Undersampled Multi Coil Image Reconstruction for fast fMRI Using Adaptive Linear Neurons

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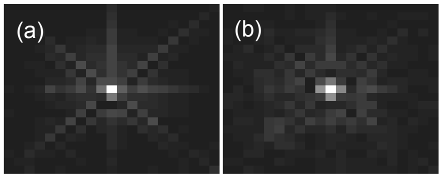

Fig.1. PSF for Tikhonov reconstruction (a) and ADALINE reconstruction (b).

Introduction: Although functional MRI is based on the detection of a rather sparsely distributed signal in the spatial domain, it is nevertheless usually measured by acquiring full resolution EPI data, which therefore limits the temporal resolution that can be achieved. Recently, regularized non-cartesian image reconstruction combined with multiple coils was used to demonstrate the feasibility of fMRI in the highly undersampled regime [1,2,3] to increase the temporal resolution by an order of magnitude. There, strongly undersampled fMRI data were acquired and l_2-norm Tikhonov regularization was used to perform image reconstruction. Tikhonov regularized reconstruction still leads to strong streaking artefacts in the resulting activation maps. Here we would like to introduce a new approach, based on neural networks, to reconstruct the undersampled fMRI data that offers a significantly improved point spread function (PSF) with reduced spatial spread and hence improved spatial localization of activation.

Methods: Let A be the forward operator that yields the measured data b for all coils when applied to an image z, i.e. $\mathrm{Az=b}$. A set of training data $\{\mathrm{z_i,b_i}\}$, $\mathrm{i=1,\dots,N}$ can be generated using the forward operation and a set of arbitrary images $\mathrm{z_i}$. In practice the $\mathrm{z_i}$ can be chosen to be e.g. randomly distributed Gaussian functions. Image reconstruction is based on finding the linear operation W, that gives a good approximation $\mathrm{Wb_i} \approx \mathrm{z_i}$ for all $\mathrm{i=1,\dots,N}$. This actually represents a very simple form of a neural network called adaptive linear neuron (ADALINE) and the weight matrix W is usually found by using a gradient descent method [4]. However, in this special case a simpler way to compute W is to minimize the sum of square residual errors $\min_{\mathrm{W}}\left\{\sum_i \left\|\mathrm{Wb_i}-\mathrm{z_i}\right\|^2\right\}$ with respect to W. It can be shown that the solution for W can be written in analytic form as $\mathrm{W=CA^\dagger(ACA^\dagger)^{-1}}$, where C is the covariance of the $\mathrm{z_i}$, and † denotes the adjoint. In the limit of an infinite number of random training data and Gaussian training data, C is equal to a convolution with a Gaussian kernel. Since $\mathrm{ACA^\dagger}$ is not necessarily invertible the inversion is stabilized by an additional regularization term. To test this approach, simulations were performed using a 3D radial trajectory with 20 spokes, which results in an undersampling factor of R≈200 for a 64^3 image, and an artificial fMRI data set containing two activated regions with 3x3x3 voxels. Additionally, experiments were performed on a 3T Tim Trio with a 32 channel head coil array (Siemens, Erlangen, Germany). For visual stimulation a checkerboard paradigm was used. The stimulus presentation followed a block design with 3 periods, each consisting of 15s of activation followed by 15s of rest. Data was acquired with TR/TE=100ms/30ms using a 3D rosette trajectory [2] with 40 petals (R≈100).

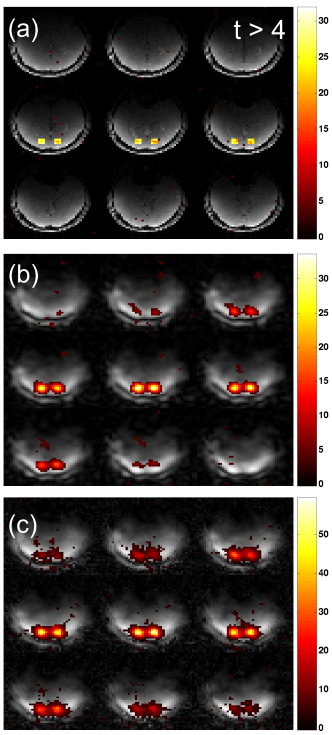

Fig.2. t-map overlays of the essential slices of the simulations using two cubic regions of activation: Reference (a), ADALINE (b) and Tikhonov reconstruction (c).

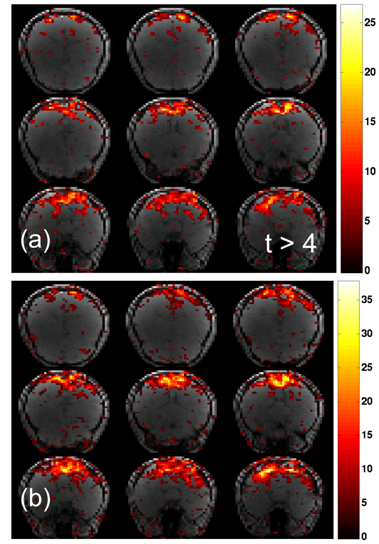

Fig.3. t-map overlays of the central 9 slices of the slab: ADALINE (a) and Tikhonov reconstruction (b).

Results: In Fig.1 the 2D point spread function of a voxel in the visual cortex can be seen for Tikhonov reconstruction (a) and the proposed method (b) for a radial trajectory with 4 spokes. While the overall spatial spread is similar, the advantage of method (b) clearly is the high radial symmetry of its PSF and the absence of streaking artefacts. Fig.2 shows the results of the simulations, with the fMRI reference timeseries (a), the standard Tikhonov reconstruction (b) and the ADALINE reconstruction (c). It can be observed that the overall spatial localization is slightly better and the streaking is less prominent in the proposed approach compared to l_2-norm regularization. In Fig.3 the experimental results are displayed. It can be observed that streaking and smearing for the proposed approach is significantly reduced compared to Tikhonov reconstruction and localization of activation is improved.

Discussion: By acquiring only a fraction of k-space to increase the temporal resolution of fMRI experiments, image reconstruction becomes a strongly underdetermined inverse problem. Solutions are bound to have a lower spatial resolution and spatially variable, anisotropic point spread functions. The PSF of the ADALINE reconstruction is demonstrated to yield high radial symmetry to evenly distribute the spatial smearing of information and thus is more favourable compared to standard Tikhonov reconstruction. Apart from the regularization parameter, ADALINE introduces additional degrees of freedom through the choice of the training data. Additional work is required to identify optimal parameter for robust and reliable reconstruction for general applications.

References:

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