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Local Maximum Edge Binary Patterns for Medical Image Segmentation

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Abstract:

In this paper, local maximum edge binary patterns (LMEBP) feature extractor is proposed for medical image segmentation. The local region of image is represented by LMEBP, which are evaluated by taking into consideration the magnitude of local difference between the center pixel and its neighbors. First, image split in to sub blocks and LMEBP features are extracted from each sub block. 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 MRI database for medical image segmentation application. Results after being investigated, proposed method shows a significant improvement for segmentation of images.

Keywords **— Medical Image Segmentation; Local Binary Patterns (LBP); Texture.**

I. INTRODUCTION

A. Motivation

Nowadays lot of medical images are available and this data need to be stored for particular time period to maintain the medical data about the patient. But with data medical hospitals are not getting any benefit from the storage. From this an idea of using this data for automatic medical applications like medical image segmentation, medical image retrieval etc. 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 [2]. Rotational invariant texture classification using feature distributions is proposed in [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 local binary patterns (DLBP) for texture classification [6]. Guo et al. developed the completed LBP (CLBP) scheme for texture classification [7]. LBP operator on facial expression analysis and recognition is successfully reported in [8] and [9]. Xi Li et al. proposed multi-scale heat kernel based face representation, for heat kernels that performs well in characterizing the topological structural information of face appearance. Further, the local binary pattern (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 is discussed in [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 has been reported in [12], [13] and [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 local binary patterns 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 MR images [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 are extracted to describe the spatial structure of the local texture according to the organization of the edge pixels in a neighborhood.

B. Main contributions

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

(1) The LMEBP operator is used for medical image segmentation.

(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 local binary patterns and LMEBP 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.

II. LOCAL PATTERNs

A. Local Binary Patterns (LBP)

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, bio-medical image retrieval and finger print recognition.

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

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

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

Where $I(g_c)$ denotes 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.

Fig. 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].

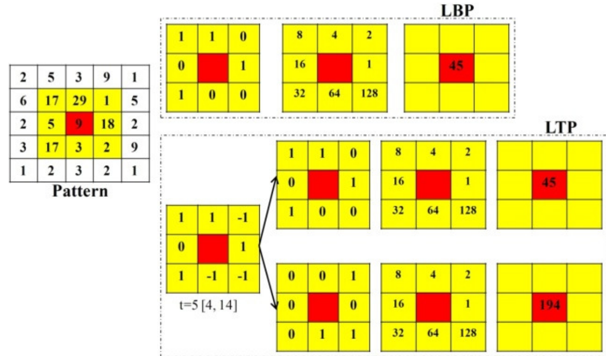

Fig. 1: Example of obtaining LBP and LTP for the 3×3 pattern

B. Local Ternary Patterns (LTP)

Tan and Triggs [11] extended the LBP to three valued code called local ternary patterns (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 (Eq. 3) and binary LBP code is replaced by a ternary LTP code as shown in Fig. 1.

$$\vec{f}(x, g_c, t) = \left.\begin{cases} +1, & x \geq g_c + t \\ 0, & |x - g_c| < t \\ -1, & x \leq g_c - t \end{cases}\right|_{x=(g_p - g_c)} \qquad (3)$$

More details about LTP can be found in [30].

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

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

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

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

C. Local Maximum Edge Binary Patterns (LMEBP)

In proposed LMEBP [18] for a given image the first maximum edge is obtained by the magnitude of local difference between the center pixel and its eight neighbors as shown below:

$$I^{'}(g_i) = I(g_c) - I(g_i); \quad i = 1, 2, \ldots, 8 \qquad (6)$$

$$i_1 = \arg_i \left(\max \left(\left| I^{'}(g_1) \right|, \left| I^{'}(g_2) \right|, \ldots, \left| I^{'}(g_8) \right| \right) \right) \qquad (7)$$

Where, *max(x)* calculates the maximum value in an array *'x'*.

If this edge is positive, assign '1' to this particular center pixel otherwise '0'.

$$I^{new}(g_c) = f\left(I^{'}(g_{i_1}) \right) \qquad (8)$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \qquad (9)$$

The LMEBP is defined as:

$$LMEBP(I(g_c)) = \left\{ I^{new}(g_c); I^{new}(g_1); I^{new}(g_2); \ldots I^{new}(g_8) \right\} \quad (10)$$

Eventually, the given image is converted to LMEBP image having values ranging from 0 to 511.

After calculation of LMEBP, the whole image is represented by building a histogram supported by Eq. (11).

$$H_{LMEBP}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f(LMEBP(j,k), l); \; l \in [0, 511] \qquad (11)$$

$$f(x, y) = \begin{cases} 1 & x = y \\ 0 & else \end{cases} \qquad (12)$$

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

Similarly, the remaining seven LMEBPs are evaluated using seven maximum edges (second maximum edge to eighth maximum edge) to obtain eight LMEBP histograms. Hence the feature vector of the proposed method is 8×512.

For rotational invariant LMEBP, we coded the LMEBP by gathering only the eight neighbors of a center pixel. Further the uniform patterns are also considered. These uniform patterns refer 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 are regarded as non-uniform patterns.

