JOINT MOTION CORRECTION AND ESTIMATION FOR T_1 MAPPING: PROOF OF CONCEPT

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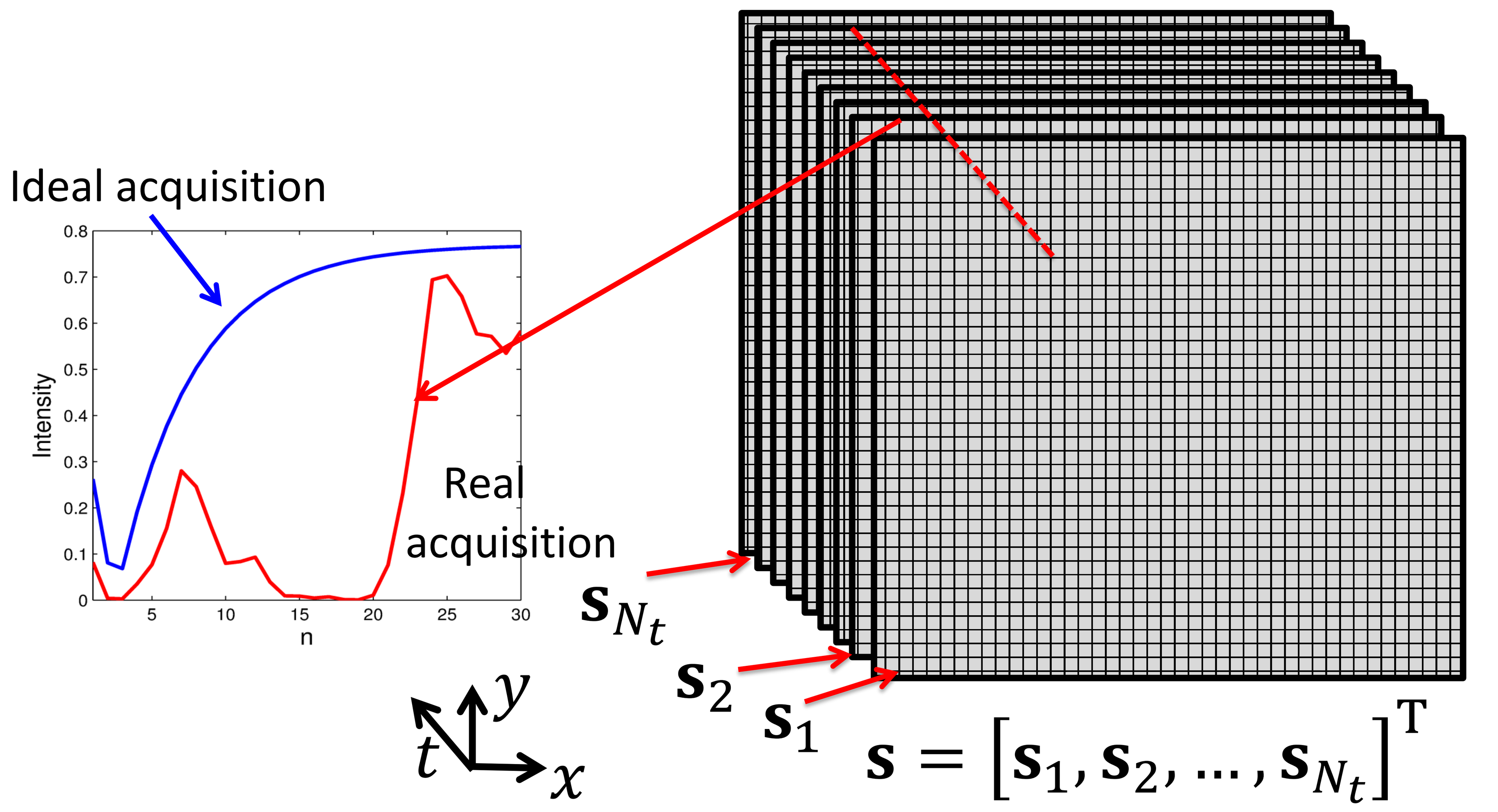
Ramos-Llordén G.[1], den Dekker A.J.[1,2], Sijbers J.[1]

