Classification of MR Tumor Images Based on Gabor Wavelet Analysis

Yi-hui Liu1,3*  Manita Muftah2  Tilak Das2  Li Bai3  Keith Robson4  Dorothee Auer2

1School of Information Science, Shandong Polytechnic University, Shandong 250353, China
2Academic Radiology, University of Nottingham, Nottingham NG7 2RD, UK
3School of Computer Science, University of Nottingham, Nottingham NG7 2RD, UK
4Neuropathology Department, Nottingham University Hospitals Trust, Nottingham NG7 2UH, UK

Abstract

Gabor wavelet analysis is used to extract the texture features of magnetic resonance (MR) tumor images to differentiate between primary central nervous system lymphoma (PCNSL) and glioblastoma multiforme (GBM). Gabor wavelet transform with eight orientations and various frequencies is performed on contrast-enhanced T1-weighted MR images to extract the discriminant features, including tumor shape information. A classification model is built based on the extracted features. Experiments show that the proposed hybrid method, which uses wavelet analysis, Gabor wavelet analysis, a support vector machine classifier, and linear discriminant analysis, can distinguish different diagnosis categories of tumor images.

Keywords: Magnetic resonance (MR) images, Gabor wavelet analysis, Feature extraction, Tumor classification

1. Introduction

Early diagnosis and treatment of brain tumors greatly affect the survival time of patients. Primary central nervous system lymphoma (PCNSL) is a highly malignant brain tumor that is on the rise in immunocompetent and immunocompromised patients [1]. Diagnosis is usually established using stereotactic biopsy. Although PCNSL has features in magnetic resonance (MR) images, it is sometimes impossible to differentiate it from high-grade glioma (HGG).

Texture analysis (TA) is an advanced image processing method for extracting and quantifying features related to local patterns in images. Texture analysis is a quantitative and systematic approach over a large range of spatial frequencies, giving it the potential to outperform expert visual pattern analysis in terms of diagnostic accuracy. Early application of texture analysis to MR images has yielded promising results for the segmentation of brain tumors [2]. Advanced texture analysis has recently shown promise in predicting clinically relevant genotypes of patients with oligodendroglioma [3].

Gabor wavelets have tunable orientation and radial frequency bandwidths, tunable center frequencies, allowing them to optimally achieve joint resolution in the spatial and frequency domains. Comparative studies [4,5] have indicated that in most cases, Gabor features outperform those obtained using other methods, such as ring wedge filters, spatial filters, quadrature mirror filters, and eigenfilters.

The present study performs texture analysis based on Gabor wavelets to improve the diagnostic accuracy of differentiating PCNSL from glioblastoma multiforme (GBM). Discriminant information is extracted from MR images to build a classification model.

2. Methods

The feature extraction of tumor images is a key step in classifying tumors. The present study uses Gabor wavelets to extract texture features from tumor images. Gabor wavelets with different directions and frequencies can detect the slight differences between various types of tumor. Wavelet decomposition is first performed to remove noise from MR images. Gabor wavelets are then used to extract the discriminant features of tumor images. Then, a support vector machine (SVM) is used to segment the tumor shape to combine texture and shape information. Finally, linear discriminant analysis (LDA) is used to evaluate the performance of the Gabor texture features based on K-fold cross-validation experiments. Figure 1 shows the proposed method. For each
MR tumor image, 2-5 adjacent slices, whose diameters are equal to or larger than 1.5 cm, are selected for calculating the combined texture features to evaluate performance.

2.1 Tumor data

From the audit database, immunocompetent patients with histologically proven PCNSL and patients with proven GBM were identified. Only those studies complying with a uniform clinical protocol for axial spin-echo T1 weighted scans (TR/TE=539/10 ms, 4-mm slice thickness, 1-mm gap, 512x256 matrix, 80% rectangular field of view of 230 mm, 1 average) at 3 Tesla (Philips Achieva) were included. Images were anonymized and analyzed off-line with the operator undertaking the analysis blinded to the subject’s status. Eight PCNSL cases and 10 GBM cases were considered.

2.2 Preprocessing tumor images based on two-dimensional discrete wavelet analysis

The preprocessing of tumor images is an important step in extracting texture information from tumor areas. When the Gabor wavelet transform is performed to extract texture information, the two main features of the frequency and space are obtained. Frequency is used to measure the texture of tumor areas. However, the noise in an image, which is sensitive to high frequencies, affects the performance of Gabor wavelet analysis. A two-dimensional (2D) discrete wavelet transform (DWT) is thus performed to remove noise.

