Saturation Adaptive Quantizer Design for Synthetic Aperture Radar Data Compression

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***Abstract*— The essence of remote sensing resides in the acquisition of information about remote targets for further processing. As a high resolution microwave remote sensing instrument, the Synthetic Aperture Radar (SAR) has been more and more widely used. The data compression is one of the most important digital signal processing stage in remote sensing. The traditional compression algorithm is the Block adaptive quantization (BAQ) due to its simplicity in implementation and results. The theoretical foundation of BAQ is the distribution of raw SAR data but in fact, the raw data is not Gaussian distributed especially when there is some saturation with the receiver. In order to overcome this drawback, the authors have studied the correlation between the mean value of the signal and its standard deviation. We also evaluated the correlation between the mean input signal and standard deviation of the output signal from the A/D. Monte-Carlo experiment shows that none of the above two correlations are optimal in the whole data set . Thus, we propose a new algorithm which gives optimum results irrespective of the degree of saturation in whole range of data. Results obtained from simulated data and real data show that the performance of new algorithm is better than conventional BAQ especially when raw data is heavily saturated. The authors have used data received from Indian satellite Chandrayaan-1 and European Space Agency (ESA) in order to carry out the experimental results.**

Keywords-Block Adaptive Quantizer(BAQ); Synthetic Aperture Radar(SAR);Anti saturation algorithm ; Data Compression; Saturation Degree.

I. 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 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] which requires the distribution be perfect Gaussian and deteriorates the performance of BAQ. We have designed an optimum quantizer and given 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).

II. OPTIMAL QUANTIZER DESIGN

In the basis Block Adaptive Quantization (BAQ) technique of data compression, the dynamic range of the signal power within a data block (0 to 255 or -128 to + 127) is considered to be much less than that of the whole data set In such quantizer, the first step is to divide the raw data into blocks of small size in such a way as to ensure Gaussian statistic distribution within a block and constant signal power through out the block. Since the Lloyd-Max quantizer used in Block Adaptive Quantizer is not suitable for the saturated data, we propose a new optimum non-uniform quantizer algorithm whose block arrangement and design flow charts are depicted in figures 1 and 2 respectively.

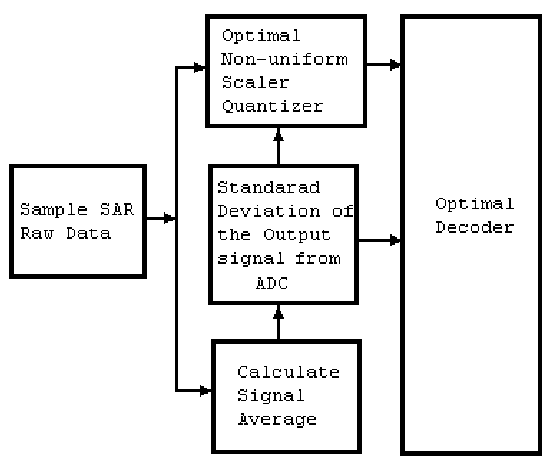

Figure 1. Non-saturated Quantizer

In this algorithm flow chart input x_j and output y_j are related by the following equation

$$x_j = \frac{y_j + y_{j-1}}{2} \quad \dots\dots j = 2,3 \dots N \qquad (1)$$

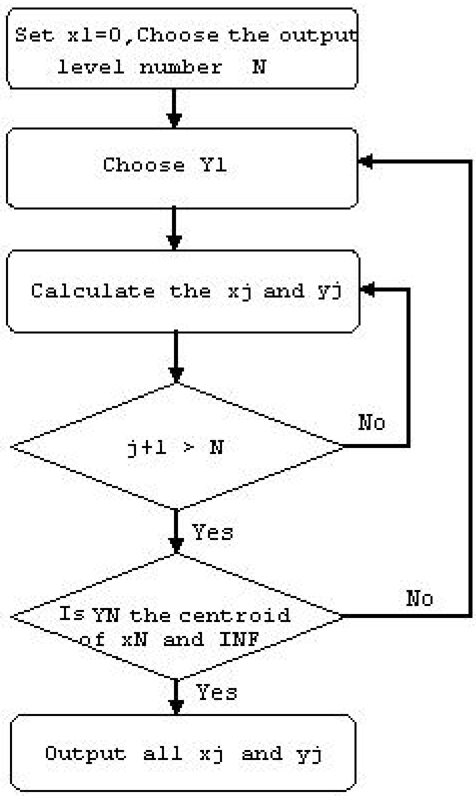

Figure 2. Algorithm Flow Chart

For the optimal operating point [1] in the flow chart, 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). This is shown in figure 3.