[1]iMinds Vision Lab, Department of Physics, University of Antwerp, Belgium, [2]Delft Center for Systems and Control, Delft University of Technology, The Netherlands

Abstract

In conventional T_1 mapping, the acquired images are registered prior to T_1 estimation. The interpolation involved in the registration step, however, introduces bias in the T_1 estimates. We propose a joint motion correction and estimation method that estimates the motion model parameters and the T_1 values simultaneously, using a Maximum Likelihood approach. Results from synthetic experiments show a bias reduction compared to prior registration as well as more accurate motion parameter estimation.

Joint Probabilistic Model



Joint probability density function of the data

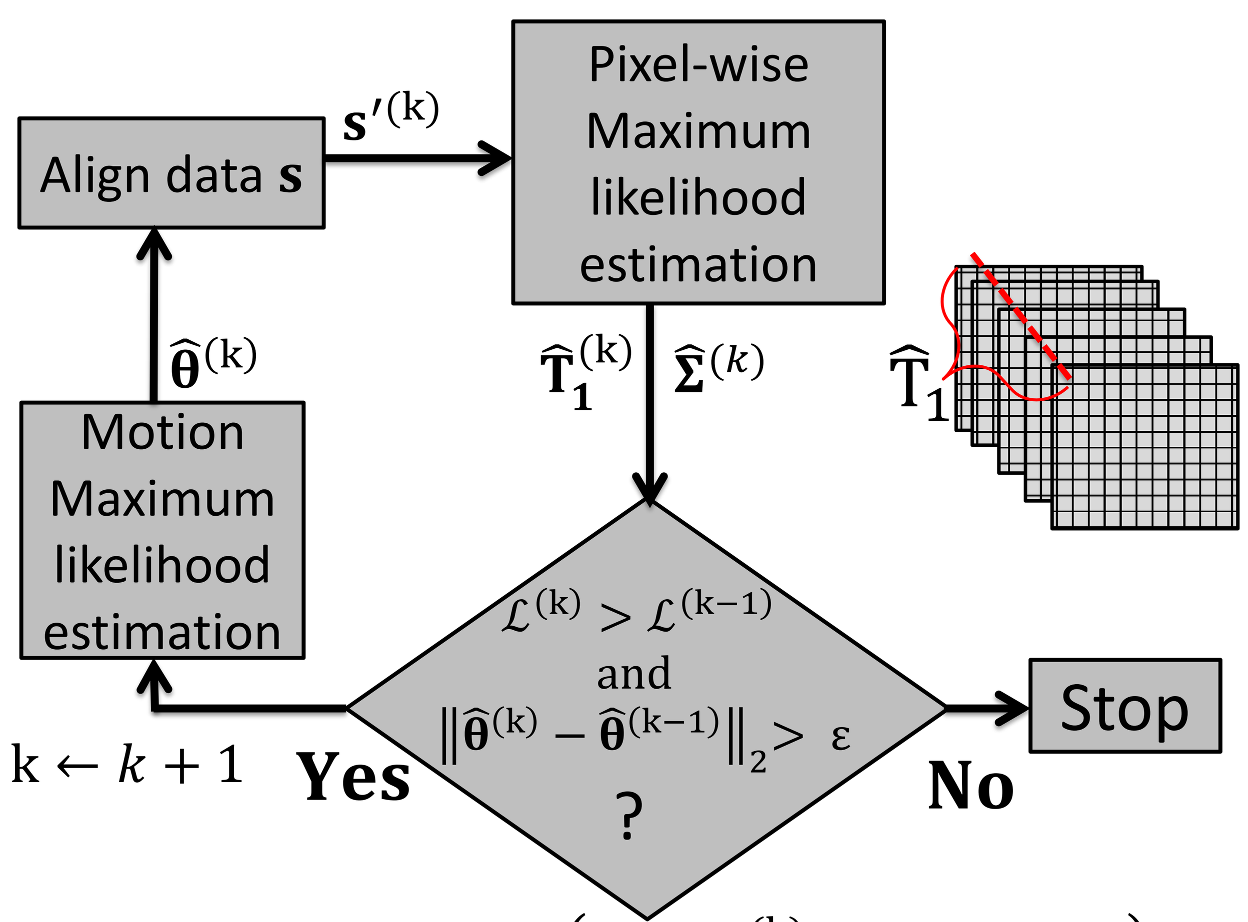
$$p_s(\mathbf{s}; \mathbf{f}(\mathbf{T}_1, \boldsymbol{\Sigma}), \boldsymbol{\theta}, \sigma) = \prod_{n=1}^{N_t} p_{s_n}(\mathbf{s}_n; \mathbf{f}_n(\mathbf{T}_1, \boldsymbol{\Sigma}), \boldsymbol{\theta}, \sigma)$$

