Automated classification of vessel disease based on high-resolution intravascular multi-parametric mapping MRI

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Audience. Cardiologists, interventionalists dieticians interested in the quantitative characterization of vessel disease.

Purpose. Distinguishing early and advanced vascular disease is crucial in assessing disease status, its progression and the effect of interventions, dietary and environmental factors (1). With high-field (3T) intravascular MRI (IVMRI) (2) probes, high-resolution (\sim 200 μ m) multi-parametric vessel mapping is now feasible (3). Given such spatial resolution, MRI could potentially characterize the disease stage with measures of T_1 , T_2 , proton density (PD), and lipid. Here, multi-parametric images from an extended population of

vessel specimens were acquired and used to train an automatic classifier, to test whether combined T_1 , T_2 , PD and lipid images could be used to stage vessel disease. Automatic disease classification was then performed, and its accuracy compared with histological observations.

The multi-parametric maps were used to train an automatic disease stage classifier based on a support-vector-machine (SVM) (6) model (3 classes, tolerance=0.05, linear kernel). The accuracy of the classifier prediction was tested by "leave one out" cross validation (7), using histological sections (Movat and VVG staining) as ground truth. The trained classifier can be applied to automatically classify disease in vessel specimens.

chemical-selective saturation methods were used for lipid

imaging.

Results. Examples of T_1 , T_2 , PD maps and a water/fat image in one specimen are shown in Fig.1. Randomly sampled data points on vessel walls from 8 vessel segments are characterized into 3 groups based on histology (Fig.2a), corresponding to smooth muscle cells (SMC; blue, "S"), early lesion (red, "E") and advanced lesion (green, "A"). The T_1 and T_2 of non-calcified formalin fixed tissue were reduced ~20% and were omitted from the analysis. The cross validation testing results (Table 1) indicate that the SVM correctly classified 89-93% of SMC and advanced lesions. Test results exemplifying automatic tissue classification in a vessel are shown on a T_1 weighted MRI in Fig.3.

Discussion. In human specimens, IVMRI-based high-resolution T_1 , T_2 , PD and fat imaging could be used to automatically

Fig 1. (a) 200 μm "Four-FA" S_2 SPGR image of a human iliac artery acquired with an IV MRI loopless antenna, p (red arrow=early lesion). (b) Combined color-coded 200 μm T_1 (ms), T_2 (ms), PD(units=% vs H_2 O) maps and Dixon fat image (blue) over-laid on the water image (gray) in (a).

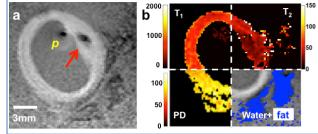
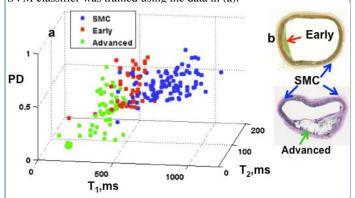


Fig. 2. (a) 3D plot of T_1 , T_2 and PD values from 3 stages of vessel disease: SMC (blue), and early (red) and advanced (green) lesions from eight vessel segments based on histology exemplified in (b). The SVM classifier was trained using the data in (a).



18

12

Table 1. "Leave one out" cross validation results of automatic lesion stage SVM classifier compared to true histology class.

S E A

Histology classification 105 43 54

Correctly classified 93 25 50

Fig 3. Classification points overlaid on MRI.

A
54
50

distinguish early and advanced vessel disease from healthy and smooth muscle. Multi-parametric MRI affords a quantitative means of staging vessel disease, which, if extended *in vivo* could offer a means of automatically documenting the stage of vessel disease and its response to intervention, diet modification etc.

(automated)

misclassified

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