Strong Regularization for Brain Myelin Water Quantification in T2 Relaxation MRI Obtained in 3.0 T

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INTRODUCTION: Myelin water fraction (MWF) is an important biomarker for understanding the development of many white matter diseases. Quantification of MWF using MRI involves the acquisition of a series of T_2 weighted multiple echo images and creating the T_2 spectrum for each image voxel from T_2 decay curves. The MWF can be obtained from integration of the short T_2 portion of the spectrum. A regularized non-negative least square (rNNLS) algorithm is commonly used to create T_2 spectrum from multiple echo data usually with a weak regularization [1-2]. Few studies have investigated the influence of the regularization on the MWF quantification. In this study, the relationship between MWF and the regularization factor was studied using simulated and in vivo T_2 decay data.

METHOD AND MATERIAL: Synthetic decay curves were created based on a bi-exponential model with T_2 component of 27 ms and 87 ms. each decay curve consists of 32 echoes with 10 ms spacing. The ratios of short T_2 to long T_2 components were 5%, 10% and 15% respectively. In vivo images were obtained from a healthy volunteer using an improved multi-echo multi-slice sequence on a Siemens 3.0T machine (total 32 echoes, the first echo time 10 ms and 10 ms echo spacing for the following echo). The T_2 spectrum consists of 80 bins logarithmically spaced between 16 ms and 2000 ms. The MWF was defined as the value of the integration of the region $T_2 < 40$ ms divided by the total area of the T_2 spectrum, obtained by minimizing the following object function:

$$\chi^2 + \lambda^2 \sum_{j=1}^{N} x_j^{\,2} \qquad (1)$$

where x is the T_2 spectrum, χ^2 is the chi-square difference between measured and fitted data and λ is the regularization parameter. For the synthetic data, a random Gaussian noise with zero mean and standard deviation equivalent to the 50 SNR was added to each fixed short T_2 component ratio. For each fixed short T_2 component ratio, 1000 noise corrupted curves were generated. The fitting of the data were performed using the NNLS routine in optimization toolbox of MATLAB. For the decay curves of each fixed short T_2 component ratio, the fitting were performed using regularization parameter λ from 0.01 to 0.5 with an increment of 0.01. On each λ, the mean and standard deviation for the curves were calculated.

RESULTS: Fig.1 shows the results of the simulated data. The mean MWF against λ is a "V" shape curve, and the standard deviation of MWF against λ is an "L" shape curve. For each fixed short T_2 component ratio, at λ=0 the MWF is the "true" value; however the stability of the fitting is the worst. This can be seen on the graph of the standard deviation. With the increase of the λ, the mean and standard deviation of MWF begin to drop. After passing through the lowest point, the mean MWF begin to increase, while the standard deviation stays low and stable. At λ=0.26, the mean MWF is equal to the mean MWF value at λ=0 and is closest to the "true" value. We suggest that this is the best regularization. The best regularization parameters are very close to each other for three different short T_2 component ratios; this indicates that we can use a single regularization value to fit all voxels with the varies short T_2 component ratios in the in vivo image. Histograms of the results of fitting 1000 curves for the short T_2 component ratio at 10% using λ=0 and λ=0.26 are shown in the right graph of Fig.1. In Fig.2, left image shows the result of using the regularization scheme suggested in literature [1], in which λ is from 0.02 to 0.03. The right image in Fig.2 shows the result of using a single value λ=0.26 as suggested by the simulation data. Comparison of the left and right images in Fig.2, we can see that fitting of MWF can be greatly improved by using a regularization value which is much stronger than previously suggested.

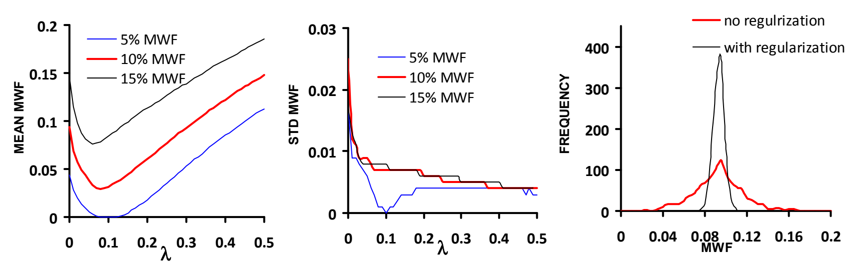

Fig.1: From left to right, the first graph shows the mean MWF as a function against λ for three different short T_2 component ratios. The second graph shows the standard deviation of MWF as a function against λ for three different short T_2 component ratios. The third graph shows the histograms of the results of fitting 1000 noise corrupted curves with a short T_2 component ratio of 10% using regularization parameter λ=0 and λ=0.26.

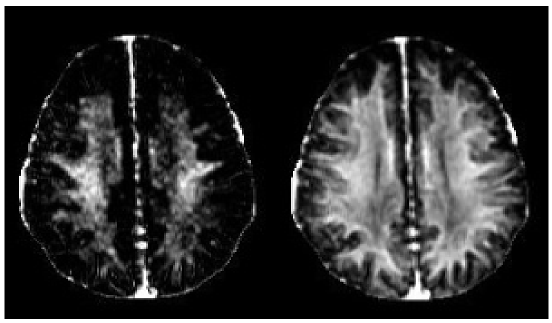

Fig.2: The fitted in vivo MWF image. On the left is the result of using the regularization scheme suggested in the previous study, On the right is the result of using the regularization factor suggested in this study (λ=0.26)

DISCUSSION AND CONCLUSIONS:
In this study, we have demonstrated that the quantification of MWF can be greatly improved using a strong regularization in the rNNLS algorithm. The previously suggested regularization is on the weak side of the "V" curve. It requires high SNR for a reasonable fit. In our study, both the synthetic and in vivo data have SNR values around 40 to 60, which are reasonable to balance the acquisition time and imaging quality; however they can not be fitted well using the previously suggested regularization. From our study, we found that the "V" curves for different short T_2 component ratios are independent of SNR and only depend on the "cut off" point for MWF calculation from T_2 spectrum. The drawback of using stronger regularization is the loss of the resolution in the T_2 spectrum.

REFERENCES: [1] Kolind, SH, et al, MRM 62;106-115 (2009) [2] Vavasour, IM et al, MRM 40;763-768 (1998)