N92-12428

# SAR DATA COMPRESSION: APPLICATION, REQUIREMENTS AND DESIGNS

J. C. Curlander and C. Y. Chang
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, CA

**Abstract.** The feasibility of reducing data volume and data rate is evaluated for the Earth Observing System (EOS) Synthetic Aperture Radar (SAR). All elements of data stream from the sensor downlink data stream to electronic delivery of browse data products are explored. This paper analyzes the factors influencing design of a data compression system including the signal data characteristics, the image quality requirements and the throughput requirements. The conclusion is that little or no reduction can be achieved in the raw signal data using traditional data compression techniques (e.g., vector quantization, adaptive discrete cosine transform) due to the induced phase errors in the output image. However, after image formation a number of techniques are effective for data compression.

## 1. Introduction

The Earth Observing System (EOS) is a joint program involving the National Aeronautics and Space Administration (NASA), the European Space Agency (ESA) and the National Space Development Agency (NASDA) [1]. Its prime objective is to provide long term monitoring of the earth as a system and quantitatively analyze the factors affecting global change. Four platforms (EOS-A, EOS-B, POEM of ESA and the NASDA platform) will be deployed, each carrying ten to twenty instruments selected to optimize the synergism resulting from simultaneous observations. Each platform is designed for a five year life cycle and will be followed by two identical platforms for a total fifteen year observation period.

In addition to the L and C band synthetic aperture radars (SARs) to be flown on the NASDA and ESA platforms respectively, a NASA sponsored SAR planned for a 1999 launch will be flown on a dedicated (Delta launched) spacecraft due to its unique characteristics [1]-[2]. The EOS SAR will operate at three frequency bands and four polarization channels similar to the SIR-C/X-SAR mission [3]. Table 1 shows the orbit and sensor characteristics of EOS SAR. The EOS SAR data will be acquired using a variety of swath and resolution modes for both strip and scanning data acquisition as shown in Table 2. The planned scenario is for the EOS SAR to collect data at an average data rate of 15 Mbps (with a peak data rate of 180 Mbps). The processor is required to operate at a throughput rate equal to the average data acquisition rate (with 50% margin) to generate the data products for delivery to the end users. Table 3 defines the various types of SAR data products. Because of the huge volume of signal data collected by the radar as well as the image data generated by the processor, efficient coding of these data would significantly decrease both the transmission and archive costs.

In this paper, we present study results on data compression for the EOS SAR applications. Section 2 discusses the SAR data characteristics with the communication system characteristics and constraints discussed in Section 3. Section 4 summarizes the performance of the evaluated data compression algorithms. Potential scientific applications and constraints of these techniques are presented in Section 5.

## 2. SAR Sensor and Data Characteristics

For any given sensor, the data characteristics establish the basis for the design of the data compression algorithm. The key parameters include the entropy, the rate distortion function and the stationarity properties of the data set. The entropy of the data determines the maximum compression ratio that can be achieved using a lossless data compression algorithm. Similarly, the rate distortion function, for a



PRECEDING PAGE BLANK NOT FILMED

given performance distortion criterion, determines the maximum compression ratio that can be achieved using a lossy data compression algorithm. Non-stationarity of the data statistics in the spatial and temporal domains imposes the requirement of adaptivity on the data compression algorithm.

For SAR signal data, the entropy is normally greater than seven bits per data sample for eight bit quantization based on a Gaussian distribution model. Previous studies have shown that a compression ratio of 3:1 (6:1) can be achieved at 12 dB (9 dB) signal-to-distortion noise ratio [4]. The degradation in image quality from this type of compression is quite severe due to distortion of the phase information required to form the image products. Compression at this stage would preclude all but the most qualitative science applications. The SAR signal data is processed into imagery using a two-dimensional matched filtering operation [5]. For a magnitude detected byte image product, the data is Rayleigh distributed with an entropy of approximately six to seven bits. Since the power of the return SAR echo is modulated by the two-way antenna pattern, the slant range attenuation and the varying resolution cell in the cross-track direction, the SAR data exhibits a wide dynamic range. Additionally, the target backscatter coefficient varies in both along-track and cross-track directions such that the stationarity is generally not valid for target areas greater than 10 $Km^2$.

