Image Content Dependent Compression of SAR Data

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Summary: Data rate and amount of SAR data exceed the capacity of usual data links and storage devices in most cases. SAR data compression is necessary to ensure efficient use of acquired data and processed images. Unfortunately, lossless compression is not possible for SAR data due to their high entropy. However, it is of major importance that no SAR applications suffer from data compression. There are several strategies:

1) *nearly lossless data compression* with a very high overall and local performance: Quantization errors do not exceed a certain (small) value for any objects in the image, the drawback is, of course, the only small compression ratio;
2) *data compression adaptive to the image contents*
   a) The coder uses more bits to quantize coefficients of regions with high activity compared to those of more homogeneous regions. For example, in SAR images point targets and edges are treated separately from the other image parts. This procedure allows a medium overall compression ratio and gives a homogeneous error distribution over the whole image.
   b) The coder uses more bits for regions of interest. Whereas methods 1 and 2a allow any application on the decompressed SAR data without loss in performance, method 2b gives the opportunity to adapt compression to a specific application and a very high compression ratio can be achieved.

In this paper we propose the combination of these methods to take optimal advantage of the whole SAR system consisting of the SAR sensor itself, the network of ground stations with high computational archiving resources and clients with usually limited computational power and low capacity links.

1 TWO-STEP DATA COMPRESSION

The most expensive parts in SAR systems, e.g. spaceborne SAR systems, are sensor development and operation. A large user community has to be served to ensure commercial and efficient use of the acquired data. However, storage capacity on board of satellites is limited. Data have to be transmitted via special links to ground stations. There has to be data compression on board which allows a longer time of data acquisition between down links and additionally a faster down link of the acquired data.

Of course, no application should suffer from this data compression. The required image quality has to be maintained as well for visual evaluation as for automatic classification and further signal processing. Examples are DEM generation and eigenvector analysis in polarimetric mode. To ensure the required quality we suggest to measure not only an overall signal-to-distortion noise ratio and rms phase error but also the distortions in dependence of image contents.

We propose a two-step compression strategy:

- *In the **first step** a nearly lossless data compression is applied.* The very high overall and local performance ensures no degradation of image quality for any application. The algorithm has to be fast, no high computational resources are allowed. We developed a flexible algorithm (FLECS) for SAR data compression [3]. In our simulation no object in the image has a phase error larger than 1° and a signal to distortion noise ratio which is less than 40 dB, if the compression ratio is below 4. This is valid for all polarimetric and interferometric channels.

  The compressed data are transmitted to the server network on the ground. There is access to high computational power and huge storage capacities. This equipment can be used to derive most advantage from remotely sensed data.
- *Here the **second step** of data compression takes place: Data compression is closely adapted to the user's requirements*:
  a) For scientific applications complex data are transmitted without further compression. The amount of data sets will be limited and thus the high data rate can be accommodated by special links. In this case also high computational power is usually available at the client.
  b) For general applications with medium requirements of reconstruction quality a medium compression ratio is used. Special algorithms are employed to avoid distortions around edges and point targets.
  c) Different treatment of regions of interest and background realizes a high compression ratio to save transmission costs and storage requirements for the client. The computational capabilities of the server network for classification of the data are used. In addition to the efficient data compression the pre-classification allows image content query in the database.

This two-step data compression requires only high computational power and storage capacity at the server network, the necessary down link capacity from the satellite is reduced by a factor of more than 3 without image quality degradation. From the server to the client only those data are transmitted which are of interest for the client thus saving lots of money and time.

