

OPTIMIZED RECONSTRUCTION PARAMETERS FOR NOISE MODELING IN MULTI-TASK BAYESIAN COMPRESSED SENSING FOR SPARSE 2D SPECTROSCOPY

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INTRODUCTION: CTPRESS is a homonuclear decoupling method that concentrates J-coupling information within metabolite molecules in a 2D frequency plane (f_1 - f_2), and has been shown to successfully detect coupled resonances such as glutamate (Glu) and glutamine (Gln) at the expense of increased total scan time in a 129-step CTPRESS experiment [1]. A 17-step CTPRESS experiment was implemented by Mayer et al [2] considering that all of the signals from a CTPRESS experiment lie close to the a diagonal in the 2D frequency plane, and therefore uniform undersampling in f_1 is possible without aliased signal overlap. Exploration of further under-sampling in 2D spectroscopy via compressed sensing appears promising as 2D spectra are naturally sparse and data sampling along the t_1 encoding direction readily accommodates flexible sampling patterns.

Metabolite spectra could be simulated and included as prior spectral information in the reconstruction of under-sampled 2D spectra via Multi-Task (MT) Bayesian CS [3]. We previously showed that MT Bayesian CS successfully reconstructed peaks of Glu and Gln even with imperfect simulated metabolite spectra as priors [4]. Spectroscopy data are intrinsically low SNR and here we extend previous work by incorporating noise modeling parameters for MT Bayesian CS and demonstrate improved reconstruction performance for under-sampled 2D spectra in CTPRESS compared to reconstruction without explicit noise modeling.

METHODS: Using SPINEVOLUTION [5], seven brain metabolites [6], (10.3 mM NAA, 9.95 mM total Cr, 1.63 mM total Cho, 12 mM Glu, 3mM Gln, 6mM myo-Inositol, 0.4mM Lac) were simulated in a uniformly undersampled, 17- t_1 step CTPRESS experiment with non-interfering aliasing as proposed by Mayer et al [2]. This 17-step, 2D experiment is considered the baseline for further undersampling in this study, and was undersampled as determined by a random draw from a uniform distribution in the t_1 dimension by a factor of R. Gaussian noise of $\sigma^2 = 0.0025$ was added such that $\text{SNR}_{\text{NAA}} = 20$ at full sampling. The seven brain metabolites were also weighted equally and summed, and the fully sampled spectrum formed the basis function for MT Bayesian CS reconstruction. In Eqs. 1, 2 and 3,

$$p(\mathbf{m}_i | \mathbf{y}_i, \boldsymbol{\alpha}, \alpha_0) = \frac{p(\mathbf{y}_i | \mathbf{m}_i, \boldsymbol{\alpha}_0) \cdot p(\mathbf{m}_i | \boldsymbol{\alpha})}{\int d\mathbf{m}_i p(\mathbf{y}_i | \mathbf{m}_i, \boldsymbol{\alpha}_0) \cdot p(\mathbf{m}_i | \boldsymbol{\alpha})} \dots \text{Eq. 1}$$

$$\boldsymbol{\mu}_i = \boldsymbol{\alpha}_0 \boldsymbol{\Sigma} \mathbf{F}_u^T \mathbf{y}_i \dots \text{Eq. 2}$$

$$\boldsymbol{\Sigma}_i = (\boldsymbol{\alpha}_0 \mathbf{F}_u^T \mathbf{F}_u + \mathbf{A})^{-1} \dots \text{Eq. 3}$$

$$\mathbf{A}_i = \text{diag}(\alpha_1 \alpha_2 \dots \alpha_i \dots \alpha_N)$$

$$p(\boldsymbol{\alpha} | c, d) = \prod \Gamma(\alpha_i | c, d) \dots \text{Eq. 4}$$

$$p(\alpha_0 | a, b) = \Gamma(\alpha_0 | a, b) \dots \text{Eq. 5}$$

$$\rightarrow E[\sigma^2] = \frac{b}{a-1}, \text{Var}[\sigma^2] = \frac{b}{(a-1)^2 \cdot (a-2)}$$

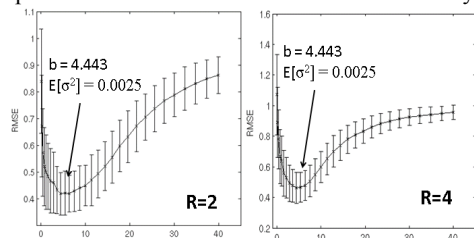


Fig. 1a and b. RMSE evaluated for low-SNR peaks evaluated with different values of b for under-sampling factor of $R = 2$ and $R = 4$ using MT-Bayesian CS with perfectly phased priors.

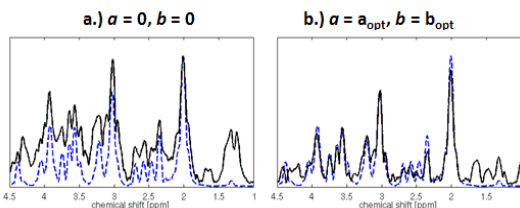


Fig. 2a and b. Diagonal spectra from reconstructed 2D CTPRESS spectra with different values of a and b for under-sampling factor $R = 4$. Blue dashed lines indicate the diagonal spectra of simulated noise-free fully sampled data.