The parameters used to characterize the SAR image quality include the resolution, sidelobe ratios and cross-channel relative phase error of the point target response functions as well as the image radiometric and geometric fidelity. A performance evaluation of the data compression algorithm should focus not only on the signal to distortion noise ratio but also on the resultant effects on these image quality parameters. Obviously, the effects of data compression on the inversion algorithms used for scientific analysis of the image products is the deciding factor as to the effectiveness of the compression operation. However, since these criteria are highly application dependent, we will only apply distortion measures to the intermediate data to which the data compression is applied.

## 3. Communication System Characteristics and Constraints

Figure 1 presents a functional block diagram of a digital communication system with source encoder (or data compressor), channel encoder (or error correction coder), modulator, demodulator, channel decoder and source decoder. In contrast to the source coding which is applied to remove redundancy from the source data, the channel coding is employed to improve the reliability of data transmission by inserting redundant data. In a conventional communication system, these components are designed and implemented independently. An efficient communication system design should consider the net compression ratio of the source data rate to the data rate transmitted through the communication channel since the channel effects can become significant for some data compression schemes. These schemes make the data more susceptible to bit errors and may not effectively provide any compression due to the overhead incurred by the required channel coding. From the end-to-end communication system point of view, the requirement should be set to maximize the number of bits per source data sample per unit bandwidth used in the analog communication channel.

There are three major segments in the communication system for the EOS SAR. The first one is from the platform via the TDRSS to the TDRSS ground receiving station at White Sands. The second one is from the White Sands ground receiving station to the designated data processing center(s). The third one is from the data processing center(s) to the end users, which is via the NASA science data network typically at a lower data rate (9600 bits per second) than the downlink.

For the data link from the platform via the TDRSS to the ground receiving station, there are two grades of services available: Grade II and Grade III services [6]. The Grade III service achieves a bit error rate of 10-5 for a 4.5 dB signal-to-noise ratio by employing a constraint length 7, rate 1/2 convolutional code modulated using QPSK. To achieve the required bit error rate, a channel coding has been employed that doubles the effective science data rate. Furthermore, the bit errors uncorrected by the convolutional code, will result in burst errors. In the Grade II service, the (255, 223) Reed-Solomon code is employed as the outer code to correct these burst errors which improves the bit error rate to 10-8 (at the same signal-to-noise ratio) with an increase in the data rate of 14%.

For the EOS SAR, the requirement is for a bit error rate of 10-5 for the SAR signal data and 10-8 for the relatively low data volume auxiliary data. Given the channel link SNR = 4.5 dB, there may well be more efficient channel coding schemes than currently offered for downlink of the SAR data stream. For example, a high rate convolutional code combined with a multi-level, phase shift keying would be a good area of research to determine if the required link capacity could be reduced without data compression [7].

## 4. Data Compression Algorithms

In general, there are two classes of data compression algorithms [8]-[10]. One is the lossless coding algorithms used for applications that require exact reconstruction of the original data set. The other is the lossy coding algorithms used for applications where some level of compression noise is acceptable. It is worth noting that under special conditions some algorithms which are normally categorized as lossy may become lossless. In the selection of data compression algorithm, four factors need to be considered. They are the compression ratios, the compute facility available at both the transmitting and receiving stations, the reconstructed image quality and its sensitivity to bit errors. A final determination of the optimal algorithm will depend on the specific application requirements.

### 4.1 Lossless Coding Algorithms

The generally used lossless coding algorithms include Huffman coding and universal noiseless coding [8], [11]. The Huffman coding algorithm requires the knowledge of the probability distribution while the universal noiseless coding algorithm only requires the probability ordering of the source data. The probability ordering characteristics can be obtained by preprocessing the data samples. For SAR data, since the entropy is high (approximately 6 to 7 bits per sample for 8 bit quantization), the maximum compression ratio is limited to $< 1.3$. Given the addition of channel coding required to protect this compressed data from bit errors, the effective reduction using lossless coding does not justify the cost and complexity of the implementation.

### 4.2 Lossy Coding Algorithms

The lossy coding algorithms can be categorized into predictive coding, transform coding, vector quantizer, and a variety of ad hoc techniques [8]-[15].

The predictive coding is a relatively simple coding algorithm that results in a small compression ratio with reasonably good image quality [12]. Its major limitation is that it cannot compress the data below one bit per pixel. For most SAR applications, the quality of a reconstructed image using one bit per sample is unacceptable. To accommodate the non-stationarity property, the input data must be buffered to update the prediction coefficients on a frame by frame basis. Note that the predictive coding algorithm becomes lossless if the dynamic range of the prediction errors is retained, in which case the compression ratio is determined by the entropy of the prediction errors.

