ICTGV Regularization for Highly Accelerated Dynamic MRI

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INTRODUCTION: Various sophisticated k-t reconstruction methods ([1, 2]) have been proposed for speeding up data acquisition of dynamic MRI applications and increased spatio-temporal image resolution. These methods depend on suitable sparsifying transforms in the temporal dimension and the appropriate use of sampling patterns for specific applications like cardiac functional imaging. Image regularization techniques such as total generalized variation (TGV) [3] were successfully applied for reconstruction of high quality images from undersampled static MR data [4]. In this work we address the important dynamic reconstruction problem from the greater point-of-view of appropriate regularization for image sequences [5], based on the TGV functional. The extension to this scenario is achieved by infimal convolution of two suitable weighted spatio-temporal TGV functionals, which automatically balances between temporal and spatial regularity in an optimal way. This poses a very general yet computationally tractable and well-studied motion model for a wide range of dynamic MR applications.

METHODS: We first consider the extension of total variational (TV) regularization for image sequences. Straight-forward spatio-temporal regularization requires a fixed weighting of regularity in space; a degree of freedom that, intuitively speaking, allows for balancing temporal consistency against spatial regularization. Given a weight ϵ, possible extension of TV to the space-time setting is as follows:

$$TV_{\{t,x\}}(u) = \int \left\| \partial_x u , \partial_y u , \partial_t u \right\|_{\epsilon_{\{x,t\}}} \text{ with either the norm } \|\,.\,\|_{\epsilon_t} = \sqrt{v_x^2 + v_y^2 + \epsilon v_t^2} \text{ or } \|\,.\,\|_{\epsilon_x} = \sqrt{\epsilon v_x^2 + \epsilon v_y^2 + v_t^2}\,.$$

Regularization with TV_{ϵ_t} is more flexible in allowing motion but lacks of temporal consistency while TV_{ϵ_x} enforces temporal consistency but leads to motion artifacts. The infimal convolution of the two TV functionals, i.e. $ICTV_{\epsilon}(u) = \min_u TV_{\epsilon_t}(u-v) + TV_{\epsilon_x}(v)$, overcomes this problem by effectively balancing the former extremes. We found the instance of the infimal convolution of two TGV functionals (ICTGV) particularly effective as reconstruction method of dynamic MRI data, building on TGV regularization for the static case. The mathematical reconstruction model, solved with a primal-dual strategy [6] with an adaptive step-size, is described as follows:

$$(1)\ \min_u ICTGV_{\beta}^2(u) + \lambda \textstyle\sum_{c,t} \left\| F_t(\, b_c\ u_t) - d_{t,c} \right\|_2^2 \quad (2)\ ICTGV_{\beta}^2(u) = \min_v TGV_{\beta_1}(u-v) + TGV_{\beta_2}(u).$$

Here F_t describes the Fourier-transform operator with time dependent k-space trajectory, b_c the c-th coil-sensitivity estimate from the time-averaged data and $d_{t,c}$ the reduced acquired data for each time-frame t. The minimization target is the whole image sequence $u = (u_t)_{t=1}^N$ for N time-frames. For validation of our proposed reconstruction we acquired fully sampled functional CINE cardiac data in short-axis view. Data was retrospectively undersampled in a variable density random fashion on a Cartesian grid for different acceleration factors. Imaging parameter for a retrospectively gated FLASH sequence on a Siemens Skyra 3T system (Siemens, Erlangen, Germany) were as follows: FOV=275x340 mm², acquisition image matrix=268x208, spatial resolution 1.63x1.63mm², flip angle=40°, TR/TE=42.72/1.78ms, rBW=940Hz/px with 25 reconstructed cardiac phases. Here ICTGV is also compared to k-t-Sparse-Sense (KTSS) [7]. A second cardiac case (four-chamber view) employing poisson-disk sampling was obtained from the ISMRM reconstruction challenge 2014.