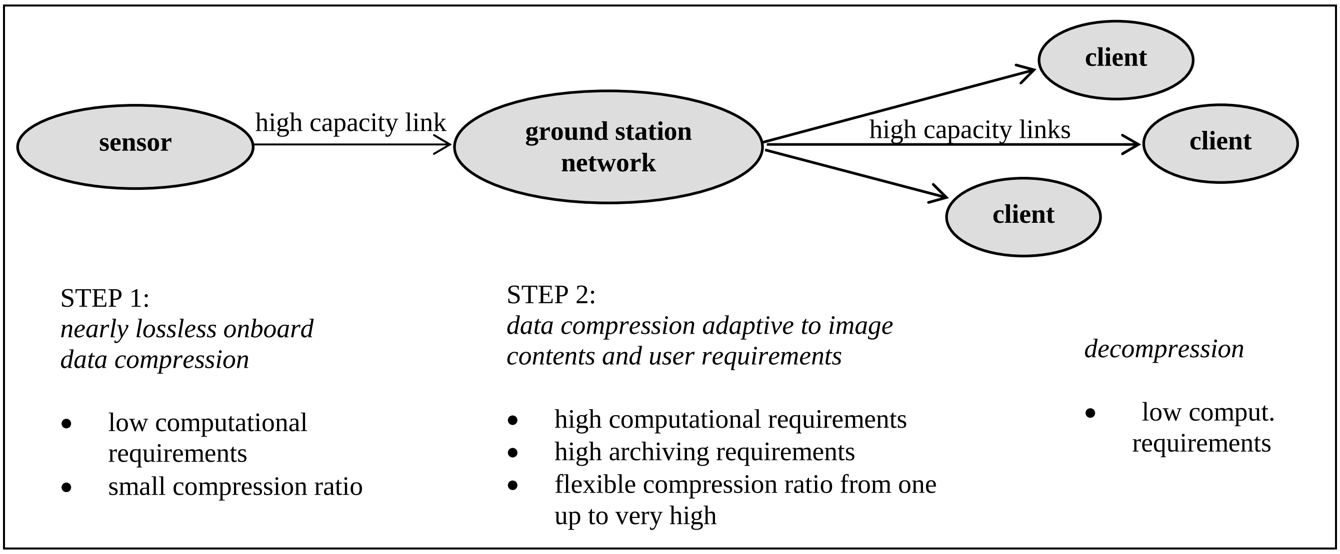


Figure 1: Two step data compression

2 ONBOARD DATA COMPRESSION (STEP 1)

We employ for onboard data compression a flexible compression of SAR data (FLECS)[3].

FLECS is a wavelet based compression algorithm. The suitability of wavelets for (SAR) data compression is shown in many publications. Important references are among others [2][15][17]. There is not only a good energy compaction and representation of high and low frequency parts, also possibilities for further signal processing are given. For example in wavelet domain, despeckling is possible [7][13]. FLECS works in polar or cartesian mode. In nearly lossless mode, compression can be regarded as a linear algorithm, and can be applied separately on real part and imaginary part of the complex SAR data. Therefore here we consider only FLECS working in cartesian mode.

A Daubechies-8 wavelet transform is applied on real and imaginary part. Quantization takes place in transform domain. In contrary to optic and acoustic data, it is not possible to neglect the higher frequencies of SAR data, if a good image quality and post-processing has to be maintained. This is due to the high dynamic and the speckle characteristic in the data. However, the subbands already contain different ac energies after one iteration. The ac energies represent different information contents. This is used to allocate different numbers of bits for each subband. There exist several approaches for proper bit allocation. We base bit allocation on the ratio of ac energy between the subbands and optimize the result by iterative training on the data of the considered sensor to gain minimum quantization distortion. The average bit number $b = (b_{LL} + b_{HH} + b_{LH} + b_{HL})/4$ is fixed to ensure the desired compression ratio. In our approach, a scalar quantizer is used up to now.

For quantization the wavelet subbands are divided into N blocks $q_i, i \le 1 \le N$. To ensure approximately constant statistic within one block, the block size is small, e.g. 8 by 8 samples. The quantizer is adapted to the dynamic range d_i of each block q_i: $d_i = \max(q_i) - \min(q_i)$ with $\max(q_i)$ and $\min(q_i)$ maximum and minimum value within quantization block q_i, respectively. The dynamic range d_i is divided into equally spaced intervals I_m, $I_m, 1 \le m \le M_i$. The available bit number b_i for quantization of block q_i gives the number $M_i = 2^{b_i}$. All quantization blocks q_i within one wavelet subband are quantized using the same bit number.

