DCE-MRI Analysis using Model-Based Classification Shapes with Non-Negative Least-Squares

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Target Audience: Clinicians and scientists interested in contrast-enhanced perfusion MRI, for applications in cancer therapy

Purpose: Dynamic contrast-enhanced (DCE) MRI is a promising method for predicting therapy response in cancer patients.[1] The predictive capability of DCE-MRI depends on the analysis technique, such as semi-quantitative or quantitative analysis.[2,3] Here, we introduce a method that combines elements of quantitative analysis with shape analysis.[4] We show that our method can predict therapy response in patients with breast cancer, and that it can outperform prediction based on quantitative analysis from a previous study.[3]

Theory: Our proposed method identifies the presence of pre-defined classification shapes (here, signal-time curves) in measured data. We define classification shapes by using the Tofts model with parameter values from the literature and an arterial input function (AIF). Here, we chose parameters from Eliat et al.[5] to define two concentration-time curves: *low permeability* ($K^{trans} = 0.14, v_e = 0.49$), and *high permeability* ($K^{trans} = 0.35, v_e = 0.43$). By taking the native tissue T1 and contrast agent relaxivity into account, the two concentration-time curves are converted to signal-time curves and then normalized to the maximum signal value in all curves (Fig 1). The classification assumes that curves in the acquired data are weighted mixtures of the low- and high-permeability shape. The weights are computed using non-negative least squares (NNLS).

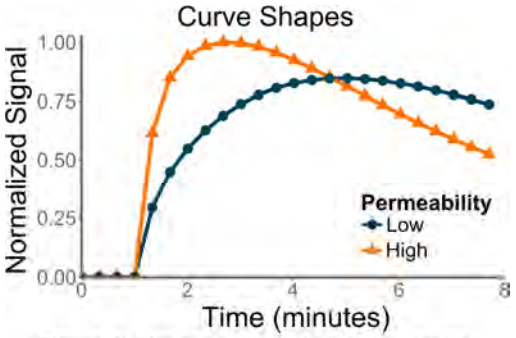

Figure 1: The normalized signal-time curves.

Methods: Our hypothesis was that the weights for patients showing pathologic complete response (pCR) would be different from those of non-pCR patients. To test this, we applied our method to the freely available "QIN Breast DCE-MRI" dataset from the Cancer Imaging Archive, originally acquired by Huang et al.[3] from 10 breast-cancer patients undergoing neoadjuvant chemotherapy. Among these patients, 3 showed pCR. We used images from the pre-treatment exam (Visit 1) and after the first treatment cycle (Visit 2). NNLS analysis returned the weights (Fig. 2) and we evaluated whether the mean weight of non-zero voxels (MeanNZ) in the tumour ROI can predict therapy response. We also evaluated whether the predictive capability of this approach is sensitive to inaccuracies in T1 or the AIF. We initially used the T1 values (ranging from 1600ms to 2500ms) and the AIF provided in the "QIN Breast DCE-MRI" dataset to define classification shapes ("Standard" in Fig. 3). We repeated the analysis using incorrect T1 values of 1000 ms and 100 ms, and after substituting the AIF by the population-based AIF model and parameters from Parker et al.[6]

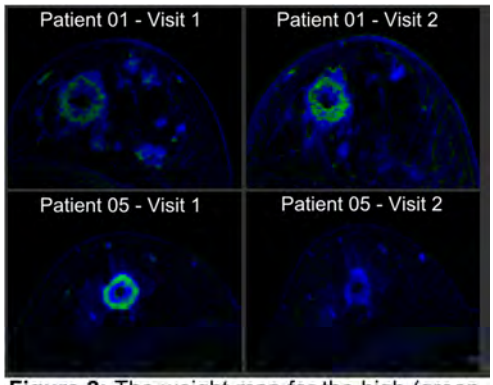

Figure 2: The weight map for the high (green channel) and low (blue channel) permeability shapes for two patients. Patient 05 showed complete response, while Patient 01 did not.

Results & Discussion: The MeanNZ for the low-permeability shape at visit 1 and for the high-permeability shape at visit 2 were both able to separate pCR from non-pCr patients (Fig. 3). The high-permeability shape at visit 1, and the low-permeability shape at visit 2, did not have predictive value. T1 errors had little impact. However, the choice of AIF had a noticeable effect, as seen in the two right-most columns of Fig. 3a. The area under the receiver operating characteristic curve (AUROC) is 1 for most cases in Fig. 3a and all cases in Fig. 3b; however, the AUROC drops to 0.952 for the low permeability shape at visit 1 when Parker's population-based AIF is used. This value is still larger than the highest pre-treatment AUROC using quantitative analysis on this same dataset (=0.857)[3]. These results show that shape analysis of perfusion MRI based on representative quantitative model curves could be a powerful analysis tool for prediction or early assessment of treatment response.

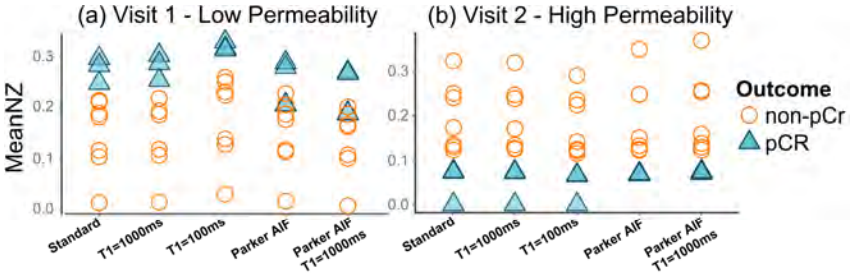

Figure 3: Each patient's mean of non-zero weight values for the low permeability shape at pre-treatment (c) and for the high permeability shape after firce cycle of therapy (b).

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References: [1] Marinovich ML, et al., Breast 2012;21:669–77. [2] Li X, et al., Magnetic Resonance in Medicine 2014;71:1592–602. [3] Huang W, et al., Translational Oncology 2014;7:153–66. [4] Lavini C, et al., Reports in Medical Imaging 2013;6:71. [5] Eliat P-A, et al., Magnetic Resonance Imaging 2004;22:475–81. [6] Parker GJM, et al., Magnetic Resonance in Medicine 2006;56:993–1000.