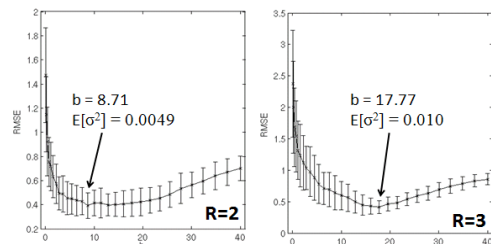


Fig. 3a and b. Fig. 2a and b. RMSE evaluated for low-SNR peaks evaluated with different values of b for under-sampling factor of $R = 2$ and $R = 3$ using MT-Bayesian CS with magnitude priors.

y_i 's represent the under-sampled complex data and fully sampled metabolite basis function. α_0 is the inverse of the noise variance σ^2 ; α_0 and \mathbf{A} are priors placed across all the spectra, and μ_i is the mean of posterior distribution for m_i and is taken as its best estimate. The evaluation of α_0 and \mathbf{A} results in a log likelihood expression conditioned upon all y_i 's and the maximization of this expression leads to evaluating μ_i and Σ_i . Gamma priors (Eqs. 4 and 5) are defined over $\boldsymbol{\alpha}$ and α_0 so that an inverse Gamma prior is introduced on σ^2 and $E[\sigma^2] = b/(a-1)$ and $\text{var}[\sigma^2] = b/((a-1)^2 \cdot (a-2))$.

To include *a priori* noise precision in the reconstruction, we minimize RMSE for the range $a = 2$ to $1E5$ and $b = 0.044$ to 40 , so that $E[\sigma^2]$ ranges from $2.5E-5$ to 0.0225 and $\text{var}[\sigma^2]$ ranges from $2.5E-5$ to $2.25E-12$. Focusing on the low-SNR peaks of Glu, NAA+Gln, and Glx between 2.25ppm - 2.35ppm , 2.35ppm - 2.47ppm and 3.69ppm - 3.80ppm respectively, reconstructed spectra were compared to the fully-sampled baseline spectra and RMSE $\|x_{\text{reconstructed}} - x_{\text{true}}\| / \|x_{\text{true}}\|$ was calculated. RMSE was evaluated for 20 noise realizations and 5 under-sampling realizations, and for under-sampling factor $R = 2, 3$ and 4 corresponding to 9, 7 and 5-step CTPRESS experiments respectively. To approximate scanning conditions where phase priors are uncertain, $Abs(m_i)$ and $Phase(m_i)$ are solved for with MT Bayesian CS using the magnitude prior of the basis function and Single-Task (ST) Bayesian CS [7] respectively.

RESULTS & DISCUSSION: Fig. 1a and b shows mean RMSE of the low SNR peaks of Glu, NAA+Gln, and Glx taken over 100 random trials for $R = 2$ and $R = 4$ assuming ideally phased priors. The minimum RMSE is at ($a_{\text{opt}} = 1778$, $b_{\text{opt}} = 4.443$) corresponding to $E[\sigma^2] = 0.0025$ for $R = 2$ and $R = 4$, which matched the noise of $\sigma^2 = 0.0025$ added to the simulated spectra. Small values of b resulted in small values for $E[\sigma^2]$, limiting the de-noising feature of MT Bayesian CS reconstructions. On the other hand, large values of b assume more noise than present in the undersampled spectra which lead to dropouts of Glu and Gln peaks in the CS reconstructions. Fig.2a shows the diagonal spectra at $R = 4$ formed from the reconstructed 2D spectra for $a = 0$ and $b = 0$ without *a priori* noise precision, and Fig 2b demonstrates the successful reconstruction of Glu and Gln peaks in the diagonal spectra formed with the suggested choice of $a = 1780$ and $b = 4.443$ that best models $\sigma^2 = 0.0025$ added to the simulated spectra.

Fig. 3a and b shows mean RMSE of the low SNR peaks taken over 100 random trials for $R = 2$ assuming non-ideal scanning conditions where phase priors are uncertain. The minimum RMSE corresponds to $E[\sigma^2] = 0.0049$ for $R = 2$ and to $E[\sigma^2] = 0.010$ for $R = 3$ which did not model the noise of $\sigma^2 = 0.0025$ added to the simulated spectra. We postulate that this discrepancy is due to insufficient modeling of Rayleigh noise with non-zero mean in the reconstruction of $Abs(m_i)$ with MT Bayesian CS.

CONCLUSION: We demonstrated the application of MT Bayesian CS to under-sampled CTPRESS data and the successful recovery of low-SNR peaks with optimized noise modeling parameters, a and b .

References: [1] Dreher et al; MRI 1999; 17:141-150 [2] Mayer D et al; MRM 2005; 54:439-442 [3] Ji et al; IEEE Trans. Sig. Proc 2009; 57:92-106 [4] Kok et al; ISMRM 2011 #1448 [5] Veshort M et al; JMR 2006; 178:248-282 [6] Traber FB et al; JMRI 2004;19:537-545. [7] Ji et al; IEEE Trans. Sig. Proc 2008; 56; 2346-2356

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