The adaptive transform coding is an algorithm capable of compressing the image data to any user specified compression ratio given that the associated image quality degradation is tolerable. Its major limitation is that it is computationally intensive and requires large buffers for both encoding and decoding. For most SAR applications, it generally yields an image quality better than other lossy coding algorithms. To accommodate the non-stationarity property, the class map which characterizes the block adaptivity must be updated every image frame. Figure 2 shows a Seasat Los Angeles image compressed by the adaptive discrete cosine transform coding algorithm with a 100:1 compression ratio.

The vector quantizer (VQ) is capable of producing good reconstructed image quality at high compression ratios. As compared to the adaptive transform coding algorithm, the primary advantage of the VQ algorithm is its simple decode procedure. The major drawback of the VQ is the complexity involved in the codebook training and data encoding. To reduce the encoding complexity, tree-searched schemes are employed such that the complexity only grows linearly rather than exponentially as the codebook size is increased. For SAR, the codebook must be updated every image frame or adaptive to the local data statistics using automatic gain control. Figure 3 shows a Seasat Beaufort Sea image compressed by a two-level tree-searched vector quantizer with a 16:1 compression ratio.

## 5. Potential EOS SAR Applications for Data Compression

There are a number of data system elements where the EOS SAR may utilize data compression. They include the downlink data stream, the primary data archive, and the image browse system.

### 5.1 Downlink of Data Stream

Spatial compression of SAR signal data is generally not feasible due to the phase fidelity required for the image formation matched filtering process. Implementation of a sophisticated, on-board data compressor which must include the SAR signal processor is a costly option that is not well accepted by the science community. There are two alternative techniques to achieve reduction in the downlink data rate. One approach is to reduce the overhead incurred by the channel coding scheme. This may be achieved by employing the high rate convolutional code combined with a multi-level, phase modulation scheme without the Reed-Solomon code as the outer code. The other approach is to employ a simple, adaptive data compression scheme, such as block floating point quantizer (BFPQ) which uses a fixed number of bits to quantize the data relative to a reference scale that is represented by additional data to characterize the global variation of data statistics. The latter approach has been successfully employed by the Magellan SAR system and will be used by SIR-C and EOS SAR.

For quick-look applications, a relatively simple on-board processor followed by a data compressor could be employed to fit the data within a low rate broadcast link (< 1 Mbps). For this quick-look application, a tree-searched vector quantizer is considered as a good candidate because it requires only a small workstation at the receiving stations for reconstruction of the compressed image data. Furthermore, its encoder can be implemented using relatively low cost, space qualified VLSI chips [16].

### 5.2 Primary Data Archive

The data set stored in the primary archive will be used by the end users for quantitative analysis which requires no loss in data information. Because of the speckle inherent in the SAR image data, only small compression ratio can be realized by lossless compressor. Using the basis that the data compression technique is only considered feasible if its implementation cost is lower than the savings from the archive storage capacity, a combination of predictive coding and universal noiseless coding appears to be a good candidate. The source data will first pass through a linear predictor. The prediction errors, which normally assume a smaller dynamic range than the source data samples and also exhibit the probability ordering characteristics, are then passed to the universal noiseless coder for removal of redundancy in the data. The implementation cost for the coding will be small since the technology for a custom hardware board is well proven [11] and little buffering capability is required.

### 5.3 Browse Data Products

The image browse system is designed for end users to quickly examine the image products that are routinely generated by the processor prior to delivery of high precision data products. The image data will be electronically transferred via a low data rate network, such as the NASA space physics analysis network (SPAN), to users with limited compute facilities available for reconstruction of compressed image data. Since there is more compute power available in the primary data processing facilities, the encoding complexity is a less critical issue than the decoding. For browse applications, image quality and transfer time corresponding to compression ratio between 10:1 and 20:1 are adequate for quick-look analysis. The tree-searched vector quantizer meets all the above requirements

## 6. Summary

This paper summarizes a variety of factors influencing the feasibility of using data compression for the EOS SAR. In consideration of an EOS SAR data compression system, several factors have been evaluated: the data characteristics, the various system elements and the cost trade-off issue. Not discussed here but of key importance is the fact that the performance evaluation of any data compression algorithm must consider the induced distortion noise from the compression operation as well as the effects on the scientific inversion algorithms. The net compression ratio of the end-to-end communication system was considered with the conclusion that for an efficient communication system design, source coding, channel coding and modulation should be integrated into a single system. The compute facility available on both the transmitting and receiving stations is also a significant factor for algorithm selection. Assuming the image quality is acceptable, the net cost impact (i.e., cost savings from reduced channel link capacity and archive storage capacity minus implementation cost) is the final determining factor that will establish the feasibility of employing data compression for the EOS SAR system. This may be significant for the SAR due to the large volume of data and high data rates involved.