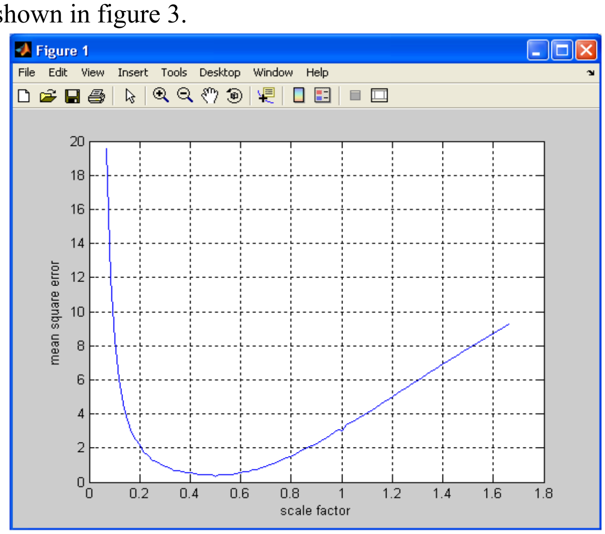

Figure 3.Mean square error curve

While designing Optimum quantizer we need to take special care in terms of block size and the number of quantization levels selection.

A. 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 root mean square (r.m.s.) signal level. Optimization of block size is done on the basis of (a) standard deviation of magnitude error and (b) 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 and shown in figure 4.

TABLE I. 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	50.88	53.28	64.12	60.72	60.77	60.56
2	34.89	35.34	36.47	37.46	37.90	37.92
3	21.76	19.59	17.95	20.48	20.48	20.52
4	11.20	11.49	11.19	11.12	10.94	11.07
5	5.23	6.0	5.94	6.56	6.26	6.20

For small block sizes, the overhead is the main constraint.

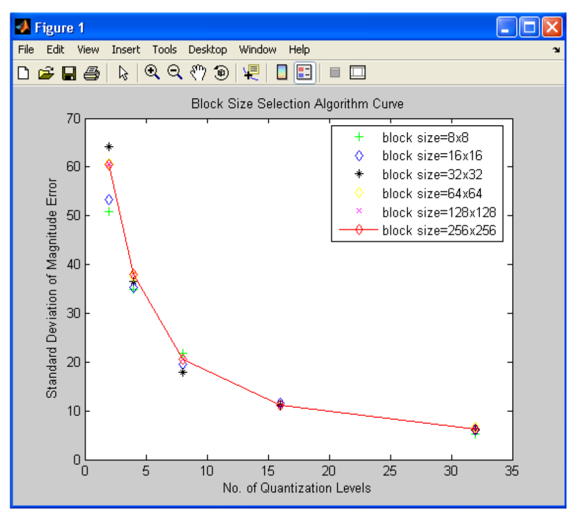

Figure 4. Magnitude error standard deviation

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:

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

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. The statistical details of the overhead ratio is summarized in table 2, indicating 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.

TABLE II. STANDARD DEVIATION OF MAGNITUDE ERROR

No. of Bits	1	2	3	4	5
Block Size	Overhead ratio				
8X8	1.2500	1.1250	1.0625	1.0313	1.0156
16X16	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

B. *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 32 x 32.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.

If we draw the histogram of the phase error as a function of the phase error and the magnitude value of the pixel for a given block size (32 x 32 pixels), it is found 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 levels 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 this algorithm sectorizes the complex plane in rectangular regions that do not match the circular properties of the SAR data. Hence an improved performance is expected in applying a quantization scheme that exploits the circular properties of the SAR raw data, such as the quantization of the polar components of the data.

