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Fast and Effective Method for the Detection of Brain Tumor using Chebyshev Harmonic Fourier Moments

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Abstract— Brain tumor is a serious type of disorder which is caused by the abnormal cells formation within the brain. The identification of brain tumor and further analysis from the Magnetic Resonance Imaging (MRI) is a vigorous process and in this paper fast and effective method is used for the tumor detection by using Chebyshev Harmonic Fourier Moments (CHFMs) on segmented magnetic resonance brain images. The proposed method is free from any overflow situations as it does not involve any factorial term and also free from underflow situations as no power terms are involved. Before the segmentation process, the feature set is extracted by using 2D Continuous Wavelet Transform (2D-CWT). Asymmetry in the MR brain image is analyzed by using 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 35 MR brain images with tumor and 65 normal MR brain images. It is observed that that the proposed method and technique is successful in 97% cases.

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

I. INTRODUCTION

This paper presents a general framework for analyzing structural asymmetry in brain images and determining the existence of tumours. 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. 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 tumours are slowly growing tumours that may appear again after surgery. It sometimes spread to the nearby healthy tissues as a higher grade tumor. Grade 3 tumours are malignant and grow more rapidly than the previous two grades. It often tends to recur as grade 4 tumor. Grade 4 tumours are most evil and look very abnormal when its cells are viewed under microscope. These tumours 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. Mass effect brain tumours cause structural asymmetry by displacing healthy tissue and may cause radiometric asymmetry in adjacent normal structures. Therefore asymmetry can be utilized as one of the major indicator for the presence of brain tumor. In this paper asymmetry is determined by Improved Incremental Self Organizing Mapping (I2SOM) based segmentation technique using Chebyshev Harmonic Fourier Moments (CHFMs). For many years, moments have been used as descriptors for the properties of the images in pattern recognition and therefore used them in many applications. Pattern recognition is used in number of image processing applications such as face recognition, fingerprint recognition, character recognition etc. There are different radial moment-based methods which can identify a pattern in terms of certain features. Some of the radial moments are like Zernike Moments (ZMs) [1], Pseudo Zernike Moments (PZMs) [2], Orthogonal Fourier Mellin Moments (OFMMs) [3] and Chebyshev- Harmonic Fourier Moments (CHFMs). CHFMs have found several applications in image processing, pattern analysis and computer vision. However, they are less popular due to their low image reconstruction capabilities and numerical instability at low order moments as compared to ZMs, PZMs, and OFMMs. The computations of CHFMs involve factorial terms, which are computation intensive. Upneja and Singh [4] have proposed fast computation of JFMs of which CHFMs are a special case. However, when the method [4] is applied on the CHFMs, the number of arithmetic operations involved in the coefficients of the recursive relation is very high. Another method uses 8-way symmetry for the computation of the radial function $R_p(r)$ involved in CHFMs [5]. In this paper, we present a recursion based fast algorithm which reduces the time complexity of the CHFMs. The fast algorithm is based on the recursive computation of the radial and angular kernel functions of the moments. The proposed recursive method not only reduces the time complexity of moment computation but also enhances numerical stability of high order moments which is reflected in the lower values of image reconstruction error. The numerical stability is enhanced due to the fact that the proposed algorithm does not involve the direct computation of the factorial terms of large integers which appear in the radial polynomial $R_p(r)$.

