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Magnetic Resonance Brain Image Segmentation and Detection of Tumor in Medical Imaging

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Abstract: Magnetic Resonance Imaging has become a widely used method of high quality medical imaging. Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. Medical imaging techniques are used to image the inner portions of the human body for medical diagnosis. Brain tumor is a serious life altering disease condition. Image segmentation plays a significant role in image processing as it helps in the extraction of suspicious regions from the medical images. In this paper we proposed segmentation of brain MRI image using Improved Incremental Self Organize Mapping (I2SOM) and Asymmetry in the MR brain image is analyzed by using Chebyshev Harmonic Fourier Moments (CHFMs) on each of the tissues segmented in the head. Once the presence of asymmetry is confirmed, it leads us to the diagnosis of the tumor. After the presence of tumor, the region of tumor is extracted by using Polar Harmonic Transforms (PHTs) as these transforms are found to be good descriptors in the field of image analysis and impose less computational complexity due to the absence of any factorial term in the calculation of radial kernels. The effectiveness of the proposed method is analyzed by doing experiments on 20 MR brain images with tumor and 20 normal MR brain images. It is observed that tumor detection is successfully realized for 20 MR brain images with tumor.

Keywords: Tumor detection, Chebyshev Harmonic Fourier Moments; Polar Harmonic Transforms; Segmentation.

I. Introduction

The tumor is basically an uncontrolled growth of cancerous cells in any part of the body, whereas a brain tumor is an uncontrolled growth of cancerous cells in the brain. A brain tumor can be benign or malignant. The benign brain tumor has uniformity in structure and does not contain active (cancer) cells, whereas malignant brain tumors have a non uniformity (heterogeneous) in structure and contain active cells. According to the World Health Organization and American Brain Tumor Association, the most common grading system uses a scale from grade I to grade IV to classify benign and malignant tumor types. Grade 1 is the least aggressive tumor and grows slowly. In such case, a surgery may be an effective treatment and normally do not appear again after surgery. Grade 2 tumors are slowly growing tumors that may appear again after surgery. It sometimes spread to the nearby healthy tissues as a higher grade tumor. Grade 3 tumors are malignant and grow more rapidly than the previous two grades. It often tends to recur as grade 4 tumor. Grade 4 tumors are most evil and look very abnormal when its cells are viewed under microscope. These tumors produce new blood vessels to maintain the growth of tumor. In common cases brain tumor blocks the cerebrospinal fluid which causes an increase in intracranial pressure which results in swelling of ventricles. This causes rise in intracranial pressure leads to "mass effect". This effect gives rise to the neurological symptoms and suggestion of CT or MRI scan. Depending on the medical illness of the patient the abnormal brain images produced by the MRI will vary since the illness will affect various parts of the brain and this will be represented in particular regions of the brain. One of the noticeable differences is that there exist obvious inequalities between the two sides of the brain. When the image shows a larger sized portion on the left side of the brain than the right side then this shows a clear case of abnormality or asymmetry across the symmetry axis and it can be measured after segmentation of Magnetic Resonance (MR) brain images. The measure of asymmetry leads us to diagnosis of tumor. Due to this reason, asymmetry can be promoted as one of the major indicator for the presence of brain tumor. To detect infected tumor tissues from medical imaging modalities, segmentation is employed. Segmentation is necessary and important step in image analysis. It is a process of separating an image into different regions or blocks sharing common and identical properties, such as color, texture, contrast, brightness, boundaries, and gray level. Brain tumor segmentation involves the process of separating the tumor tissues from normal brain tissues and solid tumors, such as White Matter (WM), Gray Matter (GM) [1] with the help of MR images or other imaging modalities [2–5]. In this paper, asymmetry is determined by Improved Incremental Self Organizing Mapping

