CIRCULAR SAR IMAGING VIA COMPRESSED SENSING

Yun Lin [1, 2, 3], Wei-xian Tan [1, 2, 3], Wen Hong [1, 2], Yan-ping Wang [1, 2], Jin-song Chong [1,2]

1 The National Key Laboratory of Microwave Imaging Technology (MITL), P. R. China
2 Institute of Electronics, Chinese Academy of Sciences (IECAS), P. R. China
3 Graduate University of Chinese Academy of Sciences (GUCAS), P. R. China
E-mail: linyun606@mails.gucas.ac.cn

ABSTRACT

Compressed sensing (CS) has been receiving a lot of interest because it provides possibilities to reconstruct signals or images from significantly fewer samples than were traditionally thought necessary. In this paper, we apply this technique to circular SAR (CSAR) and use wavelet transform matrix to improve efficiency and accuracy. The method is demonstrated with simulations.

It is well known that all humanly-intelligible signals have a sparse representation in a fixed basis, which is made use of by JPEG2000 to compress data [1]. This raises the question: since most of the data will be discarded, is it possible to acquire it in already compressed form, so that we do not need to throw away anything? “Compressed sensing” shows that this is indeed possible. Circular SAR collects wave-back data in a circular trajectory, and one of its attractions is very high spatial resolution. High resolution demands wider bandwidth and larger size of aperture, meaning that more samples are required to reconstruct image. CSAR’s circular aperture is similar to sparse antenna array, and traditional image formulation algorithms are facing the high-sidelobe problem. Recently, there have been several approaches to apply CS technique to Radar [2]-[5]. For the first time, we apply CS technique to CSAR imaging. In this paper, we’ll show that CS technique can not only reduce the number of samples beyond the Nyquist theorem [6], achieving perfect reconstruction of the original image, but also solve the high-sidelobe problem in CSAR imaging.

In the simulation section, we present two CSAR imaging examples to illustrate the performance of CS technique. In example 1, we compare the back-projection (BP) algorithm and CS algorithm through simulations of two point targets. Target A is positioned right at the pixel, and the location of target B does not match the pixel location. The results shown in Fig. 1 show that BP method suffers from high-sidelobe problem (-10.5db in this example). However, with only 0.7% of the samples, which can be even fewer, CS method is capable of reconstructing targets accurately with much lower sidelobes (-13.2db at the most), and in the case of targets matching the pixel location, there’ll be no sidelobe at all. Though CS method may have some loss in amplitude in the case of target B (the reconstructed amplitude of target B is reduced to 0.65), still it’s a promising and effective technique for SAR imaging.

In example 2, a more complicated image is utilized to illustrate the performance of CS. The results show that:
1. high-sidelobe effect of BP algorithm reduces the quality of the image severely, while CS method does not face this problem.
2. CS technique with wavelet transform performs way much better than the one without wavelet transform, especially in detail solution.
3. When the number of selected samples is not enough for the reconstruction of the whole image, the isolated strong point targets can still be solved perfectly.
4. When white Gaussian measurement noise is added to the collected samples, the image profile is solved well, while the detail of the image is missing in the reconstruction.

The preliminary results of applying CS for CSAR imaging are promising. However, there are still issues to be addressed when applying CS to real data and complex scenes. First, the robustness of CS technique needs to be improved, so it can perform better in existence of noise. Second, as the number of pixel increases, the computational burden increases

exponentially, so fast algorithm fit for large-scale data needs to be developed. Finally, the effect of the relationship between pixel spacing and the bandwidth of transmitted signal on the quality of reconstruction using CS needs to be further studied.

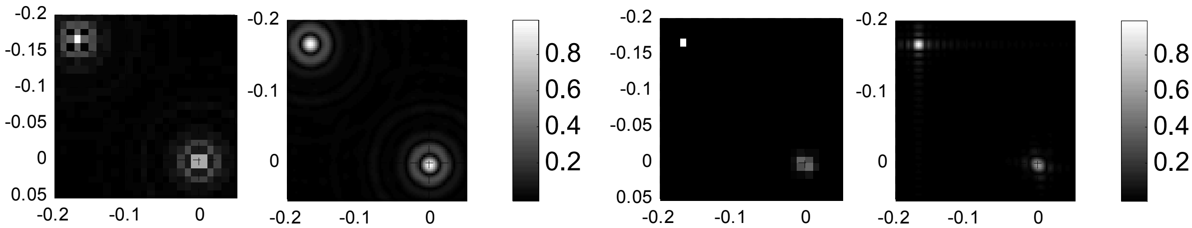

Figure 1: Images for two point targets. (a) BP, (b) upsample (a) by a factor of 7, (c) CS with J=100, (d) upsample (c) by a factor of 7.

11. REFERENCES

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