

# The Multiple Transforms Compressed Sensing for MR Angiography

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## Introduction

Compressed sensing (CS) is a newly emerging technique to reconstruct undersampled signal [1, 2]. If certain conditions, such as sparsity and incoherent sampling, are satisfied, the signal can be accurately reconstructed from undersampled data by the CS technique. Therefore, a sparsifying transform is required in the CS technique for the target signal. Conventionally, the CS uses a single sparsifying transform. However, the target signal can be more sparsely represented in some cases by adopting multiple sparsifying transforms. In this work, an adaptive CS algorithm using two transforms is proposed to reconstruct MR angiography images with high accuracy and quality.

## Methods

An angiography image consists of two different parts of images, namely background brain part and vessel part. While discrete cosine transform (DCT) is a suitable choice to sparsely encode the background image, it is not the best option for the vessel image, which has spike-like signal characteristics. Thus, wavelet transform is used instead of DCT for the vessel image to be sparsified. By using both transforms as sparsifying transforms, the angiography data can be more efficiently encoded, and consequently, a more accurate image can be reconstructed. In the original CS technique [1], the solution of underdetermined equation is calculated by minimizing the L1 norm using the following optimization equation:

$$\min \|c\|_1 \text{ s.t. } F_{\Omega}(\Psi^{-1}(c)) = y$$

where  $F_{\Omega}$  is the Fourier transform operator,  $y$  is the k-space samples,  $\Psi$  is the sparsifying transform, and  $\Psi^{-1}(c)$  is the reconstructed image. By introducing the two-sparsifying transforms, the equation can be modified as follows,

$$\min \|c_1\|_1 + \|c_2\|_1 \text{ s.t. } F_{\Omega}(\Psi_1^{-1}(c_1) + \Psi_2^{-1}(c_2)) = y$$

where  $\Psi_1$  and  $\Psi_2$  are DCT and Haar wavelet transform operators, respectively, and  $c_1$  and  $c_2$  denote coefficients of DCT and Haar wavelet transform, respectively. Then, the modified Block-Coordinate-Relaxation method was used [3] for minimization and, the image is described as  $\Psi_1^{-1}(c_1) + \Psi_2^{-1}(c_2)$ .

## Results

To compare the proposed two-transforms-based CS method with the original CS method, we applied both methods to MR angiography images, fully sampled angiography data was acquired at a 7T scanner using the following parameters: TR/TE = 22ms/3.6ms, slice thickness = 0.5mm, with time-of-flight (TOF) method. The angiography data was reconstructed to generate images having a matrix size of  $256 \times 180 \times 149$ . For the original CS method, DCT and Haar wavelet transform were separately used as sparsifying transform ( $\Psi$ ), and in case of two transforms-based method, both the DCT and Haar wavelet transform were used as sparsifying transforms ( $\Psi_1$  and  $\Psi_2$ ). In our experiments, randomly sampled data from fully acquired data was used for reconstruction, and reduction factor was approximately 4.5. When the proposed algorithm is used to reconstruct an image, intermediate images can be generated with DCT ( $\Psi_1^{-1}(c_1)$ ) and Haar wavelet transform ( $\Psi_2^{-1}(c_2)$ ) as shown in Figs. 1 (a) and (b), respectively. Then, the final image can then be acquired by summing the two intermediate images as shown in Fig. 1. (c). The images reconstructed by the proposed method were compared with the images from the original CS method as shown in Fig. 2.

Figure 2 shows the maximum intensity projection (MIP) images of the angiography data reconstructed by (b) DCT, (c) Haar wavelet, and (d) the proposed method. The corresponding absolute difference map (e-g) with respect to the fully sampled data (a) are also shown in Fig. 2. To make a quantitative evaluation, the sum of absolute difference (SAD) was also plotted in a graph as demonstrated in Fig. 3.

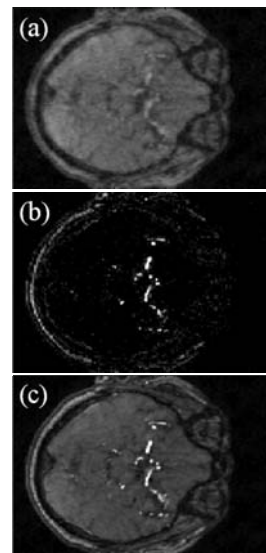


Fig. 1. Reconstructed image by sparsifying transforms: (a) DCT, (b) Haar wavelet transform, respectively. (c) result image by summing (a) and (b).

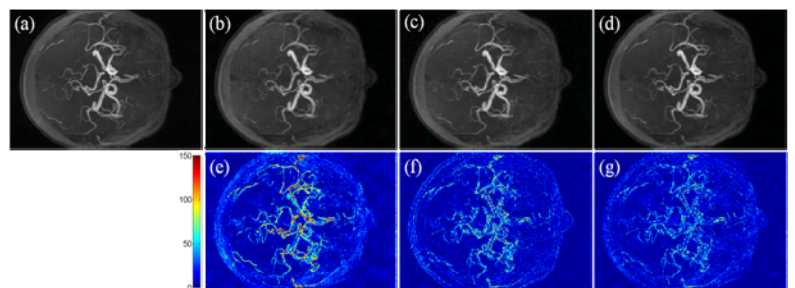


Fig. 2. (a) Fully sampled angiography using MIP. MIP images of subsampled and reconstructed data using (b) DCT, (c) Haar wavelet, and (d) both DCT and Haar wavelet. (e-g) absolute difference map between (a) and (b-d), respectively.

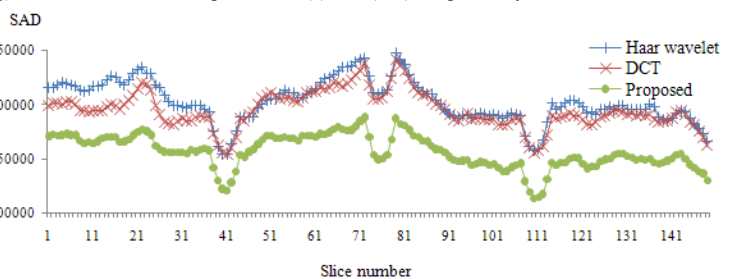


Fig. 3. Graph shows the sum of absolute difference (SAD) between the fully sampled angiography image and the reconstructed image from the CS methods for each slice of image volume with different sparsifying transforms.

## Conclusions

We presented an adaptive CS method based on two different transforms, i.e. DCT and wavelet transform, for MR angiography image. In our experiments, the proposed method provided better performance by generating more accurate images than the single transform-based method, because the adaptive method fully used the characteristics of the MR angiography image containing smooth background brain image and spike-like vessel image.

## References

[1] Donoho DL *et al.*, IEEE TIT 2006;52;1289-1306 [2] Candes E *et al.*, IEEE TIT 2006;52;489-509 [3] Stark JL *et al.*, IEEE TIP 2005;14;1570-1582

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