

Compressed sensing on TDM-SENSE with rotating RF coil

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Introduction: Compressed sensing (CS) has been applied to MRI [1,2] so as to exploit the data redundancy, based on the theory that compressible signals can be reconstructed from randomly under-sampled frequency information [3,4]. Thus, the imaging acceleration can be achieved. A number of CS variants, especially those employing the parallel imaging techniques, have been proposed with the aim to reduce the scan time and ameliorate various image artefacts [5]. Recently, Time-Division-Multiplexed Sensitivity Encoding (TDM-SENSE) scheme was proposed to perform fast data acquisition and image reconstruction using a physically rotating RF coil (RRFC) [6], with its freedom to encode with spatial and temporal changing sensitivity profiles. In this work, we applied CS with the TDM-SENSE concept to further reduce artefacts and evaluated the imaging performance of this method.

Method: CS reconstruction has two fundamental requirements [3,4]: (a) the imaging object is compressible to a large extent with a sparsifying transform; (b) the measuring matrix is incoherent to this transform basis. In other words, the sparsity basis and measurement matrix are required to be properly configured, so that good reconstruction quality and the possible under-sampling rate can be achieved. The RRFC concept [6] utilizes a single rotating RF coil and the time division multiplexing technique to generate a large number of sensitivity profiles as the coil moves about the sample. Both RF excitation and data acquisition can be encoded with the freedom of temporal and spatial varying sensitivity profile to generate a measurement matrix, which is incoherent with sparsity basis in the CS framework. In this case, a theoretical and simulated random pulse was applied, also with under-sampling in k-space phase encoding direction. The object function m can be reconstructed by solving the following optimization problem with constraints for the sparsity representation \hat{x} :

$$\hat{x} = \operatorname{argmin}(\lambda_1 \|\Psi m\|_1 + \lambda_2 TV(m)) \quad \text{s.t. } \|b - A\Psi^{-1}x\|_2 < \varepsilon \quad \text{with } m = \Psi^{-1}x$$

where Ψ and Ψ^{-1} are sparsifying transform and inverse transform with Daubechies 4 wavelet, x is wavelet transform coefficient of the imaging object, λ_1 and λ_2 are regularization factors for L1 norm of the compressible transform and total variation (TV) respectively, the optimal value of the two weighting factors is chosen by investigating the reconstruction quality in terms of specific imaging objects. TV constraints can further suppress the reconstruction noise and provide noise stability. The measurement data fidelity is ensured by minimizing the error to a tolerant level. Vector b is the measured k-space data and ε is the tolerance of reconstruction accuracy. The image encoding matrix A incorporates both transmission and reception type image encoding modulations. Details on the construction of A can be found in [6]. Except in this case, the additional random RF excitation pulse is utilized and phase encoding is shifted during excitation to achieve randomized B1 encoding. The comparison between stationary RF coil and RRFC is compared in terms of the incoherence and reconstruction performance. Without losing the generality, in Figure 1, both cases are fixed to a reduction factor of 4 and with same excitation pulse. The reconstruction is performed by modifying the sparse MRI toolbox [1] and incorporating TDM-SENSE scheme. In addition, the transform point spread function (TPSF) is used to monitor the incoherence: $TPSF(i, j) = \delta_j \Psi A^{-1} A \Psi^{-1} \delta_i$ which describes how much the j th ($i \neq j$) wavelet transform coefficient is affected by the measurement and reconstruction process from single i th wavelet transform coefficient. The proper reconstruction will be indicated by small and random statistics-like interference $TPSF(i, j)$ [3,4].

Results and Discussion:

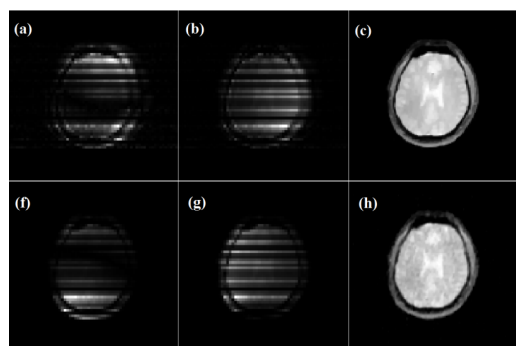


Fig.1 - 128x128 head image reconstruction with CS-TDM-SENSE: comparison of stationary and rotating RF coil case. In each case, a total of 32 frequency encodings were acquired. FLASH imaging parameters: TR=100ms, TE=10.16ms, FOV = 35x35cm, ST=5mm, FA=30°, b1(t)= hermite pulse, Tacq=10.24ms. Top row shows the rotating coil scenario. (a, b) real and imaginary part of the random B1 encoding, (c) reconstructed brain image magnitude, (d, e) TPSF of low and high frequency coefficients of wavelet basis respectively. (f-j) the corresponding plots for the stationary coil.

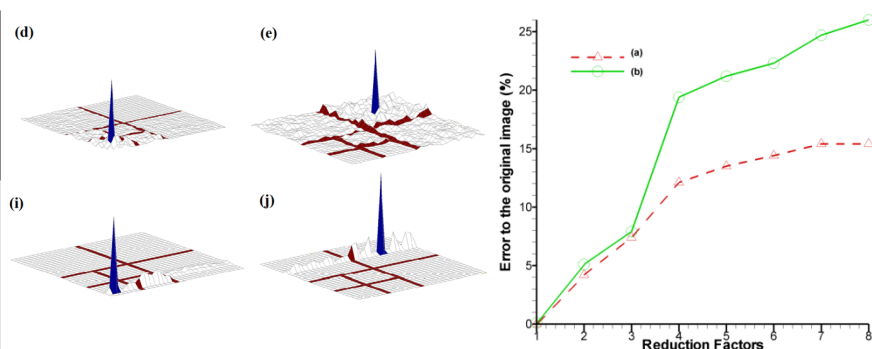


Fig.2 – The normalized relative errors of reconstructed results to original images over different reduction factors of measurement. (a) is with the proposed method; (b) is with stationary RF coil.

Fig. 1 demonstrates the improved quality of the reconstruction when CS-TDM-SENSE is applied to the measurement signals, acquired with the rotating RF coil. The coil rotates during frequency encodings in this case. The relative errors to the original image were 12.1% and 19.4% in rotating and stationary cases, respectively. TPSF of the rotating coil shows lower scale and more uniformly distributed interference, which suggests the benefit of applying CS to TDM-SENSE relates to a larger freedom of sensitivity encoding in conditioning the measurement matrix, thus higher reduction factor can be achieved without sacrificing image reconstruction quality. Fig. 2 illustrates the proposed method with RRFC concept has consistent advantages in terms of reconstruction quality across all different reduction factors.

Conclusion: CS-TDM-SENSE was presented as a new image encoding and reconstruction algorithm for RRFC concept. It presents the feasibility of using RRFC random pulse to tune measurement matrix for better reconstruction performance in the CS framework. Future work will focus on more experimental validations of this method to investigate the imaging performance and constraints by physical limits.

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References: [1] Lustig M *et al*, *MRM*, 58, 2007. [2] Sebert F *et al*, *Proc. ISMRM*, 3151, 2008. [3] Candès EJ *et al*, *IEEE Trans Inf Theory*, 52, 2006. [4] Donoho S, *IEEE Trans Inf Theory*, 52, 2006. [5] Wu B *et al*, *Proc. ISMRM*, 1480, 2008. [6] Trakic A *et al*, *Proc. ISMRM*, 3221, 2009