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Detection the Mid-Sagittal Plane in Brain Slice MR Images by Using Local Ternary Pattern

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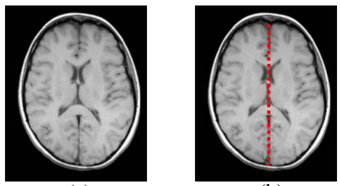
***Abstract*— The detection and localization of the mid-sagittal plane (MSP) in brain MR images is an important step in the diagnosis of brain pathologies and calculation of the symmetry between the two sides of a MSP. In this paper, a new method is proposed to locate MSP in T1-weighted MRI images, based on the computation of the different local texture between inter-hemispheric fissure (IF) region and the surrounding tissue. This method is based on local binary pattern technique. It is high-performance texture features to describe local structures. However, the LBP method is sensitive to noise. To overcome this disadvantage, we proposed a new method by using Block Local Ternary Patterns for achieving high classification accuracy thus improving the encoding of the texture feature. The proposed method is based on the second-moments method to solve the tilted brain problem; the rotation angle resulted is used to determine the initial line of the MSP. The performances of the proposed method are compared with the two extensions of LBP features, average LBP and block-based LBP. As it can be seen from the experimental data, the efficiency of the proposed method is better in comparison to the traditional LBP techniques in terms of classification accuracy.**

Keywords*— MRI Brain, Mid-Sagittal Plane(MSP), Local Binary Pattern (LBP), Local Ternary Pattern(LTP), Connected Component Labeling.

I. INTRODUCTION

Healthy regions of the brain tissues exhibit a rough bilateral symmetry. The interhemispheric fissure (IF) that bisects the brain into two brain hemispheres, which is the longitudinal dark and deep groove located in the midline boundary between the two cerebral hemispheres [1]. This fissure is commonly referred to as anatomical mid-sagittal plane (MSP), Fig. 1 shows the MRI 2-D slice brain image where the MSP is indicated by a red dotted line. Many researches have been invested recently in obtaining automatic, fast, and accurate MSP. The automatically detected location of MSP has many applications, such as image registration, and computer-aided detection (CAD) purposes, including lesion detection, diagnosis and evaluation the hemisphere symmetry [2]. In general, the present methods used for MSP detection follow either a feature based approach or a symmetry-based approach; in this paper, a feature based approach is used; the aim is to



(a) (b)

Fig. 1. Human brain MRI (a). T1-Weighted MRI brain axial slice (b) The mid-sagittal plane location on MRI brain axial slice indicated by red dotted line.

directly determine the IF according to its intensity and textural feature [3]. Textural features extraction approaches consist of two approaches: statistical and structural. A local binary pattern (LBP) operator offers a more powerful way to describe local structures. LBP has a simple theory and provides a unified description, including both properties of structural and statistical texture analysis methods [4]. To increase the discriminatory power of LBP texture features and improve classification accuracy, we propose yet another two new variants of LBP; average LBP (ALBP) and block-based LBP (BLBP) [5]. In this paper, we propose a BLTP texture feature algorithm that uses LBP techniques to find MSP in a 2-D slice, which is based on encoding the relationship between the MSP pixel's line and certain blocks of pixels in the surrounding neighbors. All the processes of detecting MSP are shown in Fig. 2.

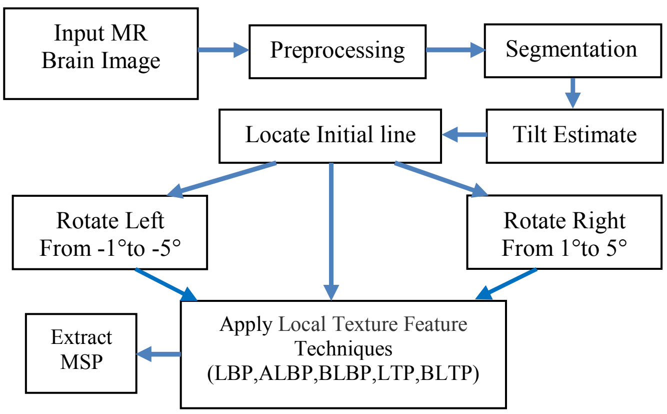


Fig. 2. Block diagram of proposed system.

