

Dynamic Update of R_2^* and Field Map in fMRI

V. Olafsson¹, J. A. Fessler¹, D. C. Noll¹

¹University of Michigan, Ann Arbor, MI, United States

Introduction

By acquiring a quantifiable measurement of the signal relaxation rate map R_2^* , we get a measurement of deoxy-hemoglobin concentration, which can be linked to CMRO2, thus making R_2^* estimation a viable method of measuring the BOLD response in fMRI [1]. The most common method for estimating R_2^* maps is the multi-echo method, which uses a log linear fit [1,2], however, this can increase the total acquisition time for a slice. Furthermore in areas of high susceptibility, using field map correction is essential when reconstructing R_2^* . Conventional methods only acquire an initial field map, which is used in reconstructing all time points. However, since respiration, subject movement and field drifts can change the field map throughout the time series, it would be desirable to update the field map for each time point. Joint estimation methods for estimating the BOLD response and field map have recently been proposed [3,4]; however the non-linearity of R_2^* and the field map, complicates the estimation.

We propose to estimate the incremental changes in the R_2^* map and field map ω , between adjacent time points in an fMRI time series, and to use those estimates to dynamically update R_2^* and ω for subsequent time points. Assuming small changes of these maps between time points, we linearize the signal equation, allowing us to solve the problem with fast iterative methods, using the conjugate gradient algorithm.

Theory

Using the signal equation that includes T_2^* decay and off resonance effects, we can write the difference signal $y(t_m; j)$, $j=1 \dots J$, for neighboring time points j and $j-1$ of an fMRI time series, as follows,

$$y(t_m; j) = s(t_m; j) - s(t_m; j-1) = \sum_{n=1}^N f_n \left(e^{-t_m z(r_n; j)} - e^{-t_m z(r_n; j-1)} \right) e^{-i2\pi(k_m \cdot r_n)} + \varepsilon(t_m), \quad m = 1 \dots M, \quad (1)$$

where $z(r_n; j) = R_2^*(r_n; j) + i\alpha(r_n; j)$, f_n is the magnetization right after the RF pulse, r_n is the spatial coordinate, ε is white Gaussian 0-mean noise, and M is the number of k-space points. By factoring the second exponential out of the parenthesis, the first exponential now contains the difference of R_2^* and ω for the neighboring time points in its exponent. Assuming that the differences of R_2^* and ω from time point to time point are small, we can linearize the exponential, as follows

$$\left(e^{-t_m z(r_n; j)} - e^{-t_m z(r_n; j-1)} \right) = e^{-t_m z(r_n; j-1)} t_m \tilde{\alpha}(r_n; j), \quad (2)$$

where $\tilde{\alpha}(r_n; j) = -[\partial R_2^*(r_n; j) + i\delta\alpha(r_n; j)]$, or the negative incremental changes in R_2^* and ω from time point $j-1$ to j .

After linearizing we use (1) to estimate $\tilde{\alpha}(r_n; j)$ using fast iterative methods. We do this by formulating the sum in (1) as a product of a vector \mathbf{x}_j , which contains $\tilde{\alpha}(r_n; j)$ as its elements, and matrix \mathbf{A} , containing the rest of the components of the summation. We then formulate a penalized least squares cost function, which is minimized to find the estimate of \mathbf{x}_j [5],

$$\hat{\mathbf{x}}_j = \operatorname{argmin}_{\mathbf{x}_j} \left[\|\mathbf{y}_j - \mathbf{A}\mathbf{x}_j\|^2 + \beta R(\mathbf{x}_j) \right]$$

with \mathbf{y}_j , containing the difference of time points j and $j-1$ as shown in (1). Furthermore, we need to collect a multi echo baseline data, from which we can estimate the baseline maps f_n , $R_2^*(r_n; 0)$ and $\alpha(r_n; 0)$, which are then used in \mathbf{A} for $j=1$. For all subsequent estimates we need to update the R_2^* and ω maps, which we do by taking the sum of $z(r_n; j-2)$ and the previous incremental changes estimated. We have then updated the \mathbf{A} matrix such that the next incremental change can be estimated.

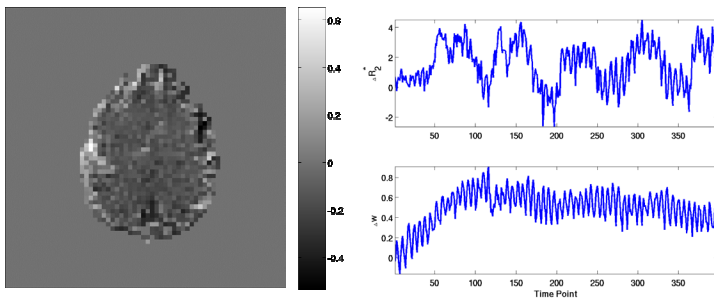


Figure 1

Figure 2

Results

One subject performed a 5 cycle block design, unilateral finger tapping task on a GE 3T scanner (two echo spiral out acquisition with TE=25ms and TR=500ms). The results can be seen in the two figures on the left. Figure 1 shows the correlation map and Figure 2 shows the two plots of ΔR_2^* (above) in units of 1/s and $\Delta\omega$ (below) in units of Hz, relative to the baseline R_2^* and ω for all time points, averaged for pixels with correlation over .5. Time point j of the plots was calculated by summing all previous estimates $\tilde{\alpha}(r_n; k)$ for $k=1 \dots j-1$, with the real part of the sum being ΔR_2^* and the imaginary part being $\Delta\omega$ at time point j .

Discussion and Conclusion

We have shown a framework in which R_2^* and ω are updated dynamically by estimating incremental changes relative to baseline estimates of f_n , R_2^* and ω . It uses linearization in order to reduce the complexity of the problem, allowing for use of fast iterative algorithms (conjugate gradient algorithm). Additionally, by linearizing for the incremental changes in R_2^* and ω instead of absolute changes relative to some baseline R_2^* and ω , we were able to decrease the chance of linearization errors in the estimates. Additional errors from previous incremental estimates have to be controlled by choosing sufficient penalization and estimating good baseline maps, even though the algorithm is somewhat self-correcting if the error is small.

The dynamic update of R_2^* and ω was shown to capture the 5 on/off task cycles in the R_2^* and respiration and field drift in the baseline ω for the fMRI time series. Using the updated field map can also help decrease the residual variance in the BOLD response. Additionally, the dynamic update also has a potential advantage when motion correction is added to the model, since the registration algorithm has access to current estimates of R_2^* and ω maps for each time point.

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References

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