BRAIN TUMOR DETECTION BY USING MOMENTS AND TRANSFORMS ON SEGEMENTED MAGNETIC RESONANCE IMAGES

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ABSTRACT

In this paper, we propose a novel approach to detect tumor in Magnetic Resonance (MR) brain images. The feature set is extracted by using 2D Continuous Wavelet Transform (2D-CWT) and segmentation is done using Improved Incremental Self Organize Mapping (I2SOM). Symmetry in the MR image is analyzed by using Zernike Moments (ZMs) or Polar Harmonic Transform (PHTs). The region of tumor is extracted by using PHTs. The effectiveness of proposed method is analyzed by experiments on 40 normal and noisy brain images. It is observed that tumor detection is successfully realized for the tumorous 20 MR brain images.

1. INTRODUCTION

In a common parlance tumor is an uncontrolled growth of the cells. In common cases brain tumor causes "mass effect" that produces asymmetry. The measure of asymmetry leads us to diagnose the tumor. Prior to segmentation phase, we need a set of features that are true representative of physical process under consideration. Dokur et al. (2000) proposed a technique based on neighborhood intensities for the classification of MR images. Another technique based on Intensity and morphological features is developed by Qian et al. (1999). Dokur (2008) developed a feature based method constructed by taking 2D-Discrete Cosine Transform (DCT) over window. Co-occurrence matrix and spatial gray level dependence matrices are also used to extract texture features in ultrasound images (Haering & Lobo, 1999; Wu et. al., 1992).

Various techniques have been evolved to carry out the process of segmentation. Modified region growing method used for segmentation includes the orientation control along with intensity (Kavitha et. al., 2012). Clustering methods, such as K-Means used for segmentation of brain tumor (Dhanalakshmi & Kanimozhi, 2013). Jose et al. (2014) proposed Fuzzy C-Means method for segmentation and Maksaud et al. (2015) discussed hybrid method that combines K-Means clustering with Fuzzy C-Means method to provide privilege of using advantages of both of these techniques. Incremental supervised neural network (ISNN) requires class of input data to be specified prior to training phase.

Asymmetry has been calculated for lateral ventricles by using boundary and medical descriptors and for anatomy of cortex (Styner & Gerig, 2001; Thompson et. al., 2001). Fazli and Nadirkhanlou (2013) computed geometrical symmetry axis for tumor detection using fast bounding box (FBB) technique. Geometric Moments (GMs) are used to determine symmetry axis (Rohit & Chitaliya, 2014).

Huang and Leng (2010) utilized Hu moments for the purpose of pattern recognition and investigated its fluctuations for invariants. Iscan et al. (2010) used Hu moments for tumor detection in MR images. Invariance properties of Zernike moments (ZMs) have exploited for the application of Optical Character Recognition (OCR) (Rao et. al., 2013). Yap and Jiang (2010) put forth feature extraction technique namely Polar Harmonic Transform (PHT) based on the orthogonal polynomials. Calculation of PHT is faster than ZMs due to absence of factorial terms.

The rest of the paper is organized as follows. An overview of segmentation technique using I2SOM, 2D-CWT, and feature extraction techniques namely radial moments and transforms are discussed in Section 2. The proposed algorithm for brain tumor detection is given in Section 3. Experiments and conclusion are included in Section 4.

2. SEGMENTATION AND FEATURE EXTRACTION

Our process includes three main steps: Segmentation, Asymmetry determination and tumor extraction.

<u>Improved Incremental Self Organize Mapping (I2SOM)</u>

We used I2SOM technique for segmentation of MR images. It is a type of unsupervised Kohonen neural network clustering technique. Automatic Threshold (AT) required for class identification can be calculated as under:

$$AT = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x_{ij} - m_j\right)^2} \quad (1)$$

In Eq. (1) x_{ij} is input feature vector selected from feature space of size $M \times N$ in which M is number of feature vectors and N represents length of each vector. m_j Denotes the mean of features in column j. Then this network is trained for the training data set using AT value to specify whether input matches with the class of the closest node.

