AUTOREGRESSIVE MODELING OF DECHIRPED SPOTLIGHT-MODE SAR RAW DATA IN TRANSFORM DOMAIN

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1. INTRODUCTION

Synthetic aperture radar (SAR) systems collect massive amounts of data that require extensive signal processing to retrieve the captured surface imagery. Due to the limited onboard computational resources, the SAR raw data must be downlinked for processing and storage. The capacity of the link, however, is typically insufficient to carry the amount of data being collected, leading to a need for compression of the SAR raw data.

Perhaps the most well-known compression technique used for SAR signals is the block adaptive quantizer (BAQ) that was employed in NASA's Magellan Mission to Venus [1]. The BAQ partitions the signal samples into blocks, estimates the signal power for each block and employs a scalar quantizer, scaled according to the estimated power of the block, to quantize the data. The motivation for the BAQ is that the in-phase (I) and quadrature (Q) components of SAR data samples are the sum of a large number of independent individual contributions, each of which represents the return from a surface element within the antenna footprint. It follows from the central limit theorem that the I and Q components are Gaussian distributed random variables. The average power, however, slowly varies as the scene changes requiring the scaling of the quantizer. Moreover, the data samples are assumed to be uncorrelated within a pulse return (in range) and across pulse returns (across range). These assumptions are supported by statistical analysis of the SAR raw data.

More recent quantizer designs have attempted to take advantage of the small correlation in the raw data (e.g., see [2–4]). In particular, [4] exploits the correlation in data over a small window due to the Doppler effect. In [2] the authors take advantage of the correlation due to the limited radar pulse bandwidth and the antenna pattern, where an along-range linear predictor is employed in order to remove the dependencies in the data followed by an adaptive quantizer. However, as pointed out earlier, SAR raw data exhibits little or no correlation. Consequently the compression ratio of these algorithms is generally low.

Variable-rate vector quantization of SAR data with range-focusing was proposed in [5] by Poggi, et al. Range focusing is the first step in the SAR image formation process and only requires a Fourier transform in range dimension of the data. Therefore, the required memory and processing power are modest. In [5] the authors demonstrate that the range-focused data from strip-mode SAR exhibits more correlation than the raw data, although without providing any theoretical foundation.

In this paper we show that for spotlight SAR, the range-wise inverse discrete Fourier transform (IDFT) of the dechirped raw data exhibits more correlation than the raw data itself. In this case the range-wise inverse discrete Fourier transform (IDFT) of the raw data is analogous to the range-focused strip-mode data in [5].

We first provide further insight into ours and Poggi's approach by analyzing the spotlight-mode SAR for a finite number of point objects on the ground patch and describe why the IDFT of the data has increased correlation. Next

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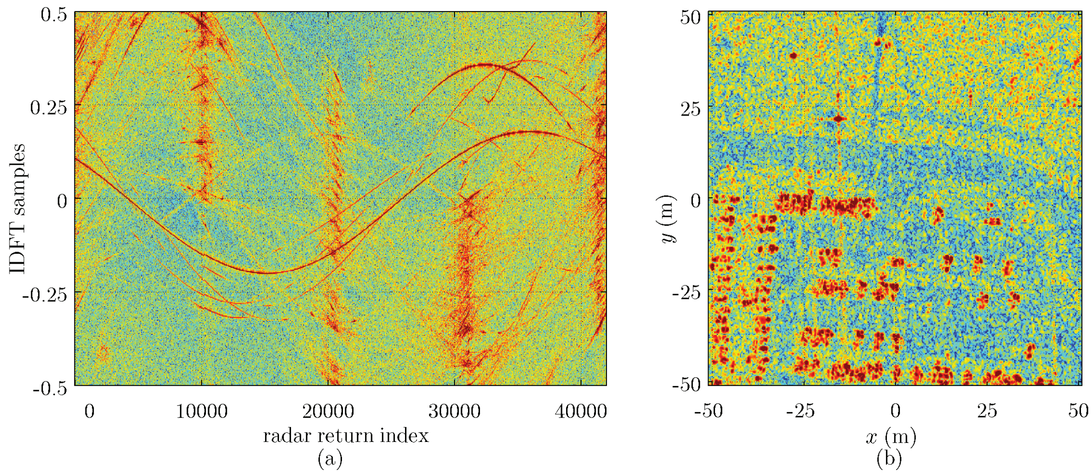