Due to the scalar quantizer, only integer bit numbers are possible. The quantizer allows a very simple implementation but reduces the flexibility. This is also the main reason, why we cannot take advantage of more than one iteration of wavelet decomposition. Further studies will include vector quantization to be able to deal with fractional bit numbers.

Decompression inverts first the linear quantization using the header information (bitmask and for each quantization block q_i maximum $\max(q_i)$ and minimum $\min(q_i)$) and secondly, performs an inverse wavelet transform.

Up to now we mainly tested the performance of our FLECS on airborne SAR data. Data of high accuracy (high geometric and radiometric resolution, polarimetric and interferometric mode) are available. Based on preliminary studies on X-SAR and ScanSAR (RadarSat) data we expect that the results will be transferable for high resolution SAR data of future spaceborne systems.

In dependence of available storage, down link capacity and required image quality, the compression ratio can be chosen between two and five. For Step 1 - compression at the sensor - we suggest a compression ratio of about 3.2 leading to 20 bits/pixel. Thus a signal-to-noise ratio of 58 dB is achieved and a phase error smaller than 1°. This is valid for all polarimetric and interferometric channels.

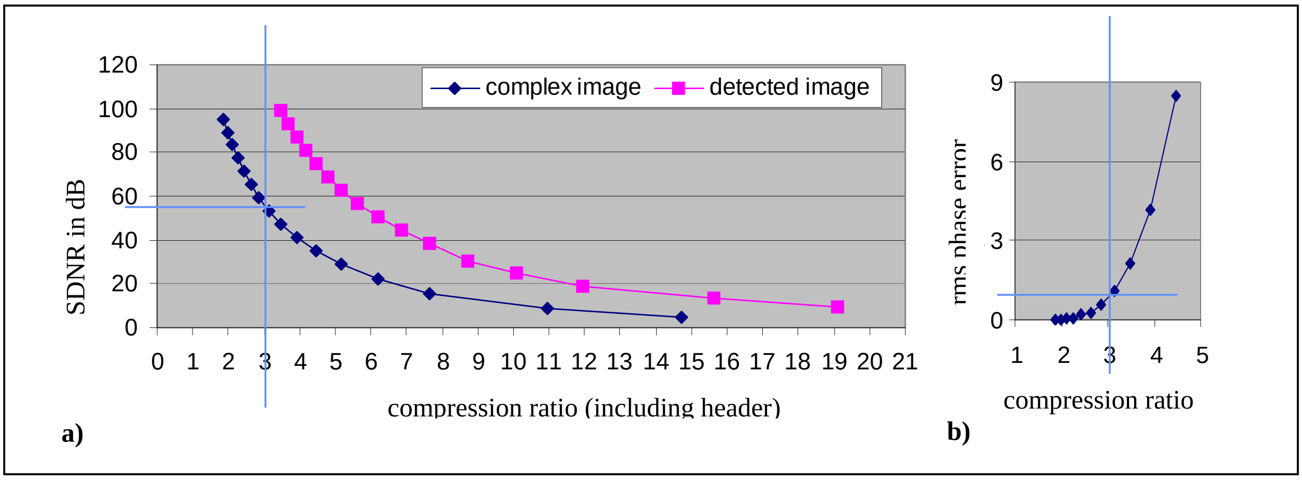


Figure 2: Performance of FLECS (Flexible Compression of SAR Data); nearly lossless for compression ratio 3

Figure 2a) shows the signal-to-distortion noise ratio of FLECS in dependence of the compression ratio, Figure 2b) the rms phase error, respectively. For compression ratio 3 a nearly lossless performance is achieved.

Following our two-step compression strategy this approach is suitable for nearly lossless compression onboard.

3 IMAGE CONTENT COMPRESSION AT THE GROUNDSTATION (STEP 2)

Few users need data without any distortion due to data compression. Only sophisticated scientific applications require perfect reconstruction. In these cases no further compression takes place at the server system. The data are transmitted directly to these clients.

