A Novel Fast Dynamic Cardiac Data Reconstruction Method Using Prior Knowledge and Adaptive Matching Pursuits

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Introduction:

Recently, several variants of matching pursuit methods such as Regularized Orthogonal Matching Pursuit (ROMP) [1], Compressive Sampling Matching Pursuit (CoSAMP) [2] and Sparsity Adaptive Matching Pursuit (SAMP) [3] have been proposed and shown to give exact reconstruction for sufficiently sparse signals. Compared to the conventional OMP [4], these variants offer faster reconstructions, as they detect multiple signal components per single iteration of the OMP algorithm. The SAMP has an advantage over the other methods that it does not require any prior knowledge about the signal sparsity which is generally the case when recovering the practical compressible signals. In this work, based on SAMP algorithm and the prior knowledge obtained from the sliding window reconstruction from the under-sampled data, we propose a scheme that can provide very fast dynamic cardiac MR reconstructions. The results show that this scheme outperforms the other existing iterative schemes in Compressed Sensing (CS) such as OMP.

Method:

An implementation of modified OMP was proposed in [5] for reconstructing the dynamic cardiac data in x-f space [6] from randomly under-sampled data. Starting from the aliased space (zero-padded reconstruction) generated from the under-sampled data, this method iteratively detects the signal components by picking the most significant component in the aliased space, calculates the interference due to detected components by convolving them with the point spread function and gets the residual by subtracting the interference due to detected components from the original aliased space. This scheme has two disadvantages: first, it requires running the OMP algorithm twice to identify and improve the dynamic parts of cardiac MR data. Secondly, it detects only one signal component per iteration. Our method is as follows: After performing the sliding window reconstruction from the under-sampled data, we calculate the dynamic energy in x-f space for each frequency encoding index as shown in Fig. 1 (a) and Fig. 1(b). From the dynamic energy profile for all the frequency encoding indices, we can identify the 'static' x-f space i.e., the x-f space containing only static signal components. For each static x-f space, we limit the maximum number of signal components to be reconstructed by our method to only those corresponding to dc frequency (f=0) in x-f space. Hence, this information acts as a prior in our proposed method. For our SAMP based implementation, starting from the aliased x-f space, we iteratively detect the signal components in multiples of step size's'. If's'=1, it corresponds to the case of single component detection per iteration (conventional OMP). The algorithm stops when maximum residual aliasing intensity in x-f space reaches the intensity level of noise or the number of already detected components reaches the maximum detectable sparsity level in case of static x-f space.

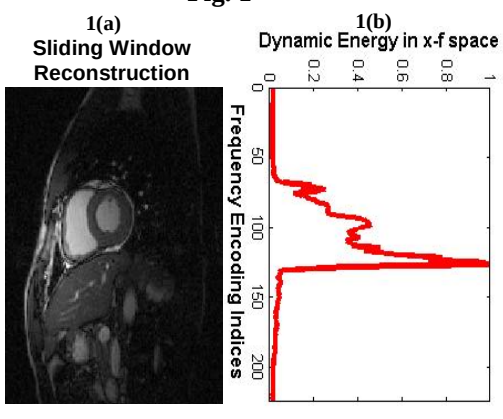
Two sets of dynamic cardiac data of size (n_f x n_p x n_t, n_f: number of frequency encoding indices, n_p: number of phase encoding indices, n_t: number of time frames) (224x155x50) and (336x178x48) were acquired with Philips MRI scanner 1.5 T, SSFP sequence, FOV 430x320 mm^2 and TE/TR: 1.46/3 ms. The under-sampled data was simulated by randomly under-sampling the dynamic cardiac data in k-t space (k: phase encoding index, t: time) with different acceleration factors. The x-f space corresponding to each frequency encoding index is independently reconstructed by OMP method proposed in [5] and our method with varying levels of step size 's'. The goal is to see up to which step size's', we can get signal reconstructions that are comparable to that for OMP method.

Results:

For the original (fully-sampled) cardiac frame shown in Fig.2 (a), the reconstruction results by OMP method with under-sampling factor (SF) of 3 and 5 are shown in Fig. 2(b) and Fig. 2(g). Fig.2(c), (d), (e) and (f) show our proposed method results with different values of 's' and SF. With MATLAB based implementation, the time for reconstructing the whole set of dynamic cardiac data (*Tr)* is also given for each case. For SF=3, Fig. 2(h) shows the variation of total reconstruction time (*Tr)* and normalized reconstruction error as functions of step size 's'. Fig.3 (a) shows one temporal profile from original dynamic cardiac data. For different values of 's' and SF in Fig.2(b-g), the corresponding reconstructed temporal profiles are shown in Fig.3(b-g).

Our proposed method gives reconstruction results comparable to OMP method up to the step size's' of 150 and 50 for SF=3 and SF=5 respectively. For SF=3, with MATLAB based implementation, the overall reconstruction time is reduced from 360 sec (s=1) to only 7.49 sec (s=150) with a speed up factor of 44. Together with the prior information (from sliding window reconstruction), the overall speed up factors of 80 and 65 are obtained for SF=3 and SF=5 respectively, when compared with the OMP method.

Fig. 1



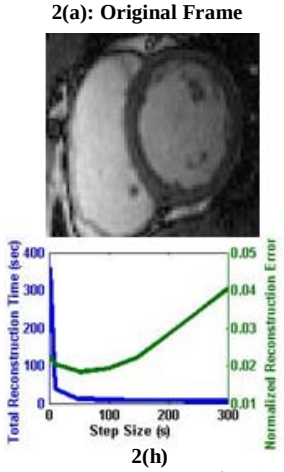
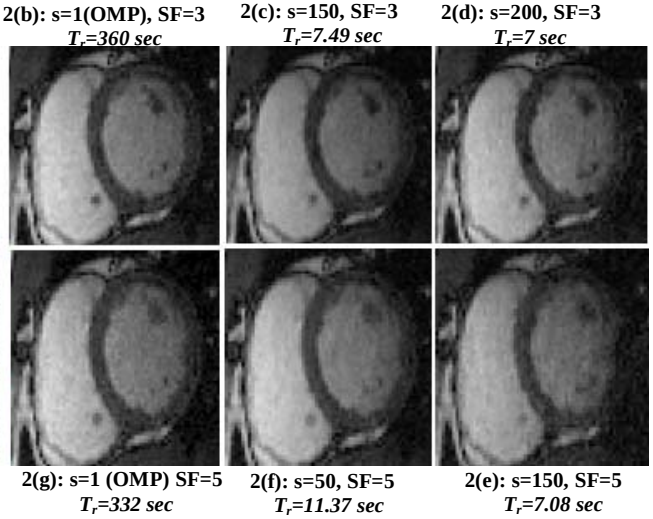


Fig. 2



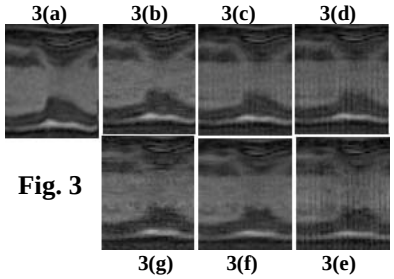


Fig. 3

Discussion:

With higher under-sampling factors (SF>3), the contrast to noise ratio in the aliased x-f space gets lower which implies that for large values of step size 's', many wrong candidates are picked from the aliased space. The fraction of overall speed up factor obtained by using prior information depends on the fraction of static signal components in the FOV. One of the main issues in CS reconstruction methods is that the reconstruction is done offline due to high computational load. Our proposed method can be further optimized to give real time CS reconstructions.

References:

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