## References


[1] *Earth Observing System: Reference Handbook*, NASA Goddard Space Flight Center, 1991.

[2] *Earth Observing System: Synthetic Aperture Radar Instrument Panel Report*, Vol. IIf, NASA, 1988.

[3] R. Jordan, B. Huneycutt and M. Werner, "SIR-C/X-SAR Synthetic Aperture Radar Systems," *Proceedings of the IEEE* (Special Issue on Spaceborne Radars for Planetary Observations), 1991.

[4] Read, C. J., Arnold, D. V., and Chabrias, D. M., "Synthetic Aperture Radar Image Formation from Compressed Data Using a New Computation Technique," *IEEE AES Magazine*, October 1988.

[5] J. C. Curlander and R. N. McDonough, *Synthetic Aperture Radar: Systems and Signal Processing*, John Wiley and Sons, 1991.

[6] *Tracking and Data Relay Satellite System (TDRSS) Users Guide*, Rev. 4, 1980, GSFC.

[7] G. Ungerboeck, "Channel Coding with Multilevel/Phase Signals," *IEEE Trans. on Information Theory*, Vol IT-28, No. 1, pp. 55-67, Jan 1982.

[8] Lynch, T., *Data Compression Techniques and Applications*, Van Nostrand, NY 1985.

[9] Jain, A., "Image Data Compression: A Review," *Proceedings of the IEEE*, Vol. 69, No. 3, pp. 349-389, March 1981.

[10] Chang, C. Y., Kwok, R., and Curlander, J., "Spatial Compression of Seasat SAR Imagery," *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 26, No. 5, pp. 673-685, September 1988.

[11] Rice, R., and Lee, J., "Real-time Data Compressor for EOS Class Mission," *Eascon '87*, October 1987.

[12] A. Habibi, "Comparison of the nth-order DPCM Encoder with Linear Transformation and Block Quantization Techniques, " *IEEE Trans. on Comm. Tech.*, Vol. COM-19, pp. 948-956, Dec 1971.

[13] P. A. Wintz, "Transform Picture Coding," *Proceedings of the IEEE*, Vol. 60, No. 7, pp. 809-820, July 1972.

[14] W. H. Chen and H. Smith, "Adaptive Coding of Monochrome and Color Images," *IEEE Trans. on Comm.*, Vol. COM-25, No. 11, pp. 1285-1292, Nov. 1977.

[15] Y. Linde, A. Buzo and R. Gray, "An Algorithm for Vector Quantizer Design," *IEEE Trans. on Comm.*, Vol. COM-28, No. 1, pp. 84-95, Jan 1980.

[16] W. C. Fang, et al, "A VLSI Design of Systolic Tree-Searched Vector Quantizer for EOS On-Board SAR Processor, " *Proceedings of GOMAC*, 1989.

| | |
|---|---|
| Altitude | 620 Km |
| Orbit | 97.9° INCLINATION |
| Platform Power | 5.8 KW PEAK POWER |
| Frequencies | L, C, X |
| Antenna Width | 1.87 m (L), 0.48 m (C), 0.26 m (X) |
| Antenna Length | 10.9 m |
| Polarization | HH, HV, VH, VV (L & C), HH OR VV (X) |
| Incidence Angle | 15°-43.5° (SINGLE, DUAL-POL), 15°-32° (QUAD-POL) |
| Prf | 1375 Hz - 2100 Hz |
| Chirp Bandwidth | 20, 15, 10, 5, 1 MHz |
| Pulse Width | 25, 34, 41, 50 usec |
| Data Rate | 180 Mbps PEAK, 15 Mbps AVERAGE |
| Bits Per Sample | 8, BFPQ |
| Peak Radiation Power | 3.6 KW (L), 2.8 KW (C) |

Table 1: EOS SAR orbit and radar characteristics.