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 tumours 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. [6] proposed a technique based on neighbourhood intensities for the classification of MR images. Another technique based on Intensity and morphological features is developed by Qian et al. [7]. 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 pre-processing was done for the analysis of influence of wavelet transform on an image. The technique of Feleppa et al. [8] is based on Fourier transform to form the features of an image. But the time complexity of this technique is very high. They also used radio frequency (RF) echo signals to diagnose prostate cancer more accurately. Database of power spectrum of RF echo signals were used to determine ranges of parameter values associated with tissues of interest. To overcome this problem, 2D-Continuous Wavelet Transform (2D-CWT) is used as a feature vector. It gives higher information level by providing space scale representation of 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. Clustering methods, such as K-Means used for segmentation of brain tumor [9] groups the image pixels according to some characteristics. Number of clusters required is specified by the programmer. Centres of the clusters determined randomly for each cluster. Then distance of each pixel is calculated with each of the centroid. Pixel is assigned to the centre with least distance and centroid is recalculated. Maksaud et al. [10] discussed hybrid method that combines K-Means clustering with Fuzzy C-Means method to provide privilege of using advantages of both of these techniques. This method is time efficient and also accurate due to involvement of fuzzy logic. K-means method can detect tumor faster than fuzzy C means method but fuzzy C means provides accuracy to detect tumor cells. Kanimozhi and Bindu [11] used Self-organize mapping (SOM) that include comparing and choosing the winner node in the output. Output nodes compete themselves and the node with the least distance from input is considered as winner node and its weights are adjusted. In such models output node is interconnected to many other nodes to form cluster. 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.

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: An overview of CHFMs and its computational framework for the images is presented in Section 2 followed by fast and computational approach for the radial polynomials and angular functions developed in Section 3. Detailed experiments are conducted in section 4 which is followed by concluding remarks in section 5.

II. CHEBYSHEV- HARMONIC FOURIER MOMENTS (CHFMMs)

CHFMs of order p and repetition q with $p \geq 0$ *and* $|q| \geq 0$ are defined in polar form as [12]

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

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

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

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 centre 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 centres 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

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

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

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

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

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

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:

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

The image reconstruction error ε is defined by

$$\varepsilon = \frac{\sum_{i=0}^{N-1}\sum_{k=0}^{N-1}\left(f(x_i,y_k)-\hat{f}(x_i,y_k)\right)^2}{\sum_{i=0}^{N-1}\sum_{k=0}^{N-1} f^2(x_i,y_k)} \quad (13)$$

II.FAST COMPUTATION OF CHFMS

It is clear from Eq. (11) that the computation of M_{pq} involves the computation of the kernel function $V_{pq}^{*}(x_i,y_k)$ at N^2 locations. The computation of $V_{pq}^{*}(x_i,y_k)$ involves the computation of the radial polynomial $R_p(r)$ and the angular kernel function $e^{-jq\theta}$ both of which require heavy computational load. The order of time complexity of a polynomial $R_p(r)$ is $O(p)$. When all CHFMs up to a maximum order $p_{\max}$ are computed then the time complexity is $O(p_{\max}^2)$. The time complexity of the angular function $e^{-jq\theta}$ is $O(q_{\max})$ which is also very high because it involves the computation of the trigonometric functions $\cos(q\theta)$ and $\sin(q\theta)$ which are computation intensive. The recursive method [13] reduces the time complexity of a polynomial from $O(p)$ to $O(1)$ and time complexity of all CHFMs from $O(p_{\max}^2)$ to $O(p_{\max})$. Also, the angular functions are computed using recursion without making use of trigonometric functions [14].

III. EXPERIMENTAL ANALYSIS

In this paper we used fast and effective method based on Chebyshev Harmonic Fourier Moments (CHFMs) for the diagnosis of brain tumor using structural MR brain images. The database of 100 MR brain images (35 MR brain images with tumor and 65 normal MR brain images) are used for experiments. These images are generated by 1.5T MR scanner with different size and locations of tumor.

Table 1 represents measure of asymmetry by computing Euclidean Distance of all 35 MR brain images with tumor through CHFMs.

Table 1. Euclidean distance of MR brain images with tumor

Euclidean Distance (Brain with Tumor)	13.5425	8.6886	10.9098	12.1386	8.9596
	9.4395	10.9956	12.4636	7.1882	9.9673
	12.8384	10.809	9.0239	8.4634	17.6313
	8.6258	8.7172	7.4266	6.2862	6.3727
	10.963	15.6777	8.981	10.6848	9.4465
	9.576	9.3739	10.4459	11.2346	12.1626
	13.764	7.9112	14.7183	9.4837	15.7057

Table 2 represents measure of asymmetry by computing Euclidean Distance of all 65 MR brain images (Healthy Brain) through CHFMs.