II. RELATED WORKS

Various LBP techniques for texture feature representation and classification have been proposed; the LBP features have been applied in many applications, such as Image retrieval, texture analysis and face recognition. In image retrieval the frequencies of different local image intensity patterns are calculated and used as feature vectors to retrieve similar image [6]-[8]. The texture analysis, that represented the rotation invariant texture classification based on local binary patterns [9] [10]. Finally, face recognition, the LBP has been widely used in various computer vision applications because of its simplicity and robustness to illumination variations [4] [11]-[13]. Ahmet Ekin [3] tried to detect midsagittal plane for MR brain images, in the first step; to test if the slice image has an interhemispheric fissure by analyzing the intensity profile along each image line, in second step; to detect the feature points that correspond to the interhemispheric fissure and finally, outlier-robust RANSAC algorithm is applying for fitting a mid-sagittal line. G. MALYADRI [14] attempted to detect brain tumor, in the first step; preprocess the brain slice image by bias field correction and histogram matching are used, in second step, separated the interest of the region from the background by applying the cluster algorithm, finally the feature extraction from image texture by used LBP. In this work, we have found that LBP is effective in representing and classifying textures between MSP and neighboring pixels of brain tissue.

III. PREPROCESSING

In this phase, image is enhanced where finer details are improved and noise is removed from the image. Image enhancement is a technique that increases contrast, improves quality and highlights an object of interest in an image. Basically, this process is based on apply different filtering techniques. In this paper, the Preprocessing proposed consists of two steps: median filter and sharpening filter. Median filter is used to remove the noise from the images like salt and pepper. In the median filter value of pixel is computed by the median of the neighboring pixels. The sharpening filter can be achieved by using different high pass filters to an image. It is used to highlight the fine details and to remove blurring from edges of an image and make it sharper [15]. In this paper, Gaussian high pass filter is used to enhance the boundaries of the brain object in an image.

IV. SEGMENTATION

Image segmentation is a useful operation in many image processing applications. Segmentation divides the image into several regions based on the unique homogeneous image pixel. In this paper, we used connected component labeling algorithm that helped the system to distinguish and separate the brain slice object from background object. It is used to detect connected regions in binary digital images, by using 0's and 1's pixels, where 1's represent foreground pixels, and 0's the background pixels [16]. Connected component labeling works by scanning an image, pixel-by-pixel (from top to bottom and left to right) based on pixel connectivity, i.e. all pixels in a connected component that share the same set of pixels intensity values. To find and extract all the connected components, we apply the following iterative procedure [17]:

$$X_k = (X_{k-1} \oplus B) \cap A \;, k = 1,2,3,... \tag{1}$$

Where A is a test image that contains one or more connected components, B is an appropriate structuring element. The iterative procedure is terminated, when $X_k = X_{k-1}$ and X_k contain all the connected components of A.

V. TILT ESTIMATE

In some cases, the patient's head may be tilted during the scanning process. MSP is the plane that travels vertically and divides the brain into similar hemispheres. MSP is employed to correct rotation and tilting of the brain slice [18]. Many practical applications emphasize on the important role of the rotation angle; the simple and efficient method uses the orientation of the inertial ellipse for a given closed region. The proposed method is based on the second-order area moments method to detecting the brain tilted angle, by calculate the angle between the x-axis and the major axis of the brain ellipse. The rotation angle resulted is used to determine the initial line of the MSP [19]. Moments are generally classified by the order; the zeroth moment (m_{00}) represents the total number of pixels in the object, *i.e.* the object's area. The two first-order moments (m_{10}, m_{01}) are used to locate the center of mass of the object (x_c, y_c) . Second order moments, (m_{11}, m_{02}, m_{20}), known as the moments of inertia, may be used to determine several useful object features, such as *principal axes* of the object (major and minor principal axes respectively), which are used to calculated the orientation of angle ϕ between the major axis (long line) and the x-axis see [20].

$$x_c = \frac{m_{10}}{m_{00}}, \quad y_c = \frac{m_{01}}{m_{00}} \tag{2}$$

$$a = \frac{m_{20}}{m_{00}} - x_c^2 \;, \; b = 2\left(\frac{m_{11}}{m_{00}} - x_c y_c\right), \; c = \frac{m_{02}}{m_{00}} - y_c^2$$

$$w = \sqrt{6(a + c - \sqrt{b^2 + (a-c)^2})} \tag{3}$$

$$l = \sqrt{6(a + c + \sqrt{b^2 + (a-c)^2})} \tag{4}$$

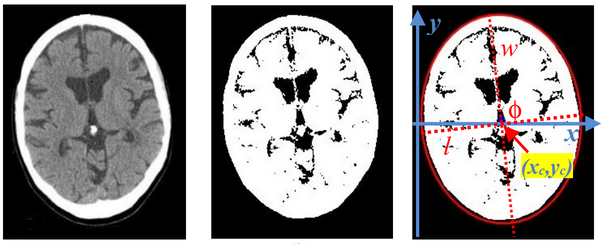
$$\phi = \frac{\tan^{-1}\left(\frac{b}{a-c}\right)}{2} \tag{5}$$

