High-Resolution Millimeter Wave Ground Based-SAR Imaging via Compressed Sensing

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Compressed sensing (CS) is a technique which reconstructs an approximated full image using reduced samples. With the CS technique, the measurement time is reduced and high-resolution reconstructed data is obtained. On the other hand, the computational time is increased because the CS algorithm requires slightly more time than conventional reconstruction algorithms. Therefore, reducing the computational time is a critical issue. In this paper, an improved CS algorithm is proposed. The proposed algorithm is based on a greedy algorithm which solves CS problems using an iteration method. By reducing the number of iterations, the computational time of the proposed algorithm is reduced. The proposed CS algorithm is applied to a simple discrete Fourier transform (DFT) problem and to millimeter-wave ground-based synthetic aperture radar (GB-SAR) imaging for verification.

Index Terms- Compressed sensing, microwave imaging, millimeter wave radar, synthetic aperture radar

I. INTRODUCTION

There are many studies of millimeter-wave synthetic aperture radar (SAR) due to its high resolutions and because this type of radar is not affected by weather. Millimeter-wave SAR imaging requires a considerable amount of data and takes a long time to measure the data. With compressed sensing (CS), the required amount of data is reduced, as is the measurement time. Nevertheless, CS reconstruction takes slightly more computational time than that used by conventional reconstruction methods. To reduce the overall implementation time, reducing the computational time is necessary.

There are many types of CS algorithms, and they can generally be divided in two types. The first of these solves the l1 norm minimization problem, while the second type consists of greedy algorithms such as Orthogonal Matching Pursuit (OMP) [1], Compressed Sensing Matching Pursuit (CoSaMP), and the Bayesian Fast Relevance Vector Machine (RVM). A greedy algorithm can find a solution more rapidly than those in the first group [2]. Therefore, this paper proposes an improved CS algorithm based on the OMP algorithm.

The proposed algorithm is verified by successfully applying it to a simple discrete Fourier transform (DFT) problem and to millimeter-wave ground-based SAR (GB-SAR) imaging.

II. BRIEF OVERVIEW OF THE OMP ALGORITHM

The OMP algorithm proposed by mallat is based on an iteration method [3]. Let \mathbf{x} be the sampled measurement data and \mathbf{s} be the same signal represented in the sparse domain. The matrix \mathbf{A} is a transformation matrix between \mathbf{x} and \mathbf{s} .

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

A flowchart of the OMP algorithm is shown in Fig. 1 (a).

After initialization, OMP estimates the support of the largest component of signal **s** using the signal proxy \mathbf{x}_s . The next step estimates the sparse signal \hat{s}_i using least square method. The residual is then calculated and the previous steps are repeated until the number of iterations reaches the sparsity level SL. A detailed explanation of each step and parameter will be given in the full paper.

III. PROPOSED ALGORITHM

A flowchart of the proposed algorithm is shown in Fig. 1 (b). Most steps are similar to those used with the OMP, but the process of estimating the support of the largest component of signal \mathbf{s} has been modified.

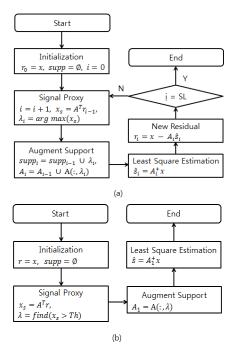


Fig. 1. Flowchart of the algorithm. (a) OMP, (b) Proposed algorithm.

Instead of finding the support of the largest component in sequence through repetition, the proposed algorithm uses a threshold value. The proposed algorithm obtains the support of the signal \mathbf{s} with a value greater than a certain threshold, here denoted as Th. In this way, the number of iterations can be reduced to one. The proposed algorithm thus reduces the number of iterations to one, which, reduces the computation time.

IV. SIMULATED RESULTS

The proposed algorithm is applied to a simple DFT problem for verification. The full signal is composed of four different frequencies, as shown below.

$$y = \sum_{k=1}^{4} \sin(2\pi f_k t)$$

$$f_1 = 130 \text{Hz}, f_2 = 220 \text{Hz}, f_3 = 300 \text{Hz}, f_4 = 440 \text{Hz}.$$
(2)

A sampling matrix is a random matrix which randomly samples only 10% of the data. A representation matrix is an inverse DFT matrix. The result is shown below in Fig. 2. It is clear that the signal is successfully reconstructed only with 10 % of the data. The computational time is reduced by approximately 43%.

The proposed CS algorithm is also applied to millimeterwave GB-SAR imaging. A detailed description of the received signal and field calculation will be given in the full paper. The received data was obtained in a 10 dB SNR environment and the frequency range is 80 to 110 GHz. A SAR algorithm based on the frequency domain, the range migration algorithm (RMA) in this case, is used [4]. The detailed process of applying CS to RMA will be shown in the full paper.

For data obtained at observation point intervals that do not meet the nyquist criterion, the resolution is reduced. Applying CS allows a higher resolution image to be reconstructed by simply changing the sampling matrix. However, when CS is applied, the computational time is increased, and the computational time can be reduced by the proposed algorithm.

The targets are shown in Fig. 3 (a). After reconstructing the image using the conventional RMA, the conventional OMP applied RMA, and the proposed algorithm, the image shown in Fig. 3 (b)-(d) was obtained. The computational times required for the reconstruction of the image with the three algorithms and the integrated side lobe ratio (ISLR) [5] of the reconstructed images are shown in Table 1.

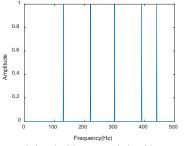


Fig. 2. Reconstructed signal with proposed algorithm.

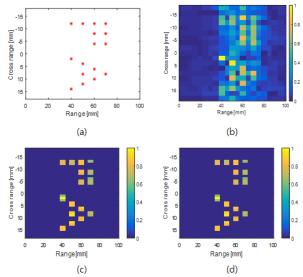


Fig. 3. (a) Location of targets, (b) Reconstructed image (RMA), (c) Reconstructed image (OMP applied RMA), (d) Reconstructed image (proposed algorithm)

The proposed algorithm offers a higher resolution than the conventional RMA, and the computational time is reduced by about 44% compared to the conventional OMP applied RMA.

TABLE I Comparison of Three Algorithms

	RMA	OMP applied RMA	Proposed algorithm
Calculation time (sec)	0.043	0.494	0.275
ISLR (dB)	7.118	0.471	0.471

V.CONCLUSION

A millimeter-wave ground-based SAR imaging using an improved compressed sensing method is proposed and verified in a numerical simulation. The proposed algorithm can obtain images at a higher resolution than the conventional RMA, and it requires less computation time than the conventional OMP.

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