Adaptive Quantized Algorithm for Compression of Synthetic Aperture Radar (SAR) Raw Data

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Abstract

Synthetic Aperture Radar (SAR) data distribution is Gaussian in nature having linear as well as nonlinear region. In order to encode these data, we wish to choose the quantization step size large enough to accommodate the maximum peak-to-peak range of the signal. On the other hand we would like to make the quantization step small so as to minimize the quantization noise, which consists of Slope overload error as well as granular error. This is further compounded by nonlinear and saturated nature of the raw data or SAR image. Extremes of these data call for use of non-uniform quantizer. An alternate approach is to adapt the properties of the quantizer to the level of the input signal. In the present paper authors have studied implementation of both the input as well as output standard deviations correlated with the mean for calculating the scale factor for minimum mean square error (MSE) or maximizing the Signal to Noise ratio (SNR). The results show that none of the approach is optimum so we have combined the techniques and run an algorithm when the linearity between the mean and standard deviation breaks. For the linear part the scale factor Δ is calculated to be 1.2533 while the nonlinear part begins after the input signal average value of 47.

Keywords : SAR, BAQ, BMPQ, Data Compression, Quantization

1. Introduction

Synthetic Aperture Radar (SAR) image compression is very important in reducing the burden of data storage and transmission in relatively slow channels. With the development of modern SAR system towards high resolution, multi-polarization, three-dimensional [7, 10] mapping, wide swath, multi-frequency, and multi-operation mode [11], the quantity of SAR raw data is even larger. Therefore, raw data must be compressed before downlink. Block adaptive quantization (BAQ) has been successfully utilized in Magellan [8] mission, ENVISAT ASAR and RADARSAT-2 satellites due to its simple structure but there is a problem of the high dynamic range of SAR echo. This makes the analog to digital converter (ADC) saturate. In this situation, the output of ADC is truncated Gauss random signal, not satisfying the precondition of Lloyd-Max quantizer [6] that requires the distribution be perfect Gaussian and deteriorates the performance of BAQ. This paper firstly points out the optimization of the BAQ designing and then try to give solution to the problem of saturated data compression by devising a new algorithm based on the relationship between the standard deviation of the output of A/D converter and the average signal mean (ASM).

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2. Block Adaptive Quantization (BAQ) and Optimization

BAQ algorithm is based on the fact that the dynamic range of the signal power within a data block (0 to 255 or -128 to + 127) is much less than that of the whole data set. Basic block arrangement for data compression using BAQ [7] is shown in figure 1.

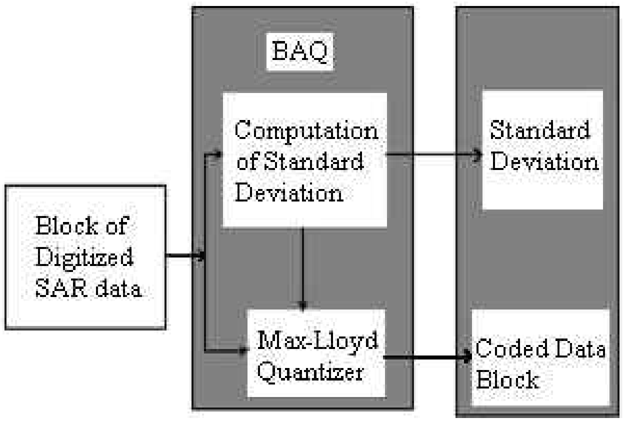

Figure 1 : Basic BAQ algorithm

The first step is to divide the raw data into blocks of small size with respect to the whole data set. The minimum block size is selected in such a way as to ensure Gaussian statistic distribution within a block and the maximum block size is limited by signal power, which should remain constant through out the block. The standard deviation of each block is estimated by the Following formula.

$$\sigma = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} x_{ij}^2} \quad \ldots\ldots(1)$$

Where *M, N* are the sample numbers of the row and the column of the block respectively. For the optimal operating point[1], the threshold values (delta) are proportional to the standard deviation of each data block in order to yield minimum distortion[6] in terms of mean square error(MSE).

