PREDICTIVE QUANTIZATION OF DECHIRPED SPOTLIGHT-MODE SAR RAW DATA IN TRANSFORM DOMAIN

*Takeshi Ikuma, Mort Naraghi-Pour**

Dept. of Electrical and Computer Engineering
Louisiana State University
Baton Rouge, LA 70803

Thomas Lewis

Air Force Research laboratory
Bldg 620 Northeast Delivery Dock
2241 Avionics Circle
Wright-Patterson AFB, OH 45433

1. INTRODUCTION

Synthetic aperture radar (SAR) is a high resolution technique for target imaging and terrain mapping. Large volumes of data are generated on airborne SAR platforms that need to be down linked over bandlimited channels for processing or storage. There is therefore a major interest in efficient compression of SAR data. The most notable compression algorithm for SAR data is the block adaptive quantization (BAQ) algorithm [1] (and its variants), which has been implemented in a number of SAR systems, including NASA's Magellan Mission to Venus and Shuttle Imaging Radar Mission C (SIR-C). The BAQ algorithm is a scalar quantization algorithm with varying threshold levels determined by a scale factor depending on the signal variance. Other techniques include vector quantization [2, 3], quantization in various transforms-domains [4–7], wavelet and wavelet packets [8, 9], trellis-coded quantization [10, 11], entropy-constrained quantization [12], predictive coding [13], and compressive sensing [14].

Compression of SAR raw data is a challenging problem due to the statistical properties of the data. A widely used statistical model for the SAR raw data, established in [1], is that the in-phase (I) and quadrature (Q) components of SAR data samples are the sum of a very large number of independent contributions, each of which represents the return from a surface element within the antenna footprint [1]. It follows from the central limit theorem that the I and Q samples are Gaussian distributed with zero mean and slowly varying average power. Moreover, the data samples are uncorrelated within a pulse return (in range) and across pulse returns (across range).

To improve the data compression performance further, it is critical to identify correlation in the SAR raw data. One promising possibility is presented with the variable-rate vector quantization with range-focusing by Poggi et. al. [6]. Range focusing is the first step in the SAR image formation process, and [6] demonstrated that the range-focused data exhibit more correlation than the raw data. Furthermore, in [15], we extended Poggi's findings by analyzing the inverse Fourier transform of the dechirped raw data for spotlight-mode SAR. This approach for spotlight mode SAR is comparable to the range-focused data for strip-mode SAR in [6]). Furthermore, it is shown in [15] that, over a short window across pulse returns, the inverse Fourier transform of the raw data is well modeled by an autoregressive (AR) process [16].

Based on our findings in [15], in this paper we propose two AR-model based quantization algorithms: transform-domain block predictive quantization (TDBPQ) and transform-domain block predictive vector quantization (TDBPVQ). Both methods operate on the inverse discrete Fourier transform (IDFT) of the dechirped SAR data. Implementation of IDFT does not require a great deal of computational power since it can be performed very efficiently using fast Fourier transform. Furthermore, since it is performed only in one dimension (range), and on

*This work was supported by the Minority Leaders Program of the Air Force Research Laboratory/Clarkson Aerospace Corporation under Prime Contract FA8650-05-D-1912.

short blocks, the memory requirements are low. After the IDFT operation the AR parameters and the variance of the innovation process are estimated over short strips of the IDFT data across the SAR returns (range). Although any AR estimators can be utilized, we use Yule-Walker method [16] for its computational efficiency.