$\mathbf{T_1}$	T_1 parameter vector
$\mathbf{f}_n(\mathbf{T}_1, \boldsymbol{\Sigma})$	Pulse Sequence value at nth acquisition
$\boldsymbol{\Sigma}$	Nuisance parameters of $\mathbf{f}(\mathbf{T_1},.)$: proton density ($\boldsymbol{\rho}$), flip angle,…
$\boldsymbol{\theta}$	Motion parameters
σ	Standard deviation of the noise

Maximum Likelihood estimator (MLE)

$$\{\widehat{\mathbf{T}}_1, \widehat{\boldsymbol{\Sigma}}, \widehat{\boldsymbol{\theta}}\} = \arg\max_{\mathbf{T_1}, \boldsymbol{\Sigma}, \boldsymbol{\theta}} \log(\, p_s(\mathbf{s}; \mathbf{f}_n(\mathbf{T}_1, \boldsymbol{\Sigma}), \boldsymbol{\theta}, \sigma)\,)$$

Iterative algorithm



$$\mathcal{L}^{(k)} \triangleq \log\left(p_s\left(\mathbf{s}; \mathbf{f}_n(\widehat{\mathbf{T}}_1^{(k)}, \widehat{\boldsymbol{\Sigma}}^{(k)}), \widehat{\boldsymbol{\theta}}^{(k)}, \sigma\right)\right)$$

