Morphometry of Intratumoral Enhancement Patterns on 4D Spectral Images for Differential Diagnosis of Breast Tumors in Dynamic Contrast-enhanced MRI

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Materials and Methods

Twenty female patients were recruited to this study and one primary lesion from each patient was used for analysis. DCE MRI was carried out on a 1.5T scanner (Magnetom Sonata; Siemens, Erlangen, Germany) using T1-weighted 3D FLASH sequence: 448×448, TE=1.83 msec, TR=4.9 msec, angle=12°, slice thickness=1-1.5 mm without a gap, temporal resolution=84 sec per 96-111 slices. One pre-enhanced and four post-enhanced series following a bolus injection of Gd-DTPA (Magnevist, Schering, Berlin, Germany; 0.1 mmol/kg at 2 ml/sec for 5 sec) were acquired as unilateral sagittal images. After 3D rigid registration of MR-time-series, our proposed perfusion index (PI) map was generated for enhanced tumor contrast, which widens the difference of variations in enhancement kinetic features between a lesion and normal parenchyma and allows effective identification of tumors [2]. On the PI map, tumor segmentation was performed by using Otsu thresholding, 3D region growing algorithm, hole-filling and iterative morphological erosion and dilation. Temporal enhancement (TE) features were extracted by singular value decomposition (SVD) of a lower-triangular Toeplitz matrix representing convolution operation, and their SVD-based eigenvalue (EV) maps were generated. The spatial variations of EVs within each tumor were captured by 3D geometric moment invariants (GMIs) [3]. The binary classification for tumor differentiation was performed by Least Square Support Vector Machines (LS-SVM) with a Radial Basis Function (RBF) kernel. Leave-one-out cross-validation was used in the classification process, which was repeated fifty times by iteratively retraining the LS-SVM in order to obtain an average test result. The average test performance showed the area under ROC curve (AUC) of 0.795 (95% confidence interval, 0.768-0.819) with sensitivity and specificity of 96.4% (95% confidence interval, 94.4-97.9%) and 75.6% (95% confidence interval, 71.5-79.3%), using LS-SVM RBF applied to the SVD-based GMI features.

Results

All of the malignant lesions were 10 invasive ductal carcinomas and the histological distributions of the benign lesions were 2 fibroadenomas, 3 papilomas, 3 phylloides tumors, 1 hamartoma and 1 atypical hyperplasia. The PI map successfully identified the margins of tumors in most instances and the segmentation results showed good agreement with tumor boundaries. A total of twenty-four SVD-based GMI features were extracted from each tumor to represent the spatio-temporal properties within the tumor. In an evaluation experiment with 10 malignant and 10 benign cases, the average test performance showed the area under ROC curve (AUC) of 0.795 (95% confidence interval, 0.768-0.819) with sensitivity and specificity of 96.4% (95% confidence interval, 94.4-97.9%) and 75.6% (95% confidence interval, 71.5-79.3%), using LS-SVM RBF applied to the SVD-based GMI features.

Conclusion

With this pilot study for MR-based computer-aided diagnosis (CAD) of breast tumors, we have shown that: (1) 3D tumor segmentation problem of breast tumors in DCE-MRI can be solved effectively in the way that made the best use of tumor perfusion characteristics; (2) Combination of SVD and 3D GMI yields a promising descriptor to characterize and differentiate the spatio-temporal enhancement patterns within tumors in breast DCE-MRI.

References