III. PROPOSED SEGMENTATION ALGORITHM

A. Proposed System Framework

Algorithm:

Input: Image; Output: Retrieval result

1. Load the gray scale image
2. Calculate the LMEBP features from an image.
3. Divide the LMEBP map in to sub blocks.
4. Apply the similarity between the sub blocks.
5. Based on the similarity merge the sub blocks.
6. Form the regions (segments) for final segmentation.

B. Block Matching

Feature vector for block-1, Q is represented as $f_Q = (f_{Q_1}, f_{Q_1}, \ldots f_{Q_{Lg}})$ obtained after the feature extraction. Similarly block-2 feature vector $f_{DB_i} = (f_{DB_{i1}}, f_{DB_{i1}}, \ldots f_{DB_{iLg}}); i = 1, 2, \ldots, |DB|$.

The goal is to select n best blocks that resemble the same region.

In order to match the sub blocks we used d_1 similarity distance metric computed by Eq. (13).

$$D(Q, DB) = \sum_{i=1}^{Lg} \left| \frac{f_{DB_{ji}} - f_{Q_i}}{1 + f_{DB_{ji}} + f_{Q_i}} \right| \qquad (13)$$

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

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In order to verify the effectiveness of the proposed algorithm, experiments were conducted on two brain 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 (CT) on OASIS-MRI dataset.

Fig. 2 and Fig. 3 illustrate the segmentation results of the proposed algorithm. Table 1 to Table 6 illustrates the results of 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.

Table 1: Comparison of various techniques in terms of score on Image (a) at different Salt-Pepper noise

Cl: Cluster

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	0.40	0.59	0.82	0.41	0.51	0.76	0.41	0.47	0.72	0.41	0.44	0.69
LMEBP	0.48	0.63	0.74	0.35	0.50	0.67	0.30	0.45	0.61	0.26	0.41	0.57

Table 2: Comparison of various techniques in terms of score on Image (b) at different Salt-Pepper noise

Cl: Cluster

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	0.44	0.52	0.65	0.44	0.50	0.71	0.39	0.43	0.65	0.42	0.43	0.56
LMEBP	0.46	0.55	0.69	0.49	0.54	0.74	0.43	0.47	0.68	0.46	0.48	0.60

Table 3: Comparison of various techniques in terms of score on Image (a) at different Gaussian noise

Cl: Cluster

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	0.40	0.59	0.82	0.41	0.51	0.76	0.41	0.47	0.72	0.41	0.44	0.69
LMEBP	0.48	0.63	0.74	0.35	0.50	0.67	0.30	0.45	0.61	0.26	0.41	0.57

Table 4: Comparison of various techniques in terms of score on Image (b) at different Gaussian noise

Cl: Cluster

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	0.83	0.82	0.83	0.50	0.57	0.65	0.47	0.58	0.65	0.47	0.54	0.67
LMEBP	0.85	0.86	0.85	0.56	0.61	0.69	0.53	0.64	0.67	0.51	0.58	0.64

Table 5: Comparison of various techniques in terms of number of iterations and execution time at different Salt-Pepper noise on Image (a)

NI: Number of iterations; TM: Execution Time (Sec.)

Method	Salt-Pepper 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
LMEBP	22	0.57	23	0.65	23	0.60	30	0.81

Table 6: Comparison of various techniques in terms of number of iterations and execution time at different Gaussian Noise on Image (a)

NI: Number of iterations; TM: Execution Time (Sec.)

Method	Gaussian Noise							
	5%		10%		15%		20%	
	NI	TM	NI	TM	NI	TM	NI	TM
LBP	24	0.50	26	0.56	22	0.46	28	0.40
LMEBP	19	0.45	18	0.45	18	0.41	21	0.35

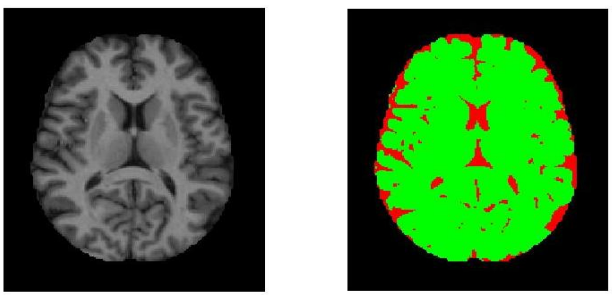

Fig. 2: Segmentation results of proposed method.

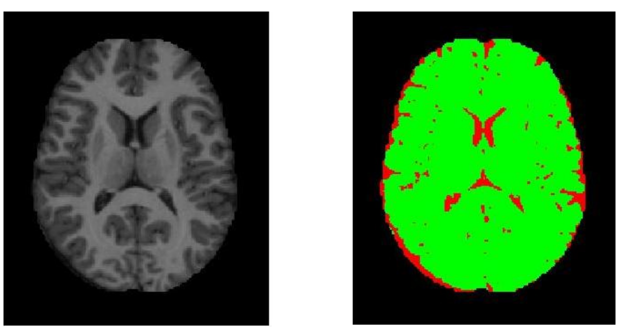

Fig. 3: Segmentation results of proposed method.

V. CONCLUSIONS

A novel methodology based on feature descriptors is proposed for medical image retrieval application. For feature extraction LMEBP is used and then merging of sub blocks concept is used for segmentation. The performance of the proposed method is tested on benchmark database. The results after being investigated proposed method outperforms the other existing methods in terms of segmentation score, number of iterations and time.

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