Current case of study

$\boldsymbol{\theta} = \{n\Delta_x, n\Delta_y\}$ Translation motion

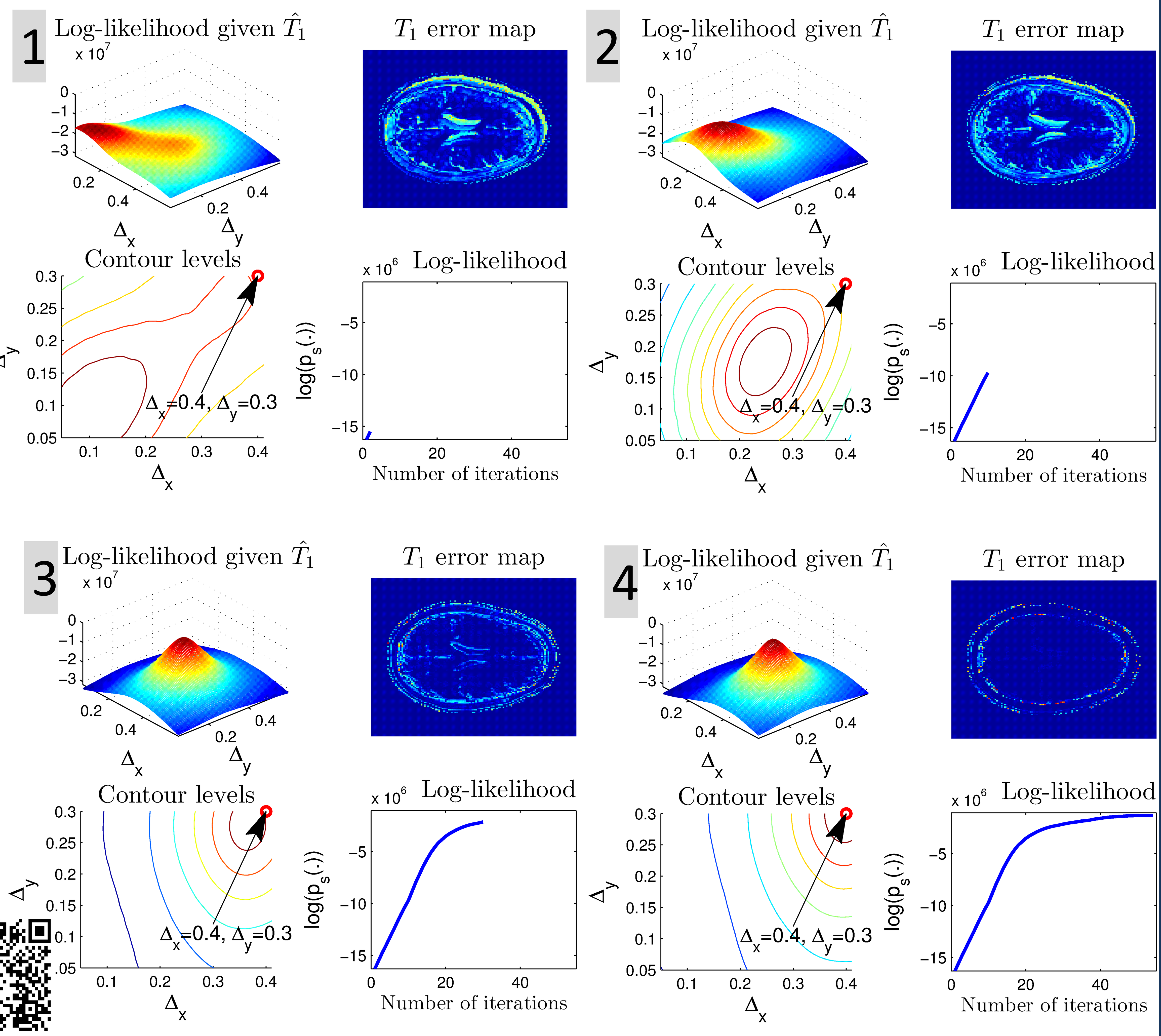
$\mathbf{f}_n(\mathbf{T}_1, \boldsymbol{\Sigma} = \boldsymbol{\rho}) = \boldsymbol{\rho}|1 - 2\exp(^{-TI_n}/_{\mathbf{T}_1})|$ Inversion Recovery (IR)

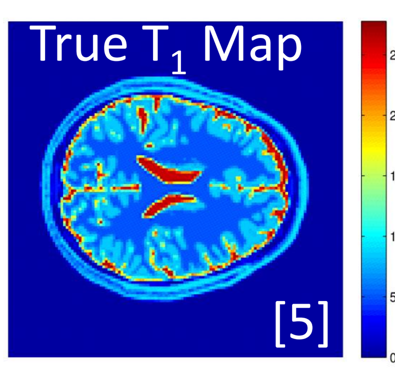
$\mathbf{s}_n$ non Central Chi Squared data

$\mathrm{E}[\mathbf{s}_n] = 2 + \boldsymbol{\lambda}_n$

$\boldsymbol{\lambda}_n = \frac{(\mathbf{F}_n(\boldsymbol{\theta})\mathbf{f}_n)^2}{\sigma^2}$ Non centrality parameter

$\mathbf{F}_n(\boldsymbol{\theta})$ 2D Shift Shannon operator [3]





Scan to see an animated demo!

