Spectral denoising for MR Spectroscopic Imaging using Non-Local Means

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Purpose

Magnetic resonance spectroscopic imaging (MRSI) is an imaging modality used for studying tissues in-vivo in order to assess and quantify metabolites for diagnostic purposes. However, long scanning times, low spatial resolution, poor signal-to-noise ratio (SNR) and the subsequent noise-sensitive non-linear model fitting are major roadblocks in accurately quantifying the metabolite concentration. In this work, we propose a spectrally adaptive method for denoising of MRSI spectra based on the concept of Non-Local Means (NLM)^{1,2} which relies on spectral redundancy in the given data-set. Due to lack of phase information in the acquired data, we perform a 'spectral dephasing' step to consider a wide range of phase variations to improve the NLM-based pattern analysis. We evaluated our method on human in-vivo data and assessed the improvement in SNR for NAA.

Methods

Non-Local Means: For the spectra to be denoised, the NLM filter^{1,2} searches for other similar spectra patches in the frequency-phase space in the given data-set. A weighted average is performed using these patches with a higher weight being assigned to highly similar spectra. This is represented as:

$$\hat{S}_{ij}(\omega) = \sum_{x_{kl} \in \Omega^3} w(x_{ij}, x_{kl}) S_{kl}(\omega)$$

Spectral dephasing: For each voxel x_{ij} , the signal is shifted by a set of phase angles Θ :

 $S_{ij}^{\Theta}(t) = S_{ij}(t).e^{-(i\Theta)}$, where $\Theta \in [-n_1\pi, (n_2+2)\pi], \{n_1, n_2 \in \mathbb{R} \mid n_1, n_2 \geq 0\}$

The real component of these dephased signals are then combined to generate a 2D frequency-phase matrix.

Spectral Rephasing: Post-NLM, the spectra in the frequency-phase space for each voxel undergo an inverse phase shift to remove the dephasing effect. The rephased spectra are averaged over all Θ to generate a single complex denoised spectra. The SNR is then calculated by dividing the maximum value of the metabolite peak with the standard deviation of the spectral region having pure noise.

Data acquisition: We acquired 2D-brain MRSI data of a healthy human volunteer on a GE 3T scanner using a PRESS sequence with TE/TR = 35/2000 msec, spectral bandwidth = 1kHz. The data was zero-filled and reconstructed to generate a grid of 32x32 voxels and 256 spectral points. We acquired data with 6 (ground truth), 3 and 1 averages with a total scan duration of 33 minutes.

Results and Discussion

The experimental results are summarized in the table below. The Full-Width Half Maximum (FWHM) of the water peak either remained the same or reduced post-NLM which indicated that the spatial resolution was preserved. The images for NAA are shown in Fig. 1. The corresponding SNR and FWHM are shown in Table 1.



Fig. 1: (A) Original human in-vivo brain MRSI data with the excitation region shown (white grid). (From Top) Row 1 & 2: SNR of NAA and the corresponding WM voxel spectra in: (B) 6-averages data, (C) 3-averages data (original) and (D) denoised, (E) single-scan data (original) and (F) denoised with corresponding spectra. Row 3: LCModel based absolute concentration estimate of NAA in: 6-averages data, 3-averages data (original) and denoised, 1-average data (original) and denoised. The NAA concentration estimate and spectral SNR improve considerably as seen in columns D (SNR = 23.29) and F (SNR = 11.38) against the ground-truth (SNR = 11.44).

Conclusion

Our proposed denoising method using a spatially adaptive NLM was evaluated on in-vivo MRSI data and showed a significant improvement in SNR. The 3-averages data had an SNR improvement by a factor of over 2 as compared to the ground-truth data. This would potentially accelerate acquisition by taking fewer scan averages. Future work would involve assessing our method for lower concentration metabolites such as Glu and improving computational efficiency.

References

[1] Buades et al., Computer Vision and Pattern 2005; 2(0):60-65.

[2] Coupe et al., IEEE Trans Medical Imaging 2008; 27(4):425-441.