Iterative Approach to Atlas Based Sparsification of Image and Theoretical Estimation (iterative ABSINTHE)

E. Y. Pierre[1], N. Seiberlich[2], S. Yutzy[1], V. Gulani[2], F. Breuer[3], and M. Griswold[2]

[1]Biomedical Engineering, Case Western Reserve University, Cleveland, Ohio, United States, [2]Departments of Radiology, Case Western Reserve University, Cleveland, Ohio, United States, [3]Research Center Magnetic Resonance Bavaria e.V., Würzburg, Germany

Introduction: By using a training set to identify the common features in a given image and remove them, the Atlas Based Sparsification of Image aNd THeoretical Estimation (ABSINTHE) technique yields sparse under-sampled images which can be reconstructed using parallel imaging methods. ABSINTHE works by combining the eigenvectors from this training set of images in order to reduce the number of pixels which must be unaliased[1][2]. This method has been shown to improve GRAPPA reconstruction for high reduction factors and to potentially allow even higher reduction factors in the case of longitudinal studies[3]. Because the quality of the approximation of the image to reconstruct determines the performance of ABSINTHE, we propose an iterative version of ABSINTHE which can lead to a better eigenvector approximation. In Iterative ABSINTHE, the reconstruction of the undersampled difference data is improved by using the approximation of the previous reconstruction using fully sampled eigenvectors. This results in images that are even sparser than when using the original ABSINTHE method, which can then be reconstructed using GRAPPA.

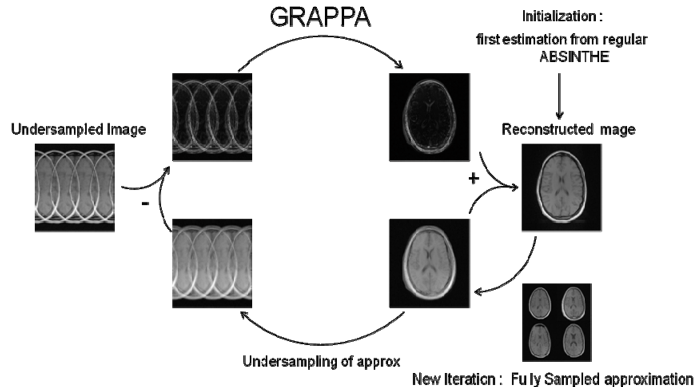

Figure 1: Schematic of the ABSINTHE reconstruction as described in the text.

Theory: A diagram of the iterative ABSINTHE method is shown in fig 1. The brains in the database (lower right) have identical coil configuration and similar contrast. The undersampled image (R=4) is shown on the far left. First a fully-sampled (FS) estimate of the k-space data is obtained using the original ABSINTHE method[4], and is shown on the far right. This method uses an US base of eigenvectors to calculate an US approximation of the data. However, as the US eigenvectors are derived from FS eigenvectors, they are not necessarily orthogonal to one another. This means that the PCA coefficients obtained by projection of the US data onto the US eigenvector base may not be optimal. In order to do improve the US PCA approximation, iterative ABSINTHE projects the FS estimate onto the orthogonal FS base of eigenvectors, yielding more accurate PCA coefficients. The newly obtained FS approximation is then undersampled, and its difference image with the US k-space data is computed, which is now sparser than in the previous iteration. As the approximation of the US data becomes more accurate, the difference image becomes sparser and fewer artifacts remain in the FS k-space estimation, further improving the final GRAPPA reconstruction.

Methods: A training set was first generated in Matlab from 120 T1-weighted central slice images provided by the Open Access Series of Imaging Studies (OASIS), using a numerical 12-channel coil. A 121st brain was selected and undersampled by a factor of R=6, and reconstructed using GRAPPA, standard ABSINTHE, and iterative ABSINTHE as described above, and the artifact powers calculated relative to the fully-sampled images. Additionally, to demonstrate the power of ABSINTHE in longitudinal studies, the simulated data from OASIS were again used as the training data. One image was selected at random and a small circle added in order to simulate a growing tumor. The image with tumor was undersampled by a factor of R=8 and also reconstructed using GRAPPA, standard ABSINTHE, and iterative ABSINTHE. In order to show how the sparsity increases with ABSINTHE iterations, the decreasing L1 norm in the image domain of the undersampled data in the longitudinal study simulation is computed for each step in the iterative ABSINTHE method.