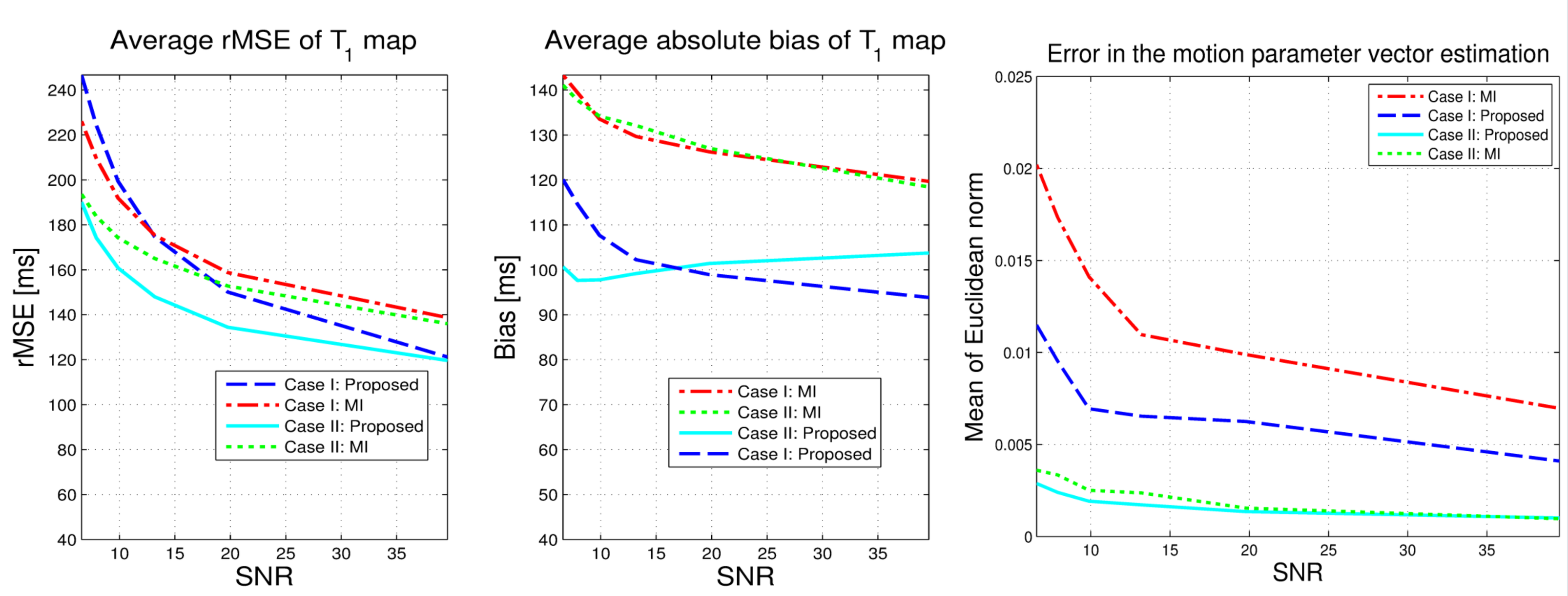
Simulation Results

The new method is compared to Mutual Information (MI) based registration [4] prior to Maximum Likelihood estimation.

$SNR \triangleq {}^{mean(\boldsymbol{\rho})}/_{\sigma}$

Case I: 10 Equally Spaced Inversion times (0.2s, 3s)

Case II: 30 Equally Spaced Inversion times (0.2s, 3s)



Discussion

MI registration introduces bias in the T_1 map independently of the SNR and the number of inversion times. In addition to the improvement in the accuracy of motion parameter estimation, the rMSE is always lower in our proposed method, except at very low SNR. We hypothesize that the interpolation in MI acts as a pre-filtering method in nearly constant regions.

Future steps

1)Extension of the Motion and IR model. 2) Global optimization method to obtain the MLE. 3) Real data testing.

References

[1] J.Sijbers *et.al.* (1999) Int. J Imaging Syst. Technol. [2] JK Barral *et.al.* (2010) MRM. [3] NA Woods *et.al* (2006) IEEE TIP. [4] D. Mattes *et.al.* (2001) SPIE Medical Imaging. [5] C.A. Cocosco *et.al.* (1997) Neuroimage

Contact

Gabriel.Ramos-Llorden@uantwerpen.be

http://www.visielab.ua.ac.be/people/gabriel-ramos-llorden