Multifarious Kinetic Analysis for Differentiation of Prostate Cancer and Benign Prostatic Hyperplasia in DCE-MRI

S. Lee[1], J. Kim[1,2], J. Cho[2,3], S. Kim[2,3], I. Song[3], H. Kim[3], and S. Kim[2,3]

[1]Interdisciplinary Program in Radiation Applied Life Science, Seoul National University College of Medicine, Seoul, Korea, Republic of, [2]Department of Radiology, Seoul National University College of Medicine, Seoul, Korea, Republic of, [3]Department of Radiology, Seoul National University Hospital, Seoul, Korea, Republic of

Introduction

Prostate cancer (PC) and benign prostatic hyperplasia (BPH) are the most common diseases diagnosed in men, early and accurate differential diagnosis of which is an important task. DCE-MRI plays an essential role for cancer detection and characterization. Previous studies have tried to characterize time-enhancement curves of malignant and benign prostate tissues, and thereby to deduce the best distinguishing parameters in DCE-MRI. However, the best diagnostic criteria still remain inexplicit due to their own analysis schemes and assumptions. The significant tissue parameters may take the form of synergistic subsets in the combinatorial space of multifarious kinetic features. In this study, we postulate that extending the individual analysis schemes of contrast enhancement kinetics to a hybrid analysis scheme and that selecting a meaningful feature subset from a combined feature pool may allow an improved performance for lesion classification. Based on this postulation, we propose a novel approach to prostate MRI computer-aided diagnosis (CAD) using multifarious kinetic parameters in DCE-MR images.

Materials and Methods

We retrospectively analyzed DCE-MRI examinations of 38 patients, who underwent retropublic radical prostatectomy or robot-assisted laparoscopic prostatectomy, and found 38 PCs and 37 BPHs. All MR examinations were performed on a 3T GE Signa EXCITE scanner (GE Healthcare, Milwaukee, WI, USA) using an external phased array coil. The DCE-MR images from the apex to the base of the prostate were obtained prior, during and after a bolus injection of 0.5 mmol/kg of body weight of gadopentetate dimeglumine using a 3D T_1-weighted fast spoiled gradient echo (FSPGR) sequence with temporal resolution of 12 s during 6 min. The imaging parameters included the following: TR/TE=5.426/1.432 ms, 20° flip angle (FA), 3.5 mm slice thickness, 22 cm field of view, 256x256 matrix, and 24 slices. Native tissue T_1 (T_{10}) was determined using 5 separate FA acquisitions of 2°, 5°, 8°, 11°, and 14° with TR/TE=3.432/1.392 ms. For lesion segmentation on DCE-MR images, a box-shaped 3D volume of interest (VOI) was selected to contain the lesion for each case. A fuzzy c-means (FCM) clustering algorithm was applied to segment lesion out of background tissue within the 3D VOI. Adaptive mean shift (AMS) based clustering was employed to classify time-enhancement curves within the FCM segmented region without prior knowledge of the number of spatially contiguous clusters. The AMS cluster centroid with the largest L2-norm was selected as the representative enhancement curve (REC) of each lesion. Model-free and model-based parametric analysis was performed with the REC. The model-free approach described the shape of the REC by using peak enhancement (PE), time-to-peak (TTP), wash-in slope (WIS), and wash-out slope (WOS). The model-based approach was applied to the REC by using the signal enhancements ($S1$ and $S2$) at 1 and 6 min, and signal enhancement ratio (SER) based on the three-time-points (3TP) method as well as Brix model, Tofts model, Hayton-Brady model, and open two compartment model with an arterial input function estimation in automatically segmented 3D iliac arteries. A total of 23 initial features were extracted including T_{10}. Three optimized feature sets were identified among the model-free, model-based and their combined multifarious kinetic features based on a feature ranking criterion using a support vector machine based recursive feature elimination algorithm, respectively. A least-squares support vector machine (LS-SVM) classifier was used for tumor differentiation and the performances were evaluated using a leave-one-out testing. Area under the ROC curve (A_z) was used as a performance measure in the binary classification of PC and BPH.

Results

By using a LS-SVM classifier with the optimized multifarious kinetic feature set, the CAD scheme showed A_z of 0.86 in classification of PC and BPH. When this performance was compared to the same LS-SVM classifier with the optimized model-free (A_z=0.7) or model-based kinetic feature set (A_z=0.84), the experimental results exhibited that the multifarious kinetic analysis strategy yields superior performance.

Table 1. Comparison of performances among different optimal feature sets as evaluated with leave-one-out A_z of LS-SVM classifier.

Feature		A_z (mean±1.96 SE)	Sensitivity (%)	Specificity (%)
Optimized model-free kinetic feature set	WOS, PE, TTP, WIS	0.7±0.11	53	92
Optimized model-based kinetic feature set	A^H (Brix model), T_{10}, $S2$	0.84±0.09	76	84
Optimized multifarious kinetic feature set	T_{10}, TTP, $S2$, b (Hayton-Brady model), PE, $S1$, k_{el} (Brix model), A^H (Brix model)	0.86±0.08	84	84

Conclusion

We presented a framework for capturing the multifarious kinetic features for differentiation of PC and BPH in DCE-MRI. The results demonstrated that the multifarious kinetic analysis strategy effectively characterizes the heterogeneous enhancement patterns of the lesions with combination of the model-free and model-based kinetic features, which in turn leads to an improved lesion classification. The proposed CAD scheme has a potential for improving diagnostic performance in prostate DCE-MRI.

References

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