Zernike Moments (ZMs)

ZMs are calculated over polar coordinates (r, θ) and condition $|r| \leq 1$, therefore firstly image is mapped to unit circle to get its coordinates in the polar domain. This mapping can be outer circle or inner circle. Discrete approximation of the continuous ZMs is given below:

$$Z_{pq} = \frac{p+1}{\pi}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} V_{pq}^{*}\left(x_i, y_j\right) f\left(x_i, y_j\right) \Delta x \Delta y \quad (2)$$

In our study we are using outer circle mapping. Therefore values of x_i, y_j and Δx, Δy are calculated as follow:

$$x_i = \frac{2i+1-N}{N\sqrt{2}}, y_j = \frac{2j+1-N}{N\sqrt{2}} \text{ and } \Delta x = \Delta y = \frac{\sqrt{2}}{N} \quad (3)$$

ZMs have high computational complexity due to the involvement of factorial terms. To avoid this state, recursion method is used for the calculation of radial polynomial [5].

Polar Harmonic Transforms (PHTs)

Three types of transforms are collectively taken under the heading of PHTs namely Polar Complex Exponential Transform (PCETs), Polar Sine Transform (PSTs), and Polar Cosine Transform (PCTs) [12]. For an image $f(r, \theta)$ mapped over a unit circle, two dimensional PHTs of order p and repetition q are given as follow:

$$M_{pq} = \lambda \sum_{\substack{i=0 \\ x_i^2 + y_k^2 \leq 1}}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) H_{pq}^{*}(x_i, y_k) \Delta x_i \Delta y_k \quad (4)$$

Here $H_{pq}^{*}(r, \theta)$ is the complex conjugate of the base function $H_{pq}(r, \theta)$ given as:

$$H_{pq}(r, \theta) = R_p(r) e^{iq\theta} \quad (5)$$

Where $R_p(r)$ is the radial kernel, $j = \sqrt{-1}$ and $\theta = \tan^{-1}(y/x)$. Radial kernels are calculated as given in below:

$$R_p(r) = e^{j2\pi pr^2};\ R_p^C(r) = \cos(\pi pr^2);\ R_p^S(r) = \sin(\pi pr^2)$$

3. PROPOSED METHOD

Feature vectors of the image are extracted utilizing powerful feature representation of 2D-CWT. Transforms are taken at a number of different scales. After this, I2SOM is used to segment the different tissues of the brain. Brain region is then extracted from the background by assigning high intensity values to the brain region and low intensity values to the background. Symmetry axis of the brain area can be calculated by using following linear equation:

$$y_{sym} = x.\cos(\theta_h) + y.\sin(-\theta_h) \quad (6)$$

Eq. (6) represents symmetry axis y_{sym} making an angle θ_h with y-axis. θ_h can be obtained from following expression:

$$\theta = \frac{1}{2} Arc\tan\left(\frac{2m_{11}}{m_{20} - m_{02}}\right) \quad (7)$$

m_{11}, m_{20}, and m_{02} are the geometrical moments. Next part of the process is to split the image into two parts at its symmetry axis. ZMs and PHTs are calculated on each of these images of hemispheres. Calculated Moments and transforms are then compared using Euclidean distance (ED) to find the degree of asymmetry across symmetry axis to find out the presence of tumor cells.

Finally tumor region can be extracted by using PHTs. Minimum intensity values present in left and right hemispheres are calculated and taken as L_{min} and R_{min} respectively. Mean of the pixel intensity values, which lie on the symmetry axis, is derived and denoted as I_{mean}. Pixels with intensity values in range $[L_{min}: I_{mean}]$ and $[R_{min}: I_{mean}]$ in left and right hemispheres are kept, and otherwise discarded by assigning them 0 intensity value. It gives an image $L(x, y)$. In the next part, PHTs of the image is calculated. Mean of real and imaginary parts of lower order transforms are derived and denoted as μ_1 and μ_2 respectively. For higher order mean for real and imaginary parts is represented as μ_3 and μ_4 respectively. Threshold intensity value can be calculated as:

$$T = \frac{\mu_5+\mu_6}{2} \qquad (8)$$

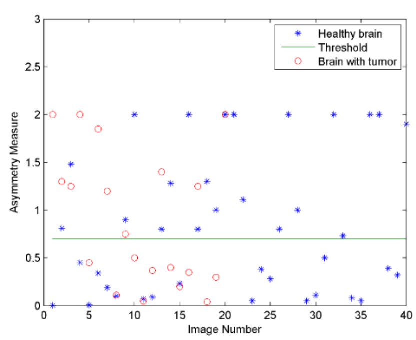
Where $\mu_5 = \mu_3 - \mu_1$ and $\mu_6 = \mu_4 - \mu_2$

