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Brain tumors detection and segmentation in MRI Images

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ABSTRACT

The procedure of detecting brain tumors in a magnetic resonance images (MRI) is a difficult procedure due to the variability and complexity of the data size, data shape and texture of the MRI brain image which consist of lesions. The similarity of intensity between the normal tissue and the lesions leads to special approached in MRI scans. Due to overwhelming cost considerations the need a special approach is required to detect the lesions using single spectral MRI images. In this paper, we have proposed an automatic system which is able to detect the lesion, tumor area. The experimental result demonstrates the success of segmenting brain tumor with high accuracy and less computational complexity, the paper includes the study of comparison of Gabor wavelet with effective feature extarction as a contribution towards tumor segmentation.

Keywords: MR

INTRODOCTION

The significant role of medical imaging in diagnosis of brain tumors helps in handling the disease effectively. Magnetic resonance imaging is the only popular method used due to its nature of showing various tissues with high resolution and contrast. The contrast visualizing capabilities helps to apply various image acquisition techniques which provides additional information for a same tissue region. This kind of information helps the researchers to analyze the brain pathology precisely. The more complex side of handling MRI image is the partition of tissues which is done through segmentation either manually or automatically for partitioning the image with set of relative regions. The segmentation method helps in finding the lesion accurately leads to the requirement of automated brain tumor segmentation. The proposed paper is an automated algorithm for tumor detection and segmentation based on a two dimensional single spectral anatomical MRI image. The algorithm includes tumor detection, tumor segmentation and evaluation of feature sets. The tumor detection technique based on comparison of mutual information of histograms of the two brain hemispheres. The detection of an image slice, which includes tumor tissue, is forwarded for the segmentation stage in order to delineate the tumorous area. The post-processing method is applied to remove the false positives and false negatives.

Since MRI images has various tissues like white matter, gray matter and cerebrospinal fluid efficient feature extraction method like Gabor wavelet feature extraction method is used to capture locality, orientation and frequency providing multi resolution texture information about the spatial domain and frequency domain. Then followed by machine learning technique to effectively identify the tumors in the brain.

1.1 Contributions

Our contribution is about the computational efficiency combined with accuracy. It is based on single-spectral MRI. The method is also fully automatic in implementing texture-based statistical feature extraction methods for tumor segmentation by using the fact that brain tumors often have special structures

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compared to healthy brain tissues owing to the effect of angiogenesis. The main contribution is efficacy of features with the widely used Gabor wavelet features.

The rest of the paper is organized as follows. Section 2 summarizes the feature-extraction method, the experimental methodology includes data preparation in Section 3. The experimental results and discussion are in Section 4 while the conclusion is in Section 5.

2. Texture based feature extraction technique

The paper includes Gabor wavelet features which are extracted using Gabor wavelet transform. The most commonly used tool for analyzing frequency properties is Fourier transform, there is an uncertainty between the time and frequency resolution of window function used in analysis is well known that when the time duration get larger, the bandwidth becomes smaller. Several ways has been proposed to find the uncertainty bound, the commonly used is standard deviation.

Dennis Gabor is known as the father of holography, with respect of his development of theory in 1947. We are concerned with the theory of communication. Gabor's theory addresses complete aspect of the nature of communication. It also provides a basis for the representation and processing of information in vision and other sensory modalities.

We have seen that any (finite energy) one-dimensional function v: R→R can be represented as a linear superposition of Gabor elementary functions, each of which represents one logon or quantum of information about the function. Although we thought of these functions as time-varying signals v(t), it should be clear that this is not essential to the theory. v(x) could also represent a spatial pattern, in which case the Gabor elementary functions represent information cells localized in space and spatial frequency. We must make the change to the spatial domain when we come to problems in vision, where it is necessary to consider two-dimensional functions v: $R^2 \longrightarrow R$, where v(x, y) represents the intensity at spatial location (x, y).

