

A Novel Method of Combining Multi-coil MRI Images: The Level-Weighted Wavelet Fusion

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Introduction: Multi-coil MR images are conventionally combined using a magnitude sum. A problem with this approach is the loss of contrast due to the global lowpass filtering operation. Wavelet methods have been shown to be useful for reducing receiver sensitivity inhomogeneity in multi-coil applications (1,2), but not much work has been done to alleviate the loss of resolution. We present a novel Level-Weighted Wavelet Fusion (LWWF) scheme to address this. We show that the method is successful improving the contrast in multi-coil brain images at 3T.

Theory: Fusion methods typically employ hard decision maps (3). The “choose one over the rest” rule of hard decision maps forces the deletion of coefficients in wavelet space, which creates undesirable pseudo-Gibb ringing artifacts (4).

As a solution, the utilization of soft decision maps creates smooth neighbor-dependent, intrascale transitions upon summing, minimizing contrast reduction and incidence of ringing artifacts. Furthermore, LWWF efficiently encompasses the inherent intrascale and interscale correlation of the wavelet coefficients. This information is incorporated upon the calculation of the decision maps. Lastly, LWWF elects to use the stationary wavelet transform (SWT) over the discrete wavelet transform; thus acquiring shift invariance (5), enabling us to supplement the technique with de-noising algorithms (6). To illustrate the fusion process, a high-level block diagram is shown in Fig. 1. Mathematically, let N be the number of input images, and K the lowest level of wavelet decomposition. Denote $W_{n,k}^A$, $W_{n,k}^H$, $W_{n,k}^V$, and $W_{n,k}^D$ as the k^{th} level approximation, horizontal detail, vertical detail, and diagonal detail wavelet coefficient maps, respectively, of source image n . The calculation of the soft decision maps can be summarized as the level sums:

$$\sum_{k=1}^K W_{n,k}^A, \sum_{k=1}^K W_{n,k}^H, \sum_{k=1}^K W_{n,k}^V, \sum_{k=1}^K W_{n,k}^D, \quad \text{for } n=1,2,\dots,N,$$

before final normalization to remove bias towards individual sources.

Methods and Results: The method was tested on brain MRI images acquired using an eight-channel receiver coil on a Siemens 3T whole body scanner. The sequence was a standard gradient echo FLASH with parameters TR/TE=500/5 ms, 22 cm FOV, 128x128 matrix, 5 mm thick slices, and 30° flip angle. Image processing was performed in Matlab. Brain images from a typical human volunteer are shown in Fig. 2 (a-c). Fig. 2 (d) displays zoomed versions of the fused images. Note lack of contrast in the mean images. To quantify contrast enhancement, in Fig. 2 (e) we summed the frequency power coefficients of the fused images over a selected bandwidth, and normalized over the sum of the entire power spectrum. The summed energy for the LWWF is always greater than the average image, indicating greater higher frequency power. Fig. 2 (f) shows a plot of SNR versus noise factor. Notice that, even without de-noising, the LWWF achieves much better SNR than the averaged image.

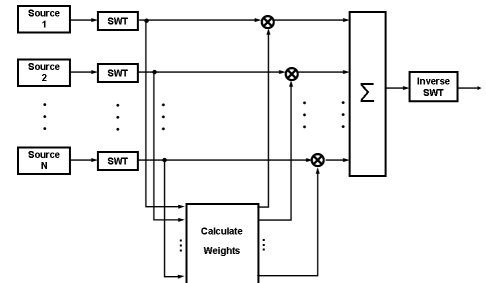


Fig. 1. High-level block diagram of fusion process. Weights correspond to values of the calculated soft decision map. The SWT coefficients are combined through a weighted average, where the multiplication indicated in the diagram denote an element-by-element

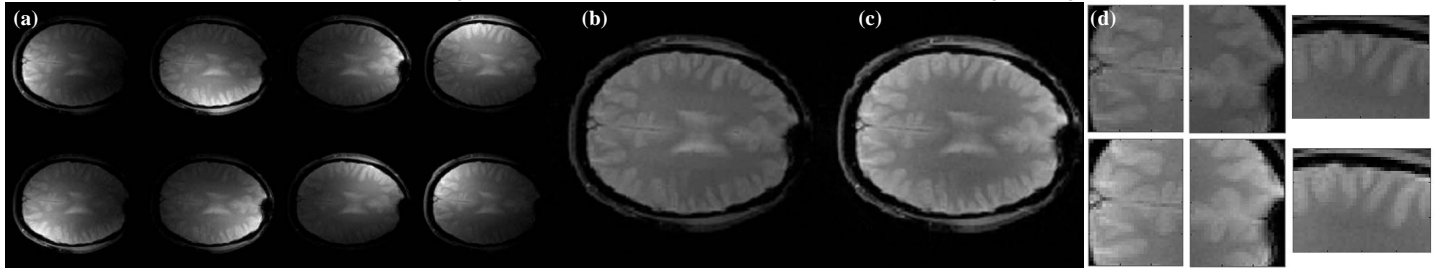


Fig. 2 (a) Individual coil images, (b) mean, and (c) LWWF. (d) Zoomed ROI's from (top) mean and (bottom) LWWF. (e) Frequency power vs. bandwidth. We summed over a centered annulus with five pixel annular width. The abscissa indicates increasing radius of the smaller circle of the annulus (summing over regions of increasing frequency while maintaining constant bandwidth). (f) Comparison of SNR vs. noise amplitude. Gaussian noise of standard deviation σ was added to the complex multi-coil images; m is the maximum pixel magnitude and a is a scale factor. SNR was determined using

$$\text{SNR} = \log(\text{var}S / \text{var}N),$$

where S is the signal and N is the noise. We assumed the unaltered source images were noiseless.

Conclusions: We have presented an image fusion method using soft decision maps for multi-coil MRI images that improves contrast with minimal ringing artifacts. We also show that image de-noising can be easily added as well. Future work will look at image bias to receiver inhomogeneity.

References: (1) F-H Lin *et al.* Human Brain Mapping, vol. 19, pp. 96-111, 2003. (2) C. Han *et al.* JMRI, vol. 13, pp. 428-436, 2001. (3) A. B. Hamza *et al.* J. Integrated Computer-Aided Engineering, vol. 12, no.2, pp. 135-146, 2005. (4) R. R. Coifman *et al.* Lecture Notes in Statistics: Wavelets and Statistics, pp. 125-150, 1995. (5) D. L. Donoho *et al.* Biometrika, vol. 81, pp. 425-455, 1994. (6) Z. Zhang *et al.* Proceedings of the IEEE, vol. 87, no.8, pp.1315-1326, 1999.

