The simultaneous multiple-voxel processing of MRI data using Bayesian random effects modelling

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Introduction

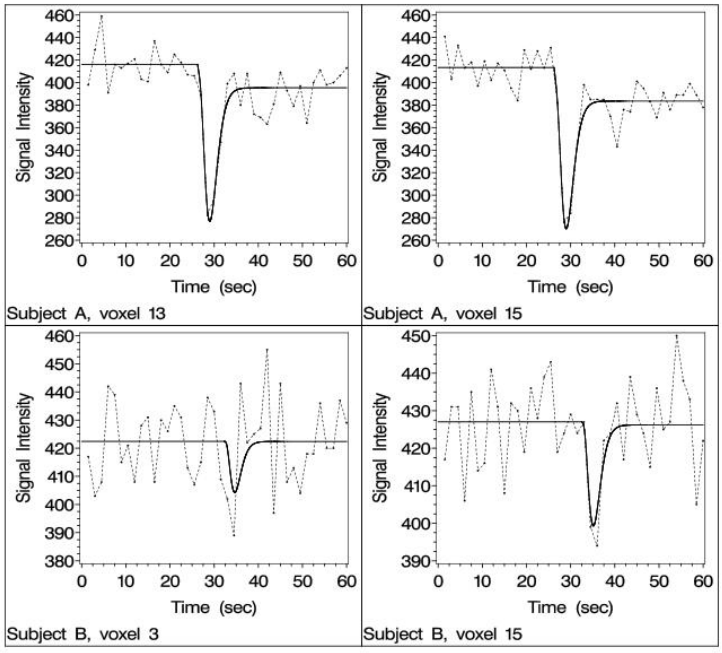
A common feature of many MRI data processing methods is the voxel-by-voxel manner in which processing is performed. In general, however, MR image voxels are not expected to exhibit statistical independence, as opposed to some kind of spatial structure, rendering an independent-voxels treatment inefficient. This inefficiency can be overcome by using Bayesian random effect models. The distinguishing feature of this approach is simultaneous, multiple-voxel processing based on some suitable spatial and/or non-spatial statistical distribution. It is the resulting information-borrowing behaviour of Bayesian random effect models that leads to improved estimation.

Random effect models have received little attention in the MR literature, with the notable exception of functional MRI. We have previously outlined a Bayesian random effects treatment of both multiple directions diffusion data [1] and longitudinal MR diffusion data [2]. The purpose of this work is to provide a further illustration of the advantages of random effects modelling with a view to promoting its more widespread use in the treatment of MR data. We demonstrate the method using the results generated from a Bayesian spatiotemporal random effects modelling of the time-dependent signal intensity data obtained with dynamic susceptibility contrast (DSC) perfusion imaging. The modelling was performed using Markov chain Monte Carlo (MCMC). We suggest that this kind of approach is expected to be beneficial in many MRI applications.

Methods

The children investigated in this study attended Great Ormond Street Hospital for Children to undergo a variety of clinical investigations, but subsequently showed no signs of brain abnormality. DSC MRI data were acquired on a 1.5T Siemens Magnetom Vision system, using a spin-echo EPI sequence (TR 1.25 or 1.5s; TE 100ms; matrix size 128x128, FOV 250x250mm, 5mm slice thickness). After approximately 15 baseline acquisitions, Gd-DTPA was administered by intravenous injection (0.15mmol/kg), followed by a saline flush. A 16-voxel (4-by-4) region was selected from within the thalamus of each of five subjects, positioned to achieve a high level of uniformity in the first baseline T_2-weighted image. A small region was selected for the purpose of illustration and to reduce CPU demands.