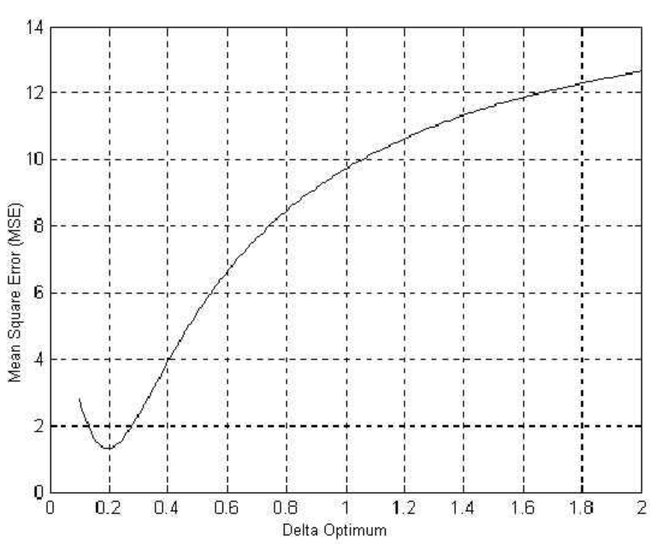

Figure 2 : Mean square error curve

This is shown in figure 2. While designing BAQ we need to take special care in terms of block size and the number of quantization levels selection in order to get optimum output.

2.1 Block Size Selection

The criteria for selection of the block size is a trade-off as it must be large enough to contain sufficient samples to fill the distribution model for SAR signal data and to achieve the desired compression ratio, while remaining small enough to track variations in r.m.s. signal level. Optimization of block size is done on the basis of standard deviation of magnitude error and overhead ratio.The standard deviation calculated is useful while encoding as well as while decoding the data; hence it is to be stored in memory thus creating an overhead. We have calculated standard deviation of magnitude error for different block sizes and for different number of quantization levels. It is found that the performance is worse for the maximum block size of 256 x 256 pixels. This is due to the worse adaptation to the power of the signal within the block.Thus, block size equal to or larger than 256 x 256 pixels are discarded. This sets upper limit on the block size.The value of standard deviation of magnitude error and corresponding quantization level are summarized in table 1.

Table 1. Standard Deviation of Magnitude Error

Block size	8 x 8	16 x 16	32 x 32	64 x 64	128 x 128	256 x 256
No.of Bits	Standard deviation of Magnitude error					
1	29.39	41.58	34.99	34.51	35.13	35.80
2	12.77	13.45	12.27	13.32	12.83	12.75
3	9.32	11.03	8.97	9.15	9.36	9.31
4	11.28	8.21	9.80	9.17	9.42	9.22
5	9.54	7.70	10.32	8.79	9.26	18.24

For small block sizes, the overhead is the main constraint. In order to set the lower limit of the block size, we observe the effect of the resulting overhead for different block sizes with the following ratio:

$$Over\ Head(OH) = \frac{(n^2\ M + \delta)}{n^2 M} \quad ..(2)$$

Where n is the size of the block in each dimension, M is the number of quantization levels and δ corresponds to the 32 bits to encode the standard deviation value of each block.

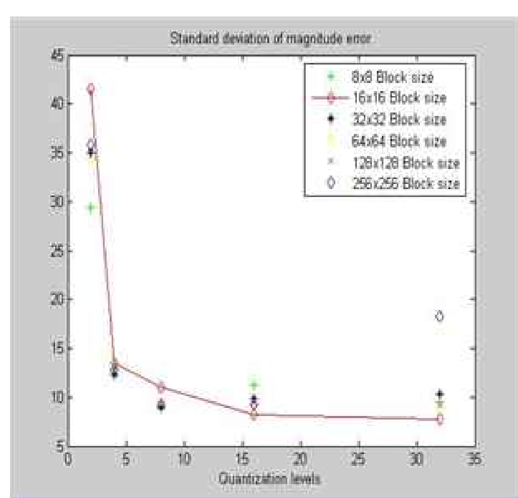

Figure 3 : Magnitude error standard deviation

The statistical details of the overhead ratio are summarized in table 2.