2. PREDICTIVE QUANTIZATION METHODS

Having estimated the parameters of the AR model, we employ a predictive quantization scheme to compress the IDFT transformed SAR signals. Specifically, we use the differential pulse code modulation (DPCM) algorithm [17]. The DPCM technique was also utilized by Magli and Olmo [13]. However, they applied the DPCM algorithm directly to the down-converted SAR raw data. Preprocessing the signal through IDFT improves the performance of the compression algorithm as it reveals the underlying correlation behavior of the SAR return signals. The predictor order is chosen as four since this oder is shown to remove most of the correlation in the Gotcha SAR data set [15]. As described above the predictor coefficients are estimated for each data strip (a frame in the azimuth direction) using the Yule-Walker method. The input to the quantizer can be approximated by the innovation process of the AR model. Since the SAR data is Gaussian distributed, one may assume that the innovation process is also Gaussian. Furthermore, as mentioned previously, the variance of the samples of the innovation process for each data strip are estimated by the Yule-Walker method. Therefore, the quantizer is designed for a Gaussian distributed input which is scaled according to the estimated variance of the innovation process. This choice of the predictor and quantizer are not necessarily optimal [18]. In a closed loop DPCM system the predictor inputs are not the actual samples of the data and the quantizer does not operate on the innovation process. However, it is well known that for high signal to noise ratios, these choices of predictor and quantizer are close to optimal.

Next we extend the TDBPQ to TDBPVQ using predictive vector quantization, [19], to code multiple IDFT data strips together across azimuth (hereafter we denote this set of data strips as a data block). For a typical (linear) predictive vector quantization application, a two-dimensional AR model needs to be employed in order to take advantage of the correlation across the vector elements. With the IDFT of the SAR raw data, however, for the majority of the blocks the strips in the block are either not correlated or have low correlation. There are, however, some blocks that show correlation between the strips. Therefore to reduce the complexity of AR estimation, we use a one dimensional AR model for each strip. During the encoding process a vector of K samples comprising of one sample from each strip enters the encoder. The predictor operates on the K components of this vector as if they were independent with each sample predicted with its own predictor. The K residuals from the predictors form a vector that is quantized by the vector quantizer. The vector quantizer codebook is designed using the LBG (K-means) algorithms [20].

3. NUMERICAL RESULTS

To show the efficacy of our approach we apply the compression techniques proposed here to the AFRL's Gotcha SAR Dataset [21]. In Table 1 we summarize the performance of the two methods proposed here with that of the block adaptive quantization (BAQ). All three methods quantize data samples at 2 bits/sample. Both the BAQ and TDBPQ algorithms use a data strip of 128 samples across the returns (range). The TDBPVQ also uses 128 sample data strips and forms a data block by stacking two strips (across azimuth) together. The vector quantizer's codebook is designed using a larger block of 106×256 samples. As mentioned previously we have used an AR model of order four for both TDBPQ and TDBPVQ.

As shown in Table 1, the TDBPQ outperforms the BAQ by at least 6.0 dB in average signal-to-noise ratio (SNR). This is a significant gain and translates into a bit rate reduction of nearly one bit per sample. The TDBPVQ improves over the TDBPQ performance by 0.6 dB on average. As mentioned earlier, the correlation between data strips is highly low and highly varying, with some portions of data show more correlation than others. Fig. 1 demonstrates this as it shows the short-term average SNR over the full dataset. The SNR for each of the three schemes experiences

Table 1. Performance Summary of Three Quantizers

Method	Macro-Block Size	Overhead (#coef/sample)	SNR (dB)
BAQ	1×128	0.0078	7.86
TDBPQ	1×128	0.0703	13.81
TDBPVQ	106×256	0.1002	14.68

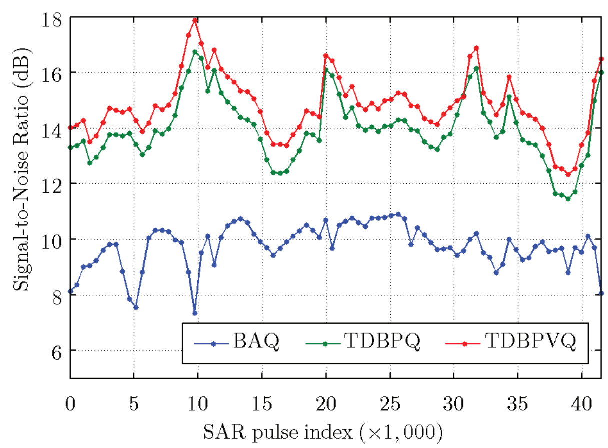

Fig. 1. SNR performance of three compression methods on Gotcha data.

fluctuations. However, the fluctuations are higher for TDBPVQ (as much as 6 dB) followed by TDBPQ (as much as 4 dB). The largest SNR improvement of TDBPVQ over TDBPQ is about 1.5 dB. Finally in Table 1 we have included a brief study of each scheme's overhead in terms of the number of coefficients and parameters per data sample. The overhead for our two methods is less than 10% and for the BAQ it is less than one 1%. However, the increase in the overhead is expected as the proposed quantization methods are more complex and is well warranted by the resulting improvement in signal to noise ratio.

