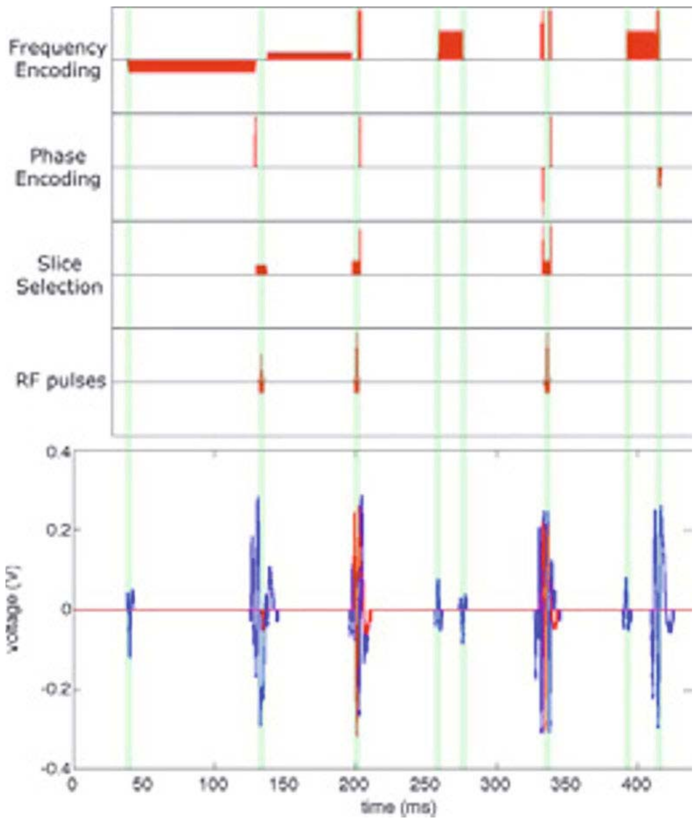

Figure: Sequence listing of a TSE sequence (TR=500ms, TE=200ms, Turbo-Factor=2) with chronological order of the radio frequency excitation (RF) and magnetic-field-gradients (see above), measurement data of the ultrasound transducer without wanted signal and without random noise in MRI with sequence operation (below). The induced voltages are visible through RF excitation (red) and through and through the turn-on and turn-off of the magnetic-field-gradients (blue).

Discussion/Conclusion: The CTG recording during the MR-imaging acquisition is feasible but the calculation of the FHR can be disturbed by induced voltages. Those interferences can be predicted in the frequency domain by an MR-sequence that is constant in time and that can be filtered.

References:
[1] Poutamo, J., 1998, Prenatal diag, 18(11): p. 1149-1154
[2] Michel, S.C.A., 2003, AJR, 180(4): p. 1159

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Retrospective blind motion correction of MR images

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Introduction: We present a retrospective method, which significantly reduces ghosting and blurring artifacts due to subject motion. No modifications to the sequence (as in [2, 3]), or the use of additional equipment (as in [1]) are required. Our method iteratively searches for the transformation, that -- applied to the lines in k-space -- yields the sparsest Laplacian filter output in the spatial domain.

Methods: We limit ourselves to Cartesian acquisitions and assume that the subject is rigidly moving. The forward model is linear and can hence be written as a matrix that decomposes into blocks. Matrix vector multiplications (MVMs) are efficient i.e. O(nlogn). The vector is the volume in k-space stacked into a column vector of complex numbers. Such an MVM is appropriate, since both rigid rotation around the center and translation in image space correspond to rotation and pointwise phase multiplication in k-space, respectively. Our optimization algorithm (sketched in Fig. 1) searches for the motion parameters for each k-space line (fully specifying the transformation matrix) which transforms the acquired image such that the outputs of a 3D Laplacian filter are as sparse as possible. This reduces blurring and ghosting artifacts because blur and echoes correspond to less sharp images and hence less sparse filter outputs.

Results: We evaluate our algorithm on both synthetic and real data. Synthetic data were generated by applying the forward model to raw k-space data, with motion trajectories extracted from previous fMRI measurements with significant subject motion. More realistic volumetric data were acquired by a Siemens 3T Trio scanner, where we moved the subject by extracting and retracting the scanner's support table. This ensured precise control over the motion produced. The degraded volume was composed of k-space lines randomly taken from volumes with different positions of the support table. Our algorithm is able to reduce artifacts in both scenarios. Figure 2 shows the output of the algorithm applied to compositions of the real volumes.

Conclusion: Our results show consistently improved MR images over a range of different motion trajectories/k-space compositions on both synthetic and real data. In the future, we will extend the algorithm to be able to handle stronger motions, which -- at the moment -- are difficult to tackle due to local minima in the energy landscape.

References:
[1] Zaitsev et al., NeuroImage, 2006, 1038-1050
[2] Bourgeois et al., JMR, 2003, 277-287
[3] Johnson et al., IEEE Transactions on Medical Imaging, 2011, 655-665

Fig.1 Optimization outline:

$$\hat{\theta} = \arg\min_{\theta} ||\Delta \mathbf{X}_{\theta} \mathbf{y}||_1$$

$\mathbf{X}_{\theta}$ - rigid motion transformation matrix
θ - motion parameters (for each k-space line)
$\mathbf{y}$ - observed degraded volume
Δ - discrete 3D Laplace operator
$\hat{\theta}$ - estimated motion

Fig 2 Slice from the corrupted volume (A), the volume corrected with our algorithm (B), clean non-degraded volume