Where (x_c, y_c) is the object center, w and l are the major and minor axis lengths, and ϕ is the angle between the x-axis and the major axis. The ellipse fit is computing by matching second-order moments. The measurements used to compute an ellipse based on second moment method, these measurements are: Major axis length (*w)*, Minor axis length (*l)* and Orientation (ϕ). The mathematical formula used to plot an ellipse can be explained by equations:

$$X(t) = x_c + w \cos t \cos \phi - l \sin t \sin \phi \tag{6}$$

$$Y(t) = y_c + w \cos t \sin \phi + l \sin t \cos \phi \tag{7}$$

The values of an angle (ϕ) range from 90° to -90°. Fig. 3 illustrates an example of computing the tile angle based on the major axis of the brain image ellipse, Fig.3-a shows the original T1-Weighted MRI brain axial slice image, while Fig. 3-b shows the result of the image after applying the preprocessing stage, which will convert the input image to the binary image, remove the noise, and extract connected object. Fig. 3-c shows the enclosing ellipse in order to determine the tilt angle. The solid blue lines represent the (x,y) axes, the red dots lines represent the major and minor lengths, and ϕ is the orientation angle between the x-axis and the dotted line of the major axis.



(a) (b) (c)

Fig. 3. detection the tilt angle of MRI scan slice brain image, (a) original image,(b) binary image after preprocessing and segmentationt, (c) detection the tilt angle based on compute ϕ between major axis of the ellipse and x-axis.

VI. LOCAL BINARY PATTERN

Local binary pattern is a powerful tool to describe the local attributes of a texture. The characteristic of LBP's are computationally efficient and simple nonparametric [12]. It was initially introduced by Ojala et al. [21].The original LBP operator describes the texture in the image by divides the image into cells. In each cell, comparing the intensity values of its neighboring pixels with the gray value of its center pixel and representing the result as a binary code, which is usually converted to decimal number for convenience [6].

$$LBP_{g,r} = \sum_{g=0}^{g-1} S(t_g - t_c)2^g \tag{8}$$

Where t_c is the gray value of the central pixel, t_g is the value of its neighbors; for neighborhoods pixels, we will use the notation (g,r) where g is the number of neighbors point $(g \geq 8)$ on a circle of radius $r > 0$, and the result of $S(t_g - t_c) = 1$ if $t_g > t_c$ and $S(t_g - t_c) = 0$ if $t_g \leq t_c$, Fig. 4 illustrates an example of the binary thresholding process of the circular $((g,r) = (8, 1))$ neighborhood. The LBP code is then calculated in a clockwise direction. In this paper, the features extract of the MSP based on total the LBP codes along the tested line.

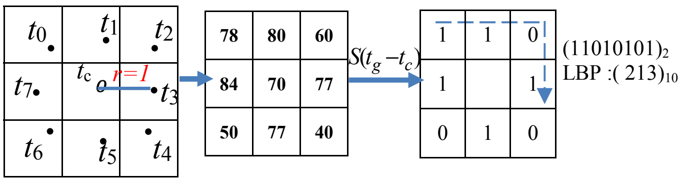


Fig. 4. An example of basic LBP operator

A. Average Local Binary Pattern

In order to improve texture encoding, we propose a new variant of LBP feature, so-called the average LBP (ALBP). ALBP is extensions to LBP feature in describing local texture structure. An LBP feature can describe the relationship between the center pixel and its neighbors, whereas an ALBP feature represent more specific relations and looking at intensity differences among the neighbors pixels. This method is based on comparing each neighbor pixel around the center pixel with the computed average value of all neighbors' pixels around its center [22].

$$ALBP_{g,r} = \sum_{g=0}^{g-1} S(t_g - t_e)2^g \tag{9}$$

$$\text{Where} \quad t_e = (\sum_{g=0}^{g-1} t_g) / g$$

Where t_e is the average gray scale value of all neighbors pixels (t_g), g is the total number of neighbors pixels and r is a radius. The changes in the values parameters g and r, cause a variety of ALBP feature vectors.