The wavelet transform method proposed by Grossmann and Morlet [6] transforms a signal from the time domain into the time-frequency domain for analysis. The DWT of images corresponds to a multi-resolution decomposition process [7]. In 2D wavelet decomposition, an image is represented by one approximation and three detailed images, representing the low- and high-frequency content of the image, respectively. The approximation can be further decomposed to produce one approximation and three detailed images at the next level of decomposition, and so on, until the required level is reached. The rows of the approximation coefficients are convolved with both a low-pass filter and a high-pass filter and the results are column downsampled (only even indexed columns are kept). The columns of both downsampled results are convolved with both a low-pass filter and a high-pass filter and the results are row downsampled (only even indexed rows are kept). The resulting four matrices are the next level approximation and three detailed coefficients, respectively. The 2D wavelet decomposition process is shown in Fig. 2. A1 and A2 represent the wavelet approximations at the 1st and 2nd levels, which are the low-frequency components of an image. H1, V1, and D1, and H2, V2, and D2 represent the details of the horizontal, vertical, and diagonal directions at the 1st and 2nd levels, respectively; they are the high-frequency components of an image. Figure 3 shows slices of contrast-enhanced T1-weighted MR images. Figure 3(a) shows a slice of a GBM tumor, and Fig. 3(b) shows a slice of a PCNSL tumor. The green rectangular areas represent the tumor regions of interest (ROIs). After 2D wavelet decomposition at the 2nd level is performed on the ROIs, the approximation at the 2nd level is obtained to replace the original image for texture analysis. Figure 4 shows the wavelet approximation and details in the horizontal, vertical, and diagonal directions at the 2nd level of wavelet decomposition. The approximation at the 2nd level is more homogeneous than the original ROIs after high-frequency information (details) has been removed. Texture features based on Gabor wavelets are more significant, using approximation at the 2nd level instead of the original image.
2.3 Extraction of texture features based on Gabor wavelets

This section presents the Gabor wavelet analysis of the ROIs of a tumor image for extracting the texture features. The Gabor wavelets, whose kernels are similar to the 2D receptive field profiles of mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity. Because Gabor wavelets capture the local structure corresponding to spatial frequency (scales), spatial localization, and orientation selectivity [8], they are widely applied in many research areas, such as texture analysis and image segmentation [9-11].

A 2D Gabor filter is a product of an elliptical Gaussian in any rotation and a complex exponential representing a sinusoidal plane wave [12,13]. The sharpness of the filter is controlled through the major axis and minor axis, which is perpendicular to the wave. The filter can be defined as:

\[ \psi(x, y; f, \theta) = \frac{1}{2 \pi \eta^2} e^{-\left(\frac{x^2}{\gamma^2} + \frac{y^2}{\eta^2}\right)} e^{j2\pi f t} \]  

(1)

\[ x' = x \cos \theta + y \sin \theta \]

\[ y' = -x \sin \theta + y \cos \theta \]

where \( f \) is the central frequency of the sinusoidal plane wave, \( \theta \) is the rotation angle of both the Gaussian major axis and the plane wave, \( \gamma \) is the sharpness along the major axis, and \( \eta \) is the sharpness along the minor axis. The sharpness values along the major axis \( \gamma \) and along the minor axis \( \eta \) are set to 1.

Image texture features can be extracted by convolving the image \( M(x, y) \) with Gabor filters:

\[ g(x, y; f, \theta) = M \ast \psi(x, y; f, \theta) \]  

(2)

Gabor filters with different frequencies \( f_i \) and orientations \( \theta_j \) are selected to obtain the texture features of the tumor area.

\[ f_i = 0.3 + 0.05i, \quad i = 1, 2, ..., N \]  

(3)

\[ \theta_j = \frac{j \pi}{8}, \quad j = 0, 7 \]  

(4)

where \( N \) represents the number of selected Gabor filters (set to 20). After the image of the tumor area is convolved with Gabor wavelets with different frequencies and orientations, the extracted texture features, \( G \), are obtained as:

\[ G = \{ g_{ij}(x, y; f_i, \theta_j) \mid i = 1, ..., N; j = 0, 7 \} \]

where \( g_{ij}(x, y; f_i, \theta_j) = \left\| M \ast \psi(x, y; f_i, \theta_j) \right\| \), which is the magnitude of the Gabor filter response. By averaging the magnitude values of pixels of the tumor area over all directions, the different frequency features \( \nu_i \), which represent the texture features of the tumor area, are obtained.

\[ V = (\nu_0, \nu_1, ..., \nu_7), \quad i = 1, ..., N \%

where \( V \) is the texture feature vector of the tumor area.