It might be expected that two-dimensional signals could be represented in terms of two-dimensional analogues of Gabor elementary functions, and in the early 1980s a number of researchers suggested Gaussian-modulated sinusoids as models of the receptive fields of simple cells in visual cortex, Daugman proved two-dimensional analogues of Gabor's Uncertainty Principle, $\Delta x \Delta u \geq \frac{1}{4\pi}, \Delta y \Delta v \geq \frac{1}{4\pi}$ $(Equ\ 1.)$ Where Δv and Δu are the uncertainties in the x and y spatial frequencies), and showed that the Gabor elementary functions of the form: $\phi_{pqw}(x,y)$ =

$$\exp\left\{-\pi\left[\frac{(x-p)^2}{\alpha^2}+\frac{(y-q)^2}{\beta^2}\right]\right\}\exp\{2\pi i[u(x-p)+v(y-q)]\}\ (Equ\ 2.)$$

The first factor is a two-dimensional Gaussian distribution centered on the point (p, q); the second factor is the conjugate exponential form of the trigonometric functions, also centered on (p, q). The parameters (u, v) determine the wave packet's location in the frequency domain just as (p, q) determine its location in the spatial domain. The x-spread and y-spread of Gabor function is represented using α and β and so these parameters determine its two-dimensional shape and spread. We make use of Gabor elementary functions located on a regular grid in the spatial and spectral domains. In this case we index the functions by the quantum numbers j, k, l, m; $\phi_{jklm}(x,y)$ =

$$\exp\left\{-\pi\left[\frac{(x-j\Delta x)^2}{\alpha^2}+\frac{(y-k\Delta y)^2}{\beta^2}\right]\right\}\exp\{2\pi i[l\Delta u(x-j\Delta x)+m\Delta v(y-k\Delta y)]\}\ (Equ\ 3.)$$

Where the spacing is determined by Δx Δv =1 and Δy Δv =1. The spatial frequency of the function $f = \sqrt{(u^2-v^2)}$ and its orientation is ϴ= arctan(v/u). Conversely, u = f cos ϴ and v = f sinϴ. This gives an alternate form for the elementary functions

$\phi_{pdf\Theta}(x,y)$ =

$$\exp\left\{-\pi\left[\frac{(x-p)^2}{\alpha^2}+\frac{(y-q)^2}{\beta^2}\right]\right\}\exp\{2\pi if[(x-p)cos\theta+(y-q)sin\theta]\}\ (Equ\ 4.)$$

The structure of Eq. 6.15 may be easier to understand by writing it in vector form; let x = (x, y) be an arbitrary point in the plane, let p = (p, q) be the center of the function, let u = (u, v) be the wave vector (which represents the packet's frequency along each axis). Finally, let the diagonal matrix $S = \begin{pmatrix} \alpha^{-1} & 0 \\ 0 & \beta^{-1} \end{pmatrix}$ represent the function's shape.

Then,

$$\phi_{pu}(x) = \exp\{-\pi\,||S\,(x-p)||^2\}\exp[2\pi iu.(x-p)].\ (Equ\ 5.)$$

now it is clear that the 2D Gaussian envelope falls with the square of the distance from p scaled in accord with S. Similarly, the periodic part has its origin at p. Since u.(x-p) projects x-p onto u, the phase of the periodic function is constant in a direction perpendicular to the wave-vector u. Thus the orientation of the periodic part is given by u and its frequency is given by ||u|| = f

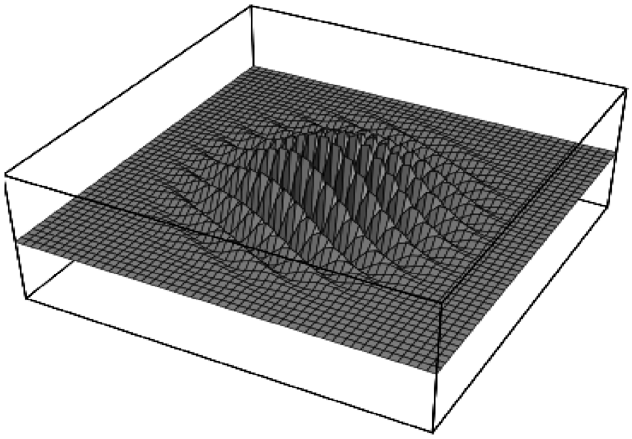

Fig 1: The even cosine component of a 2D Gabor elementary function. The function shown has $\alpha^2 = \beta^2 = 20, u = \frac{1}{2}, v = 1, and\ p = q = 0. it\ is\ plotted\ for\ all\ x, y \in [6, -6]$