Image $TR(x,y)$ highlighting the tumor region constructed by using the threshold intensity value calculated in Eq. (8) as:

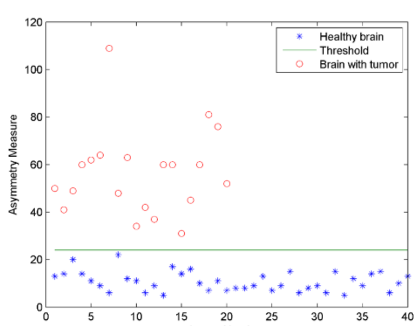
$$TR(x,y) = \begin{cases} I(x,y) if L(x,y) < T \\ 0 \qquad\qquad otherwise \end{cases}$$

4. RESULTS AND CONCLUSION

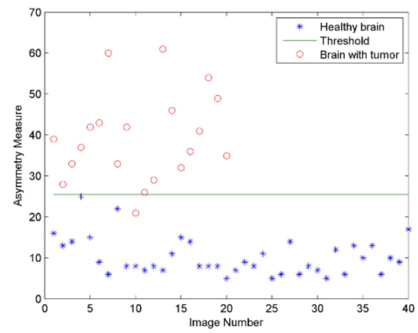
Feature vector space is formed by taking transforms of an image at scale values (0.8, 1.4, 2.0, 2.6, 3.2, 3.8, 4.4 and 5.0). Learning rate of I2SOM is kept constant ($\mu = 0.05$). Solutions of the I2SOM are used to get segmented image. ZMs and PHT of order 15 with outer circle mapping are calculated for each hemisphere. Asymmetry measure between these two feature sets gives the indication about tumor.
Figure 1 shows the plots for three different techniques including previous technique using Hu Moments. In these plots horizontal line in the middle of the plot represent threshold value signify decision boundary about state of the brain.



(a)



(b)



(c)

Figure 1 (a) Asymmetry Measure using Hu moments (Previous Method) (b) Asymmetry Measure using Zernike moments (c) Asymmetry Measure using PHT.

We check robustness of our method by adding Rician noise of standard deviation 10 in images. It was investigated that our methods works well in this case also without any need to change the threshold value. Figure 2 shows the results for the noisy images.

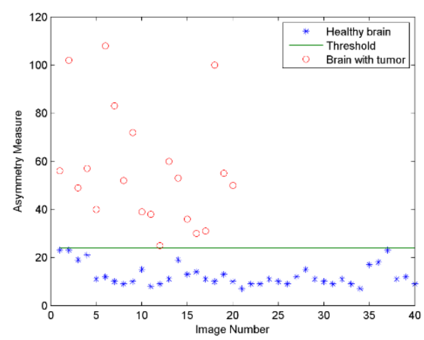
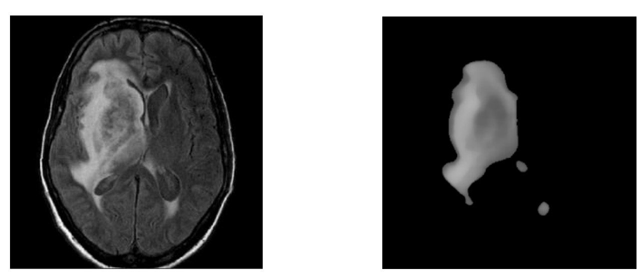


Figure 2 Asymmetry measure for noisy images

Tumor region can be derived by using the technique as discussed earlier as shown in Figure 3.



(a) (b)

Figure 3 (a) Brain image with tumor (b) Derived tumor region.