Fig. 1. Gotcha data: (a) the range-wise IDFT of the dechirped raw data, and (b) the formed surface image.

we derive an autoregressive (AR) model of the IDFT of the dechirped SAR raw data. Such a statistical model that captures the essential features of the SAR data not only helps in developing efficient compression methods, but can also be used to investigate performance tradeoffs of any coding techniques through rate distortion theory. The AR model is then applied to the SAR data from AFRL's Gotcha Dataset [6]. Since IDFT operation can be performed very efficiently using fast Fourier transform our study provides an effective method for compression of SAR data. Using this IDFT of the SAR data and this AR model we have developed data compression techniques for SAR raw data which is reported in a companion paper [7].

2. TOMOGRAPHIC FORMULATION AND AR MODEL

The starting point of our study is the tomographic formulation of the spotlight-mode SAR by Munson et al. [8], namely that a dechirped radar return (i.e., the raw data in the range direction) consists mainly of the Fourier transform of the projected surface reflectivity at the angle of the SAR with respect to the center of the ground patch. Therefore, the range-wise IDFT of the dechirped raw data is the collection of the projected reflectivity as the SAR platform travels. This leads to the following: if the SAR platform encircles the illuminated ground patch at a constant speed, an isotropic point object on the patch is represented by a single-period of a sinusoidal trace on the IDFT of the dechirped raw data. The magnitude and phase of the sinusoidal trace depend on the location of the point object with respect to the center of the patch. Furthermore, the IDFT values on the sinusoidal trace have constant magnitude that is proportional to the magnitude of the reflectivity of the point-object. However, the phase of the IDFT on the sinusoidal trace varies across the azimuth and is non-linear. Extending this example to the case of N point-objects, the IDFT of the raw data then exhibits N sinusoidal traces with different parameters. Every point object on the patch corresponds to a unique sinusoidal trace. Such sinusoidal traces are also present in the IDFT of SAR data from an urban scene where highly reflective man-made objects are present (see Fig. 1).

Consider a window of IDFT samples (K samples in the azimuth direction). If K is sufficiently small, a sinusoidal trace in this window can be approximated by a line segment. Moreover, the phase nonlinearity can be approximated to be linear. Hence, the windowed IDFT values can be viewed as a complex sinusoid having constant amplitude and linear phase change. As a result the data samples in windows containing these sinusoidal traces exhibit high sample-to-sample correlation. If multiple traces cross over within the data window, the data can be viewed as a sum of complex sinusoids.

The sum-of-complex-sinusoids does not adequately model the homogeneous regions of the ground patch which do not include highly reflective point objects. However, an AR process can effectively model the correlation in each window of IDFT samples, where poles close to the unit circle capture the behavior of complex sinusoids while poles