3. Experimental Methodology

The automated algorithm proposed includes the detection of slices than contains tumor, the intensity normalization of MRI, windowing, feature extraction, dimensionality reduction, and classification, post-processing and feature efficiency evaluation. The methodology concentrates on the tumor slice detection based on histogram asymmetry within the brain hemisphere. The brain is divided into two hemispheres and the longest diameter is identified using the brain midline. Using the histogram asymmetry each hemisphere is obtained, with the available information of histogram hemisphere the tumor containing portion is determined. Then the segmentation stage come in to localize the tumor tissue area, the obtained tumor region is used with the sliding window made to sweep all through, so that all the brain tissue in the detected slice. Then several tumor classification method is applied on every instance of the window classifying the tumor tissue. If at all the classified region seems to be healthy post-processing method can be applied to remove the false positives and false negatives. Several classification methods like SVM, KNN, SRC, NSC and K-means applied for the evaluation of the features.

3.1. Performance Criteria

The Gabor wavelet features is capable for accurate MRI lesion segmentation. A multistage algorithm is employed for the calculating the performance criteria like sensitivity, specificity and accuracy the definition is as follows.

True Positive (TP) = positive examples that are correctly classified represented as η_{TP}

True Negative (TN) = negative examples that are correctly classified represented as η_{TN}

False Negative (FN) = positive examples that are incorrectly classified represented as η_{FN}

False Positive (FP) = negative examples that are incorrectly classified represented as η_{FP}

Sensitivity = $\frac{\eta_{TP}}{(\eta_{TP}+\eta_{FN})} 100\%$

Specificity = $\frac{\eta_{TN}}{(\eta_{TN}+\eta_{Fp})} 100\%$

Accuracy = $\frac{\eta_{TP}+\eta_{TN}}{(\eta_{Tp}+\eta_{TN}+\eta_{Fp}+\eta_{FN})} 100\%$

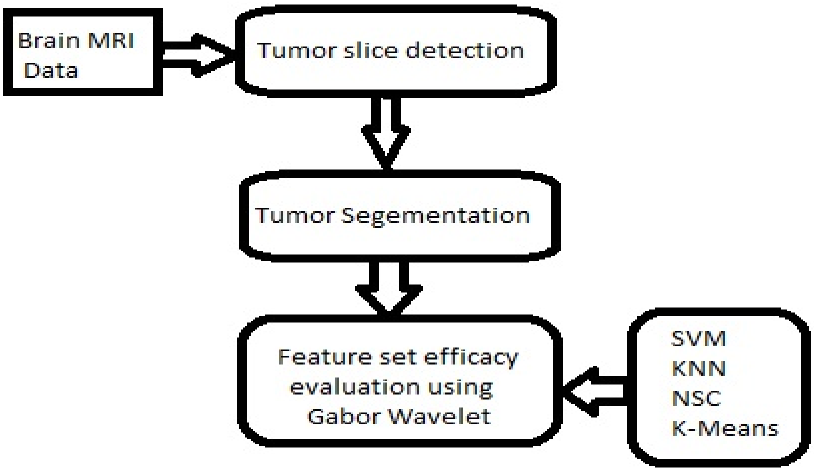

Fig 2: Experimental Methodology

3.2. Tumor Slices Detection

Tumor slice detection uses histogram asymmetry between two brain hemispheres, achieved by brain midline of longest diameter. First we have to identify the brain from the background then using the center mass algorithm brain center is identified, the brain borderline need to be identified followed identification of brain diameter, next to designate the longest diameter as the brain midline finally identify the tumor slice based on hemisphere information

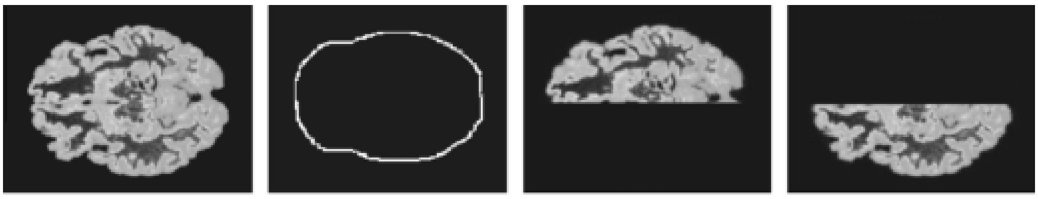

Fig 3: (a) Original image (b) Brain border line (c), (d) Brain Hemisphere

3.3 Intensity Normalization of MRI Image

Intensity normalization is very much necessary in texture analysis quantitatively, the histogram normalizations method is used for quantitative texture analysis, and it basically stretches and shifts the original image to include the gray scale level of the image defined as

$$f(x,y) = \frac{GWM - BWM}{h_{max} - h_{min}}(h(x,y) - h_{min}) + BWM \quad (Equ\ 6.)$$

Original histogram of image is h(x,y), new histogram is f(x,y), large and small gray scale represented using h_{max} and h_{min} respectively, new minimum and new maximum intensity levels are GWM and BWM.