4. CONCLUSION

Based on our findings in [15], in this paper we propose two AR-model based quantization algorithms: transform-domain block predictive quantization (TDBPQ) and transform-domain block predictive vector quantization (TDBPVQ). Both methods operate on the inverse discrete Fourier transform (IDFT) of the dechirped SAR data. It is shown that as a result of the correlation in the IDFT of the SAR data, the predictive quantization can provide up to 6 dB improvement in signal to noise ratio.

5. 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] A. Moreira and F. Blaser, "Fusion of block adaptive and vector quantizer for efficient sar data compression," in *IEEE IGARSS*, Tokyo, Japan, 1993, vol. 4, pp. 1583–1585.

[3] J. M. Moureaux, P. Gauthier, M. Barlaud, and P. Bellemain, "Raw sar data compression using vector quantization," *Int. J. Remote Sens.*, vol. 16, no. 16, pp. 3179–3187, 1995.

[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] Johanna Bolle, "Coding of sar raw data using reversible transforms," in *3rd IARSCE*, Copenhagen, Denmark, 1997, Third International Airborne Remote Sensing Conference and Exhibition.

[6] 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.

[7] R. A. Baxter, "Sar image compression with the gabor transform," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 1, pp. 574–588, 1999.

[8] V. Pascazio and G. Schirinzi, "Sar raw data compression by subband coding," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, no. 5, pp. 964–976, 2003.

[9] Giacomo Capizzi, Salvatore Coco, Antonio Laudani, and Giuseppe Pappalardo, "A new methodology for synthetic aperture radar (sar) raw data compression based on wavelet transform and neural networks," in *7th ICAISC*, pp. 676–681. 2004.

[10] J. W. Owens, M. W. Marcellin, B. R. Hunt, and M. Kleine, "Compression of synthetic aperture radar video phase history data using trellis-coded quantization techniques," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 2, pp. 1080–1085, 1999.

[11] C. D'Elia, G. Poggi, and L. Verdoliva, "Compression of sar raw data through range focusing and variable-rate trellis-coded quantization," *IEEE Trans. Image Process.*, vol. 10, no. 9, pp. 1278–1287, 2001.

[12] T. Algra, "Compression of raw sar data using entropy-constrained quantization," in *IEEE IGARSS*, Honolulu, HI, 2000, vol. 6, pp. 2660–2662.

[13] 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.

[14] Sujit Bhattacharya, Thomas Blumensath, Bernard Mulgrew, and Mike Davies, "Fast encoding of synthetic aperture radar raw data using compressed sensing," in *14th IEEE SSP Workshop*, Madison, WI, 2007, pp. 448–452.

[15] Takeshi Ikuma and Mort Naraghi-Pour, "Autoregressive modeling of dechirped spotlight-mode sar raw data in transformed domain," in *IEEE IGARSS*, 2010, submitted.

[16] Charles W. Therrien, *Discrete Random Signals and Statistical Signal Processing*, Prentice Hall Signal Processing Series. Prentice Hall, Englewood Cliffs, NJ, 1992.

[17] John G. Proakis, *Digital Communications*, McGraw Hill, Boston, 4th edition, 2000.

[18] M. Naraghi-Pour and D. Neuhoff, "Mismatched dpcm encoding of autoregressive processes," *IEEE Trans. Inf. Theory*, vol. 36, no. 2, pp. 305–311, 1990.

[19] Allen Gersho and Robert M. Gray, *Vector Quantization and Signal Compression*, Kluwer, Boston, 1992.

[20] Y. Linde, A. Buzo, and R. Gray, "An algorithm for vector quantizer design," *IEEE Trans. Commun.*, vol. 28, no. 1, pp. 84–95, 1980.

[21] Air Force Research Laboratory, "Gotcha volumetric sar data set," 2007.