Figure 5 shows the real parts of Gabor wavelets with frequencies of 0.8, 0.6, 0.4, and 0.2 and eight directions. Figure 6 shows the magnitudes of Gabor wavelets (modulus of a complex number) with the four frequencies. The real parts of Gabor wavelets for tumor ROIs with frequencies of 0.8, 0.6, 0.4, and 0.2 along eight directions are shown in Fig. 7. The magnitudes of Gabor filters for tumor ROIs with the four frequencies and eight orientations are shown in Fig. 8. The figures show that finer texture features are detected using higher-frequency Gabor filters.

2.4 Segmentation of tumor shape based on SVM classifier

The tumor area must be segmented for its texture features to be accurately calculated. SVMs, which originate from the idea of structural risk minimization developed by Vapnik [14], are used here to build the segmentation model. SVMs are an effective algorithm for finding the maximum-margin hyperplane for separating two classes of patterns. A transform that nonlinearly maps the data into a higher-dimensional space allows a linear separation of classes that cannot be linearly separated in the original space. This study chooses a linear kernel function.

In order to build the segmentation model, training samples of a tumor area and a non-tumor area are needed. Five rectangles inside a tumor area and a non-tumor area, which cover different regions to characterize the features of the two types of area, were selected respectively to train the SVM model. For each selected rectangle, four vertices and one centre point of the rectangle were considered. Five points are shown in Fig. 9. For each point, the position and intensity are used to form the training vector.

\[ I_i = (x_i, y_i, I_i(x_i, y_i)), i = 1, ..., L \]

where \( I_i \) and \( L \) represent the \( i \)th training vector and the number of training vectors, respectively. \((x_i, y_i)\) and \(I_i(x_i, y_i)\) represent the position and intensity of the selected points, respectively.

5 rectangles, each with 5 points, were selected to cover the tumor area and non-tumor area, respectively, for a total of 25 training samples for each type of area. Then, the samples were
Figure 5. Real part of Gabor wavelets with frequencies of 0.8, 0.6, 0.4, and 0.2 (from top to bottom) and eight directions.

Figure 6. Magnitudes of Gabor wavelets with frequencies of 0.8, 0.6, 0.4, and 0.2 (left to right).

Figure 7. Real part of Gabor wavelets for tumor ROIs with frequencies of 0.8, 0.6, 0.4, and 0.2 (top to bottom) and eight directions.
Gabor wavelets for MR tumor images

3. Results

18 cases (10 GBM and 8 PCNSL) were considered. Texture analysis was performed on 2-5 adjacent slices, whose tumor diameters were equal to or larger than 1.5 cm. For each case, the results of all selected slices were averaged. Experiments were performed to evaluate the performance of two types of ROI. One is the pink rectangular ROIs, which are manually selected from the tumor area [3]. The other is the red segmented ROIs. Gabor wavelet features were extracted at frequencies from 0.3 to 1.3. Figure 12 shows the results of the manually positioned ROIs based on Gabor wavelet features. There is no clear separation line between the GBM tumor and PCNSL tumor. Because the results of texture features depend on manual selection, different selections may lead to different results. The results are thus unreliable. Figure 13 shows the results of the segmented ROIs based on texture analysis. The Gabor features extracted at frequencies above 0.7 can be used to classify GBM and PCNSL tumors.

When one key feature is selected based on Student’s t-test value ($p = 0$), the frequency of 0.75 is detected. When two key features are calculated based on Student’s t-test, the frequencies of 0.75 and 0.8 are detected. The key features were used to build the classifier to distinguish the diagnostic categories. The classifier was built based on LDA [15]. K-fold cross-validation experiments were used to evaluate the performance of Gabor texture features. K-fold cross-validation randomly generates indices which contain equal (or approximately equal) proportions of the integers 1 through K that define a partition of the N observations into K disjoint subsets. In K-fold cross-validation, K-1 folds are used for training and the last fold is used for evaluation. This process is repeated K times, leaving a different fold for evaluation each time. In this study, 3-, 4-, and 5-fold cross-validation experiments were used to evaluate the proposed method. Classification accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were used to evaluate the performance of the proposed method. Let $TP$, $TN$, $FP$, and $FN$ be the numbers of true positive (GBM), true negative (PCNSL), false positive, and false negative samples, respectively.
Figure 10. Segmentation process of tumor. Five rectangles selected from a tumor area and five rectangle selected from a non-tumor area were used to train the SVM classifier. Five training samples were obtained from each rectangular area, giving a $25 \times 3$ training matrix of the tumor area and a $25 \times 3$ matrix of the non-tumor area.

Figure 11. Segmentation results for GBM and PCNSL tumors. (a) Slice of GBM tumor and (b) slice of PCNSL tumor. The pink rectangular ROIs were manually selected from the tumor area.