3.4 Windowing

Using the brain midline and border line the window is restricted to cover the brain tissue from the background, here the same-sized sliding window sweeps over the brain excluding the area outside the borderline. Gabor wavelet is used as a feature extraction method.

3.5 Feature Aggregation

The Gabor wavelet kernels with five different scales and eight orientations in three window sizes 33, 45, 65 windows. The length of feature vector is 43560, 81000, and 169000 respectively.
3.6 Dimensionality reduction

Principle Component Analysis mathematical tool is used for dimensionality reduction which produces linearly uncorrelated data called principle components, it maintains the variability of data for all extracted features obtaining principles features with highest eigenvalues, the optimal number of selected features is identified using the reconstruction ratio $\gamma = \frac{\sum_{i=1}^{M} \lambda_i}{\sum_{i=1}^{N} \lambda_i}$(Equ. 7.)

To the maximum of 20 feature are considered to satisfy the constraint.

3.7 Feature classifications

The techniques like SVM, KNN, NSC, unsupervised clustering method k-means is employed. The recognition rate of classifier on data which is unseen during the learning phase can be used as an indictor of performance in tumor segmentation.

4. Results and Discussion

4.1 Training examples

Brain tumor image data used is obtained from Mega Scan center Multimodal Brain Tumor Segmentation, each window is treated as a separate training example, described as a feature vector. The training examples as positive or negative. An example is labeled as positive if tumor pixels cover more than half of the window

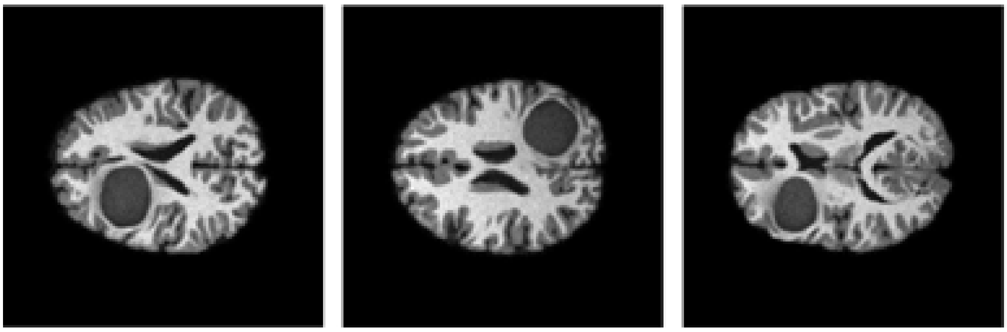

Fig 4: T1- Weight brain images

4.2 Tumor Segmentation results

Once a slice is identified with tumor, segmentation process should be used to visualize the tumor area, the sliding window sweeps the whole brain to identify the tumor regions, Gabor wavelet extracts the instance from the window, and the PCA reduces the dimensions of features then applied for classification process.

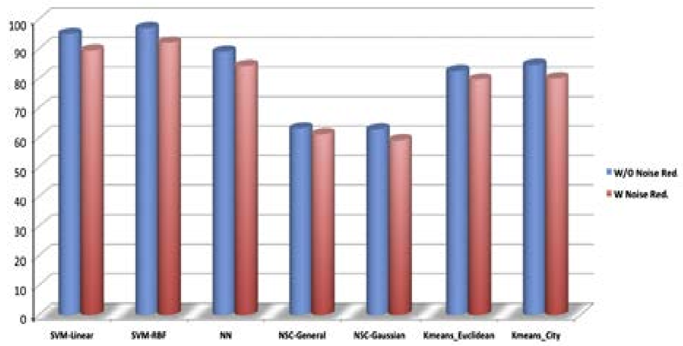

Fig 5: Comparison of different Classification Methods with Gabor wavelet features