B. Block Local Binary Pattern

In this paper, another new variant of LBP features is proposed, it's called Block LBP; BLBP features provide the discriminatory power of LBP texture features, and improve the encoding of LBP texture features and classification accuracy. The BLBP feature extracts intensity differences between the center pixel and surrounding average intensity values of pixels in blocks, thus can be shared more intensity values of pixels in blocks, that contain different information that is not captured by the original LBP features. The mathematical formula used to calculate the BLBP values is given by the following equation [5]:

$$BLBP_{P,R} = \sum_{P=0}^{P-1} S(g_{p,s} - g_c)2^p \quad \text{where} \tag{10}$$

$$g_{p,s} = (\sum_{r=0}^{R} g_{p,r}) / R + 1$$

Where $g_{p,r}$ is the gray scale value of all neighbor pixels in block with radius r *and* $g_{p,s}$ represent the average intensity value of all the pixels along the p^{th} neighbor's pixels direction that are surrounding the center pixel g_c with radius R.

VII. *Local Ternary Pattern (LTP)*

The LBP is sensitive to noise, because a small gray change of the central pixel may causes drastic change of the LBP code. In order to address such a flaw, Tan and Triggs [23] extended the basic LBP to a version with three-value codes (-1, 0 and 1), that is less sensitive to the noise and more discriminatory in uniform regions called local ternary pattern (LTP). LTP is a ternary or a 3-valued code, instead of a binary pattern includes a constant $\pm t$ threshold around zero to make the thresholding more tolerable to noise. The LTP code is generated by comparing the intensity values of the neighboring pixels with the gray value of its center pixel, threshold (*t*) used to improved resistance to noise. Based on this comparison the neighborhood pixels values will be assigned one of the three values +1 or 0 or -1, the LTP equation can be written as [12]:

$$LTP(T_i) = \begin{cases} 1 & P_i \geq (i_c + t) \\ 0 & |P_i - i_c| \leq t \\ -1 & P_i \leq (i_c - t) \end{cases} \qquad (11)$$

Where P_i and i_c represents the grey level intensity values of the neighboring pixels and the central pixel respectively, (*t*) is a user-defined threshold and (*i*) is the number of neighboring pixels surrounding the center pixel (*c*). Fig. 5 illustrates an example of computing the LTP code with t=5, the zone of width ±5 is [65,75]. The length of the pattern string with ternary representation is very high (3^n). In order to reduce the feature dimension of the pattern histogram and gain simplicity, the ternary pattern is converted into a binary pattern (2^n) by splitting each ternary pattern into two different parts; positive (high) and negative (low) [24].

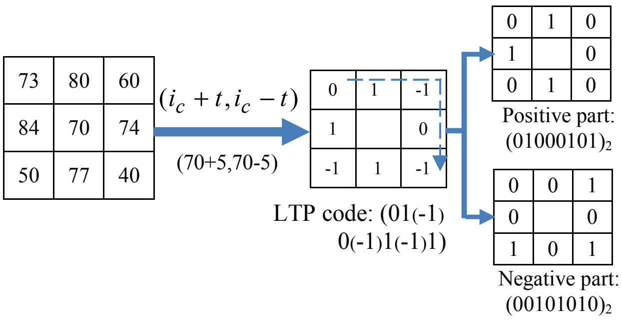


Fig. 5. An example to compute the LTP encoding procedure with eight neighboring pixels,

A. *Block Local Ternary pattern*

Block-LTP is an extension of LTP that is less sensitive to noise and able to capture larger texture structures, to enrich the texture feature encoding and classification macrostructure information [25]. The encoding procedure of Block-LTP is based on two stages: first, the intensity average of all surrounding blocks of pixels is computed and create a new window with size (*g,r*), where *g* is the gray scale value of all neighbor pixel in block with radius *r*, and second, LTP method to compute LTP code and produce positive and negative parts. Fig. 6 illustrates an example of computing the Block-LTP. texture features between MSP region is indicated by red dotted line and surrounding tissue.