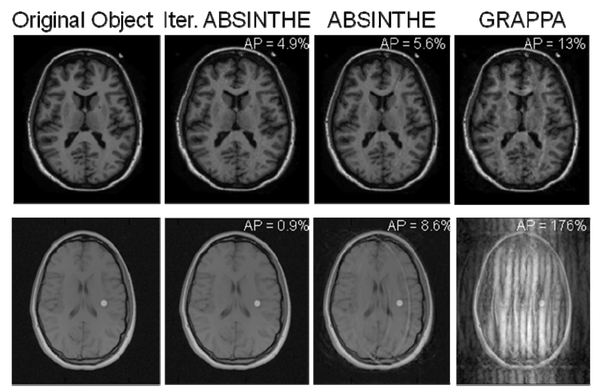

Figure 2: Simulated (top) and simulated longitudinal in vivo (bottom) examples of the original image (left) for iterative ABSINTHE (2nd row), ABSINTHE (3rd row), and GRAPPA (right). The artifact powers (%) for the reconstructions are shown as insets.

Results: The results from the simulations are shown in Fig. 2. For the first simulation (top row), the artifact power is significantly reduced in the R=6 ABSINTHE image (4.9%) compared with GRAPPA (13%) and standard ABSINTHE (5.6%). Fig. 2 also shows the results of the simulated longitudinal study, where the image without tumor is included in the training set used to reconstruct the image with tumor. Because the iteratively approximated PCA image removes nearly all of the signal, only the sparse tumor remains to be reconstructed, yielding an iterative ABSINTHE image with nearly no residual artifacts (evidenced by the low artifact power of 0.9%) as compared with standard ABSINTHE (8.6%) or GRAPPA (176%). Fig. 3 shows the increase in sparsity (decrease in L1 norm in image domain) introduced by the ABSINTHE approximation and the subsequent iterative ABSINTHE approximations.

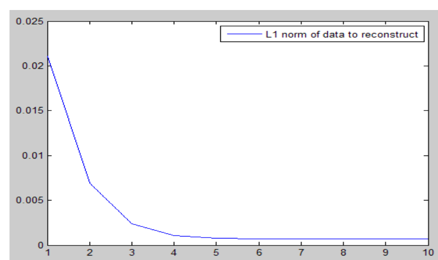

Figure 3: Plot of theL1 norm in image domain of the original undersampled data (1), undersampled data after sparsification with ABSINTHE (2), and subsequence sparsification with each iteration of iterative ABINTHE (3-10)

Discussion: Iterative ABSINTHE shows significant improvement in reconstruction image quality over GRAPPA and standard ABSINTHE. This is due to the iterative improvement in the PCA approximation of the undersampled image to be reconstructed, which leads to sparser images and therefore an improved GRAPPA reconstruction. In the case of longitudinal studies, where only small changes appear in otherwise identical images, the data suggest that extremely high undersampling factors, which would not be possible without this sparsifying step, can be employed. Future work involves confirming the results of the simulated longitudinal study, as well as acquiring a large and varied in vivo training set comprised of different anatomical images, contrasts, and receiver coil sensitivity profiles in order to demonstrate the utility of iterative ABSINTHE in *in vivo* applications.

References : [1] Blaimer M, et al. ISMRM 2007, abstract 3339, pg 639. [2] Griswold MA, et al. MRM 2005 Dec;54(6):1553-6. [3] Pierre EY, et al. 3rd International Workshop on Parallel MRI, *Atlas Based Sparsification of Image and Theoretical Estimation (ABSINTHE)*[4] Pierre EY, et al. ISMRM 2009; abstract 4554 p.516. Acknowledgements : The OASIS database. This study was partially funded by Siemens Healthcare.