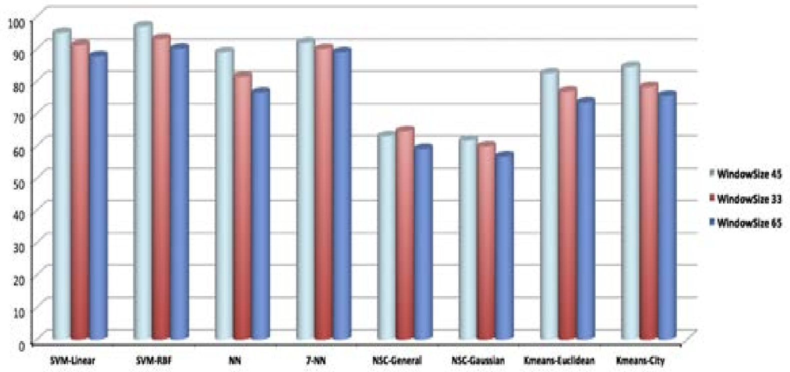

Fig 6: Comparison of different classification methods with different window sizes 45, 33 and 65.

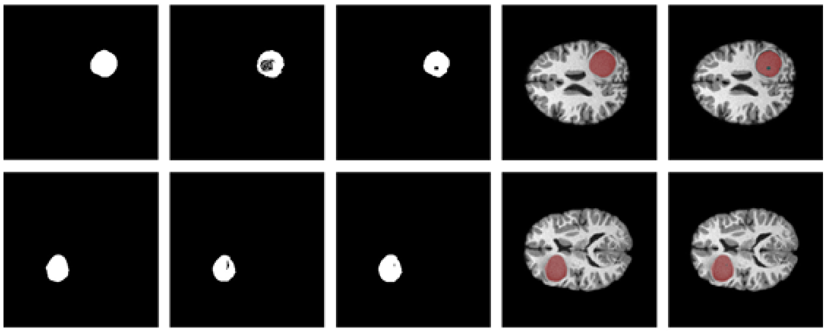

Fig 7: Tumor lesion segmentation on T1-weighted simulated data.

Table 1

Results Table **Classification methods**	**Gabor Wavelet Features**		
	Sensitivity	Specificity	Accuracy
SVM with Linear Kernel	90.6 ± 0.4	91.8 ± 0.9	92.2 ± 0.5
SVM with RBF Kernel	95.4 ± 1.3	93.9 ± 0.2	95.3 ± 0.4
KNN (K=1)	87.7 ± 0.3	87.4 ± 0.5	88.1 ± 0.6
KNN (K=7)	89.6 ± 0.5	90.9 ± 0.2	90.4 ± 0.7
NSC with Gaussian case	60.6 ± 0.9	61.7 ± 0.4	61.4 ± 1.2
NSC with general case	64.8 ± 1.1	62.7 ± 1.3	63.2 ± 1.3
K-Means with Euclidian Distance	68.5 ± 1.2	70.8 ± 0.5	70.1 ± 0.5
K-Means with city Block Distance	70.8 ± 1.1	71.3 ± 0.7	70.9 ± 0.3

Table 2:

Algorithm Step	**Time (mins)**
Tumor Slice Detection	12
Gabor wavelet feature extraction	17
PCA on Gabor wavelet feature	59

It can be seen that statistical features lead to significantly better results for all three criteria in the case of SVM with linear and RBF kernels, KNN (k = 1), NSC with Gaussian under-sampling, and k-means clustering. In NSC with general under-sampling Gabor wavelets features lead to better results for all three criteria. Gabor wavelets are employed widely in computer vision and medical image processing owing to their effective directional selectivity, they occupy a large amount of memory and bit slow in computation but Gabor wavelet features have the potential to be highly valuable in tumor segmentation methods.

5. Conclusion

In this paper, automated mechanism is able to detect MR images containing tumor and then segment the tumor is implemented on T1-w and FLAIR sequence, The accuracy of the algorithm in tumor segmentation has low computational complexity demonstrates the efficiency of the method. The advantage is from atlas registration, prior anatomical knowledge, bias corrections that restrict the application. The benefit of the proposed method is the use of single-spectral MRI while address the intensity similarities between tumor and healthy tissues in type of anatomical MR image is collected due to time, and cost. This makes the proposed algorithm much more robust and general than other methods. Our results indicate the higher accuracy of Gabor wavelet features. Gabor wavelets features occupy a large amount of memory effective computational costs. These observations seem to prove that sufficiently adequate to discriminate tumor tissues from other tissue types in T1-w and FLAIR images.

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