Table 2. Effect of Block Size on Overhead

No. of Bits	**1**	**2**	**3**	**4**	**5**
Block Size	Overhead ratio				
8X8	1.2500	1.1250	1.0625	1.0313	1.0156
16X1 6	1.0625	1.0313	1.0156	1.0078	1.0039
32X32	1.0156	1.0078	1.0039	1.0020	1.0010
128X128	1.0010	1.0065	1.0002	1.0001	1.0001
256X256	1.0002	1.0001	1.0001	1.0000	1.0000

Above data show that overhead ratio achieves a constant value for block size equal or greater than 32 pixels (in each dimension) hence this size is the lower limit shown in figure 3.

2.2 Quantization Levels

Once the block size has been fixed, and we start applying re-quantization on the data set, it is observed that for a coarser quantization the associated data degradation is larger. This is supported by the histogram of the quantization error in magnitude and the phase of the complex image for a fixed block size say 64 x 64.

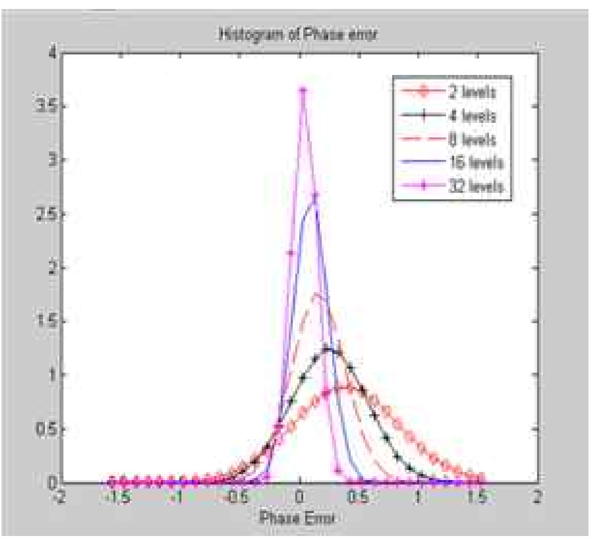

Figure 4 : Phase error histogram

For each of the Cartesian component if we draw the histogram for different quantization levels or number of bits, it looks Rayleigh distributed and is found that the standard deviation is wider for lower number of quantization levels. Thus larger error is observed for coarser quantization.

In the figure 4 the histogram as a function of the phase error and the magnitude value of the pixel for a given block size (64 x 64 pixels), suggests that there is a higher concentration of the phase error in the regions of the very low magnitude values, this is due to the quantization error which increases with those pixels lying near to the boundaries of the quantization regions. Thus the dependence of the phase error with the number of quantization has the same behavior as the magnitude error i.e. wider standard deviation for coarser quantization.

We conclude that the compression of SAR raw data applying BAQ results severe errors in terms of phase for very low bit rate as BAQ algorithm sectorizes the complex plane in rectangular regions which do not match the circular properties of the SAR data. Hence an improved performance is expected in applying a quantization scheme, which calls for magnitude-phase algorithm (BMPQ) exploiting the circular properties of the SAR raw data.

3. Sar Raw Data Characteristics

SAR raw data procured from the scattered echoes in the form of I (real) and Q (Imaginary) channels is Gaussian distributed with zero mean according to the central limit theorem. Thus the amplitude of the echo has Rayleigh distribution and the phase is uniformly distributed in the interval [$-\pi$, π]. This is depicted in figure 5(a&b).