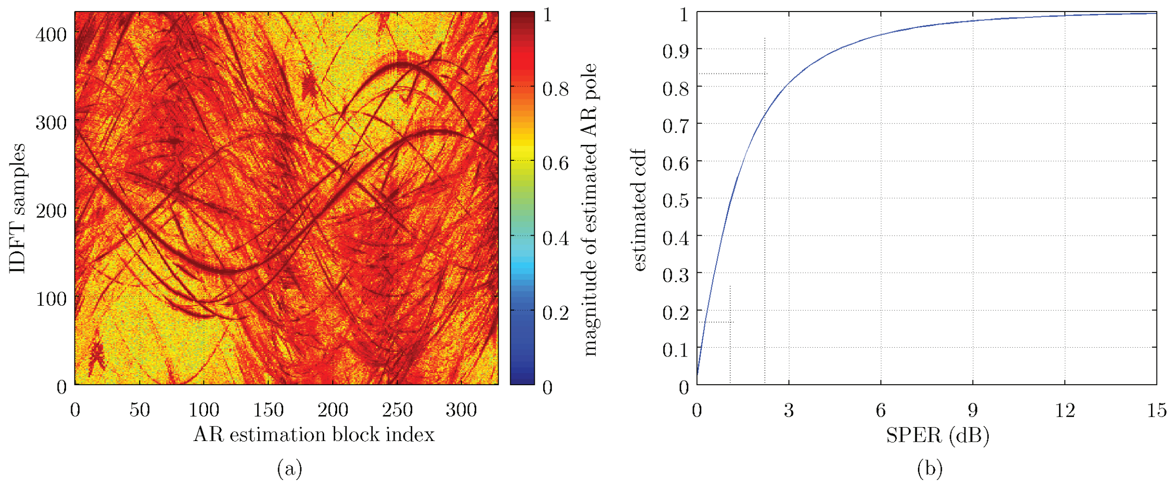

Fig. 2. AR(1) modeling (1x128-sample blocks) of Fig. 1a: (a) magnitude of the poles and (b) estimated cdf of SPER (in dB)).

away from the unit circle can be used to model the homogeneous regions.

We use the Gotcha data set [6] to illustrate the effectiveness of the AR model. Fig. 1a shows the range-wise IDFT of the dechirped raw data over the full circular path, and Fig. 1b shows the reconstructed surface image using the convolution back-projection algorithm [8]. The sinusoidal traces are clearly visible in Fig. 1a. The most prominent sinusoid belongs to the "top hat", a metallic cylinder located at (-17, 21) in Fig. 1b. We should point out that for some of the sinusoidal traces a full period may not be present due to the anisotropic nature of the reflecting object (e.g., cars).

Fig. 2 shows the result of the first-order AR (denoted AR(1)) modeling of the data in Fig. 1 whereby the complex data in Fig. 1 a is divided into blocks of 1×128 samples and for each block a first-order AR model is selected. The magnitude of the single pole for each block is shown in 2a where the coordinates of the pixel are the coordinates of the selected block in Fig. 1 a. It can be seen from this figure that the pole magnitude for all blocks containing sinusoidal segments are relatively high (> 0.8) with the highest magnitude found to be 0.99. Fig. 2b shows the cumulative distribution function (CDF) of the ratio of the signal power to the variance of the AR prediction error (SPER). This figure shows that more for than 20% of data blocks the variance of the prediction error is at least by 3 dB below the variance of the original samples.

Fig. 3 shows the average SPER as a function of two modeling parameters: AR order (Fig. 3a) and the block size (Fig. 3b). The plots labeled "overall" indicate the average SPER over all the IDFT blocks, The other plots in these figures show the average SPER for a subset of blocks, where the blocks are grouped by the signal power of the IDFT blocks. Typically, blocks with higher signal power are those containing the sinusoidal traces while blocks with low power corresponds to the "noise-like" regions in Fig. 1a.

The blocks with higher power are , consequently, more predictable, resulting in higher average SPER, as demonstrated in Fig. 3a. For example the 5% of the blocks with the highest power attains a 10 dB gain in the average SPER with a first-order AR model. For 75% of the blocks which have the lowest power the gain in SPER is small and reaches 3 dB for an AR order of 20. From this figure it is evident that most of the prediction gain can be realized with AR model of order 10 with an order of 4 being a good compromise between prediction gain and complexity.

The average SPER as a function of block-size, shown in Fig. 3b, exhibits a downward trend in general; all blocks have higher average SPER as block-size decreases. This behavior is expected since as the window size increases the correlation between adjacent samples decreases. In particular, for larger windows, the window may not contain only a segment of a sinusoidal trace and the line segment approximation of these traces will also not be valid. Therefore, prediction gain is higher for smaller windows. However, choosing smaller windows increase the overhead of the compression scheme. Again a window size of 64 or 128 provides a good compromise in this regard.