(I2SOM) based segmentation technique using CHFMs.In this study, different magnetic resonance imaging (MRI) sequences of brain images are employed for diagnosis. Once a brain tumor is clinically suspected, radiological evaluation is required to determine its location, its size, and impact on the surrounding areas. On the basis of this information the best therapy, surgery, radiation, or chemotherapy, is decided. It is evident that the chances of survival of a tumor-infected patient can be increased significantly if the tumor is detected accurately in its early stage [6]. Medical image segmentation for detection of brain tumor from the Magnetic Resonance (MR) images or from other medical imaging modalities is a very important process for deciding right therapy at the right time. Many techniques have been proposed for classification of brain tumors in MR images. Major steps in the diagnosis of tumor include segmentation of MR image followed by asymmetry calculation. Prior to segmentation phase, we need a set of features that are true representative of physical process under consideration. Dokur et al. [7] 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. [8]. In which five statistical features are calculated from wavelet transformed image for inquiring computer assisted diagnosis for breast cancer screening. In their study comparison of discriminant ability of the features extracted with or without the wavelet based image preprocessing was done for the analysis of influence of wavelet transform on an image. Image segmentation is an important part in our study to reach at reliable result. Various techniques have been evolved to carry out this process. Watershed segmentation along with Computer Aided Diagnosis (CAD) is used to detect tumor. Watershed segmentation is the idea of taking the image into three dimensions. In this model a plane represents the coordinates of the image and values above this plane shows the intensity values. Thus the whole view gives a 3D model which is further used for segmentation. Modified region growing method used for segmentation to diagnose brain tumor. Modified region growing is different from region growing in the sense orientation control is also provided along with intensity constraint. But it requires user interference to specify seed to initiate the region growing process. Incremental SOM (ISOM) for segmentation of medical images use a two layer network, in which first layer include input nodes of neural network model and second layer holds information about class of output node. Number of input nodes is determined automatically during learning. Input is presented to network and distance is calculated for all the neurons present in the network. Least distance is then compared with threshold value. If the distance value is less than threshold value then corresponding neuron get fired otherwise input is added along with neurons as a new node of the network Manual setting of threshold value raises some problem in this technique. It requires a number of trials to find out the required value of threshold. Incremental supervised neural network (ISNN) presented for the segmentation of the MR brain images for the purpose of tumor diagnosis requires class of input data to be specified prior to training phase. During segmentation process input is simply compared with the nodes of the neural network and node with the least distance is inquired for its class is matching with that of input. After this comparison same procedure is followed as that in SOM. Improved Incremental SOM (I2SOM) is a choice for segmentation for our study as this requires no pre-determination of class of input data. Moreover, it includes the formulation for determining automatic threshold that eliminates the problem of setting of appropriate threshold value. Mathematical formulation is used to calculate the threshold value which makes it easy to calculate threshold values based upon the type of input data.

A healthy brain is highly symmetric across mid-sagittal plane. This property can be exploited to determine tumor in the brain. Symmetry axis is calculated to calculate asymmetry in hippocampi and other neurological structures for diagnosis of related neurological diseases. First of all a plane is calculated from ellipsoid of inertia of image. This plane is then shifted according to algorithm to get symmetric plane. Fazli and Nadirkhanlou [9] computed geometrical symmetry axis for tumor detection using fast bounding box (FBB) technique. Many feature extraction techniques has been evolved throughout the years for pattern recognition applications. Huang and Leng [10] utilized Hu moments for the purpose of pattern recognition and investigated its fluctuations for invariants. Iscan et al. [11] used Hu moments for tumor detection in MR images. Hu invariants calculated across mid sagittal plane of the segmented brain image corresponding to various tissues of brain. Then vectors computed from these invariants across the symmetry axis of the brain compared to get the asymmetry value. In early approaches of tumor detection, various techniques of segmentation have been used. Segmentation using SOM needs classes and threshold value to be specified respectively. Some techniques such as region growing and K-means demands user intervention to specify important parameters that decreases reliability and increases complexity. Asymmetry is calculated for cranial tissue only and ignoring other tissues. In our study, Improved Incremental Self Organization Mapping (I2SOM) is implemented to segment the brain image. This technique accepts raw input data and segments it without the user involvement. It calculates the Automatic Threshold (AT), which automatically controls the number of segmented classes. To calculate asymmetry Chebyshev Harmonic Fourier Moments (CHFMs) and PHTs is used which generate global and

geometric feature set of an image. It omits the limitation of previous method of taking only one tissue under consideration while calculating asymmetry.

