#### Estimation of water/fat images, B<sub>0</sub> field map and T<sub>2</sub>\* map using VARPRO

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### INTRODUCTION

Conventional water/fat separation methods based on Dixon-type acquisitions do not account for the  $T_2*$  decay effect, which leads to underestimated intensities of the water/fat components in regions where the decay is significant [1,2]. It is, therefore, desirable to estimate the  $T_2*$  in order to improve the quality of water/fat decomposition. Furthermore, the  $T_2*$  map itself is of clinical value, e.g., for the diagnosis of iron overload [2,3]. Here we propose a novel method, based on the variable projection (VARPRO) formulation [4], for robust and efficient estimation of water/fat images, field map and  $T_2*$  map.

## **METHODS**

In a Dixon acquisition with N images acquired at echo times  $TE=t_n$ , n=1,...,N, the signal at a given voxel can be modeled as

$$\mathbf{s}(\rho_{W},\rho_{F},f_{B},R_{2}^{*}) = \begin{pmatrix} e^{j2\pi t_{1}f_{B}}e^{-t_{1}R_{2}^{*}} & e^{j2\pi t_{1}(f_{B}+f_{F})}e^{-t_{1}R_{2}^{*}} \\ \vdots & \vdots \\ e^{j2\pi t_{N}f_{B}}e^{-t_{N}R_{2}^{*}} & e^{j2\pi t_{N}(f_{B}+f_{F})}e^{-t_{N}R_{2}^{*}} \end{pmatrix} \begin{pmatrix} \rho_{W} \\ \rho_{F} \end{pmatrix} = \mathbf{\Phi}(f_{B},R_{2}^{*})\mathbf{\rho}$$

$$\text{where } \mathbf{s} = [s(t_{1}) \ s(t_{2}) \cdots \ s(t_{N})]^{\mathsf{T}} \quad \text{is the signal vector, } \boldsymbol{\rho}_{W} \text{ and } \boldsymbol{\rho}_{F} \text{ are the complex-valued water and fat amplitudes, respectively, } f_{F} \text{ is the fat chemical}$$

where  $\mathbf{s} = [s(t_1) \ s(t_2) \ \cdots \ s(t_N)]^t$  is the signal vector,  $\boldsymbol{\rho}_W$  and  $\boldsymbol{\rho}_F$  are the complex-valued water and fat amplitudes, respectively,  $f_F$  is the fat chemical shift (e.g., -220 Hz at 1.5 T),  $f_B$  is the frequency shift due to  $B_0$  field inhomogeneity, and  $R_2^* = 1/T_2^*$ . Assuming white Gaussian noise, the maximum-likelihood estimation of  $(\boldsymbol{\rho}_W, \boldsymbol{\rho}_F, f_B, R_2^*)$  is a nonlinear least-squares problem (i.e., minimizing  $L(\boldsymbol{\rho}, f_B, R_2^*) = \|\mathbf{s}_{meas} - \boldsymbol{\Phi}(f_B, R_2^*)\boldsymbol{\rho}\|_2^2$ ). However, using VARPRO, this problem is equivalent to minimizing  $L(f_B, R_2^*) = \|\mathbf{s}_{meas} - \boldsymbol{\Phi}(f_B, R_2^*)\boldsymbol{\Phi}^{\dagger}(f_B, R_2^*)\boldsymbol{\sigma}\|_2^2$ , where  $^{\dagger}$  denotes pseudoinverse. This minimization can be performed by evaluating  $L(f_B, R_2^*)$  on a 2D grid and directly picking the minimum.

The VARPRO formulation has several desirable features: it avoids the local convergence of iterative search algorithms. It also enables the use of prior constraints on  $R_2$ \*. Finally, it allows effective field map regularization (which is the most challenging aspect of the whole estimation process).

One drawback of this approach is its computational cost, since evaluation of  $L(f_B, R_2^*)$  on a 2D grid is relatively time-consuming. However, Cramer-Rao bound (CRB) analysis of the signal model in Eq. (1) indicates that, for an efficient estimator, the estimates for  $f_B$  and  $R_2^*$  are uncorrelated (i.e., the corresponding cross-term in the CRB matrix is zero for all the combinations of parameter values we have tried). This observation leads to the following efficient *decoupled* VARPRO method: 1) Estimate the regularized field map using the original VARPRO method (assuming no decay). 2) Given the estimated field map, obtain  $R_2^*$  at each voxel using VARPRO. 3) Given the field map and  $R_2^*$  map, estimate  $\rho_W$  and  $\rho_F$  at each voxel by solving the corresponding linear problem in Eq. (1). This method requires two 1D searches, instead of one 2D search, resulting in notable computational savings.

## **RESULTS**

Cardiac images were acquired using a multi-echo GRE sequence on a Siemens ESPREE 1.5T. A total of 13 TEs were acquired to provide a "gold standard". Estimates were obtained using both joint and decoupled estimation, from a varying number of TEs, producing the results shown in Fig. 1.

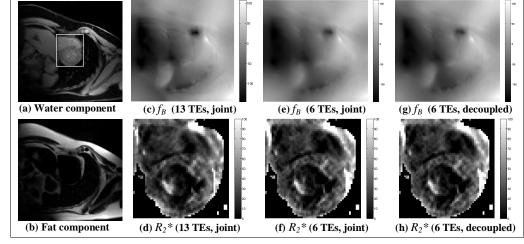


Figure 1. (a)-(b) Water/fat decomposition estimated from 13 TEs. (c)-(d) "Goldstandard" field map and  $R_2$ \* map, jointly estimated using all 13 TEs. The estimated  $R_2$ \* is shown for the ROI displayed within the water image. (e)-(f) Field map and  $R_2$ \* map, jointly estimated using 6 TEs. (g)-(h) Field map and  $R_2^*$  map, estimated using decoupled VARPRO with the same 6 TEs. Note the high-quality of the estimates obtained from 6 TEs. Furthermore, the joint and decoupled estimation of field map and  $R_2$ \* map produce very similar results (the relative difference in  $R_2$ \* over the ROI was 1.2%). However, joint estimation required 15,000 evaluations of  $L(f_B,R_2^*)$  per voxel, whereas decoupled estimation required 350.

Equation (1) assumes a unique  $R_2^*$  value per voxel. In voxels where both water and fat are present, this estimation will provide an "effective"  $R_2^*$  estimate [2]. VARPRO can be easily adapted to estimate two distinct decay constants, although this will result in noisier estimates and increased computational times. Note also that a common method for  $R_2^*$  estimation is to assume a single spectral component and fit an exponential to the signal magnitude. This method produces significantly worse results than the method proposed here in the presence of several spectral components.

#### **CONCLUSION**

This work presents a method for estimating  $B_{0^-}$  and  $T_2$ \*-maps along with water/fat images from Dixon acquisitions, by extending a recently proposed variable projection method. This method provides accurate estimates regardless of the nonconvexity of the corresponding estimation problem.

# REFERENCES

- [1] S. Reeder et al., Magn Reson Med 2005, 54:636-644.
- [2] H. Yu et al., J Magn Reson Imaging 2007, 26:1153-1161
- [3] P. Clark et al., Magn Reson Med 2003, 49:572-575.
- [4] D. Hernando et al., Magn Reson Med, accepted.