Compressed Medical Imaging using Doubly Parseval Frame Sparsity Averaging

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Abstract

In this paper, a novel sparsity basis is proposed by doubling the bases concatenation from sparsity averaging prior compressed medical imaging, referred to as doubly concatenated sparsity averaging with reweighted analysis (DC-SARA). The performance of DCSARA is based on a reformulated analysis through simulation on medical images via spread-spectrum measurement techniques and conducted further testing using random Gaussian measurement techniques. The performance of DCSARA outperforms sparsity averaging reweighted analysis (SARA).

Ⅰ. Introduction

Compressed sensing (CS) presents a new signal compression framework for recovering sparse signals from compressed measurements through fixed linear combination measurements with a nonlinear reconstruction process which surpasses the Nyquist sampling theory [1].

The standard CS reported in [2] has been extended to repetitive dictionaries and coherent nature, based on the condition of the measurement matrix, resulting in the assurance of a dictionary (D-RIP). Numerous random matrices are characterized by both RIP and D-RIP, such as the Bernoulli or Gaussian matrices. Additionally a fast sensing operator, which can be modeled by multi-plying a Fourier matrix with a random sign matrix, is also characterized by the D-RIP [3]. Interestingly, the work reported in [4] proposed spread-spectrum frame-work, with a subsampled Fourier matrix.

Average sparsity was previously included in the context of generic press imaging in CS theory, with a coherent exaggerated dictionary. The related reconstruction algorithm, based on the analysis of reweighted`1formulations, is referred to as Sparsity Averaging Reweighted Analysis (SARA) [4]. Furthermore, an approach improves SARA by doubling the parseval frame is proposed in this paper, dubbed doubly concatenated sparsity averaging with reweighted analysis(DCSARA). The performance of DCSARA is tested through computer simulations, using spread-spectrum measurement schemes and the results demonstrate that DCSARA outperforms SARA.

Ⅱ. Doubly Parseval Frame Sparsity Basis

Medical images are usually complex, incorporating various types of structures that yield sparse descriptions in various bases. For example, gradient sparsity is exhibited by piece-wise smooth structures, whereas wavelet bases can better encapsulate extended structures. Hence, advancing the basis concatenation with sparsity averaging, rather than a single basis, is remarkably effective [5]. In this paper, a dictionary comprising a concatenation from d frames $\Psi(p,f)$ is presented, with $1 \le f \le d$ and p for the number of multi-frame. The special case of the concatenation of Parseval frame is considered, producing the Parseval frame $\Psi(p,d) \in CM \times D$, having $M<D$.

Ⅲ. Experimental Results

To estimate the performance of the proposed DC-SARA method, an MRI image having a dimension of 256×256 was recovered from compressive measurements. For the DCSARA dictionary, Db1-Db8 concatenations were used, while the spread-spectrum method [8] that obeys D-RIP was applied to obtain a fast measurement operator.

The performance comparison of the proposed DC-SARA technique was conducted with analogous algorithms and their reweighted versions by varying the dictionary sparsity, i.e., (1) and (6). The associated algorithm is BPSA and it's dictionaries are the Db1-Db8concatenation whereas the reweighted versions are de-noted SARA. The additional constraints on all problems as the input image interest is positive. For the performance metric, a reconstruction quality metric is used, i.e., standard signal to noise ratio (SNR).

For the first test, the reconstruction performance of DCSA and DCSARA (a reweighted version of DCSA)w.r.t the ratio of M/N was performed. The ISNR is set as 30 dB while varrying the undersampling ratio from 0.1 to 0.9. The benchmark results of DCSARA with other methods including SARA, are depicted in Fig.1(b). The results confirm that the DCSA method outperforms the BPSA method, while the proposed DC-SARA outperforms all benchmarked methods, including SARA for all samplings ratio. The DCSA method achieves a better gain, between 2.1-9 dB, where the highest gain is seen for sampling ratios within the range0.1-0.5. As shown in Fig. 1(b), the proposed DCSARA method obtained a better SNR than SARA, with a gain of 3 dB.

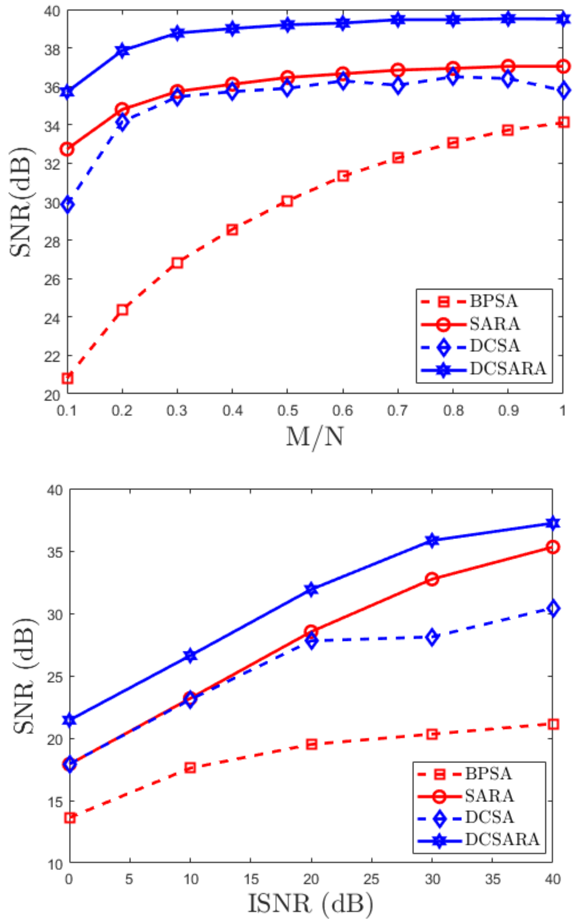

Fig. 2. MRI images reconstruction quality. From top to bottom, SNR results w.r.t sampling ratio (ISNR=30 dB) and SNR result w.r.t ISNR (M=0.1N).

The subsequent experimental results demonstrate that the proposed DCSARA method is robust against noise in the measurement setting when using the spread-spectrum method. M=0.1N was fixed while the ISNR was adjusted within the range 0-40 dB. As shown in Fig. 1(c), there is a linear association between SNR and ISNR, with a slope of 1 for low ISNR values until it becomes high enough due to the bound of (2). Here, the under-sampling effect dominates the reconstruction quality. As can be observed in Fig. 1(c), the proposed DCSARA outperforms the SARA for all ISNR, generating a 20 dB SNR for an ISNR of 0 dB. Fig. 1(c) further.

IV. Conclusion

DCSARA is proposed for improving the sparsity of medical images and a reweighted version using the BPDN reconstruction method from CS measurements. The novel DCSARA method for medical imaging in a conceptual meaning of CS, with a coherent exaggerated dictionary. This strategy depends on the concept that natural images exhibit strong mean sparsity and multiple base sparsity. The performance of DCSARA is evaluated using spread-spectrum measurements schemes. The experimental results show the proposed doubly concatenated bases of average sparsity outperform the previous SARA, based on a single frame or sparsity gradient with respect to both SNR and from a visual perspective.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2019R1A2C1089542).

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