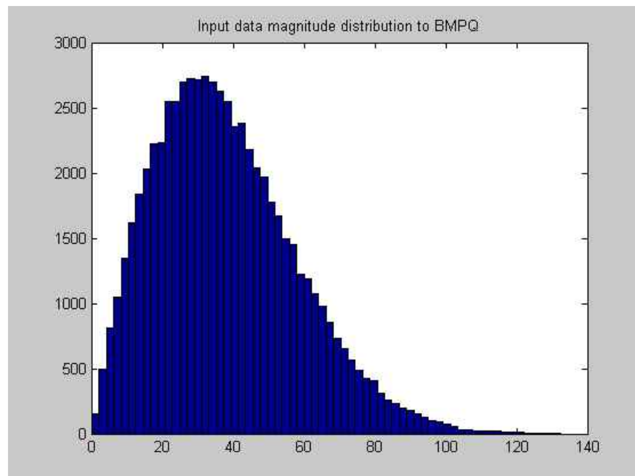

Figure 5 (a) : Histogram of the amplitude of raw data.

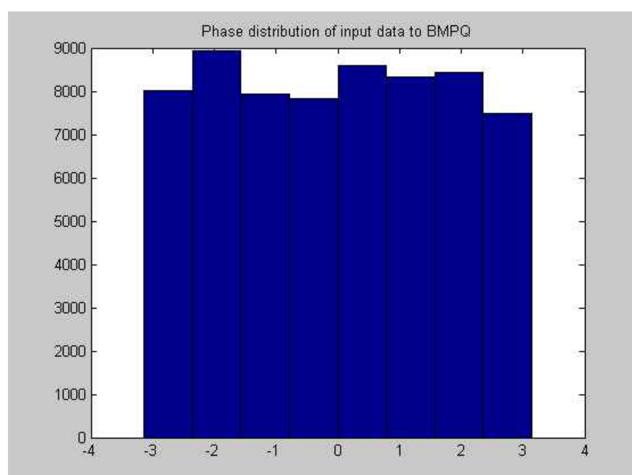

Figure 5 (b) : Histogram of the Phase of raw data.

Input signal mean and standard deviations can be related by equation (3).

$$|\bar{I}| = |\bar{Q}| = 127.5 - \sum_{n=0}^{127} \operatorname{erf}\left(\frac{n+1}{\sqrt{2}\sigma}\right) \quad \text{...(3)}$$

$$\textit{Where} \qquad \operatorname{erf}(x) = \frac{2}{\sqrt{x}} \int_0^x e^{-t^2}\, dt$$

For Gaussian distributed SAR raw data the pre assumption is given as also increases and output power of ADC experiences heavy los... Thus, using input sta... ...alize the saturated ... ...hich input signal mean and standard deviation of the output of ADC is correlated to normalize the saturated data. The output standard deviation is obtained from equation (6).

$$|\bar{I}| = |\bar{Q}| = 2\sum_{n=0}^{N-1}(x_n + 0.5)\int_{x_n}^{x_{n+1}} p(x)\,dx \quad ..(4)$$

$$127.5 - \sum_{n=0}^{126} erf\left(\frac{n+1}{\sqrt{2}\sigma}\right) \quad ....(5)$$

Equations (5) and (6) result implicit function between mean and standard deviation from ADC with the help of the following relation