Figure 12. Results of manually selected ROIs based on texture analysis.

Figure 13. Results of segmented ROIs based on texture analysis. The key frequencies selected based on t-test analysis, are 0.75 and 0.80.

Table 1. Results of K-fold cross-validation experiments.

<table>
<thead>
<tr>
<th>Number of features</th>
<th>Number of folds</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>PPV</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 feature</td>
<td>3</td>
<td>0.989</td>
<td>1.000</td>
<td>0.980</td>
<td>0.976</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.990</td>
<td>1.000</td>
<td>0.982</td>
<td>0.978</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.993</td>
<td>1.000</td>
<td>0.988</td>
<td>0.986</td>
<td>1.000</td>
</tr>
<tr>
<td>2 features</td>
<td>3</td>
<td>0.986</td>
<td>1.000</td>
<td>0.975</td>
<td>0.969</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.989</td>
<td>1.000</td>
<td>0.980</td>
<td>0.976</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.991</td>
<td>1.000</td>
<td>0.984</td>
<td>0.981</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Sensitivity is defined as $\frac{TP}{TP + FN}$; specificity is defined as $\frac{TN}{TN + FP}$; positive predictive value is defined as $\frac{TP}{TP + FP}$; negative predictive value is defined as $\frac{TN}{TN + FN}$; accuracy is defined as $\frac{TP + TN}{TP + FN + FP + FN}$.

When the key frequency of 0.75 was used for 3-, 4-, and 5-fold cross-validation experiments, 98.9%, 99%, and 99.3% accuracies were achieved, respectively. Accuracies of 98.6%, 98.9%, and 99.1% were achieved when two key features were selected. The results of 3-, 4-, and 5-fold cross-validation experiments are shown in Table 1.

The accuracy of the reporting radiologist’s diagnosis was analyzed. The classification results from the clinical reports had an accuracy of 88.9% with an acceptable sensitivity of 75% and an excellent specificity of 100%. The proposed method based on texture analysis yielded better recognition rates, and may thus help radiologists differentiate between GBM and PCNSL tumors in the future.

4. Discussion and conclusion

A classifier model was proposed for identifying PCNSL from GBM tumors based on Gabor wavelet analysis. A set of Gabor wavelet filters with different frequencies and eight key frequencies were selected based on t-test analysis. The key frequencies selected are 0.75 and 0.80.

Table 1. Results of K-fold cross-validation experiments.
directions are applied to contrast-enhanced T1-weighted MR images to extract tumor texture features and tumor shape information. Experimental results show that segmented ROIs with tumor shape information achieve good results. Figure 13 shows a clear difference between PCNSL and GBM at frequencies from 0.7 to 1.25 for frequency amplitude of 0.6. The classification model achieves 100% sensitivity and 98% specificity in 3-fold cross-validation experiments. After a tumor is segmented, the texture information of the segmented tumor ROIs includes whole tumor information, and is more accurate than one of manually selected ROIs. The size of tumor ROIs may thus affect the results. Because Gabor wavelets capture the local structure information corresponding to the spatial frequency, spatial localization, and orientation selectivity, they can be used to detect the edge information of a segmented tumor, which is combined into the texture information of tumor ROIs. The tumor shape information thus affects the performance of texture analysis. More research needs to be done to link the tumor shape information with medical interpretations. Gabor wavelet features based on manually selected ROIs show poor performance because manual selection leads to loss of tumor shape information and relies on operator knowledge. The performance of “random” selection may vary from case to case, so the classification performance is unreliable.

Gabor wavelet features obtained at frequencies from 0.7 to 1.25 show good performance. The texture of different types of tumor only has slight differences. High-frequency Gabor wavelet filters can detect fine texture features of tumors. Tumor images are often contaminated by noise during acquisition, which affects the performance of high-frequency Gabor wavelet filters. 2D DWT is thus performed before Gabor wavelet analysis to remove noise. The proposed classification model achieved a 98.9% accuracy in 3-fold cross-validation experiments, and better than 88.9% accuracy based on the imaging diagnosis of radiologist.

An advanced image processing approach with SVM-based tumor segmentation, 2D DWT for noise reduction, Gabor wavelet analysis for image feature extraction, and LDA for the classification of PCNSL and GBM was proposed. Results indicate the applicability of advanced texture analysis for diagnostic cancer imaging.

Acknowledgements

This work was supported by the Natural Science Foundation of Shandong Province (Y2008G30), China, International Collaboration Project of Shandong Province Education Department, China, and Libyan Cultural Affairs, London, UK.

References