The rest of the paper is organized as follows: Section 2 presents the computational framework of CHFMs, followed by the mathematical framework of PHTs in Section 3, Section 4 presents the experimental part, and finally Section 5 contains the conclusion.

II. Computational Framework of Chebyshev- Harmonic Fourier Moments

CHFMs of order p and repetition q with $p \geq 0$ *and* $|q| \geq 0$ are defined in polar form as

$$M_{pq} = \frac{1}{2\pi} \int_0^{2\pi} \int_0^1 f(r,\theta) V_{pq}^*(r,\theta)\, r\, dr\, d\theta, \tag{1}$$

Where *p* is a non-negative integer and *q* is an integer.

The function $V_{pq}^*(x,y)$ is the complex conjugate of the CHFMs basis function $V_{pq}(x,y)$ defined by

$$V_{pq}(x,y) = R_p(r) e^{jq\theta}, \tag{2}$$

where $r = \sqrt{x^2 + y^2}$,

The radial part of the basis function is

$$R_p(r) = \sqrt{\frac{8}{\pi}} \left(\frac{1-r}{r}\right)^{1/4} \sum_{k=0}^{\lfloor p/2 \rfloor} (-1)^k \frac{(p-k)!}{k!\,(p-2k)!} \times (2(2r-1))^{p-2k} \tag{3}$$

The orthogonal property for radial kernel is given as

$$\int_0^1 R_p(r)\, R_k(r)\, r\, dr = \delta_{pk} \tag{4}$$

The orthogonality of basis function is given as

$$\int_0^{2\pi} \int_0^1 V_{pq}(r,\theta) V_{p'q'}^*(r,\theta)\, r\, dr\, d\theta = 2\pi\, \delta_{pp'}\, \delta_{qq'} \tag{5}$$

For $p=p_{max}$, $q=q_{max}$, the total number of CHFMs is $(1+p_{\max})(1+2q_{\max})$.

In digital image processing, the image function $f(r,\theta)$ is discrete and defined in a rectangular domain with the pixel locations identified by the row and column arrangement. Let (i,k) be a pixel, the index *i* denotes the row position and *k* the column, with $i,\ k = 0, 1, \ldots, N-1,$ where the resolution of the image is $N \times N$ pixels. The top left corner of the rectangular domain represents the origin $(0,0)$ of the image. We map the pixel location (i,k) into the coordinates (x_i, y_k) within the unit disk using the following transformation:

$$x_i = \frac{2i+1-N}{D},\ y_k = \frac{2k+1-N}{D},\ i,\ k = 0, 1, \ldots, N-1 \tag{6}$$

where

$$D = \begin{cases} N & \textit{for inscribed circular disk contained in the square image} \\ N\sqrt{2} & \textit{for outer circular disk containing the whole square image} \end{cases} \tag{7}$$

The coordinate (x_i, y_k) represents the center of the (i,k) pixel grid with the two opposite vertices defined by $\left[x_i - \frac{\Delta x}{2}, x_i + \frac{\Delta x}{2}\right] \times \left[y_k - \frac{\Delta y}{2}, y_k + \frac{\Delta y}{2}\right]$ where Δx and Δy represent the horizontal and vertical separation between the centers of two pixels which are expressed as

$$\Delta x = \Delta y = \frac{2}{D} \tag{8}$$

The CHFMs can now be described in the Cartesian coordinates and their discrete formulation can be facilitated by converting Eq.(1) into Cartesian system defined by

$$M_{pq} = \frac{1}{2\pi} \iint_{x_i^2+y_k^2 \le 1} f(x,y) V_{pq}^*(x,y) dxdy \,, \tag{9}$$