In most cases further data compression is possible saving transmission time and costs for clients and provider. Here image content dependent data compression gains major advantages:

– Separate treatment of regions with high or low activity allows adjusting the bit rate and still achieving a sufficient image quality with an overall reduced bit rate. In addition to data compression, discrimination between different activity zones is necessary.

– Separate treatment of relevant and irrelevant information allows transmission of the very information, which is of interest for the client. Huge compression ratios are possible. In addition to data compression, a classification map has to be evaluated and transformed to a significance map in transform domain.

3.1 SEPARATE TREATMENT OF REGIONS WITH HIGH OR LOW ACTIVITY

In FLECS, higher compression ratios lead to blocking effects around point targets and edges. The linear quantizer is well adapted to maximum dynamic, but does not simultaneously represent small values with sufficient accuracy. Logarithmic converters do neither solve this problem in a suitable way. The response of the point target, e.g. a corner reflector would be distorted to some degree. However, perfect reconstruction of those targets is important for calibration and geocoding. Only separate treatment of very high coefficients in the wavelet subbands allows perfect reconstruction of both, strong and weak scatterers. A homogeneous signal-to-noise ratio and equally distributed phase errors can be achieved. Blocking effects vanish. A more detailed description can be found in [8].

A similar problem arises around edges. They are characterized by a transition between different statistics with a varying standard deviation. This deteriorates the performance of the quantizer. Distortion can be avoided if edge regions are separated from the more homogeneous regions. Figure 3 shows a SAR intensity image with the corresponding edge map, derived by our fuzzy edge detector (FED) [6]. Other edge detectors can be used, if they detect not only a single edge line, but like FED the whole transition region. Figure 3c–f show simulation results for amplitude and phase error in false colors (Figure 3c,e without separate treatment of edges, Figure 3 d,f with an increased number of quantization bits for those coefficients belonging to an edge.

