Compressed Sensing reconstruction based on Maximum Intensity Projection images

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Introduction

Compressed sensing (CS) has been shown to be a very powerful method for undersampling k-space data [1]. The algorithm is best fit for images that can have sparse representations such as angiographic MR images or catheter visualization in interventional MR. While the sparse nature of these individual images make CS recon readily compatible, in many applications, the 3D volumetric information is best viewed using a maximum intensity projection (MIP) image format. MIP images themselves can also be regarded to be semi sparse, or as we will do here, can be transformed to a sparser domain and therefore can be applicable using the CS algorithm. In this abstract, we apply CS reconstruction directly to MIP images and investigate on the usefulness of this approach. The underlying assumption is that the MIP image is the final image which will be of interest to the user rather than the full 3D volumetric image set.

Methods

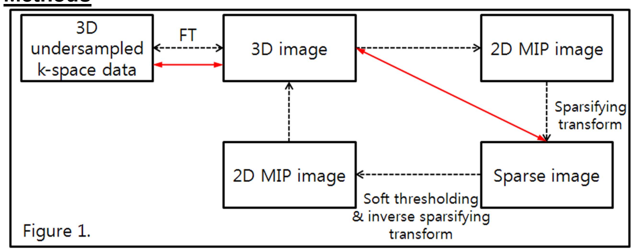


Figure 1.

Fig. 1 shows the general 3D CS algorithm (solid red line) along with our modified MIP-based CS algorithm (dotted line). The general CS recon method is applied to individual slice images and the MIP image is generated after all the reconstruction is finished. In our case, we apply CS recon on the MIP image itself while continuously updating the missing k-space samples. Mathematically, the modified MIP-based CS algorithm can be written as

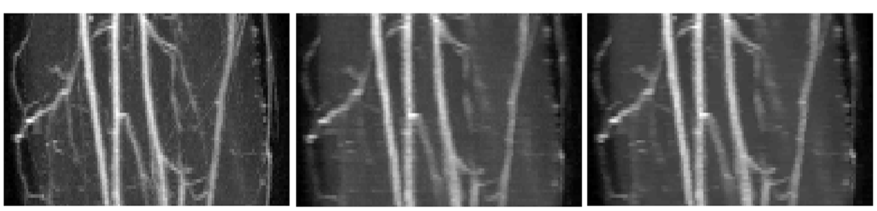
$$\text{minimize } \|\Psi\, \mathrm{MIP}(m)\|_1 + \alpha\, TV(m) \quad s.t.\ \|F_u(m) - y\|_2 < \varepsilon,$$

where vector m represents the image of interest, Ψ denotes the sparsifying transform, F_u is the (undersampled) Fourier transform, MIP is the maximum intensity projection process, y is the measured k-space data, TV is the total-variation and its weighting is determined by an empirical value for α.

In the actual implementation, at first iteration the 3D undersampled k-space data are Fourier transformed into 3D image which is subsequently converted into an MIP image. After sparsifying transform, soft-thresholding is applied to denoise error components in the sparse image. This reconstructed MIP image fills in the first slice of the 3D zero image. After the first iteration, this updated 3D zero image is subsequently applied. For the sparsifying transform, we used a contourlet transform [2] which has been shown to be useful for sparsifying images containing contours as in the case of MIP image.

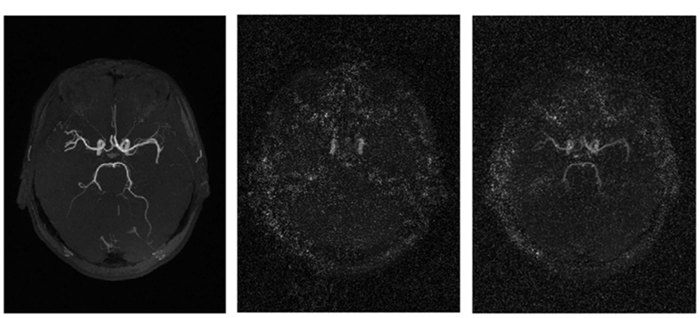
To illustrate the usefulness of the contourlet compared to the wavelet, we applied the CS recon to 3D k-space data obtained from the peripheral leg [3]. Here, data were reconstructed using just the general CS algorithm. Images were reconstructed using 20% of the samples. After reconstruction, MIP image was constructed. The PSNR (Peak SNR) values were compared for the two methods.

In vivo MR angiographic 3D data were collected from the brain using a GRE sequence (TR = 21ms, TE = 3.7ms FOV = 188 x 250mm, flip = 18°, 1.1 x 0.6 x 0.6mm^3 resolution, 3T Siemens). Reconstruction of the MIP was performed using general CS algorithm and our modified MIP-based algorithm. 20% of the whole 3D k-space data were randomly selected for the reconstruction from the two phase-encode directions. For the general CS algorithm, MIP images were constructed after all the reconstruction was performed.



(a) Reference (b) Contourlet (c) Wavelet

Figure 2.



(a) Reference (b) General (c) MIP based

Figure 3.

Results

Fig. 2 shows MIP images reconstructed using the contourlet versus the wavelet as the sparsifying transform. The images reconstructed using the contourlet transform resulted in higher PSNR compared to wavelets (PSNR: (b) 10.46, (c) 10.13). Therfore, background noise suppression was better using the contourlets. In Fig. 3, MIP images are shown using the general CS recon algorithm versus our modified algorithm for the 3D brain data collected. As can be seen, the final MIP images using our modified CS recon algorithm resulted in finer detail regarding the vessels. Although the individual slices reconstructed by the general CS algorithm gave a good sparse image, when this was converted to a MIP image, fine detail information was lost as shown in Fig. 3(b).

Conclusion

We applied CS reconstruction using MIP image as the reference. The algorithm enhances sparsity of the MIP images directly rather than on the individual 2D images. By using a directional filter bank such as the contourlet transform, sparser representation of the MIP image can be achieved compared to wavelets. The method can be useful when only the MIP images are of interest to the user. Such cases are often encountered for MR angiography or MR intervention applications.

References

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