Tikhonov regularization: effects on the detection of activations in SENSE functional MRI

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Introduction

Parallel reconstruction methods are at the moment extensively used in MRI. In particular, they are applied to the reconstruction of functional MRI series, which are post-treated to detect brain cortex activations. Moreover, regularisation is a popular way to increase SNR in parallel-reconstructed images. This is due to the well known lost of SNR due to a reduced data acquisition. However, studies quantifying the effects of regularisation in the detection of activations are missing. This abstract asserts that regularisation indeed affects the detection of activations; moreover this effect can be undesirable. We choose a regularized version of SENSE [1] for this test. Tikhonov is selected as regularisation method for its successfully application in this context [2] [3]. We show the behaviour of Tikhonov regularization parameter for the detection of cortex activations in a visual experiment. We present cases where the detection is severely affected.

Description of the method

SENSE reconstruction is based on a matrix $R = (S^H \Psi^{-1} S)^{-1} S^H \Psi^{-1}$, where S is the *sensitivity matrix* and Ψ is the receiver noise matrix. The superscript ^{H} indicates a Hermitian transposition. We choose to apply Tikhonov regularization [4] for the stabilisation of R. This technique has already been applied in the context of SENSE reconstruction, see [2] and [3]. We perform a Singular Value Decomposition (SVD) of matrix S:

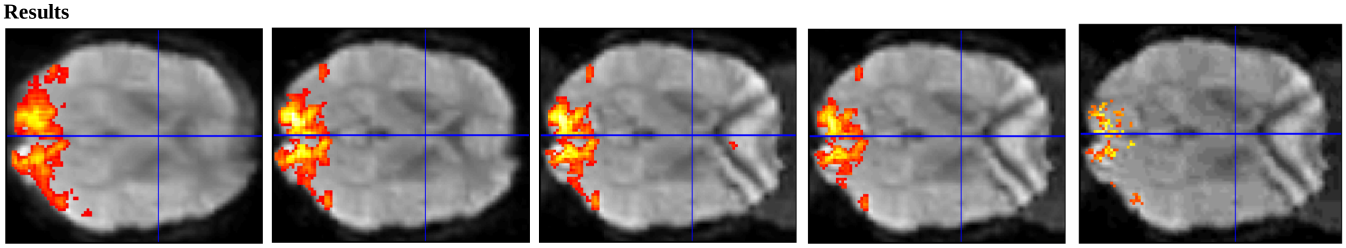
$$S = U\Sigma V^H = \sum_{i=1}^{n} \mathbf{u}_i \sigma_i \mathbf{v}_i^H ,$$

where $U = (\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_n)$ and $V = (\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n)$ are complex matrices with orthonormal columns, and $\Sigma = \mathrm{diagonal}(\sigma_1, \sigma_2, \ldots, \sigma_n)$ is a real matrix containing non-negative diagonal elements appearing in non-increasing order such that $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_n \geq 0$. A stable inverse of R when Ψ is not used can be calculated in the Tikhonov sense by $R^{-TIK} = V\Sigma^{-TIK} U^H$, where $\Sigma^{-TIK} = \mathrm{diagonal}(f_1/\sigma_1, f_2/\sigma_2, \ldots, f_n/\sigma_n)$ with $f_i = \sigma_i^2 / (\sigma_i^2 + \lambda^2)$. In our implementation, a unique Tikhonov parameter λ is chosen for the whole image.

Materials and Methods

A functional MRI (fMRI) was performed on a healthy volunteer using a 1.5T GE Signa scanner and an 8 channel head coil array. Two EPI sequences at reduction factor 1 and 2 were acquired. The volunteer was instructed to visualize the image of a contrast-reversing chessboard. The experiment was composed of 4 rest/stimulus periods: a rest period consisting of the visualization of a black image during 19.5 seconds and a stimulus period consisting of the visualization of the flashing chessboard during 19.5 seconds. We used a 64x64 sum-of-squares image to create the Sensitivity Maps for SENSE. The sequences and reconstruction software are entirely implemented in the NMR-Neurospin library developed at the French Center of Atomic Energy (CEA), Saclay , France. For the detection of functional activations, reconstructed images at reduction factor 1 and 2 were processed with SPM2 (Statistical Parameter Mapping software, version II), [5].

Results



R=1 R=2, λ=0.2 R=2, λ=5 R=2, λ=10 R=2, λ=20

Figure 1. Activation maps extracted from fMRI series using reduction factor 1 (R=1, left image) and 2 (R=2, rest of the images). R=2 series are reconstructed using SENSE with different Tikhonov parameters (λ).

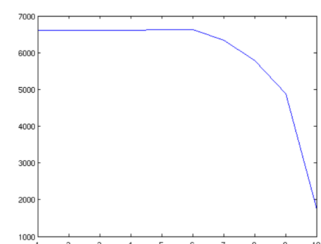


Figure 2. Detected activated voxels versus Tikhonov parameter

In Figure 1 we show activation maps calculated by use of SPM2. We superpose the activations to the original EPI images used for their detection. The activations on the left hand side image of the figure are extracted from a reference series at reduction factor 1 (R=1), the rest of the maps are extracted from R=2 series reconstructed by SENSE, using different Tikhonov parameters. In Figure 2 we draw a curve showing the number of detected activated voxels (Y axis) against different regularization parameters (X axis). Note that units in X axis are monotonically increasing but not constant, the aim of the figure is to show the general behaviour, for small and big values, of the parameter around its maximum. Tested parameters are: λ=0, λ=0.00001, λ=0.05, λ=0.1, λ=0.2, λ=0.5, λ=1, λ=5, λ=10, and λ=20).

Discussion

We see in Figure 1 that for different parameters we obtain different number of activations. Moreover, from Figure 2 the effect of the Tikhonov parameter appears clearly: an initial plateau of acceptable parameters should not be abandoned, because the number of detected voxels is strongly decreased. In the plateau the maximum of detections is obtained by λ=0.2, where 7076 activated voxels are found while 8980 are detected at R=1. We note that the optimal parameter for the detection of the activations is not necessarily the one that obtains the best visual appearance. This study is indeed useful to choose a correct regularisation parameter that detects the more activations as possible. However, each point used in plotting Figure 2 implies the realisation of time consuming reconstructions, batching and SPM analysis. A relatively high number of points have to be used and such a parameter test can easily take a working day. It will be then interesting the development of quick criteria for optimal cortex activation not based in an SPM analysis.

Conclusion

We evaluated the effect of Tikhonov regularization on the detection of activations in fMRI using SENSE.

References: [1] Pruessmann et al. MRM, 1999, 42:952-962. [2] King, Angelos. ISMRM, 2001, 1771. [3] Lin et al. MRM 2004;51:559-567. [4] Tikhonov, Arsenin. *Solution of ill-posed problems.* 1977. [5] http://www.fil.ion.ucl.ac.uk/spm/