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Compressed Sensing SAR Through-the-Wall Imaging with Side Information

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***Abstract*—In this paper an l1-l1 minimization technique is applied on real Through-the-Wall imaging data. It allows adding side information into the compressed sensing minimization algorithm. This technique is evaluated and compared to the conventional CS approach and the common coherent background subtraction method.**

I. Introduction

Suppose $x \in \mathbb{C}^n$ to be an unknown sparse signal, with s non-zero elements. This signal is sensed by performing m linear measurements:

$$y = Ax \tag{1}$$

Compressed Sensing (CS) theory [1] states that a unique solution can be obtained, with high probability, even from a very low number of measurements $m << n$. This unique solution can be found by solving the following Basis Pursuit problem [2]:

$$\min \|x\|_1 \quad \text{s.t.} \quad \|Ax - y\|_2 \leqslant \epsilon, \tag{2}$$

The new bound for the sampling rate for CS reconstruction is function of the sparsity s of the signal. In our application x represents the reflection coefficients of each pixel of a 2-D horizontal slice through the scene and y are the measurements obtained with a SAR system. The applicability of Compressed Sensing for the reconstruction of scenes is jeopardized by the presence of high clutter, caused by the front wall, distortions, reverberations in the walls and multipath effects [3]. These effects have a severe impact on the sparsity and thus on the subsampling bound.

In many cases, sparseness is not the only prior knowledge that can be added to the underdetermined set of equations. In this work, we suppose to have access to a fully sampled similar measurement, which can be a prior or a synthetically built measurement. A common TWI technique is to perform coherent background subtraction: the difference between the old and the new raw data is computed and compressed to obtain the sparse background subtracted image. In [4] a new methodology is proposed to add the side information into the CS minimization problem:

$$\min \|x\|_1 + \|x - w\|_1 \quad \text{s.t.} \quad \|Ax - y\|_2 \leqslant \epsilon, \tag{3}$$

where w is the reconstructed image obtained from the prior measurement.

II. Main Results

These three CS methods were applied on real TWI FMCW SAR data. Fig. 1 shows the fully sampled compressed TWI of an empty room and a room with three persons. The images are clearly contaminated with wall ringing effects and ghost targets.

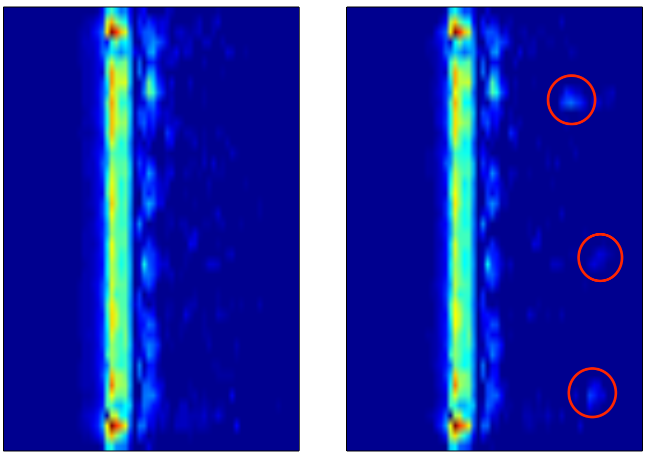

Fig. 1. On the left hand side: reconstruction of the prior fully sampled measurement: an empty room. On the right hand side: reconstruction of the fully sampled measurement from the same room with three persons inside (encircled in red).

Fig 2 shows the reconstructed scene using only 20% of the original number of Nyquist samples using three different CS approaches: (1) Conventional CS; (2) CS with coherent background subtraction; (3) CS with l1-l1 minimization. Only the third approach allows for the visual detection of the three persons hidden behind the wall.

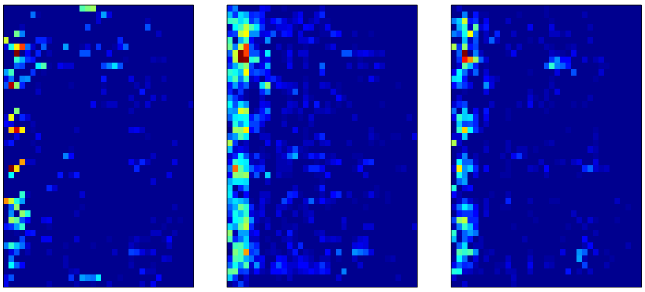

Fig. 2. from left to right: conventional CS reconstruction; coherent background subtraction and CS with l1-l1 minimization. Only the area behind the wall is shown.

III. Conclusion

The l1-l1 minimization clearly outperforms both conventional CS and CS with coherent background subtraction in TWI SAR.

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