| Operation Mode | Resolution | Swath | Frequency | Polarization |
| --- | --- | --- | --- | --- |
| Local, High Resolution Mode | 20 - 30 m | 30 - 45 Km or 80 - 90 Km | L & C or L & C & X | Quad-Pol or Single-Pol |
| Regional, Medium Resolution Mode (3 Scans) | 80 - 110 m | 150 - 240 Km | L & C or C & X | Single-Pol |
| Global, Low Resolution Mode (6 Scans) | 250 m | ~360 Km | L & C | Single-Pol |

Table 2: EOS SAR operation modes.

| | |
|---|---|
| Level 0: | Reconstructed unprocessed instrument data at full resolution. |
| Level 1A: | Reconstructed unprocessed instrument data at full resolution, time referenced, and annotated with ancillary information, including radiometric and geometric calibration coefficients and georeferencing parameters (i.e., platform ephemeris) computed and appended but not applied to the level 0 data. |
| Level 1B: | Level 1A data that has been processed to sensor units (i.e., radar backscatter cross-section). Standard SAR product. |
| Level 2: | Derived geophysical parameters (e.g., ocean wave height, soil moisture, ice concentration) mapped on some uniform time/space grid with processing parameters appended. |
| Level 3: | Geophysical data mapped on uniform space-time grid scales, usually with some completeness and consistency properties (e.g., missing points interpolated, complete regions mosaicked together from multiple orbits) |
| Level 4: | Model output or results from analysis of low-level data (i.e., geophysical data not measured by the instruments but derived from instrument measurements). |

Table 3: SAR data product level definitions.