In this paper, segmentation process is combined with orthogonal polynomial based feature extraction technique to isolate healthy and infected cases. To realize the segmentation process, 2D-CWT and I2SOM are exploited together. ZMs and PHTs are calculated for each hemispheres of the brain to form feature sets for both hemispheres. 72 features of each hemisphere are calculated and compared to measure asymmetry. Threshold value for both the noisy and normal images remains 23 units. Resolution (minimum isolation between normal and tumorous cases) is 9 units of distance and 2 units for noisy images.

REFERENCES

[1] A. Jose, S. Ravi & M. Sambath, Brain tumor segmentation using K-Means Clustering and Fuzzy C-Means algorithms and its area calculation, *"International Journal of Innovative Research in Computer and Communication Engineering"*, 2, 3496-3501, 2014.

[2] A. K. Rohit & M. G. Chitaliya, A novel approach for content based MRI brain image retrieval, *"International Journal of Soft computing and Engineering"*, 4, 21-29, 2014.

[3] A. R. Kavitha, C. Chellamuthu, & K. Rupa, An efficient approach for brain tumor detection based on modified region growing and neural network in MRI images, *"Proceedings of International Conference on Computing, Electronics and Electrical Technologies, IEEE"*, 2012.

[4] C. M. Wu, Y. C. Chen & K. S. Hsieh, Texture feature for classification of ultrasound liver images, *"IEEE Transactions on Medical Imaging"*, 11, 141-152, 1992.

[5] C. Singh & R. Upneja, Fast and accurate method for high order Zernike moments computation, *"ScienceDirect: Applied Mathematics and Computation"*, 218, 7759-7773, 2012.

[6] E.A. Maksaud, M. Emlogy & R. Al-Awadi, Brain tumor segmentation based on a hybrid clustering technique, *"ScienceDirect: Egyptian Informatics Journal"*, 16, 71-81, 2015.

[7] M. Styner & G. Gerig, Medial models incorporating object variability for 3D shape analysis, *"Information Processing in Medical Imaging, Springer"*, 2082, 502-516, 2001.

[8] N. Haering & V. Lobo, Features and classification methods to locate deciduous trees in images, *"Computer Vision and Image Understanding"*, 75, 133-149, 1999.

[9] P. B. Rao, D. V. Prasad & P. Kumar, Feature extraction using Zernike Moments. *"International Journal of Latest Trends in Engineering and Technology"*, 2, 228-234, 2013.

[10] P. Dhanalakshmi & T. Kanimozhi, Automatic segmentation of brain tumor using K-Means Clustering and its area calculation, *"International Journal of Advanced Electrical and Electronics Engineering"*, 2, 130-134, 2013.

[11] P. M. Thompson, M. S. Mega, C. Vidal, J. L. Rapoport & A. W. Toga, Detecting disease-specific patterns of brain structure using cortical pattern matching and a population-based probabilistic brain atlas, *"Inf Process Med Imaging, Springer-Verlag Berlin Heidelberg"*, 2082, 488-501, 2001.

[12] P. T. Yap, X. Jiang & A. C. Kot, Two-dimensional Polar Harmonic Transforms for invariant image representation, *"IEEE Transactions on Pattern Analysis and Machine Intelligence"*, 32, 1259-1270, 2010.

[13] S. Fazli & P. Nadirkhanlou, A novel method for automatic segmentation of brain tumors in MR images, *"Cornell University Library, Computer Vision and Pattern Recognition",* 2013.

[14] W. Qian, L. Li & P. Clarke, Image feature extraction for mass detection in digital mammography: Influence of wavelet analysis, *"Medical Physics"*, 26, 402-408, 1999.

[15] Z. Dokur and T. Olmez, Classification of magnetic resonance images using a novel neural network, "*Proceedings of the IEEE-EMBS Asia Pacific conference on biomedical engineering*", 2000.

[16] Z. Dokur, A unified framework for image compression and segmentation by using an incremental neural network, "*ScienceDirect: Expert systems with applications*", 34, 611-619, 2008.

[17] Z. Huang & J. Leng, Analysis of Hu's Moment invariants on image scaling and rotation, "*Proceedings of IEEE International Conference on Computer Engineering and Technology",* 2010.

[18] Z. Iscan, Z. Dokur & T. Olmez, Tumor detection by using Zernike Moments on segmented magnetic resonance brain images, *"ScienceDirect: Expert Systems with Applications"*, 37, 2540-2549, 2010.