Table 2. Euclidean distance of MR images of Healthy Brain

Euclidean Distance (Healthy Brain)	5.3881	2.8615	3.5671	2.7209	3.7228
	2.2839	4.2657	1.5779	2.9359	4.4801
	3.4908	5.1336	4.0568	2.7507	4.2182
	3.2037	5.6194	4.8106	5.7236	4.693
	3.5198	3.4037	3.3872	4.2086	4.532
	4.0648	3.2985	1.688	5.9958	3.7302
	2.7778	3.2284	5.8724	6.2461	6.8864
	4.5466	3.2779	3.2055	4.2901	4.3249
	4.2845	4.1112	2.9446	4.8153	5.2306
	3.8144	2.3822	5.5675	2.6633	4.0237
	5.0676	1.0387	4.4412	2.6125	2.3056
	2.2774	2.7745	3.5336	3.3405	4.3857
	3.157	4.3143	5.033	4.5956	3.6481

Here the threshold value (6.5863) can be considered as the decision boundary to make decision about the state of brain whether it is healthy one or tumorous case. From tables 1 & 2 it is clear that all the ED values (Brain with tumor) are greater than the threshold value (6.5863) except two values (6.2862 & 6.3727) and ED values (Healthy brain) are less than the threshold value (6.5863) except one value (6.8864).

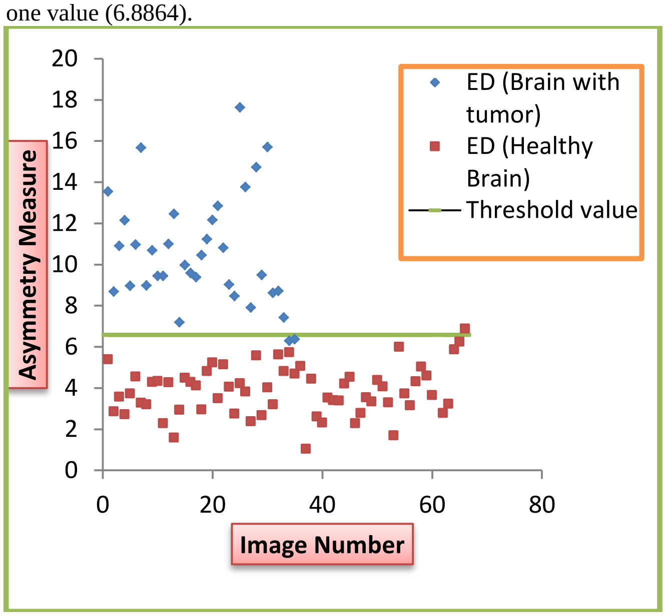

Fig 1: Asymmetry Measure using CHFMs

Fig 1 represents the measure of asymmetry by computing the ED through CHFMs with threshold value 6.5863. Here the value of ED is greater than the threshold value for all tumours cases (except image 34 & 35, table 1) and less than the threshold value for healthy ones (except image 65, table 2).

Referring to this plot it can be concluded that CHFMs gives good isolation of healthy and tumorous cases and the results proved that the accuracy is 97% in all the cases.

IV. CONCLUSION

In this study, total 100 original MR brain images were used in which 35 MR brain images were with tumor and 65 normal MR brain images. The feature set was extracted by using 2D Continuous Wavelet Transform (2D-CWT) before the segmentation process. Asymmetry in the MR brain image is analyzed by using CHFMs and once the presence of asymmetry is confirmed, it can be used as an estimator for the diagnosis of tumor. From the above experiments performed it is concluded that the proposed method and technique is successful in 97% cases.

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