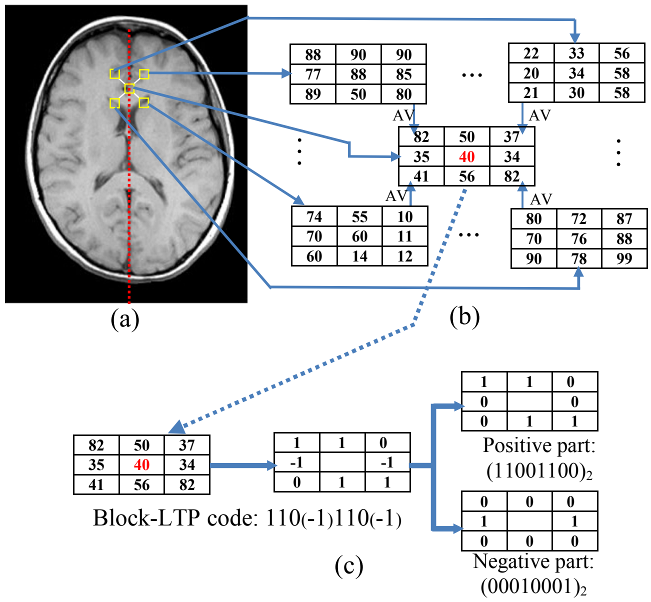


Fig. 6. Illustration of Block-LTP operator (a) Original brain slices image where MSP is indicated by a red dotted line, (b) calculation of the new block based on blocks average (AV) results. (c) Block-LTP Code and their Positive and Negative codes.

VIII. Proposed Work

A. *Algorithm for calculating the Block-LTP code*

The first step is to convert RGB color space image to the grey scale image. Second step a new block is computed based on intensity average of all surrounding blocks of pixels. Finally, compute Block-LTP code and produce positive and negative parts. The following steps are followed to compute Block-LTP:

- Input the training image from the image set,
- Initialize the values of radius r_1 *and* r_2,
- Convert RGB color space image into a gray scale,
- **For** each center pixel t_{c1} at radius r_1 **do**
- **For** each neighbor pixel t_{g1} around the t_{c1} **do**
- Calculate the average value to the all neighbors pixels t_{g2} around the center pixel t_{c2} at radius r_2,
- Create a new window with size (t_{g1}, r_1),
- Compute the LTP code number by applying (11),
- splitting the LTP code result into two different parts; positive (high) and negative (low),
- **End For**
- **End For**
- Calculate the summation of each part of LTP code separately.

B. Algorithm for Detecting Mid-sagittal Plane

The inter-hemispheric fissure contains cerebral spinal fluid (CSF) that gives a weak MR signal on T1-weighted images. Therefore, image intensity in this region is generally low [1]. In this paper, the extract MSP based on compute the intensity differences between IF and the surrounding tissue, by applying LBP techniques. The proposed algorithm for detecting the MSP line is implemented in following steps:

- Convert RGB image to grey scale and binary images applying Otsu's method [26],
- Calculate the connected components of the objects of the binary image by applying (1) and select the maximum connected components object area,
- Generate an initial line depend on:
    1. Calculate the centroid of the segment object image by applying (2)
    2. Calculate the length values of major-axis by applying (3),
    3. Calculate the angle of a rotating object ϕ by applying (5),
- rotate the initial line from 1°to 5° and -1°to -5° by 1° degree increment,
- **For** each rotate angle **do**
- Compute the LBP's techniques and Block-LTP by applying Algorithm (*A*) with keeping a track of the angle.
- **End For**
- Estimate the best-fit line by taking the minimum of sum results among the values of Low-LTP and Low-BLTP; and High of sum results among the values of High-LTP and High-BLTP.

IX. EXPERIMENTS AND RESULTS

In this work, all stages of detecting MSP line system are implemented in MATLAB R2016A with a set of 50 brains MRI images, all the tested images are stored in JPEG format in different sizes. The proposed system consists of four stages: preprocessing, segmentation, Tilt Estimate and applying LBP's techniques. For testing the algorithm of detection MSP, Fig. 7 illustrates an example to detect MSP line; Fig.7-a shows image brain slice, Fig.7-b shows the result of the image after pre-processing and segmentation. The value of the tilt angle is used to determine the slope of the initial line that represent MSP in the brain slice; this line passes through the centroid of the brain object's slice. In this example the value of tilt angle is -83.5° as shown in Fig.7-c. Fig.7-d shows the initial line on gray scale image. To improve accuracy MSP detection, we tested the neighbor area around the initial line, by applying a number of rotation angles e.g. from 1°to 4° by 1° degree increment i.e. clockwise direction as shown in Fig.7-e through Fig.7-h. Fig.7-i through Fig.7-l representing the rotation angles e.g. from -1°to -4° i.e. anticlockwise directions around the center. In this paper, the features extract of the MSP for each LBP's application, such as (LBP, ALBP, BLBP, LTP, and BLTP), is based on calculating the sum of all codes along the tested initial line as shown in Table I.

