# Dictionary-Based Sparsification and Reconstruction (DIBSAR)

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**Introduction:** Parallel imaging and atlas-based sparsification can be used together to achieve higher acceleration factors in brain MR imaging [1]. The concept is based on the fact that there is little new information contained in brain images that describe a pathology. If redundant "expected" anatomy can be subtracted from an aliased image, then there would be a significant decrease in the number of aliased pixels. Then GRAPPA [2] can be used to reconstruct a difference (or error) image, and that image can be added to the expected brain image. The subtraction of the expected brain sparsifies the data, and it has been shown that GRAPPA reconstruction can achieve higher acceleration factors, with small noise enhancement, when applied to sparse images [3]. K-SVD is an algorithm that is used to design dictionaries for sparse representation [4]. K-SVD provides flexibility of dictionary design parameters which can be important for the image approximation. K-SVD can also offer a more sparse representation of the image as compared to Principle Component Analysis (PCA).

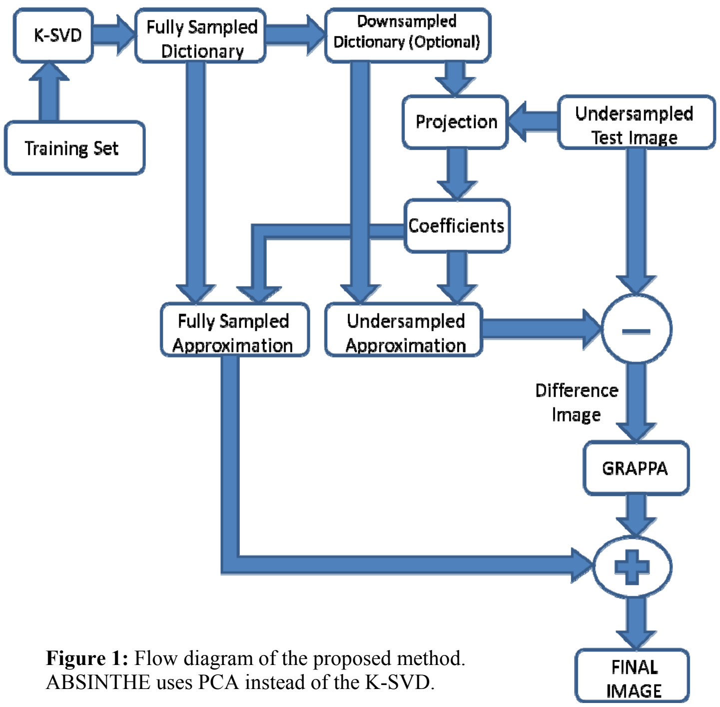


**Figure 1:** Flow diagram of the proposed method. ABSINTHE uses PCA instead of the K-SVD.

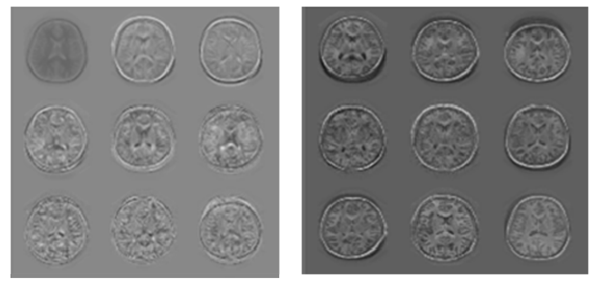

**Figure 2:** Left: PCA eigenvectors (eigenbrains) . Right: K-SVD dictionary atoms. Note that K-SVD atoms are sharper than most of the PCA eigenvectors.

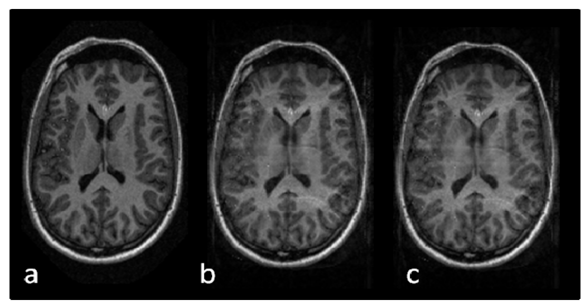


**Figure 3: a)** Original image, **b)** ABSINTHE, 128 basis images, PSNR=31.07dB **c)** K-SVD reconstruction, 64 basis images, PSNR=30.85dB. Acceleration factor=6.

ABSINTHE achieves sparsification by performing a principle component analysis (PCA) on the aliased undersampled image. It uses a database of images that are anatomically similar to the undersampled image in that analysis. This makes it possible to extract similar features from the undersampled image. On the other hand, K-SVD, which is an iterative method that generalizes the k-means clustering algorithm [5], allows selection of the number of the dictionary atoms and gives freedom with the sparsity constraints. Figure 1 shows a flow diagram of the proposed method.

**Methods:** Code was written in MATLAB (Mathworks Inc., Natuck, MA, USA) for simulations. K-SVD simulations were performed with the help of K-SVD MATLAB code available online [6]. The OASIS (The Open Access Series of Imaging Studies) database was accessed to acquire sample brain images. 35 datasets were acquired from the database and 128 center slices were extracted from those 35 datasets. Then, each slice was multiplied with the coil sensitivity maps to simulate 8-channel coil data.

**Results:** The K-SVD dictionary, created from the training dataset, consisted of 64 basis images (atoms), which is half the number of the basis images (eigenvectors) that are required by ABSINTHE to obtain similar visual results. A sample of the basis images for K-SVD and ABSINTHE are shown in Figure 2. The reconstruction results were visually similar to the original ABSINTHE while using half the number of atoms/eigenvectors that PCA required. Mean squared error (MSE) values for the two approaches were within 2% of each other. Example results are shown in Figure 3.

**Discussion:** K-SVD was integrated into the ABSINTHE algorithm to improve flexibility. K-SVD is able to reconstruct similar quality images in comparison to the traditional ABSINTHE method while using half the number of eigenvectors required by PCA. In these experiments, MSE was used as the error metric. However, it should be noted that K-SVD results in a smaller *l*-0 norm as compared to the PCA-based ABSINTHE. Accordingly, that error metric can show better results. More comprehensive training datasets will be included in future work to improve performance.

**References:**
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