III. INPUT OUTPUT RELATION FOR SAR RAW DATA

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

$$|\bar{I}| = |\bar{Q}| = 127\left(\frac{n+1}{\sqrt{2\sigma}}\right).5 - \sum_{n=0}^{127} \mathrm{erf} \qquad (3)$$

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

Here 8 bit ADC is used for preconditioning [4] of raw data. The above equation has a tiny mistake which can be solved as given in Appendix – ‘A’.
The final result, after solving the equation is given by

$$127.5 - \sum_{n=0}^{126} erf\left(\frac{n+1}{\sqrt{2\sigma}}\right) \qquad (4)$$

This equation do not have n= 127 in the summation item. If we draw curves corresponding to equations (3), and (4) then we get figure 5 which shows overlapping nature of the response.

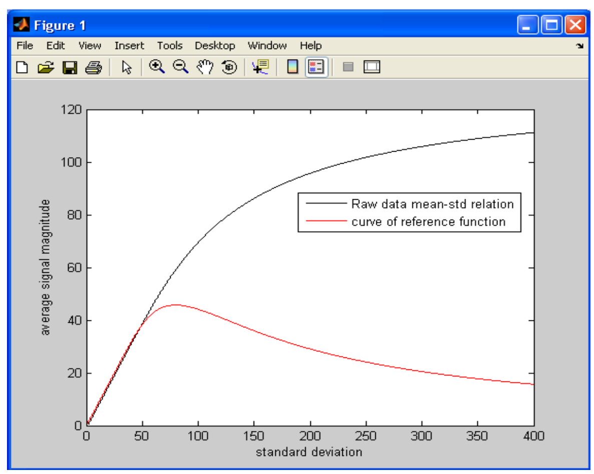

Figure 5.Raw data mean-standard deviation curve

When ADC is heavily saturated, the output power of ADC experiences heavy loss because of the truncated effect of ADC. Thus, using input standard deviation doesn’t effectively normalize the saturated data. So, we study the relation between input signal mean and standard deviation of the output of ADC and this standard deviation is used to normalize the saturated data. The variance is defined as

$$Dx = Ex^2 - (Ex)^2 \qquad (5)$$

Since in-phase and Quadrature phase components of SAR raw data obey zero mean Gauss distribution,

$E_x = 0$, then $D_x = E_x^2$

Output standard deviation is obtained from equation (6). Equations (4) and (6) result implicit function between mean and standard deviation from ADC. When we compare [2, 3] the above two performances, we find that the linear parts of these two curves are nearly overlapped but the non linear parts of these two curves are opposite. The SD is defined as

$$\rho = \frac{M}{N} X\ \mathbf{100\%}$$

Where M is the number of saturated data and N is the total number of sampled data.

IV. TRADE-OFF APPROACH FOR THE WHOLE SET OF DATA

The above algorithm is used to normalize the saturated signal so as to approach the optimal non-uniform scalar quantizer according to saturated Gauss signal. This approach is combined with Lloyd-Max quantizer for the sub-optimal scalar quantizer.