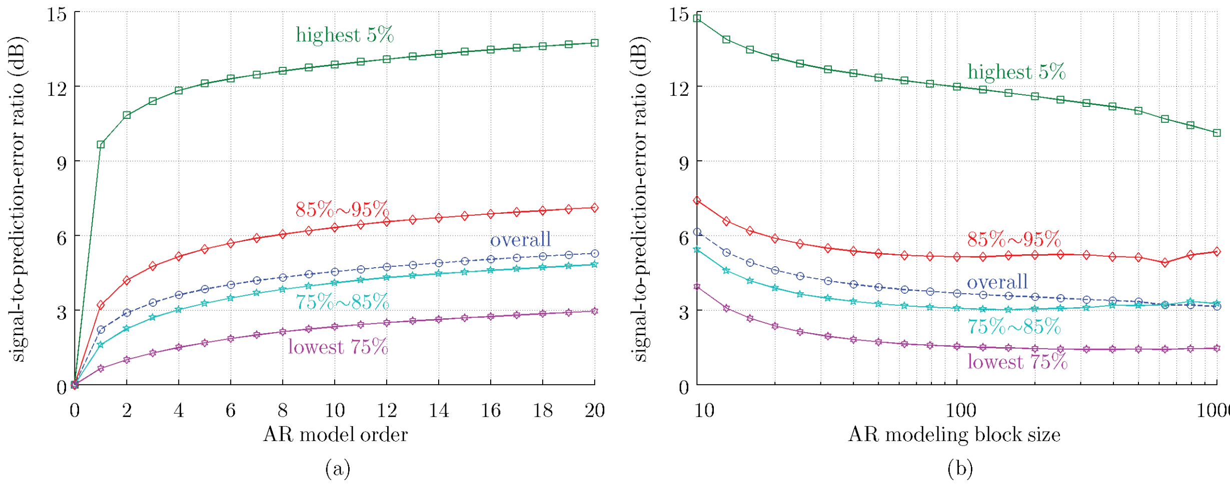

Fig. 3. AR modeling outcomes: (a) average SPER as a function of AR order ($K = 128$) and (b) AR(4) average SPER as a function of block size (average SPERs over all the blocks and over 4 subsets of blocks (split according to their signal power).

3. CONCLUSION

It is shown that for spotlight SAR, the range-wise inverse discrete Fourier transform (IDFT) of the dechirped raw data exhibits more correlation than the raw data itself. One source of this additional correlation is that an isotropic point object on the ground patch is represented by a sinusoidal trace in the IDFT of the data. An autoregressive (AR) model for the IDFT data is presented and, for the Gotcha data set, we show the prediction gain for different block sizes and AR order. Since IDFT operation can be performed very efficiently using fast Fourier transform our study provides an effective method for compression of SAR data. The results of this study have been used in predictive quantization SAR data and are presented in a companion paper.

4. REFERENCES

[1] R. Kwok and W. T. K. Johnson, "Block adaptive quantization of magellan SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 27, no. 4, pp. 375–383, 1989.

[2] Enrico Magli and Gabriella Olmo, "Lossy predictive coding of SAR raw data," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 5, pp. 977–987, 2003.

[3] S. M. Parkes and H. L. Clifton, "The compression of raw SAR and SAR image data," *Int. J. Remote Sens.*, vol. 20, no. 18, pp. 3563–3581, 1999.

[4] U. Benz, K. Strodl, and A. Moreira, "A comparison of several algorithms for SAR raw data compression," *IEEE Trans. Geosci. Remote Sens.*, vol. 33, no. 5, pp. 1266–1276, 1995.

[5] G. Poggi, A. R. P. Ragozini, and L. Verdoliva, "Compression of SAR data through range focusing and variable-rate vector quantization," *IEEE Trans. Geosci. Remote Sens.*, vol. 38, no. 3, pp. 1282–1289, 2000.

[6] Air Force Research Laboratory, "Gotcha volumetric SAR data set," 2007.

[7] M. Naraghi-Pour Ikuma, T. and T. Lewis, "Predictive quantization of dechirped spotlight-mode SAR raw data in transform domain," in *IEEE IGARSS*, 2010, submitted.

[8] Jr. Munson, D. C., J. D. O'Brien, and W. K. Jenkins, "A tomographic formulation of spotlight-mode synthetic aperture radar," *Proc. IEEE*, vol. 71, no. 8, pp. 917–925, 1983.