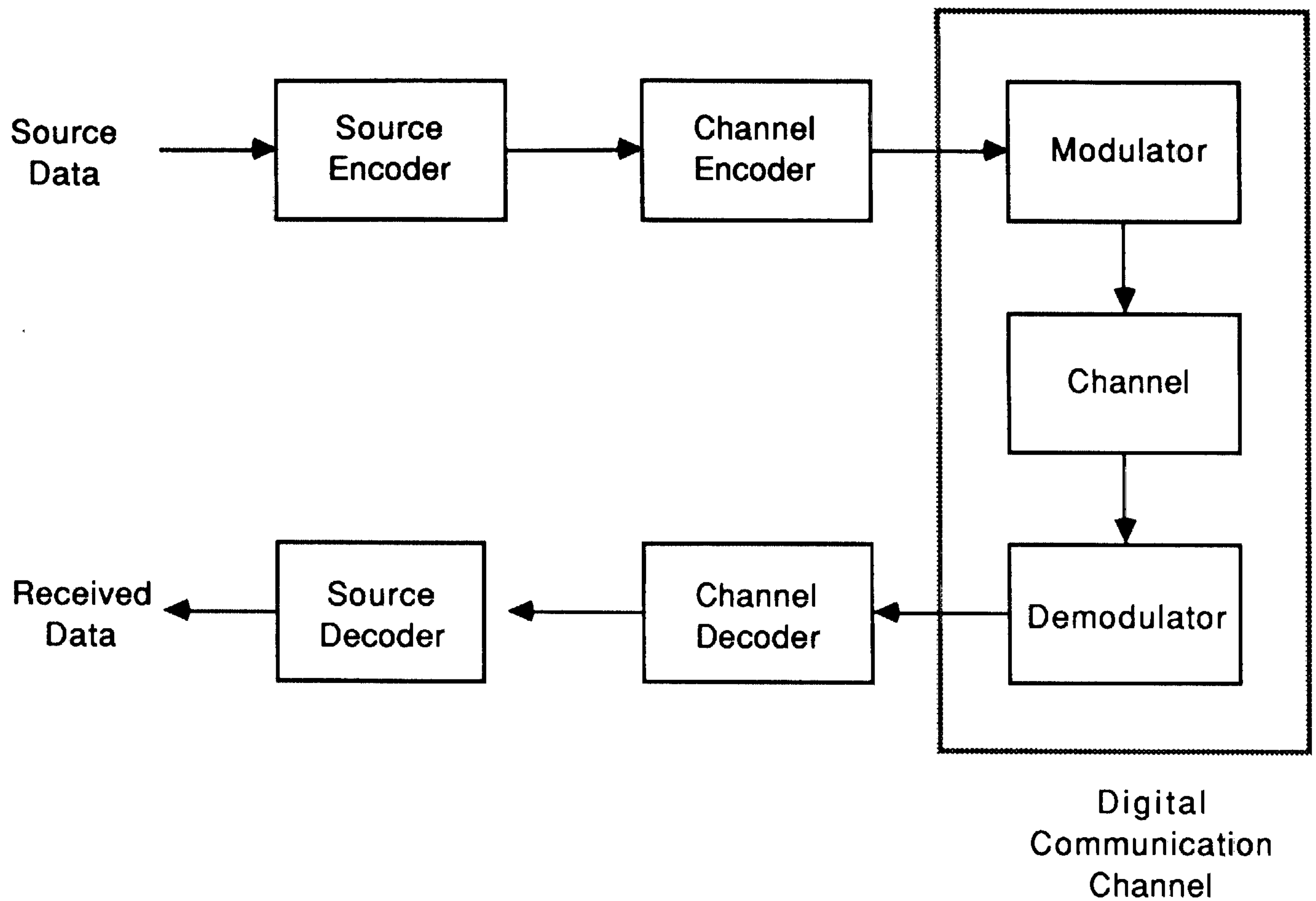


Figure 1: End-to-end communication system.