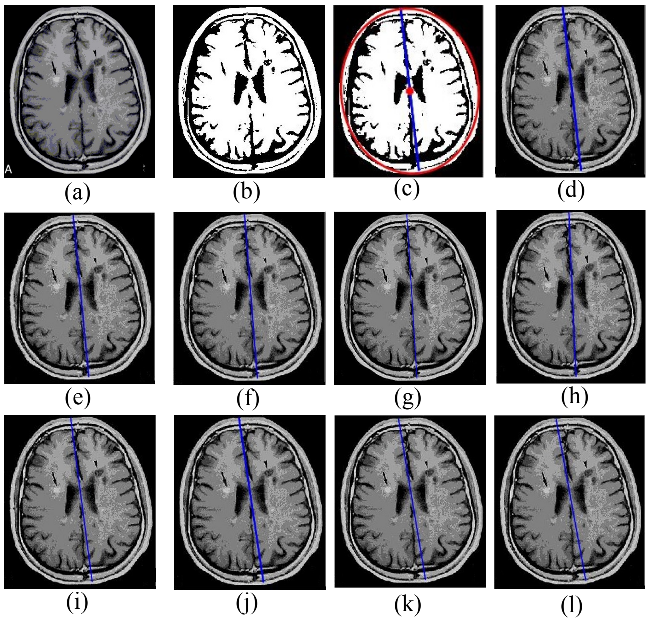


Fig. 7. An example of detect of MSP. (a) Original brain slices image, (b) pre-processing and segmentation image, (c) detection the tilt angle of the brain object, (d) the initial line on gray scale image, (e-h) rotation the initial line from 1° to 4°, and (i-l) rotation the initial line from -1° to -4°.

In order to evaluated the performance of the presented algorithm in terms of accuracy by using the following accuracy gauge:

$$Accuracy = \frac{Number\ of\ located\ MSP}{Number\ of\ images\ in\ the\ dataset} \times 100 \quad (12)$$

TABLE I. EXAMPLE OF COMPUTING THE FEATURES EXTRACT OF THE MSP FOR EACH LBP'S APPLICATION WITH RANGE ANGLES FROM -1° TO -4° AND 1° TO 4°

Rotation angle	LBP	ALBP	BLBP	LTP-High	LTP-Low	BLTP High	BLTP Low
Initial line (-83.5°)	39316	69568	18838	34325	40713	18049	66252
+1°	38077	63174	18774	33073	42219	16710	65511
+2°	35393	66577	17703	31472	44246	16161	66542
+3°	38556	61043	18685	33864	39477	15709	63928
+4°	**44111**	**59618**	**22077**	**39867**	**35589**	**19102**	**62258**
-1°	41228	71485	14846	35668	37636	13537	70744
-2°	42673	73927	8664	36881	37178	6763	75954
-3°	39322	76354	5461	34075	39184	5114	79622
-4°	41621	77929	6557	35701	37703	5464	79343

For testing the performance of proposed system by using accuracy measure and consuming time: the accuracy of detecting MSP is calculated by using (12) and the average processing time of all stages of proposed system steps on an Intel core processor i7 (2.4 GHz) with 160G memory are shown in Table II.

TABLE II. PERFORMANCE OF PROPOSED SYSTEM

Performa-nce	Features						
	LBP	**ALBP**	**BLBP**	**LTP-High**	**LTP-Low**	**BLTP High**	**BLTP Low**
Accurancy (%)	0.73	0.67	0.87	0.8	0.75	0.89	0.93
Consumer time(s)	0.64	0.65	0.68	0.73	0.75	0.77	0.76

X. CONCLUSION

This paper introduces local texture features techniques applied on T1-Weighted MRI brain axial slice images to achieve automatic detection of MSP. New variants of LTP features, high BLTP and low BLTP, are proposed. The new variants are less sensitive to noise and able to capture larger texture structures and classification macrostructure information than the original LBP features. There are two conclusions, the first conclusion, The MSP detection accuracy increases when the intensity of the differences between the IF and surrounding tissue is high, as shown in Table I, the best result is achieved at angle +4°, where the highest values at (LBP, BLBP, high LTP, and high BLTP) and lowest values at (ALBP, Low LTP and low BLTP). The second conclusion, there are some cases of brain slice with tumors; the MSP was detected accurately in slices that have smaller tumors. The comparison among the performances of LBP, ALBP, BLBP, LTP, and BLTP, shows that the best result is achieved by using the BLTP method which reaches the best overall performance as shown in Table II.

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