Equation (9) can be derived from Eq.(1) after replacing $r = \sqrt{x^2+y^2}$ and θ by $\tan^{-1}(y/x)$. The discrete implementation of Eq.(9) assumes the form

$$M_{pq} = \frac{1}{2\pi} \sum_{i=0}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) \iint_{x_i^2+y_k^2 \le 1} V_{pq}^*(x,y) dxdy \,, \tag{10}$$

It is difficult to derive an analytical solution to the double integration on the R.H.S of Eq. (10), therefore, normally a zeroth order approximation is considered for its evaluation. This leads to

$$M_{pq} = \frac{4}{2\pi D^2} \sum_{\substack{i=0 \\ x_i^2+y_k^2 \le 1}}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) V_{pq}^*(x_i, y_k) \,. \tag{11}$$

Suppose that moments of all orders $p \le p_{\max}$ and repetition $q \le q_{\max}$ are given, then the image is reconstructed as follows:

$$\hat{f}(x_i, y_k) = \sum_{p=0}^{p_{\max}} \sum_{q=-q_{\max}}^{q_{\max}} M_{pq} V_{pq}(x_i, y_k), \; i, k = 0, 1, \ldots, N-1 \,. \tag{12}$$

III. Mathematical Framework of Polar Harmomictransforms (PHTS)

PHT is another effective method to generate orthogonal and rotation invariant features of an image. Derivation of features from an image using PHTs impose less computational complexity as there are no factorial terms involved in the calculation of radial kernels. Thus it increases the speed of overall process. There are three types of transforms which are collectively taken under the heading of PHTs namely Polar Complex Exponential Transforms (PCETs), Polar Sine Transforms (PSTs), and Polar Cosine Transforms (PCTs) [12].The kernel of PCETs, PSTs and PCTs is the set of orthogonal complex functions defined inside a unit circle over the polar coordinate space, which are grouped under the category of PHTs and can be decomposed into radial and circular components. For an image $f(r,\theta)$ mapped over a unit circle, two dimensional PHTs of order p and repetition q are given as follows:

$$M_{pq} = \lambda \int_0^{2\pi} \int_0^1 f(r,\theta) H_{pq}^*(r,\theta) r dr d\theta \tag{13}$$

where

$|p| \ge 0, |q| \ge 0 \; and \lambda = \frac{1}{\pi}$ for PCET

$p \ge 0, |q| \ge 0 \; and \lambda = \frac{1}{\pi} if p = 0, \lambda = \frac{2}{\pi} if p \ne 0$ for PCT

$p \ge 1, |q| \ge 0 \; and \lambda = \frac{2}{\pi}$ for PST

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

$$H_{pq}(r,\theta) = R_p(r) e^{iq\theta} \tag{14}$$

Where $R_p(r)$ is the radial kernel, $j = \sqrt{-1}$ and $\theta = \tan^{-1}(y/x)$. Similarly PCT and PST are defined, respectively, as under:

$$H_{pq}(r,\theta) = R_p^C(r)e^{iq\theta}$$
$$H_{pq}(r,\theta) = R_p^S(r)e^{iq\theta} \quad (15)$$

Whereas radial kernels are calculated as:

$$R_p(r) = e^{j2\pi p r^2}$$
$$R_p^C(r) = \cos(\pi p r^2)$$
$$R_p^s(r) = \sin(\pi p r^2) \quad (16)$$