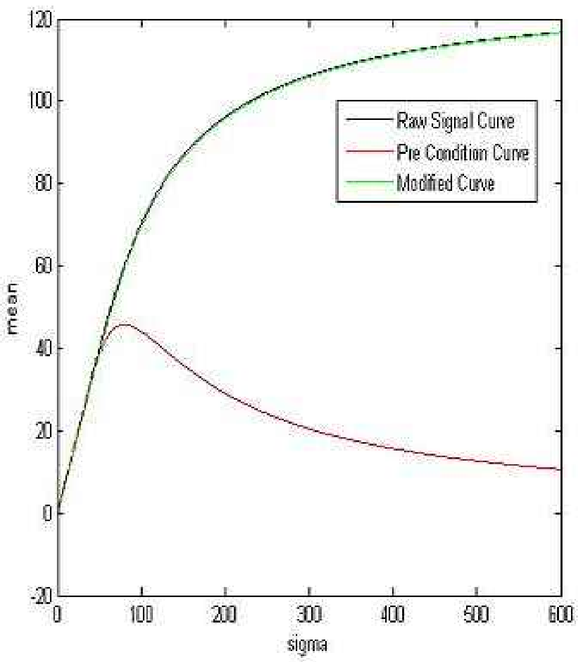

Figure 6 : Raw data mean-standard deviation curves

$$\sigma = \Delta e|x| \quad ......(7)$$

For a certain average input signal, we can search the whole set of Δ and for every Δ, we can obtain a corresponding SNR [5]. The fact is that the largest SNR is corresponding to the optimal Δ. The algorithm is shown in figure 7.

If we repaeat this procedure by using different mean values, we can obtain the mapping of mean and sigma by using Δ. It is found that when mean is below 46.9, the two curves nearly overlapped. Thus, in that case we only search Δ when the mean is above 47. When the ASM is below 47, we choose the value of Δ be 1.2533 as proved below

$$= 2\sum_{n=0}^{N-1}(x_n + 0.5)^2\int_{x_n}^{x_{n+1}} p(x)\,dx + 2[(X_N + 0.5)^2\int_{x_N}^{\infty} p(x)\,dx \quad ....(6)$$

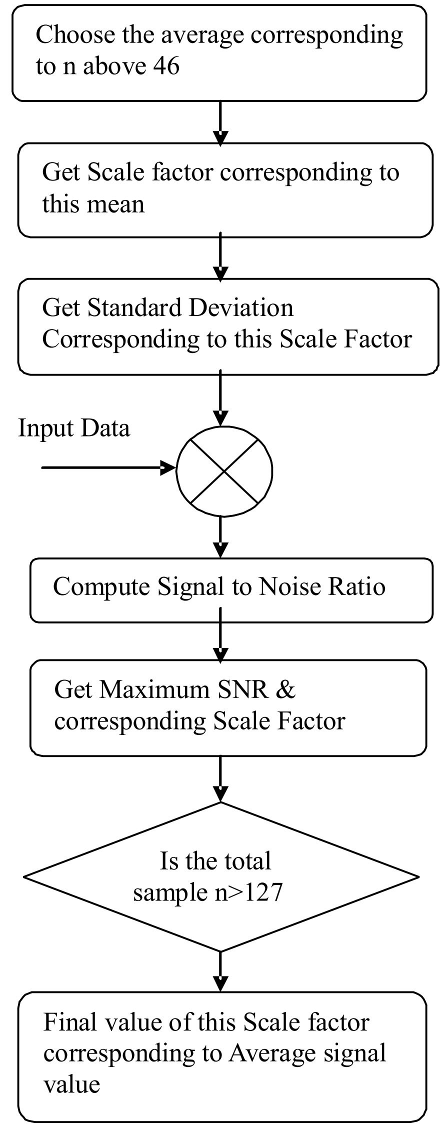

Figure 7 : Algorithm Flow chart

K is $\sqrt{\frac{\pi}{2}}$ i.e. 1.2533

$$E|x| = 2\int_0^{\infty} x\, p(x)\,dx = 2\int_0^{\infty} x \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-x^2}{2\sigma^2}}\,dx = \sqrt{\frac{2}{\pi}}\,\sigma\int_0^{\infty} e^{\frac{-x^2}{2\sigma^2}}\,d\left(\frac{x^2}{2\sigma^2}\right) = \sqrt{\frac{2}{\pi}}\,\sigma$$

If the mean is below 47 we just normalize the data with this factor and if it is above 47 then we run the algorithm to get the scale or multiplying factor s... error and maximum SNR. However, with SD (Saturation Degree) increasing, the performances of th... therefore, we use automatic gain con... dynamic range of input signal under t... ADC in practice. The saturation of ADC ... by AGC and losing control of AGC can ... algorithm. Figure 8 plots the w... [13]. The SD of this real data is 29.97%. The SN... ventional BAQ using 2 bits /sample is 10.55 dB compa... 13.68 dB of new algorithm. Therefore, when SAR raw ... turated, the performance of the new algorithm is better t... of BAQ.