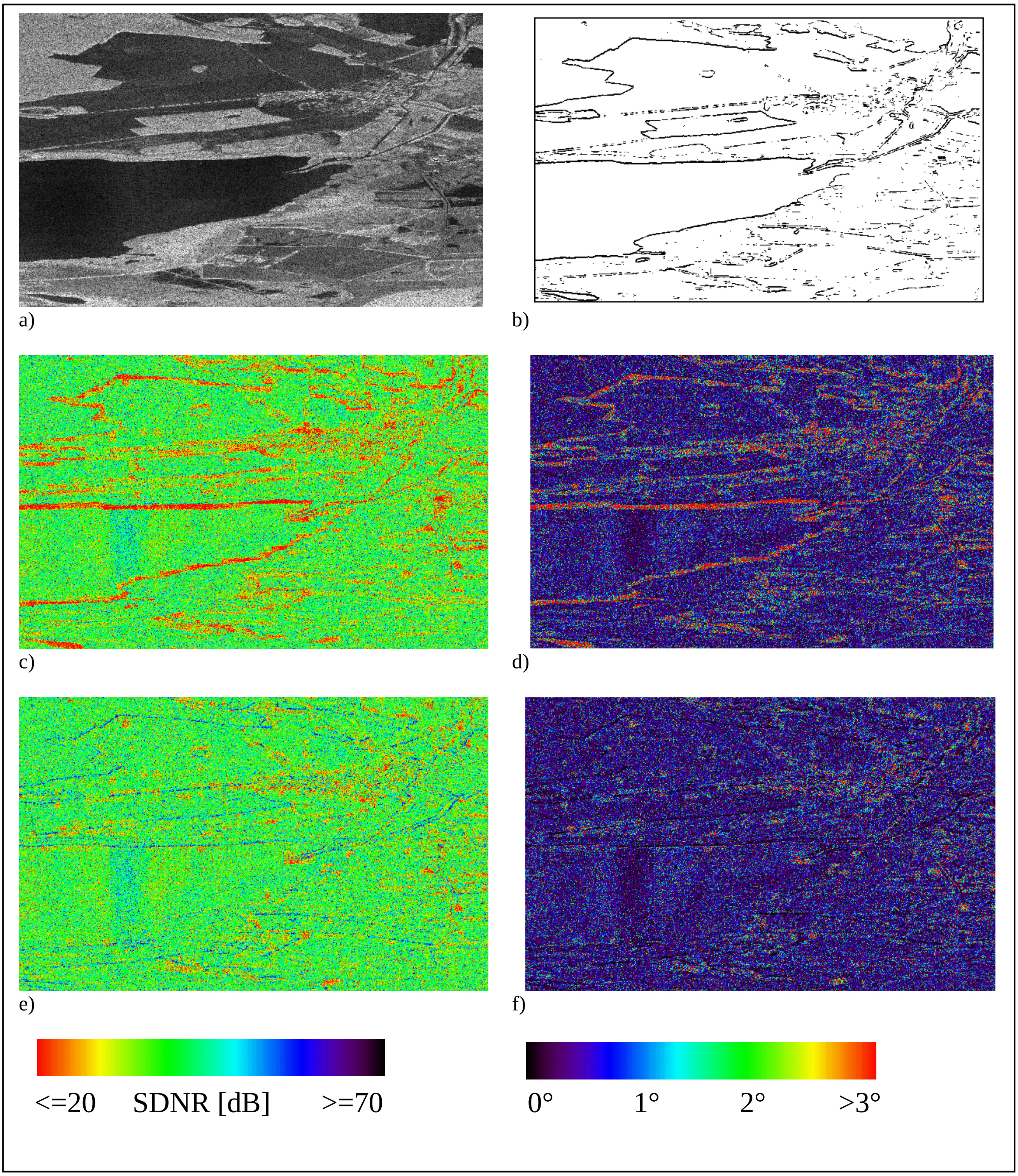


Figure 3: a) SAR image, b) edge regions derived with fuzzy edge detection, c) SDNR map prior e) after edge preservation, d) phase error prior f) after edge preservation

3.2 SEPARATE TREATMENT OF RELEVANT AND IRRELEVANT INFORMATION

The advantages of compression adapted to image content are mentioned in several papers of IGARSS 99. High compression ratios can be achieved without degradation of relevant information. Special algorithms for ice detection [11] were presented or for compression of only non-textured or only textured regions [1]. However, these approaches are either restricted to a single application or cannot be further adapted to different applications.

In our approach we overcome this problem. We combine a flexible classification algorithm with data compression.

Classification delivers a classification map, which can be used to separate relevant from irrelevant information, to divide background from regions of interest. The classification map can be derived using any supervised approach. We suggest a fuzzy approach to gain maximum robustness and gather the uncertainty in SAR data themselves and in class assignment.

3.2.1 A Fuzzy Approach for Generation of Classification and Significance Map

We derive a classification map for basic classes, e.g. urban, high vegetation (forest), medium and low vegetation and smooth surfaces using a *supervised fuzzy learning system*. In our simulation example we applied the *fuzzy nearest prototype algorithm* [12], which is implemented in our *fuzzy interactive analysis system for SAR images FIAS* [4]. To this end, we chose as feature vectors the ordered intensities of a 7 by 7 neighborhood centered at the considered pixel. We selected 30 test samples for each of the five classes. After ordering the windows to 49-dimensional vectors $a_i^{class} = (a_1^i, ..., a_{49}^i)$ with $a_1^i \le ... \le a_{49}^i, i = 1, ..., 30$, we averaged these vectors for each class to produce a typical test sample $T^{class} = 1/30 \sum_{i=1}^{30} a_i^{class}$. The values of the components of T^{class} are considered to be typical for the values of the class.

For *classification* the ordered feature vector $v = (v_1, ..., v_{49})$ of a pixel *p* is compared to the typical test samples T^{class} and a grade of membership is computed with the formula

$$m(p, class) = \frac{\dfrac{1}{d(v, T^{class})}}{\sum_{class'} \dfrac{1}{d(v, T^{class'})}},$$

which is interpreted as similarity of the pixel to the class. This is the fuzzy output for a pixel. Defuzzyfication with the rule

p is of *class k* if $m(p, class\ k) \ge m(p, class\ i)$ for all *i* and $m(p, class\ k) \ge t$,

where *t* is a classification threshold, leads to a crisp classification. For more details to our fuzzy classification please refer to [4].

