Eliminating streaking artifacts in quantitative susceptibility mapping using L1 norm minimization

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Introduction: Quantitative susceptibility mapping (QSM) has been developed as a technique that uses the phase information from the MRI measurements to estimate susceptibility changes in the imaged object. Moreover, it is possible to estimate the magnetic moment of the region of interest, which gives way to quantitative imaging of tracer particles in MRI. However, the inverse problem that needs to be solved to recover the susceptibility map from the phase image is ill-posed: 1), the dipole kernel that links the two maps has a cone of zeros in Fourier domain, and 2), regions of strong susceptibility change have low intensity (and hence, unreliable phase data) due to T2* dephasing. In this work, we use total variation-based regularization to tackle the inverse problem. Compared to original weighted quadratic regularization in [1], the proposed TV regularization significantly reduces the streaking artifacts from the areas of susceptibility change. This is particularly important in animal imaging where eventual air bubbles and/or voxel misclassifications at the segmentation stage could lead to strong under-estimation of the quantities of particles of interest.

Theory: The original QSM method computes the susceptibility distribution χ by minimizing the penalty function:

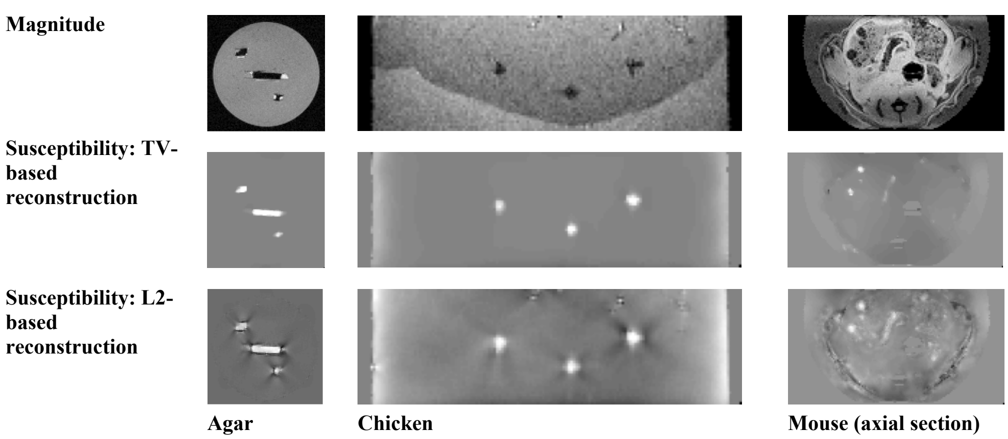
$$\chi = \operatorname{argmin} \sum \left\| w(r) \times (\delta_B(r) - d \otimes \chi) \right\|_2^2 + \left\| w_G(r) \times G\chi \right\|_2^2,$$

where δ_B is the measured field map, $w(r)$ and $w_G(r)$ are weighting matrices that account for non uniform phase noise, d is the unit dipole response. In this sum, the first term represents the data fidelity, while the second one provides regularization.

From experimental data, we have identified that all streaking artifacts are associated with locations with strong susceptibility changes. The L2 norm minimization only imposes a smooth solution, allowing streaking artifacts. We propose a L1 norm minimization that imposes sparse solution and hence eliminates streaking artifacts. In the implementation reported here, the weighted L2-norm of the gradient in the second term was replaced with a measure of total variation of $\chi, TV(\chi) = \|G\chi\|_1$ [2]:

$$\chi = \operatorname{argmin} \sum \left\| w(r) \times (\delta_B(r) - d \otimes \chi) \right\|_2^2 + \lambda \left\| G\chi \right\|_1 .$$

Materials and Methods:
Three experiments were carried out test the TV regularization and to compare with L2 regularization. The first experiment was a phantom made of agarous gel and cylinders containing air, scanned at a 1.5T GE scanner. The second dataset is an MRI image of a piece of chicken meat with several Feridex (Advanced Magnetics, Inc., Cambridge, MA, USA) injections of known quantities, scanned at a 1.5T GE scanner (Waukesha, WI, USA). The third dataset is acquired from Bruker 7T scan of a mouse that has been injected with SPIO. The TV-based regularization algorithm was implemented in MATLAB.



Results: TV-based computation of the susceptibility map took about 2-3 minutes per dataset on a 2.4GHz Intel Core 2 Duo Macintosh laptop. For all three datasets, the streaking pattern in the background is strongly reduced in the TV-regularized case compared to weighted-gradient regularization. Note the reduction of the streaking artifacts in the agarous-gel-phantom and the chicken case. In the mouse image, we observed spots of the strongest contrast in the region of SPIO.

Discussion and conclusion: TV-based regularization tends to make images piecewise constant. In traditional imaging, this is known as a ladder artifact, which can be annoying. For our purpose of quantification of the susceptibility change, this is not a concern, as we use the volume integral over the region of interest to compute the magnetic moment. At the same time, the average value in the background is used as a reference, and it is important to have a robust estimation for the quantification to be meaningful. The advantage of TV-based regularization is that it significantly reduces streaking artifacts caused by the air bubbles and/or voxel misclassification. In animal imaging, where the structure of tissues is complex, this is a major benefit compared to the original approach.

In this study, we propose a TV-based regularization for QSM. In case of datasets with large signal voids, we achieve better image quality than the original QSM method.

References: [1] de Rochefort et al. MRM, *in press*; [2] Candès et al. Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information. IEEE Trans. Inform. Theory, 52 489-509.