

INCORPORATION OF GRAY MATTER T_1 AND T_2^* IMPROVES BRAIN ACTIVATION STATISTICS IN fMRI

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Purpose: The proton spin density (M_0) as well as the MR relaxivities, transverse (T_2^*), and longitudinal relaxation times, provide the basic contrast mechanisms in functional MRI (fMRI). Although the MR magnetization physically depends on tissue and imaging parameters in a nonlinear fashion, a linear model is what is conventionally used in fMRI activation studies. Furthermore, the standard practice has been to discard the first scans to avoid magnetic saturation effects even though they have important information on the MR relaxivities. It is also well-known that activation occurs in gray matter (GM) while performing a task. We present a statistical fMRI model for Differential T_2^* Contrast INcorporating T_1 and T_2^* of GM, so-called DeTeCT-ING, that uses complex-valued time courses to estimate T_1 and T_2^* for each voxel, then to incorporate GM MR relaxivities into statistical model in order to better detect brain activation, all from a single pulse sequence by utilizing the first scans. We show the performance of the DeTeCT-ING Model on an fMRI data set and compare it with the conventionally used magnitude-only (MO)¹ and newer complex-valued (CA)² fMRI models.

Methods: The temporally varying magnitude of the MR signal, M_t , can be represented by incorporating the effect of the task execution as follows: $M_t = [M_{t-1} \exp(-TR/T_1) \cos(\phi) + M_0(1 - \exp(-TR/T_1))] \sin(\phi) \exp(-TE/T_2^* + \delta z_t) + x_t \beta_1$ where ϕ is the flip angle (FA), TR and TE are the repetition and echo times, δ is the differential task signal change, the coefficient for the reference function z_t , x_t is the t^{th} row of the design matrix X , and β_1 is the linear drift coefficient. The complex-valued observations with phase θ_t at time t can therefore be described as $y_t = M_t(\cos \theta_t + i \sin \theta_t) + (\eta_{R_t} + i \eta_{I_t})$, where $(\eta_{R_t}, \eta_{I_t})' \sim N(0, \sigma^2 I_2)$. Working in the complex domain with the data having normally distributed noise allows for the use of nonlinear Least Squares estimation (NLSE). To construct a generalized likelihood ratio (GLR) test of the hypothesis, $H_0: T_1 = T_1(GM), T_2^* = T_2^*(GM), \delta = 0$ (no activation) vs. $H_1: T_1 = T_1(GM), T_2^* = T_2^*(GM), \delta \neq 0$ (activation), the likelihood function is maximized by the numerical minimization of $\sum_{t=1}^n [(y_{R_t} - M_t \cos \theta_t)^2 - (y_{I_t} - M_t \sin \theta_t)^2]$ under the null (tildes) and alternative (hats) hypothesis. The GLR statistics, $-2 \log \lambda = 2n \log(\hat{\sigma}^2 / \tilde{\sigma}^2)$, has an asymptotic χ_1^2 distribution in large samples and two-sided testing can then be done by $Z = \text{sign}(\delta) \sqrt{-2 \log \lambda}$.

An fMRI experiment with a bilateral finger-tapping task was performed on a 3T MRI scanner. The paradigm followed a block design with an initial 20s rest followed by 16 epochs of 15s on and 15s off. An echo planar pulse sequence (FA=90°, BW=125 kHz, matrix=96x96, FOV=24cm, slice thickness=2.5mm, TR=1s, repetitions=510) was used. TE was designed as: 40.4ms at first 10 TR, equispaced in [40.4,52.9] for the next 5 TR; this was repeated once again, fixed to 40.4ms at last 490 TR. Activation is thresholded with Bonferroni correction³.

Results: The parameter maps estimated from the first 20 TR images by using NLSE are shown in Figs. 1(a)-(c). Figs. 2(a)-(c) show activation images using the GLR from CA, MO and DeTeCT-ING Models.

Discussion: M_0 , T_1 , and T_2^* values are highly indicative of GM bordered in Figs. 1(a)-(c). Fig. 2 shows a high correspondence between decay coefficients deemed to be GM and bordered active areas that should be in GM. It is obvious that CA and DeTeCT-ING Models demonstrated superior power of detection over MO model in left motor cortex and supplementary motor area in which the activation occurs. Fig. 3(c) shows that DeTeCT-ING Model produces no false positives outside brain unlike CA model. A higher power of detection can be seen in the bordered left motor cortex in Fig. 2(c) compared to the corresponding areas in Figs. 2(a) and (b).

Conclusion: This works strongly indicates that modeling MR magnetization by the signal equation and incorporating MR relaxivities into the activation along with utilizing the first scans of complex-valued fMRI data provides higher power to detect the active voxels.

References: 1. Bandettini P, Jesmanowicz A, Wong E. Processing strategies for time-course data sets in functional MRI of the human brain. *Magn. Res. Med.* 1993;30(2):161-173. 2. Rowe DB, Logan BR. A complex way to compute fMRI. *NeuroImage.* 2004;23(3):1078-1092. 3. Logan BR, Rowe DB. An evaluation of thresholding techniques in fMRI analysis. *NeuroImage.* 2004;22(1):95-108.

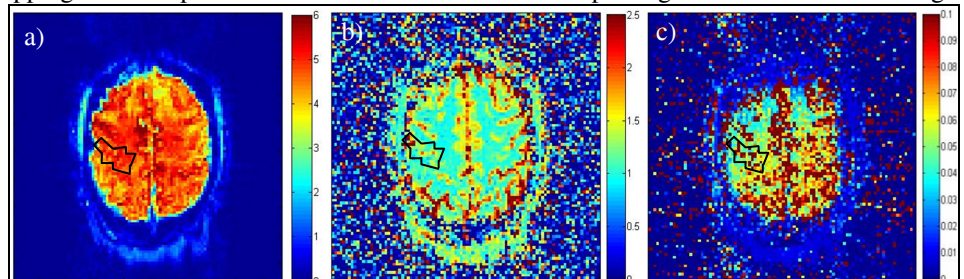


Fig. 1: Estimated tissue parameter maps. a) M_0 . b) T_1 (in ms.). c) T_2^* (in ms.).

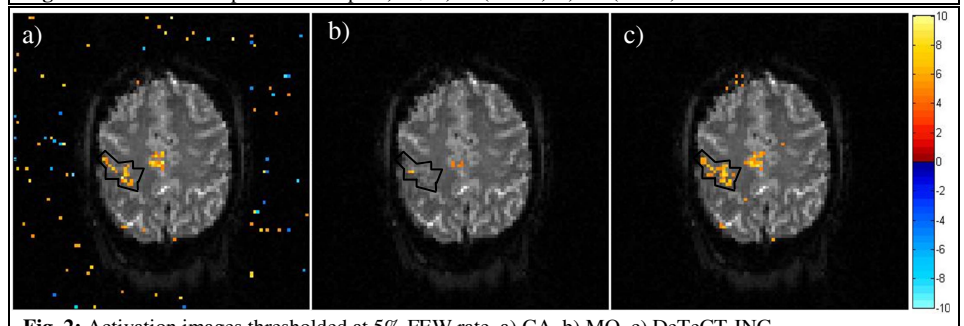


Fig. 2: Activation images thresholded at 5% FWE rate. a) CA. b) MO. c) DeTeCT-ING.