Up to now supervised classification is applied, however, future studies will consider automatic refining of the search patterns to compensate varying data take conditions.

The classification map assigns one basic class to each pixel in time domain. Data compression itself takes place in transform domain. Therefore, a significance map has to be evaluated, which indicates relevant coefficients in transform domain and allocates the number of bits for their quantization. According to the filter length *L* of the wavelet transform more coefficients have to be quantized and transmitted than the number of foreground pixels. In the worst case, instead of one single pixel L^2 coefficients in all four subbands are necessary to reconstruct the pixel with the desired quality. The more pixels of one class are in a closed region and the shorter the filter length the less disadvantageous is this effect.

In our approach the same significance map is used for all subbands. If more iterations of wavelet transform or wavelet packets are employed, significance maps for all subbands have to be evaluated. Advantageously, the effort will be small, due to the hierarchical structure of the wavelet decomposition and can follow the well-known strategies for zero-tree assignment [15] [18]. Probably, optimization will be possible to minimize the number of significant coefficients in the higher decomposition levels.

Joshi et al. [10] and Yoo et al. [19] describe another approach for classification dependent compression and the achievable gain. Here, classification does not mean assignment of physical object classes, but assignment of different data classes, according to their statistic. However, to gain the high adaptability to the user requirement, class assignment to physical object classes is necessary. Advantageously, data belonging to one object class have similar statistic and thus necessary parameters for optimal quantization are easier to choose. Up to now, we split these classes also in small data blocks as in FLECS standard mode for two reasons: Similar design for all modes makes decompression easy, which will take place at the client; data statistics are too heterogeneous for a single quantizer. Optimization of the pre-classification with respect to data compression can lead to improved results.

3.2.2 Server-Client-Link

The following strategy with seven steps is suggested.

1. At the server, the image is stored in wavelet domain, already decomposed into bit planes, which allows transmission of ordered bit planes (see step 6), plane after plane, according to the required performance.
2. The client asks for a data set.

3. First, he gets the classification map requiring a minimum number of bits. The classification map can be used by the client to identify
   – whether the correct data set is selected
   – parts of the data set for further transmission
   – classes of interest and background
   – required quality for regions of interest and background.
4. This information controls further data compression and is sent to the server.
5. Based on this information and the classification map significant coefficients in wavelet domain are assigned. The appropriate number of bits for quantization is selected.
6. A bit stream is formed and sent to the client. The arrangement of the bit stream ensures continuously improvement of image quality, e.g. if in a second request the client wants for one class a higher quality, only the missing bits are transmitted.
7. The classification map sent in the beginning serves as header information for the decompression step at the client.

Figure 5 shows a SAR intensity image with 32 bits per element and below the according classification map (5 basic classes). Three bits per element are used in our simulation. Here, entropy coding could be added and will reduce the data rate significantly.

