An adaptive Bayesian MRF approach for DCE-MR imaging

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INTRODUCTION

Quantitative analysis of dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) is typically achieved by applying pharmacokinetic (PK) models to the contrast agent concentration time series in each voxel. The quantitative PK parameters are estimated by fitting a non-linear model to the observations. We use a fully Bayesian approach to estimate the parameters. An adaptive Gaussian Markov random field (GMRF) prior [1] is placed on PK parameters in order to reduce the estimation error.

METHODS

Unlike Gauss-Newton algorithms, Bayesian approaches do not imply numerical optimization problems. A hierarchical Bayesian model is used for analysis where the observation model of gadolinium concentration $C_t(t)$ is derived from the standard compartmental model [2] $C_t(t) = K^{trans}[C_p(t) * \exp(-k_{ep}t)] + \varepsilon_t$. Parameter K^{trans} represents the transfer from the plasma to EES, k_{ep} is the rate parameter for transport from EES to the plasma, and ε_t is the observation error. Here, * denotes the convolution operator and $C_p(t)$ is the standard arterial input function (AIF) based on [3].

In the Bayesian framework, we assume the error *a priori* to have a Gaussian distribution with mean 0 and variance $1/\tau_\varepsilon$. For the PK parameters, a Gaussian Markov random field is used as the prior probability density function (PDF), i.e., the parameters K^{trans} and k_{ep} in each pixel *(x,y)* are *a priori* assumed to follow a GMRF. To account for the different smoothness properties of the tissue, the weights in the GMRF are estimated separately using an inverse Gamma distribution as prior PDF.

Data consist of a DCE-MRI scan from a breast cancer study at the Paul Strickland scanner centre. The scans were acquired with a 1.5T Siemens MAGNETOM Symphony scanner. Gd-DTPA was used as the contrast agent.

RESULTS

Fig. 1 shows the estimated K^{trans} parameter map in the region of interest estimated with our adaptive Bayesian MRF (aBMrf) approach, compared with a voxel-wise analysis. The aBMrf approach generates similar parameter estimates, but smoothness imposed by the hierarchical model suppresses unreliable outliers both within and outside the tumour, see also Fig. 3 left. Fig. 2 shows the estimates standard error of $\log(K^{trans})$ per voxel. These are noticeably reduced in the aBMrf approach. The map of the estimated log-relative weights (Figure 3 right) shows more smoothing is applied outside the tumour and the border around the tumour, along with borders of different regions within the tumour, are clearly visible as regions of little or no smoothing.

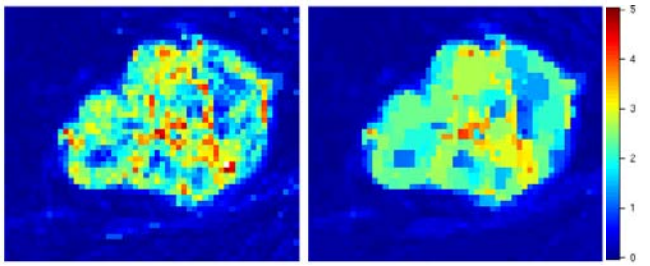

Figure 1: K^{trans} map estimated in a voxel-wise model (left) – and with the aBMrf approach (right).

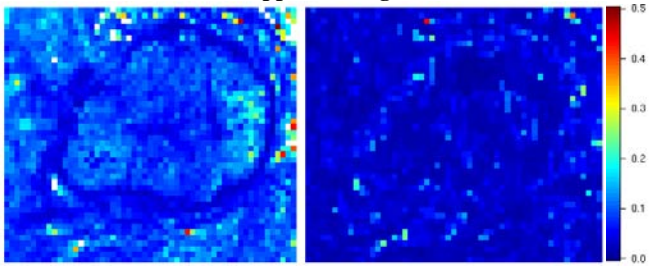

Figure 2: Estimated standard error of $\log(K^{trans})$ estimation in a voxel-wise model (left) and the aBMrf model (right).

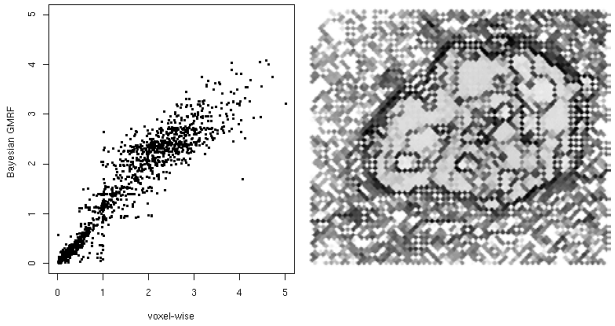

Figure 3: Scatterplot of K^{trans} estimates in the voxel-wise and the aBMrf model (left) – log-relative weights in the aBMrf approach (right).

DISCUSSION AND CONCLUSION

The use of a Bayesian framework for estimating the PK parameters for DCE-MRI is a new alternative to the usual non-linear fitting algorithms. By relying on contextual information from neighbouring pixels with a GMRF prior, the results are smoother within homogenous regions. The use of an adaptive approach is necessary to retain sharp features since tissue characteristics are heterogeneous. Estimation errors are clearly reduced in the aBMrf approach and therefore the resulting PK parameter estimates are more reliable.

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