The Realization Analysis of SAR Raw Data With Block Adaptive Vector Quantization Algorithm

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ABSTRACT
In this paper, we discuss a Block Adaptive Vector Quantization (BAVQ) Algorithm for Synthetic Aperture Radar (SAR). And we discuss a realization method of BAVQ algorithm for SAR raw data compressing in digital signal processor. Using the algorithm and the digital signal processor, we have compressed the SIR_C/X_SAR data.

KEYWORD
Synthetic Aperture Radar (SAR), Raw Data Compress, Block Adaptive Vector Quantization (BAVQ)

Introduction
Vector quantization (VQ) is a relatively new coding technique that has aroused wide interest. When applied to image coding, VQ provides many attractive features in applications where high compression ratios are desired. In these applications, the performance objective is good subjective visual quality rather than an accurate match between the original and coded video waveforms. One unique feature of VQ is that high compression ratios are possible with relatively small block sizes, unlike other compression techniques such as transform coding. Use of smaller block sizes in block coding has been known to lead to better subjective quality. A second feature of VQ is that the decoder is very simple to implement, making VQ attractive for single-encoder, multiple-decoder application.

In this paper, we first discuss the Vector Quantization principle, and then discuss the Block Adaptive Vector Quantization (BAVQ) algorithm for Synthetic Aperture Radar (SAR). Then we introduce a realization method of BAVQ algorithm for SAR raw data compressing. Using the method, we have compressed the SIR_C/X_SAR raw data. The raw data is 2048×4096 (8M_byte), after compressed the data is 2M_byte.
1. Vector Quantization

Dividing the N×K sampled data which is a raw serial \{x_i\} into N random vectors of K dimensions, forming the raw signal space \(X=\{X_1, X_2, \cdots, X_N\} (X \in \mathbb{R}^K, \mathbb{R}^K\) is Euclidean Space), the \(j\)th vector is:

\[X_j = \{x_{(j-1)K+1}, x_{(j-1)K+2}, \cdots, x_{jK}\}, \quad j = 1, 2, \cdots, N \quad (1-1)\]

Here \(X=\{X_1, X_2, \cdots, X_N\}\) and \(X_j\), called an output point, is in \(R^K\) for each \(j\). A quantizer is referred to as vector quantizer to distinguish from the special case of a one-dimensional quantizer where \(k=1\).

Associated with every \(N\) point quantizer in \(R^K\) is a partition \(R_1, R_2, \cdots, R_j\),

\[
\text{where: } R_j = Q^{-1}(x_j) = \{x \in R^k : Q(x) = x_j\} \quad (1-2)
\]

With this definition, it follows that

\[
\begin{align*}
\bigcup_{i=3}^{j} R_i &= R^K \\
R_i \cap R_j &= \emptyset, \quad i \neq j
\end{align*}
\]

(1-3)

The quantizer \(Q\) is thus uniquely defined by jointly specifying the output set \(X\) and the corresponding partition \(\{R_j\}\).

We will seek a vector \(Z_i\) each subspace \(R_j\), set substitute vector volume:

\[Z_i = \{Z_{i1}, Z_{i2}, \cdots, Z_{iN}\} \quad (1-4)\]

\(Z\) is called out-space or codebook, \(Z_i\) is called code-vector or code-word, the \(N\) is codebook length. The basic structure of vector quantization is shown in figure 1.

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**Figure 1** The Basic Structure of Vector Quantization
At the figure 1, when we ensure the vector $X_j \in R^k$ that is an input vector of vector quantization is belong to a space, the $Z_i$ will be output as the space.

We briefly describe the basic idea of a vector quantizer at figure 1 for the sake of completeness and to introduce notation. The input $X$ to seeker is a vector of $k$ dimensions. The seeker computes the distortion $d(X,Z_i)$ between the input $X$ and each codevector $Z_i$, $i=1,2,\ldots,N$ from a codebook $Z$. The optimum seeker rule is the nearest neighbor rule, in which the index $i$ is transmitted to the seeker if codevector $Z_i$ yields the least distortion. In the case of a tie, some tie-breaking rule, such as picking the smallest index, is employed. We need $\log_2 N$ bits to transmit the index if fixed length codewords are employed. The quantity $R=(1/k) \log_2 N$ is the rate of the coder in bits per pixed(bpp). The seeker simply looks up the $i$th codevector $Z_i$ from a copy of the codebook $Z$, and the output $\hat{X}$ is $Z_i$. The performance of VQ is measured by the average distortion, $D=E[d(X,\hat{X})]$, where the expectation is taken over the $k$-dimensional probability density of $X$. Since we must compute $N$ distortion values in general to encode each vector, and since $N$ grows exponentially with $R$ and $k$, both high-rate and high-dimensionality vector quantizers are impractical.

