Recovering the information in the drift of fMRI data⋆

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The purpose of this abstract is to investigate the possibility of recovering the information in the drift in fMRI data, paralleling the recovery of inter-block information in ANOVA pioneered by Yates in 1939 [1].

Introduction

The optimal stimulus paradigm for fMRI data is to vary the stimulus every ∼10s to optimize the design and maximize the efficiency of the experiment. However sometimes the stimulus is presented in very long blocks, or else is slowly varying with time. An example is a pain experiment conducted in our lab in which the stimulus was a hot pepper spice applied to the skin. The pain response builds up slowly over time, and we are interested in detecting those regions of the brain that are activated.

The usual statistical analysis of such data is frustrated by the fact that the stimulus time course closely resembles drift. Drift is usually modelled as a slowly varying function, such as a spline or low-frequency cosines, that are added to the linear model for the fMRI data [2-6]. The stimulus is almost confounded with the drift, so that removing the drift from the data by adding it it as covariates will also remove most of the stimulus. In other words, the stimulus is almost indistinguishable from drift, so it is impossible to detect.

Methods

However there is another option. We can model the drift as a *random* effect, rather than a fixed effect. To do this we must rely on the drift varying randomly across subjects, showing no preferred sign (up or down), with a mean drift of zero (over subjects). Then if the fMRI data shows a consistent temporal increase (over subjects), then this can be attributed to the stimulus, and not the drift.

The appropriate analysis can be performed by fitting a mixed effects model, preferably using the ReML criterion [7-9]. In a hierarchical design (e.g. runs, sessions, subjects), the stimulus covariates are incorporated into the linear model as fixed effects at the first level. In addition to the residual error with temporal correlation structure (e.g. AR(1) model), we add an additional term of the form $Z\Sigma Z'$ to the variance matrix of the observations, where Z is the matrix of drift covariates and Σ is their unknown variance matrix. The data must be combined over all runs/sessions/subjects in order to estimate the parameters of the model (fixed effects, random effects, and variance parameters σ^2 and Σ). In other words, the analysis cannot be broken up into separate levels as in [7-9].

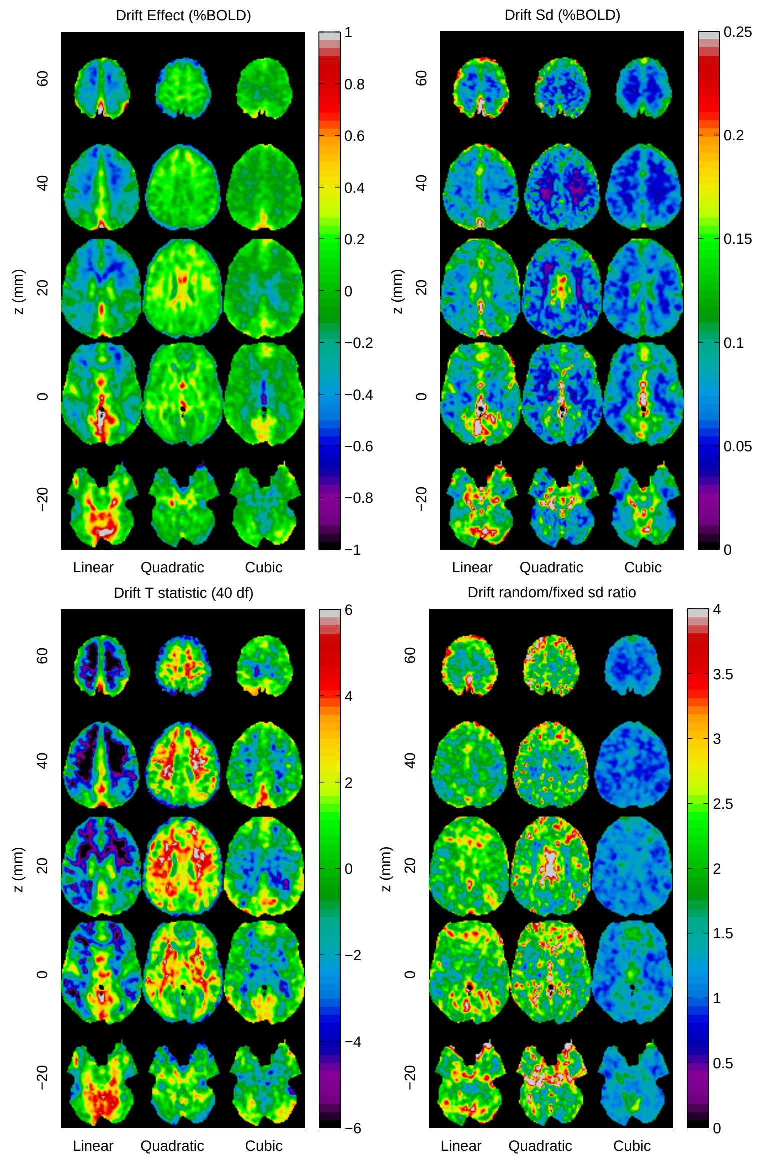
Results

Before performing such a random effects analysis, we investigate the hypothesis that the drift is random with a mean of zero. Without this assumption, the above analysis is impossible. We chose the FIAC contest data [10] with 14 subjects and a mixture of event and block designs with short epochs so that the stimulus is not confounded with the drift. We chose a cubic in the scan time t as covariates for modelling the drift. Letting $x = t - \mathrm{mran}(t)$, $u = x/\max x$, then the drift covariates were: u, u^2, u^3, each varying from -1 to 1.

The effects of the three drift terms were estimated on each run, then combined over runs using a fixed effects analysis, then combined over subjects using a mixed effects analysis, exactly as in [10]. The results are shown opposite for several Talairach slices.

The $P = 0.05$ threshold for a whole brain search of the T statistic images (40 df) is ± 5.67, so we conclude that there are consistent linear and quadratic drift effects, but not cubic. The linear drift appears to increase in white matter and decrease in grey matter, with a positive quadratic effect in white matter.

The ratio of random/fixed effects sd image is particularly interesting. It shows that there are random effects for both linear and quadratic drift that are more or less uniform throughout the brain, averaging at about 2.5. However the cubic drift term shows no evidence of a random effect, since the sd ratio is very close to 1 throughout the brain.



Conclusion

Unfortunately the results of this study show that recovering the information in the drift, as advocated above, is impossible. This is because the linear and quadratic drift exhibit consistent non-zero effects across subjects. In other words, if the stimulus varies in a linear or quadratic fashion then it is impossible to distinguish it from drift.

However the cubic drift term appears to show no consistent effects, so if the stimulus varies in a cubic fashion, then there is some hope of recovering the information in the drift.

To detect a stimulus that looks like drift, the best approach seems to be to apply the stimulus to half the runs in a cross-over design, randomising the order of the runs with and without stimulus. Then we can compare the drift of runs with the stimulus to the drift of runs without the stimulus, by the usual mixed effects analysis. This will be the subject of future work.

References

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