VAS: A Comprehensive System to Classify High Risk Atherosclerotic Plaques

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Introduction

Flow suppressed (black blood) magnetic resonance imaging (MRI) can provide detailed information of carotid atherosclerotic plaque [1]. Such information may be crucial to identify those vulnerable plaques that are likely to cause neurological symptoms. VAS, a comprehensive pattern recognition system was developed to classify patients' symptomatic states based on image features. Morphological image features and gray-level image features of atherosclerotic plaques were extracted from multi-channel MR images, which includes T1W, T2W, proton density weighted (PDW) and Time of Flight (TOF) modalities. These features include wall area, thickness, statistics of histogram and gray level co-occurrence matrix (GLCM). Due to the high dimensionality of the feature vector, a feature selection scheme was performed. The selected feature sets were used to train hidden Markov models (HMMs), which act as classifiers in our system. Moreover, an information theory based model selection algorithm was employed to obtain optimized topology for HMMs. The outputs of the HMMs for multi-channels were combined by a Bayesian classifier to finally classify the patients into symptomatic/asymptomatic groups. It is shown that the proposed system can perform the classification effectively. The conclusion is that the MR images do contain necessary information to distinguish symptomatic and asymptomatic patients, which can be effectively explored by our comprehensive pattern recognition system.

Methods

Cross sectional T1W, T2W, PDW, and TOF images of the human carotid arteries were acquired from patients on a 1.5T SIGNA scanner (GE Medical Systems). Informed consent was obtained from each patient. The parameters for the four modalities are listed in Table I.

Table I: Imaging parameters for different modalities

	TR (ms)	TE (ms)	FOV (mm×mm)	Thickness (mm)	Matrix
T1W	800.0	11.0	160×160	2.0	512×512
T2W	2769.2	71.6	160×160	2.0	512×512
PDW	2769.2	17.9	160×160	2.0	512×512
TOF	23.0	3.6	160×160	2.0/-1.0	256×256

Table II. Average classification performance

	Symptomatic	Asymptomatic
Symptomatic	74%	26%
Asymptomatic	31%	69%

The block diagram of the VAS is shown in Fig. 1. The explanation for each step is as follows:

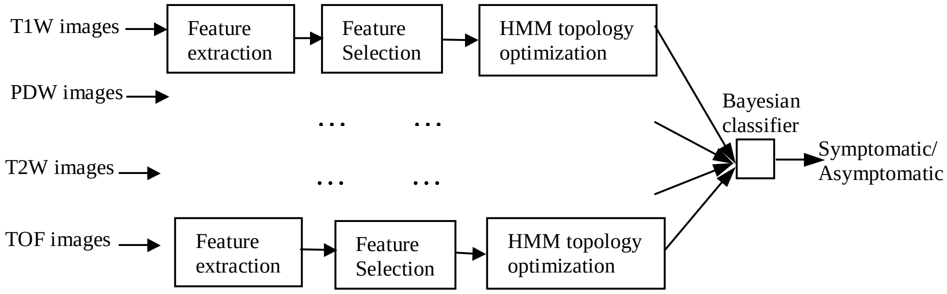
1. *Feature extraction*. To extract the plaque region, an image processing tool, Quantitative Vascular Imaging Tool (QVAS) [2], was used to trace the boundaries of lumen and vessel outer wall. Morphological features were calculated from the geometrical shapes of the plaques. These features include statistics extracted from the thickness, area and perimeter of the plaques. Gray-level image features were calculated from image intensity of the plaque region, which includes the statistics of histogram (mean, standard deviation, skewness, etc.) and GLCMs (contrast, entropy, correlation, and homogeneity, etc.).
2. *Feature selection*. A large number of features were generated by feature extraction. Because of the limited availability of patients, the dimension of feature space must be reduced to avoid overfitting. Since we do not know which features contain characteristic information to distinguish different patient groups, we developed a feature selection technique that uses a sequential floating forward search algorithm [3] to select optimal features. The feature vectors were grouped into two clusters in feature space according to the corresponding symptomatic state. The Bhattacharyya distance [4] between these two clusters were employed as the criteria to measure the optimality of the feature sets. The larger the distance, the more optimal the selected feature sets. The feature selection algorithm begins from selecting one best feature and proceeds to increase the number of features according to the Bhattacharyya distance criteria. A set of optimal features can be found for any given feature vector dimension d.
3. *Classifier topology optimization*. HMMs were employed to model the image series in order to adapt to the different number of plaque-containing slices obtained for each patients [5]. Generally, we do not know the exact physical meaning of the hidden states of HMMs for image sequence modeling problems. In order to optimize the classifier design, an information theory based model selection algorithm was developed to find optimal number of the hidden states for each class of HMM. The minimum message length (MML) [6] was used to measure the fitness of the model topology with respect to the available data.
4. *Classifier combination*. HMMs were trained for every modality of MR images. A Bayesian classifier was used to combine the HMM outputs. In this stage, the log likelihood of the data output from each HMM was fed into the Bayesian classifier to obtain the final classification result.

Results

58 patients, with 28 symptomatic and 30 asymptomatic at the time of the MRI scan were selected for testing. A cross-validation approach was employed to evaluate the performance of VAS. The training/testing procedure was performed many times. In each time, random-selected 40 patients were used for training and the left 18 were used for testing. The average classification performance was shown in Table II. Although the feature sets selected for each round of cross-validation are different, we note that the minimum lumen area (mLA) and contrast feature extracted from GLCM were consistently present in all rounds. This suggests that the severity of stenosis and the strong contrast between tissues are critical features to distinguish symptomatic and asymptomatic patients.

Conclusion

In this study VAS, a comprehensive pattern recognition system was presented to extract the features from multi-modality MR images, then select an optimal feature set and lastly classify the patients into symptomatic/asymptomatic groups. The results suggest that there are imaging features (morphologic and grey level combined) associated with the symptomatic state of patients. Our future work will involve further analysis of the technique to optimize the system design and improve the performance.



Reference

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