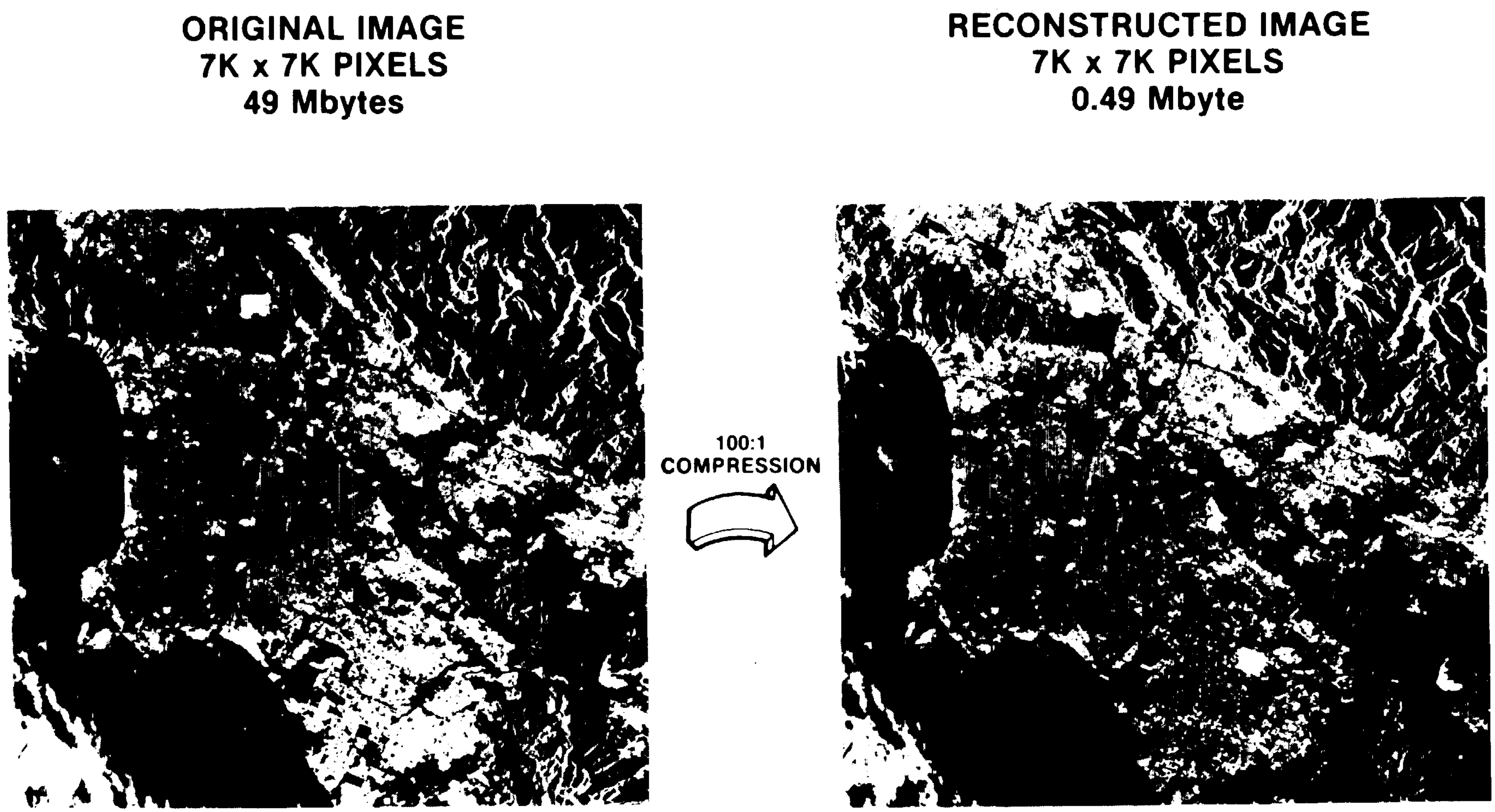


**Figure 2: Compression of SAR imagery using adaptive discrete cosine transform algorithm**

ORIGINAL IMAGE
896 x 896 PIXELS
784 Kbytes

RECONSTRUCTED IMAGE
896 x 896 PIXELS
49 Kbytes

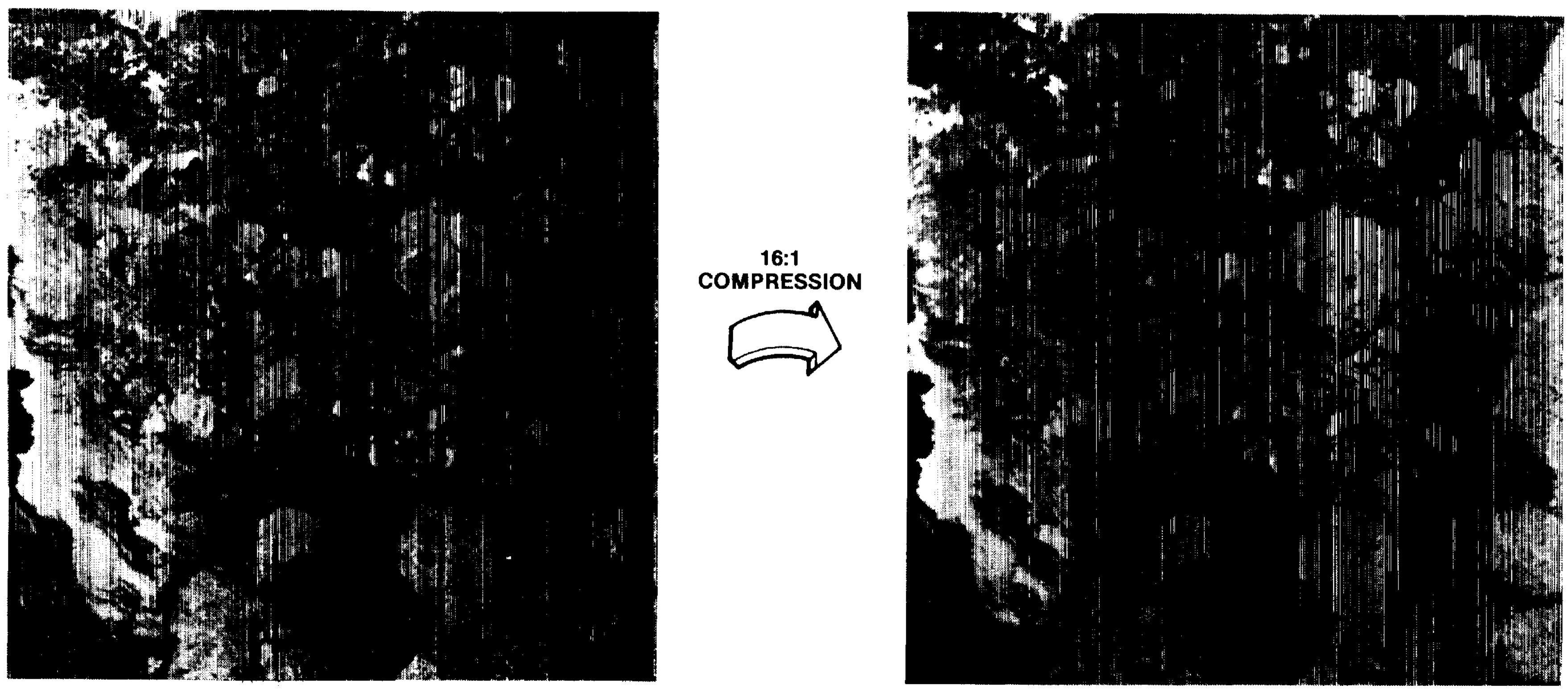


**Figure 3: Compression of SAR imagery using two-level tree-searched vector quantizer**