Integration in Eq. (15) is not applicable to an $N \times N$ image, its zeroth order approximation is given below which can be equally used for the calculation of transforms of an image:

$$M_{pq} = \lambda \sum_{\substack{i=0 \\ x_i^2+y_k^2 \le 1}}^{N-1} \sum_{k=0}^{N-1} f(x_i, y_k) H_{pq}^*(x_i, y_k) \Delta x_i \Delta y_k \quad (17)$$

where

$$x_i = \frac{2i+1-N}{N\sqrt{2}}, y_k = \frac{2k+1-N}{N\sqrt{2}} \qquad i,k = 0,1,2, \dots\dots\dots\dots N-1$$

and

$$\Delta x_i = \Delta y_k = \frac{\sqrt{2}}{N}$$

IV. Experimental Analysis

In our study, 20 healthy images and 20 MR images with tumor are tested. These images are generated by 1.5T MR scanner. Images contain brain with tumor of different sizes and present at different locations within brain. The simulations are performed on 1.70 GHz processor using MATLAB 2014a. In early phase, MR images are to be segmented using I2SOM. Feature vector space which is required for segmentation purpose is formed by taking transforms of an image at a range of scale values (0.8, 1.4, 2.0, 2.6, 3.2, 3.8, 4.4 and 5.0). These eight transformed images combined with original image gives nine dimensional feature spaces. These feature vectors delivered to I2SOM for learning. Learning rate of the network is kept constant ($\mu = 0.05$) throughout the learning stage. This value of learning rate provides a stable learning network. Symmetry axis is then calculated for the extracted brain image. Segmented image is then split into two images right at its symmetry axis. It gives two images of both the hemispheres which can be treated individually. CHFMs of order 15 with outer circle mapping are calculated for the two images of each hemisphere. Asymmetry is measured by computing ED between moments of left and right hemispheres. Table 1 represents the values of ED between the moments of left and right hemispheres of MR brain images with tumor and Healthy brain through CHFMs.

Table 1: Measure of Asymmetry by computing Euclidean Distance through CHFMs with threshold values 7.0384

Sl. No.	ED (Brain with tumor)	ED (Healthy Brain)	Threshold value
1	13.5425	5.3881	7.0384
2	8.6886	2.8615	7.0384
3	10.9098	3.5671	7.0384
4	12.1386	2.7209	7.0384
5	8.9596	3.7228	7.0384
6	10.9630	4.5466	7.0384
7	15.6777	3.2779	7.0384
8	8.9810	3.2055	7.0384
9	10.6848	4.2901	7.0384
10	9.4465	4.3249	7.0384
11	9.4395	2.2839	7.0384
12	10.9956	4.2657	7.0384
13	12.4636	1.5779	7.0384
14	34.0048	2.9359	7.0384
15	9.9673	4.4801	7.0384
16	9.5760	4.2845	7.0384

17	9.3739	4.1112	7.0384
18	10.4459	2.9446	7.0384
19	11.2346	4.8153	7.0384
20	12.1626	5.2306	7.0384