4. Conclusion

This paper describes adaptive quantization based algorithm for space-borne SAR raw data compression correspond to the whole set of saturation degree. Experimental results based on simulated data and real SAR data show that the performance of this algorithm is better than that of BAQ when the output of Analog to Digital Converter (ADC) is saturated.

5. Acknowledgement

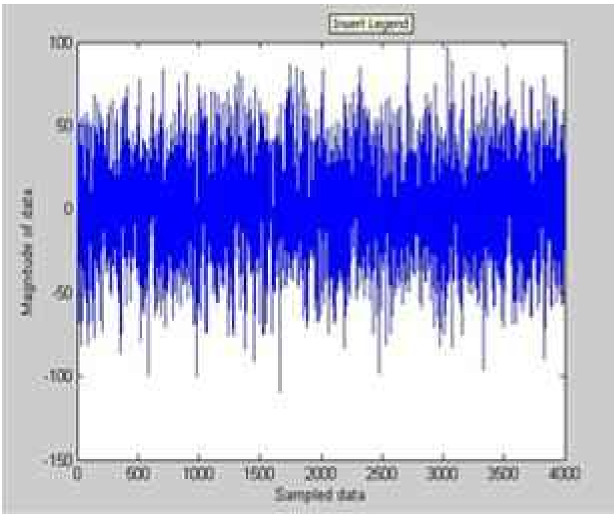

Figure 8 : Raw SAR data distribution

The authors would like to thank ESA (European Space Agency), Frascati, Italy for extending support providing the SAR raw data to carryout the experiment results.

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APPENDIX – A

The reference function for the equation is

$$|\overline{I}| = |\overline{Q}| = 2\sum_{n=0}^{N-1}(x_n + 0.5)\int_{x_n}^{x_{n+1}} p(x)\,dx$$

Where x_n is the traditional point of the ADC and the σ is the standard deviation of the input signal to the ADC. P(x) is the probability density function of the Gaussian distribution given as

$$P(x) = \frac{1}{\sqrt{2\pi\sigma}}\exp\left(-\frac{x^2}{2\sigma^2}\right)$$

Substituting this value in the above equation results

$$2\sum_{n=0}^{N-1}(x_N + 0.5)\int_{x_n}^{x_{n+1}} p(x)dx - 2\sum_{n=0}^{N-1}(x_N - x_n)\int_{xn}^{xn+1} p(x)\,dx$$

This finally leads to

$$(N + 0.5)\, erf\left(\frac{N}{\sqrt{2\sigma}}\right) - \sum_{n=0}^{N-1} \mathrm{erf}\left(\frac{n+1}{\sqrt{2\sigma}}\right)$$

if N = 128 then it results

$$127.5\, erf\left(\frac{127}{\sqrt{2\sigma}}\right) - \sum_{n=0}^{126} erf\left(\frac{n+1}{\sqrt{2\sigma}}\right)$$

Obviously, this equation is different from very first equation in which we are having n=127 term too. In order to validate the correction, we modify equation by

$$|\overline{I}| = |\overline{Q}| = 2\sum_{n=0}^{N-1}(x_n + 0.5)\int_{x_n}^{x_{n+1}} p(x)\,dx + 2[(X_{N-1} + 0.5)\int_{x_N}^{\infty} p(x)dx]$$

Where

$$2[(X_{N-1} + 0.5)\int_{x_N}^{\infty} p(x)dx]$$

is the term representing the output signal when the input signal is in the interval [Xn ,] and [ ]. With this limit the equation results

$$127.5 - \sum_{n=0}^{126} erf\left(\frac{n+1}{\sqrt{2\sigma}}\right)$$