Atlas Based Sparsification of Image and Theoretical Estimation (ABSINTHE)

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Introduction: Several authors have recently proposed that one can make the scan time in MR proportional to the amount of information in the image, and not the number of pixels. This concept has now been applied to MR angiography for example. However, no robust implementation has been proposed for static anatomical imaging. We hypothesize that the actual new information in a typical brain MRI scan can be very small, and only related to the pathology with respect to normal anatomy. By removing the portions of the image that are "expected," i.e. the standard brain, only the pathology remains, resulting in a potentially large decrease in information content, resulting in a reduction in the number of pixels which alias with one another. It has already been shown that higher parallel imaging acceleration factors can be achieved with less noise enhancement when applying the GRAPPA reconstruction [1] to sparse images [2]. The Atlas Based Sparsification of Image aNd THeoretical Estimation (ABSINTHE) method proposed here seeks to combine these ideas. The undersampled brain image to be reconstructed is first sparsified by performing a PCA analysis using a database of brain images to identify the features of the image that are common to the database and to subtract them out. This step leaves a sparse image containing only the differences from the collection of brains in the atlas, which can then be reconstructed using GRAPPA. This abstract demonstrates first results of ABSINTHE in vivo using a small training set of brain images followed by a GRAPPA reconstruction.

Theory: A diagram of the ABSINTHE method is shown in fig 1. The undersampled image (R=4) is shown on the far left. Many pixels clearly overlap, adding additional noise to a standard GRAPPA reconstruction. However, given a sufficiently large training dataset containing similar images, the under-sampled k-space data to be reconstructed can be approximated using a PCA analysis. The fully sampled eigenvectors, with channel configuration and contrast identical to the acquired data, are under-sampled using the same acceleration factor and number of ACS lines. The coefficients of the linear combination which give the best under-sampled PCA approximation are then used on the fully sampled eigenvectors to compute a fully-sampled approximation. By subtracting the undersampled PCA approximation from the original undersampled image, only a sparse difference image remains. Using this undersampled difference image, a GRAPPA reconstruction is performed, and the resulting reconstruction added to the fully-sampled PCA approximation, leading to the final image.

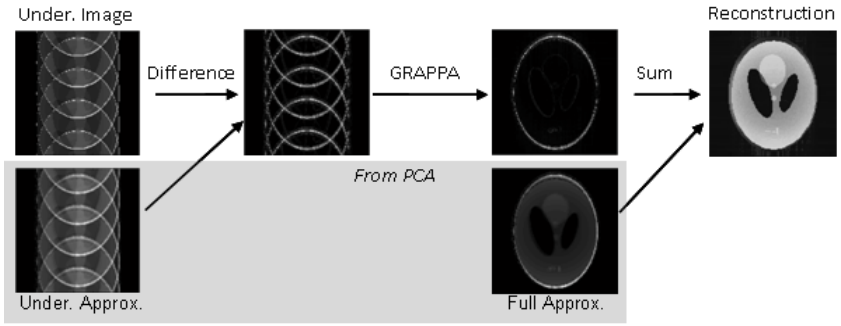

Figure 1: Schematic of the ABSINTHE reconstruction, as described in the text.

Materials and Methods: In order to test ABSINTHE, 300 randomly perturbed Shepp Logan phantoms were generated in Matlab using a numerical 8-channel coil. An additional phantom was created and undersampled by R=6, and the ABSINTHE method used to perform the reconstruction. In addition, standard GRAPPA was performed using the same kernel size and regularization as a comparison. A total of 14 in vivo head datasets were acquired using a standard 12 channel head coil on a 1.5T Siemens Avanto scanner (Siemens Medical Solutions, Erlangen, Germany), using a standard T1-weighted Spin Echo sequence (TR=500ms TE=9.5ms 2 avg, Slice=5mm, 19 slices, 5mm x 0.3 gap). In order to ensure that the positioning of the heads was similar, AutoAlign was employed, which selects a similar central slice from each brain. The data from all but one of these central slice images served without further registration as the training dataset. The remaining brain was designated as the image to be reconstructed and undersampled retrospectively to R=5. Using the training data and undersampled image, ABSINTHE was performed as described in the previous paragraph.

Results: The results from the simulations and in vivo experiments are shown in Fig. 2. The artifact power is significantly reduced in the R=6 ABSINTHE image compared with the standard GRAPPA (4.4 vs. 15.3) in the simulated images (top row), and in R=5 in vivo reconstructions (10.9 vs. 18.3, bottom row).

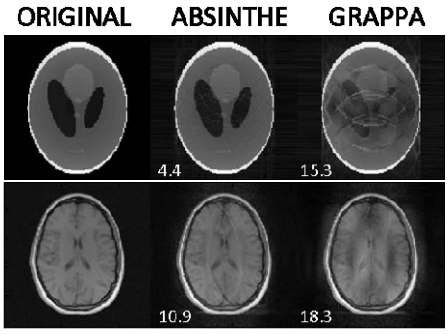

Figure 2: Simulated (top) and in vivo (bottom) examples of the original image (left) ABSINTHE (center), and GRAPPA (right). The artifact powers (%) for the reconstructions are shown as insets.

Discussion: In brain MRI, where the majority of the information acquired is "expected," prior knowledge in the form of a database of similar brain images can be used to sparsify a given undersampled image. Due to the smaller number of pixels which alias in such a sparsified undersampled image, a subsequent GRAPPA reconstruction experiences less noise enhancement and artifacts than a standard non-sparse reconstruction would. The sparsity of this difference image depends on the training set; the more similar the images in the training set are to the undersampled image, the sparser the difference image. Although the method shows significant improvement using in vivo data for a training set of only 13 images, it is expected that as the training set increases in size, the results of ABSINTHE will also improve. Thus, the more images one acquires, the better each subsequent ABSINTHE reconstructed image becomes. Moreover, the calculation of the PCA of the training set constitutes the majority of the computational load, so that the effective reconstruction time is only slightly longer than standard GRAPPA. One important consideration is that the contrast and coil set-up of the training set must be similar for a successful PCA approximation. This means that several different training sets must be established. ABSINTHE is expected to greatly improve the parallel imaging reconstruction quality for highly undersampled images, and make the use of high acceleration factors more feasible in a clinical setting.

Reference : [1] Griswold MA, et al. MRM 2005 Dec;54(6):1553-6. [2] Blaimer M, et al. ISMRM 2007, *Dynamic parallel MRI by generating sparse data: tracking temporal changes*. Acknowledgements : This study was partially supported by Siemens Healthcare.