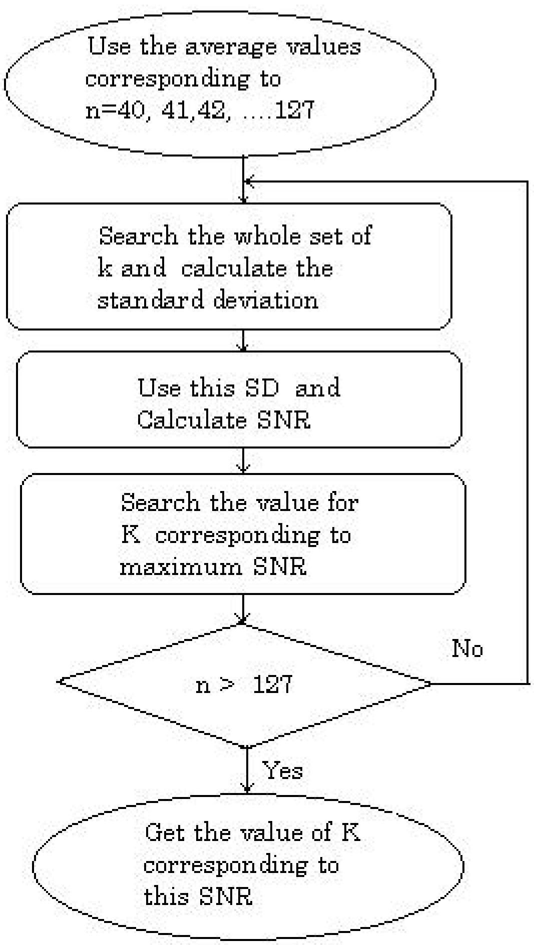

Figure 6. Algorithm Flow chart

Suppose the mapping is

$$\sigma = ke\,|x|$$

The searching algorithm in the whole set of SD can be depicted by this relation. For a certain average input signal, we can search the whole set of k and for every k, we can obtain a corresponding SNR. The fact is that the largest SNR is corresponding to the optimal *k*. The algorithm is shown in figure 6. If we repeat this procedure by using different mean values, we can obtain the mapping of mean and sigma by using *k*.

It is found that when mean is below 40.6, the two curves nearly overlapped as shown in figure 5. Thus, in that case we only search *k* when the mean is above 40. When the ASM is below 40, we propose the certification and analytical value of *k*. The certification procedure is as follows, and the parameters are the same as discussed above.

$$E|x| = 2\int_0^{\infty} x\, p(x)dx$$

$$= 2\int_0^{\infty} x\, \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}}\, dx$$

$$\sqrt{\frac{2}{\pi}}\,\sigma \int_0^{\infty} e^{\frac{-x^2}{2\sigma^2}}\, d\left(\frac{x^2}{2\sigma^2}\right)$$

$$= \sqrt{\frac{2}{\pi}}\,\sigma$$

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

If the mean is below 40 we just normalize the data with this factor and if it is above 40 then we run the algorithm to get the scale or multiplying factor so as to cause minimum error and maximum SNR. We see that the performance of piecewise linear mapping combined with Lloyd-Max quantizer is the best. However, with SD increasing, the performances of the algorithms deteriorate therefore, we use automatic gain control (AGC) to control the dynamic range of input signal under the peak to peak value of ADC in practice. The saturation of ADC due to over controlling by

AGC and losing control of AGC can be compensated by a new algorithm.

Figure 7 plots the waveform of real SAR data .The SD of this real data is 29.97%. The SNR of conventional BAQ is 10.55 dB compared with 13.68 dB of new algorithm. Therefore, when SAR raw data is saturated, the performance of the new algorithm is better than that of BAQ.

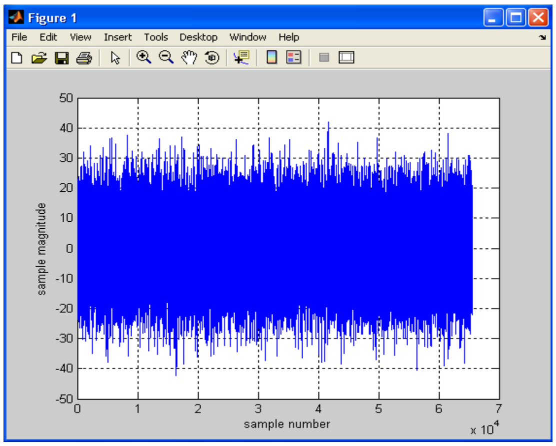

Figure 7. Raw SAR data distribution

V. CONCLUSION

This paper proposes saturation adaptive BAQ algorithm for space-borne SAR raw data compression correspond to the whole set of SD. Experimental results based on simulated data and real SAR data show that the performance of the new algorithm is better than that of BAQ when the output of ADC is saturated. Future work will focus on the non-uniform scalar quantizer design for saturated SAR raw data.

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APPENDIX - A

The reference function for the equation is

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

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

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

Substituting this value in the above equation results

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

This finally leads to

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

if N = 128 then it results

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

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

$$|\bar{I}| = |\bar{Q}| = 2\sum_{n=0}^{N-1} (\mathbf{x_n} + \mathbf{0.5}) \int_{x_n}^{x_{n+1}} \mathbf{p(x)dx} + \mathbf{2}\left[(\mathbf{X_{N-1}} + \mathbf{0.5}) \int_{x_N}^{\infty} [\![p(x)dx]\!] \right.$$

Where

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

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

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