Using the vector quantizer, we could quantize several data at one time by an input vector $X$ that has vary data.

$$X = \{X_1, X_2, \ldots, X_N\}$$

(1-5)

Using the substitute vector $Z_i = \{Z_{i1}, Z_{i2}, \ldots, Z_{iN}\}$, that is called codevector. Each codevector is coded only by codeword $W_i$, all $N$ codevectors will be composed a codebook. The $d\{Z_i,x\}$ is called distance of codevector and input vector, the $d\{Z_i,x\}$ is given by

$$d\{Z_i,x\} = (x_1 - Z_{i1})^2 + (x_2 - Z_{i2})^2 + \cdots + (x_i - Z_{iN})^2$$

(1-6)

the (6) states that the $N$ quantized data($X_1, X_2, \ldots, X_N$) will be composed a vector $X$, then seeking the vector $Z_i$ which is similitude with vector $X$ from the codebook, the vector $Z_i$ is minimum distance $d\{Z_i,x\}$. When finding the vector, the vector’s codeword $W_i$ will be transmitted to decoder, the decoder will seek the same codebook and will made the reproduction vector $Z_i$.

2. Block Adaptive Vector Quantization (BAVQ)

An $N$-level $k$-dimensional quantizer is a mapping, $q$, that assigns to each input vector, $X=\{X_1, X_2, \ldots, X_N\}$, a reproduction vector, $x=q(x)$, drawn from a finite reproduction alphabet, $A=\{y_i; i=1,\ldots,N\}$. The quantizer $q$ is completely described by the reproduction alphabet (or codebook) $A$ together with the partition, $S=\{S_i; i=1,\ldots,N\}$, of the input vector
space into the sets $S_i = \{x: q(x) = y_i\}$ of input vectors mapping into the $i^{th}$ reproduction vector (or vectorword). Such quantizers are also called block quantizers and vector quantizers.

The block adaptive vector quantizer is composed of block adaptive quantizer and vector quantizer. By using the method, we could advance the signal and noise ratio (SDNR) with BAVQ even if the input data is composed of independence random data with Gauss-distribution.

Because the orthogonal data of SAR raw data is Gauss-distribution of zero-mean, if the data is normalized a normal-distribution which is zero-mean and the squared error is one, vector quantizing all SAR raw data which is fulfilled by a matched normal-distribution codebook, the codebook data will be reduced. The SAR raw data would be divided into small block, such as: $32 \times 32$ or $64 \times 64$. To fulfill normalize the raw data, we must estimate the squared error at real-time. In fact, the block adaptive quantizer is a good normalizing processor for SAR raw data, the output data of Block Adaptive Quantization (BAQ) would be vector quantized, see figure 2. The SAR raw data will be encoded by BAQ, the BAQ encoder output two result, one is block data standard squared error which is calculated the SAR block raw data, the other is the encoded result. The output result of BAQ will be input to vector quantization encoder, and re-encoded the input data, the compressed data of vector quantization encoder and the standard squared error data will be output. There are some feature of BAVQ: (1) using the high encode-ratio of vector quantization, (2) predigest the process of vector quantization, (3) hold the feature of BAQ.

![Figure 2 BAVQ Algorithm principle](image-url)
3. The Application of BAVQ Algorithm

For realizing the compressed process at real-time, we take use of high digital signal processor (DSP) for compressing SAR raw data. At the DSP, we have realized multi-algorithm for compressing SAR raw data, such as, BAQ-algorithm, BAVQ-algorithm, and so on. According to the need, we would select different algorithm to compress SAR raw data.

The SAR raw data compressor hardware principle is described at figure 3, and the BAVQ algorithm principle at figure 4. The raw data compressor is composed with digital signal processor (DSP), duple-RAM, RAM and complex programme logical driver. Through the computer parallel, the processor receive the SAR raw data, and then according to the need, the DSP could compress the raw data with vary compressed algorithm, such as 2-bit BAQ algorithm, 4-bit BAQ algorithm and BAVQ. After compressed the data, the processor transmit the compressed-data to the computer by parallel port, and at the computer, we could decode the compressed-data and use RD or Chirp Scaling algorithm to image. Using the BAVQ algorithm, we have utilized the vector decode principle to decode the compressed raw data, see figure 4. The figure 5 is raw image which isn’t compressed, the figure 6 is decoded and imaging by the compressor.

![Figure 3 The hardware principle realization](image-url)

![Figure 4 Vector Quantizater Decode principle](image-url)
Using the Normalized Mean Squared Error (NMSE), we would analyze the compressed result of SAR raw data, the Normalized Mean Squared Error is defined:

\[
\text{NMSE}_{\text{data}} = \frac{1}{M} \sum_{i=1}^{M} (s - \tilde{s})^2 \quad (3-1)
\]

where \( s \) is input signal, \( \tilde{s} \) is the output signal of quantization, \( M \) is sample number.

Defining the signal distortion rate (SDNR) is the reciprocal of NMSE:

\[
\text{SDNR}_{\text{data}} = \frac{1}{\text{NMSE}_{\text{data}}} = 10 \log \left( \frac{1}{M} \sum_{i=1}^{M} (s - \tilde{s})^2 \right) \quad (3-2)
\]

using (7) and (8), we could evaluate the quality of the compressed algorithm for SAR raw data. Using DSP for compressing, the NMSE and SDNR of the compressed for SAR raw data is follow:

\[
\text{NMSE}_{\text{data}} = 0.010816, \quad \text{SDNR}_{\text{data}} = 19.65934\text{dB}
\]
4. Conclusion

We have applied the BAVQ algorithm for SAR raw data at DSP, the research is becoming increasingly important and the application should play an important role in future study of the real-time compressing SAR raw data at satellite and airborne.

Reference