The effect of repetition time on model selection in dynamic causal modeling

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Introduction

Dynamic causal modeling (DCM) is an important tool for analyzing functional integration between different regions of the brain (Friston et al., 2003). Apart from very few exceptions (e.g. Kasess et al., 2008) the overwhelming number of DCM studies used data with repetition times (TR) greater than 1 second. However, it seems clear that the use of shorter TRs shows a number of advantages. First, shorter TRs simply increase the number of data points resulting in improved model fitting. Higher sampling rates also allow for better coverage of the hemodynamic response, thereby enabling better coverage of possible transient effects, particularly in event-related designs. Another advantage of short TRs is that differences in slice timing become less problematic (Kiebel et al., 2007). Clearly, there are also problems using short TRs, most notably the decreased coverage of the brain leading to a possibly restricted set of regions that can be analyzed.

In this work we have investigated the effects of different repetition times at varying noise levels on the model selection outcome using simulated data based on a hypothetical 3-region network (fig. 1).

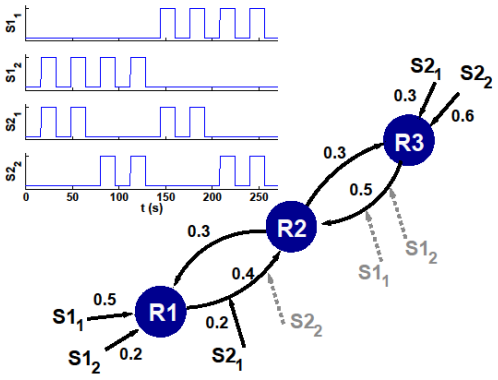

Fig. 1: Simulated Model. *Shown are the network structure of the simulated data and the stimuli (left upper panel).*

Methods

In order to test the effects of TR we used simulated data based on a network consisting of 3 regions modeling a "top-down" regulation (fig. 1) assuming that R3 is the top and R1 is the bottom region. Four stimuli were modeled representing two levels of two experimental conditions S1 and S2. Each level consisted of four blocks of duration 16s (fig. 1, upper left). Regions R1 and R3 were chosen as input regions for S1 and S2 respectively and the third region (R2) showed an interaction effect based on a "top-down" modulation by one level of S2. We tested for all combinations of 4 different modulatory influences (the true modulation and three other variants (fig. 1, dashed grey lines)). This lead to 16 different models that covered all possible combinations of two "top-down" and two "bottom-up" regulation mechanisms.

The network model was integrated at 1/16s and then sampled at 1/16, 1/8, 1/4, 1/2, 1 and 2 seconds. Furthermore, 4 different signal-to-noise ratios (SNRs) were tested (1, 2, 5, and 10). 15 subjects or datasets were simulated for each TR and SNR in order to allow testing for consistency of the model selection. Model evidence was estimated based on the 'free energy' approximation used in DCM (see e.g. Stephan et al., 2007). Model selection was evaluated in two ways: (1) by calculating the median logartihmic Bayes factor between the true model and all other models across subjects for each condition; (2) by deriving group statistics using the RFX approach recently published (Stephan et al., 2009). To quantify the results of the RFX analysis the ratio of the posterior probability between the true model and the other 15 models was calculated.

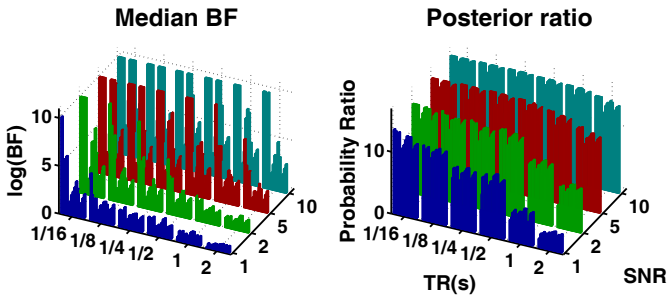

Fig. 2: Model selection. *The left panel shows the median logarithmic Bayes factor as a function of TR and SNR. To improve readability BFs were limited to a maximum of 10. The right panel shows the same for the posterior model.*

Results

The left panel of fig. 2 shows the median logarithmic Bayes factor (BF) of all 15 "false" models as compared to the true model as a function of TR and SNR. Clearly, the average BF is always larger than zero implying an advantage for the true model and therefore a correct identification. However, at low SNRs the TR has a distinct effect on the Bayes factor showing much higher factors at short TRs. For high SNRs this trend becomes much less pronounced showing a better model selection in general.

For the RFX analysis the ratio of the posterior probability of the true model with respect to the other models is shown in fig 2, right panel. Here a higher ratio implies a better model selection as the probability of the true model increases. Clearly, the multi-subject analysis shows similar trends as the BFs. At low SNRs shorter TRs show a clear advantage in model selection whereas towards higher SNRs the model selection becomes in general better and more consistent across TRs.

Conclusion

In this study we showed that the repetition time can have a marked influence on model selection. Our data indicates that high temporal resolution is beneficial for model selection. Both, the median BF that is related to a fixed effects model selection and the RFX multi-subject analysis showed better model selection for short TRs, in particular at lower SNRs. We also showed that this effect persists at higher SNRs, yet not as pronounced. Here, it is important to note that the parameter estimates of the true model were far less affected by changes in TR than the model selection.

The predominant factor determining the advantage of short TRs in these simulations is most likely the higher number of samples as the total measurement time was kept constant. Also, since a blocked design was used the increased coverage of the hemodynamic response probably plays a minor role.

Despite the aforementioned advantages, there is also a major drawback in using very low TRs as the coverage of the brain is in general reduced. This can prove problematic when important regions can not be integrated into the model. However, as previously shown (Kasess et al., 2008), even with a two region network, important conclusions can be drawn that are in good agreement with existing evidence.

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