.51	0.62	0.77	0.50	0.63	0.72
LMeP	0.79	0.82	0.88	0.59	0.69	0.81	0.56	0.66	0.80	0.54	0.66	0.74

Cl: Cluster, LBP: Local binary patterns, LMeP: Local mesh patterns

Table 5: Comparison of various techniques in terms of number of iterations and execution time at different Gaussian noise on image (a)

Method	Gaussian noise (%)							
	5		10		15		20	
	NI	TM	NI	TM	NI	TM	NI	TM
LBP	28	0.65	30	0.68	24	0.50	23	0.48
LMeP	22	0.57	23	0.65	23	0.60	30	0.81

NI: Number of iterations, TM: Execution time (S), LBP: Local binary patterns, LMeP: Local mesh patterns

Table 6: Comparison of various techniques in terms of number of iterations and execution time at different salt-pepper noise on image (a)

Method	Salt-pepper noise (%)							
	5		10		15		20	
	NI	TM	NI	TM	NI	TM	NI	TM
LBP	31	0.62	35	0.60	26	0.49	26	0.46
LMeP	26	0.52	22	0.54	21	0.36	21	0.36

NI: Number of iterations, TM: Execution time (S), LBP: Local binary patterns, LMeP: Local mesh patterns

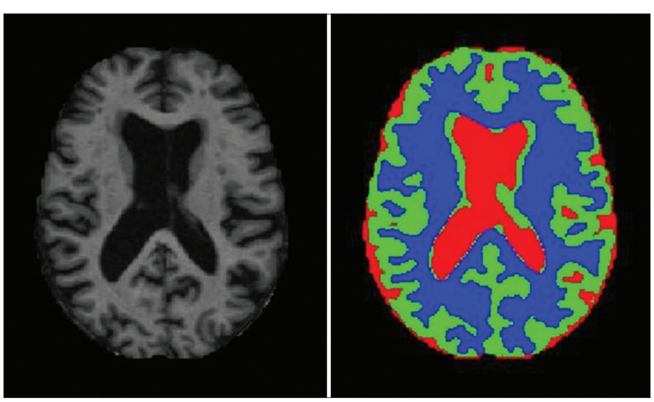

Figure 4: Segmentation results of proposed method

$$D(Q,DB)=\sum_{i=1}^{Lg}\left|\frac{f_{DB_{ji}}-f_{Q_i}}{1+f_{DB_{ji}}+f_{Q_i}}\right| \quad (9)$$

Where $f_{DB}ji$ is i^{th} feature of j^{th} image in the database |DB|.

EXPERIMENTAL RESULTS AND DISCUSSION

To verify the effectiveness of the proposed algorithm, experiments were conducted on two brain magnetic resonance images (MRIs).[19] The performance of the proposed algorithm is compared with the other existing FCM variant methods in terms of score, number of iterations (NI) and computational time on open access series of imaging studies-MRI dataset.

Figures 3 and 4 illustrate the segmentation results of the proposed algorithm. Tables 1-6 illustrates the results of the proposed algorithm for image segmentation. The results after being investigated, the proposed method outperforms the other existing method in terms of score, number of iterations, and time on benchmark database.

CONCLUSIONS

A novel methodology based on feature descriptors is proposed for medical image retrieval application. For feature extraction LMeP is used and then merging of subblocks concept is used for segmentation. The performance of the proposed method is tested on benchmark database. The results after being investigated proposed method outperform the other existing methods in terms of segmentation score.

REFERENCES

1. Ojala T, Pietikainen M, Harwood D. A comparative sudy of texture measures with classification based on feature distributions. Int J Pattern Recogn 1996;29:51-9.
2. Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with

local binary patterns. IEEE Trans Pattern Anal Mach Intell 2002;24:971-87.
3. Pietikainen M, Ojala T, Scruggs T, Bowyer KW, Jin C, Hoffman K, *et al.* Overview of the face recognition using feature distributions. Int J Pattern Recogn 2000;33:43-52.
4. Li M, Staunton RC. Optimum Gabor filter design and local binary patterns for texture segmentation. J Pattern Recogn 2008;29:664-72.
5. Guo Z, Zhang L, Zhang D. Rotation invariant texture classification using LBP variance with global matchning. Int J Pattern Recogn 2010;43:706-16.
6. Liao S, Law MW, Chung AC. Dominant local binary patterns for texture classification. IEEE Tans Image Proc 2009;18:1107-18.
7. Guo Z, Zhang L, Zhang D. A completed modeling of local binary pattern operator for texture classification. IEEE Tans Image Proc 2010;19:1657-63.
8. Ahonen T, Hadid A, Pietikainen M. Face description with local binary patterns: Applications to face recognition. IEEE Trans Pattern Anal Mach Intell 2006;28:2037-41.
9. Zhao G, Pietikainen M. Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Trans Pattern Anal Mach Intell 2007;29:915-28.
10. Li X, Hu W, Zhang Z, Wang H. Heat kernel based local binary pattern for face representation. IEEE Signal Proc Lett 2010;17:308-11.
11. Tan X, Triggs B. Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE Tans Image Proc 2010;19:1635-50.
12. Heikkil M, Pietikainen AM. A texture based method for modeling the background and detecting moving objects. IEEE Trans Pattern Anal Mach Intell 2006;28:657-62.
13. Huang X, Li SZ, Wang Y. Shape Localization Based on Statistical Method using Extended Local Binary Patterns. Proc. International. Conf. Image and Graphics; 2004. p. 184-7.
14. Heikkila M, Pietikainen M, Schmid C. Description of interest regions with local binary patterns. J Pattern Recogn 2009;42:425-36.
15. Zhao G, Barnard M, Pietikäinen M. Lipreading with local spatiotemporal descriptors. IEEE Trans Multimedia 2009;11:1257-65.
16. Unay D, Ekin A, Jasinschi RS. Local structure-based region-of-interest retrieval in brain MR images. IEEE Trans Inf Technol Biomed 2010;14:897-903.
17. Yao CH, Chen SY. Retrieval of translated, rotated and scaled color textures. Int J Pattern Recogn 2003;36:913-29.
18. Murala S, Jonathan Wu QM. Local mesh patterns versus local binary patterns: Biomedical image indexing and retrieval. IEEE J Biomed Health Inf 2014;18:929-38.
19. Marcus DS, Wang TH, Parker J, Csernansky JG, Morris JC, Buckner RL. Open access series of imaging studies (OASIS): Crosssectional MRI data in young, middle aged, nondemented, and demented older adults. J Cogn Neurosci 2007;19:1498-507.

How to cite this Article: Venu N, Sulthana A. Local mesh patterns for medical image segmentation. Asian Pac. J. Health Sci., 2018; 5(1):134-138.

Source of Support: Nil, **Conflict of Interest:** None declared.