RESULTS: Figure 2 displays ICTGV together with KTSS reconstruction for a selected systolic time-frame and two time-courses against the fully sampled reference for acceleration factors from 4 to 16. Up to acceleration factor 12, ICTGV yields a visually high quality reconstruction with details clearly visible. For acceleration factor 14 to 16 details are still observable but already smooth. Compared to KTSS, ICTGV based reconstruction yields superior quality and improved time-dynamics, above acceleration factor 8, which is rather a limit for KTSS. Reconstruction from poisson-disk sampling yields sharp details even for acceleration factors above 10 as exhibited in **Figure 1**.

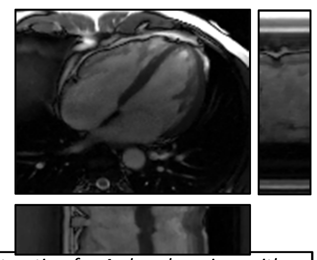

Fig 1: ICTGV reconstruction for 4-chamber view with time-lines crossing the centre; data from ISMRM reconstruction challenge (acc ~ 11); 2nd place was achieved

DISCUSSION and CONCLUSION: We present the ICTGV regularization as a new mathematical framework for highly accelerated dynamic MRI with a wide range of possible applications. Originally studied for the open topic of optimal regularization for image sequences it poses a very general motion model and is now applied in the context of MRI reconstruction. Mathematical properties are very well studied and allow for efficient numerical solution strategies with recent convex optimization methods. Acceleration factors above those achieved with state-of-the-art methods are reachable with good conservation of anatomical structures. A further, very interesting range of applications will focus on reconstruction from data acquired while free-breathing. Breathing motion often violates assumptions made in less general dynamic reconstruction methods, which might be mitigated with ICTGV reconstruction.

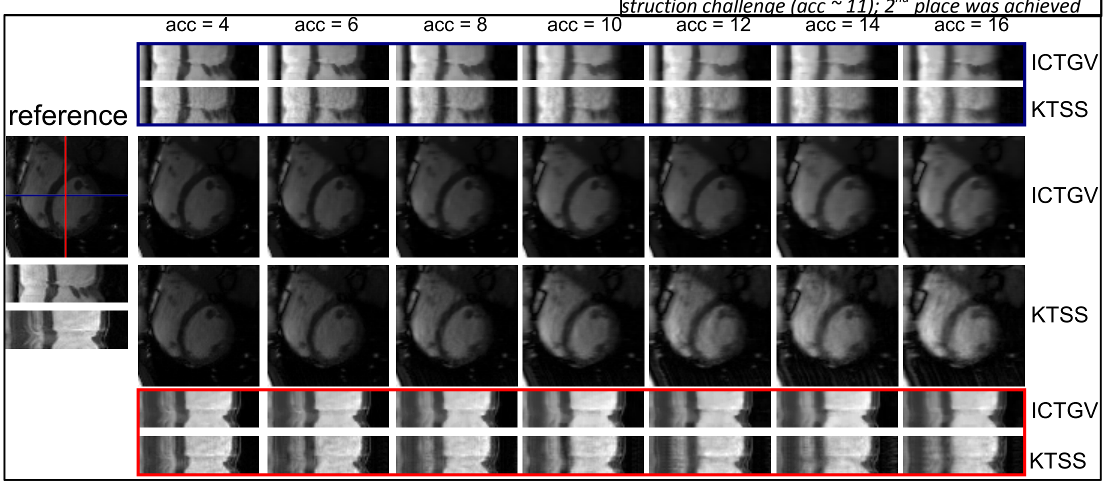

Fig 2: Selected systolic time-frame for ICTGV (3rd row) and KTSS (4th row) reconstruction for a cardiac short-axis view dataset. The fully sampled sum-of-squares reconstruction is displayed on the left side with indication of timelines (red and blue). Acceleration factors used vary from 4 to 16 on a randomized Cartesian grid.

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