The DSC signal response was modelled using a changepoint treatment [3] of bolus arrival, combined with an exponentially-damped polynomial (EDP) [4]. An EDP takes the general form $f(t) = \alpha + t^q \beta(t) e^{-\lambda t}$, $\beta(t) = \beta_0 + \beta_1 t + ... + \beta_p t^p$, $t \geq 0$, where q and p are integers. The full random coefficients, EDP spatiotemporal changepoint model took the form $y_{ij}(t_k) \sim N(\mu_{ij}(t_k), \tau_\varepsilon)$, $\mu_{ij}(t_k) = \alpha_{ij} + \beta_{0_{ij}}$, $t_k < \kappa_{ij}$, $\mu_{ij}(t_k) = \alpha_{ij} + (\beta_{0_{ij}} + \beta_{4_{ij}} t'^4_{ijk}) e^{-\lambda_{ij} t'_{ijk}}$, $t_k \geq \kappa_{ij}$, $t'_{ijk} = t_k - \kappa_{ij}$ where ~ indicates 'distributed as', and $N(\mu, \tau)$ is the normal distribution with mean μ and precision τ. $y_{ij}(t_k)$ is the DSC signal at the kth measurement occasion within the jth voxel within the ith subject, t_k is time at the kth measurement occasion, and κ_{ij} is the changepoint (bolus arrival time) in the jth voxel of the ith subject. This model for signal intensity was incorporated into a Bayesian random effects structure in which each parameter was treated as a sum of subject-specific and voxel-specific terms. In summary, the model allows for an abrupt change in signal intensity at the bolus arrival time and incorporates a flexible peak shape function. The model parameters are both voxel and subject specific, allowing a simultaneous modelling of all 5 subjects and all 16-voxels within each subject. Subjects were treated as exchangeable (i.e., invariant to permutations of the subject labels), while voxels were modelled as spatially correlated. Each of the subject-level random effect terms was assigned an appropriate hierarchical distribution. The voxel-level random effect terms were assigned a spatial CAR (conditional autoregressive) prior [5]. Gibbs sampling was performed using WinBUGS [6] in conjunction with the GeoBUGS car.normal function (http:// www.mrc-bsu.cam.ac.uk/bugs). Three parallel chains were generated, each consisting of 50,000 samples. MCMC convergence assessment was performed as in [1].



Results

The figure shows the signal intensity data in four voxels selected from two of the five subjects, with the modelled data superimposed. In subject A the bolus response is reasonably well-defined and the minima in the observed and model responses effectively coincide. In contrast, the bolus response in Subject B is partially obscured by noise, and in some voxels the model response is dominated by the spatial prior. Useful bolus response profiles are obtained for each voxel, despite the poor signal in some voxels. Further analysis indicates a lack of equivalence among the voxel-specific responses, providing justification for the spatial random effects treatment, as opposed to ROI averaging.

Discussion

The results presented here illustrate the advantages of the Bayesian random effects modelling approach as a general spatial or spatiotemporal data processing method, and suggest that it might be applied with advantage to a wide variety of MRI processing problems. We use DSC perfusion imaging for the purpose of illustration. DSC parameter estimation is challenging because it tends to suffer from low signal-to-noise ratios, compounded by the ill-conditioned inverse calculation that arises in DSC data processing. We show that a random effects analysis is capable of providing useful voxel-specific bolus response profiles, despite the low signal-to-noise ratio in the DSC data. Among the attractive properties of random effect models in general is a formal pooling of information across the entire dataset. In the present analysis this pooling occurs across subjects and across voxels within subjects.

Conclusion

There are many MR applications in which noise limits the spatial and/or temporal resolution that can be achieved. This includes diffusion imaging, spectroscopic imaging, time-resolved-MRI and the structural imaging of some pathologies. We suggest that random effect models could be used to advantage in numerous MR processing problems involving sparse and/or noisy data.

References [1] King MD et al., NeuroImage 44:753–768 (2009) [2] King MD et al., J Cerebr Blood Flow Metab 23:677–688 (2003) [3] Carlin BP et al., Appl Statist 41:389-405 (1992) [4] Crowder MJ, Tredger JA. Appl Statist 30:147-152 (1981) [5] Wakefield JC et al., In: Elliott et al. (eds). Spatial epidemiology: Methods and applications (2000) p104-127. [6] Lunn DJ et al., Statistics and Computing 10:325-337 (2000).