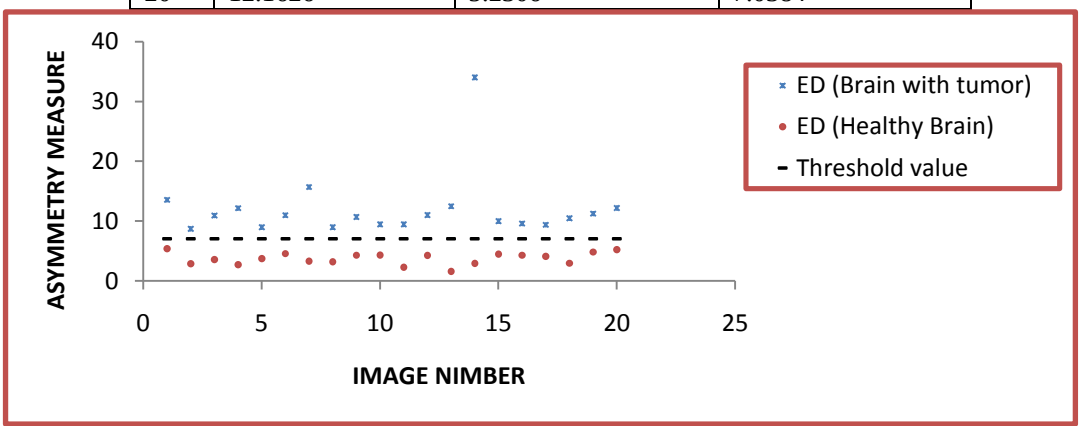

Fig. 1: Asymmetry Measure using CHFMs

Fig 1 represents the measure of asymmetry by computing the ED through CHFMs with threshold value 7.0384. Here the value of ED is greater than the threshold value for all tumors cases and less than the threshold value for healthy ones. Referring to this plot it can be concluded that CHFMs gives good isolation of healthy and tumorous cases. It also provides a good resolution and the results proved that the accuracy is 100% in all the cases.

V. Conclusion

In this study, 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 to represent MR image into ingredient tissues of brain. Different brain tissues are grouped into different corresponding clusters. Each tissue in segmented image is assigned with the intensity value which depends upon the intensity distribution for the related tissue in the original MR image. CHFMs are calculated for each hemispheres of the brain to form feature sets for both hemispheres. Afterwards Euclidean distance is measured between 2D feature arrays derived for both hemispheres of the brain. This distance gives the degree of asymmetry across the mid-sagittal plane of the brain. Tumorous cases possess higher value of asymmetry than healthy ones, therefore, asymmetry measure is used as an estimator for diagnosis of tumor.

References

[1] N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation," Magnetic Resonance Imaging, vol. 31, no. 8, pp. 1426–1438, 2013.

[2] A. Demirhan, M. Toru, and I. Guler, "Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks," *Ieee Journal Of Biomedical And Health Informatics*, vol. 19, no. 4, pp. 1451–1458, 2015.

[3] S. Madhukumar and N. Santhiyakumari, "Evaluation of k-Means and fuzzy C-means segmentation on MR images of brain," *Egyptian Journal of Radiology and Nuclear Medicine, v*ol. 46, no. 2, pp. 475–479, 2015

[4] Y. Kong, Y. Deng, and Q. Dai, "Discriminative clustering and feature selection for brain MRI segmentation," *IEEE Signal Processing Letters*, vol. 22, no. 5, pp. 573–577, 2015.

[5] M. T. El-Melegy and H. M. Mokhtar, "Tumor segmentation in brain MRI using a fuzzy approach with class center priors," *EURASIP Journal on Image and Video Processing*, vol. 2014, article no. 21, 2014.

[6] G. Coatrieux, H. Huang, H. Shu, L. Luo, and C. Roux, "A watermarking-based medical image integrity control system and an image moment signature for tampering characterization*," IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 6, pp. 1057–1067, 2013.

[7] Dokur, Z., & Olmez, T. (2000).Classification of Magnetic Resonance Images using a novel neural network, "*Proceedings of the IEEE-EMBS Asia Pacific conference on biomedical engineering".*

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

[9] Fazli, S., & Nadirkhanlou,P. (2013).A Novel Method for Automatic Segmentation of Brain Tumors in MRI Images, *"Cornell University Library, Computer Vision and Pattern Recognition".*

[10] Huang, Z., & Leng,J. (2010).Analysis of Hu's Moment Invariants on Image Scaling and Rotation, "*Proceedings of IEEE International Conference on Computer Engineering and Technology".*

[11] Iscan, Z., Dokur, Z.,& Olmez,T. (2006).Segmentation of Medical Images by Using Wavelet Transform and Incremental Self-Organizing Map, *"Springer-Verlag Berlin Heidelberg*", 4293, 800-809.

[12] Vriji K.S.A & Jayakumari K. (2011) 'Automatic Detection of Brain Tumor based on Magnetic Resonance Image using CAD System with watershed segmentation', Proceedings of International Conference on Signal Processing, Communication, Computing and Networking Technologies, *IEEE.*