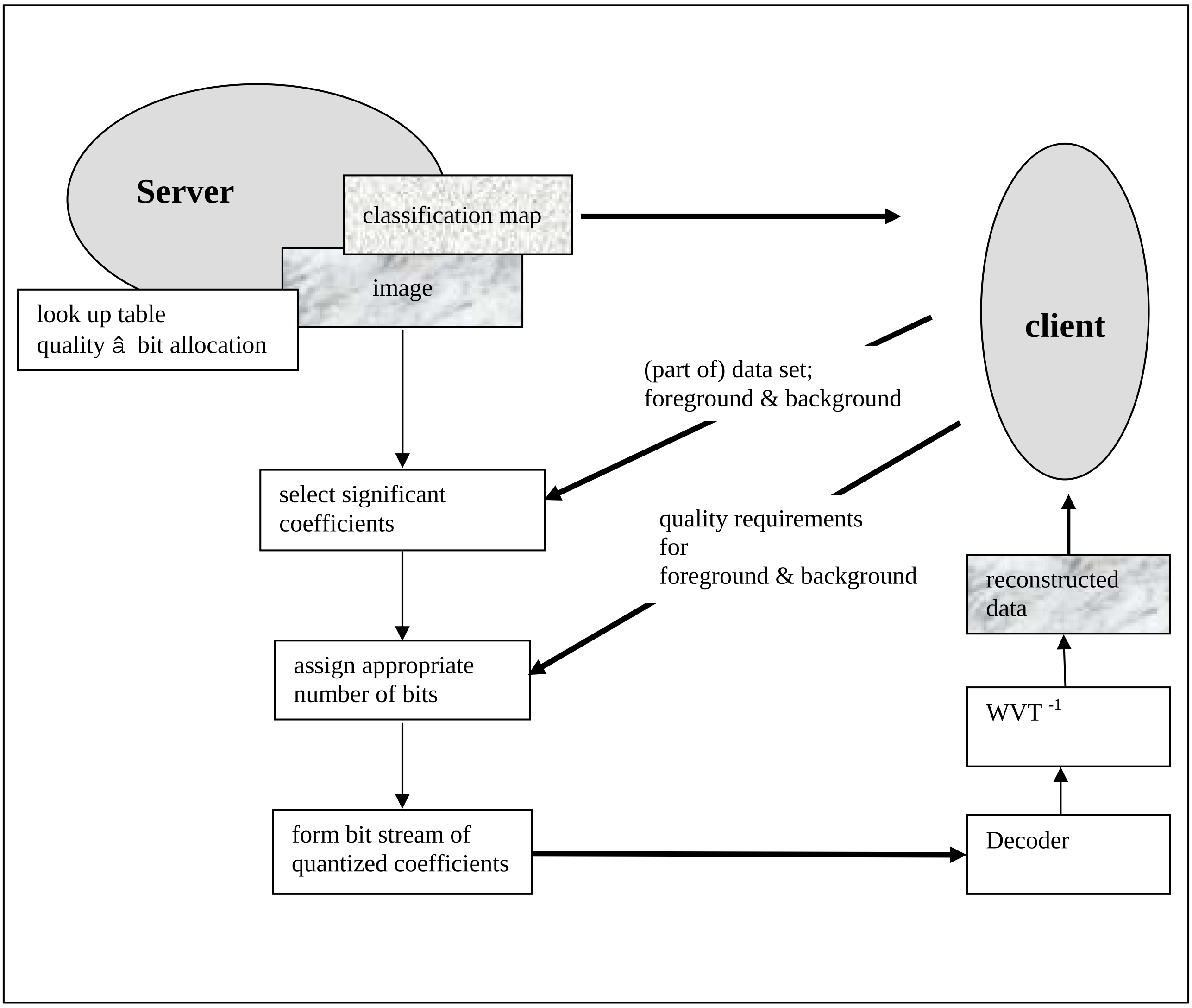


Figure 4: Server-Client-Link with strategy for progressive transmission starting with a classification map

Parts of this image are used in the following examples:

- In example 1 (Figure 7a) roads and airfields (smooth surface) are classes of interest. The compression algorithm compresses and transmits only the coefficients relevant for reconstruction of these classes. These coefficients are decoded and the inverse wavelet transform is performed. The reconstructed coefficients replace the classification map for all pixels belonging to smooth surface. This means, for this class any sophisticated further evaluation can take place, background information –

here the classfication map of the remaining classes – serves only for localization.

- Example 2 (Figure 7b) shows a similar case but now forest is considered as foreground.
- In Example 3 (Figure 7c) both background and foreground are reconstructed. However, only 1 bit per element is used for background. Foreground is transmitted without any measurable loss (no further compression in the second step). The resulting image looks much like a common SAR image, automatic classification and visual interpretation is even possible on all background regions, detailed analysis of the complex data is additionally possible on the foreground.

Figure 6 shows the performance of the extended FLECS. Of course, with an increasing ratio between the percentage of foreground to background, the overall compression ratio drops down. The performance converges to the compression ratio without image contents adaptation, however it does not get worse than the results without any adaptation.

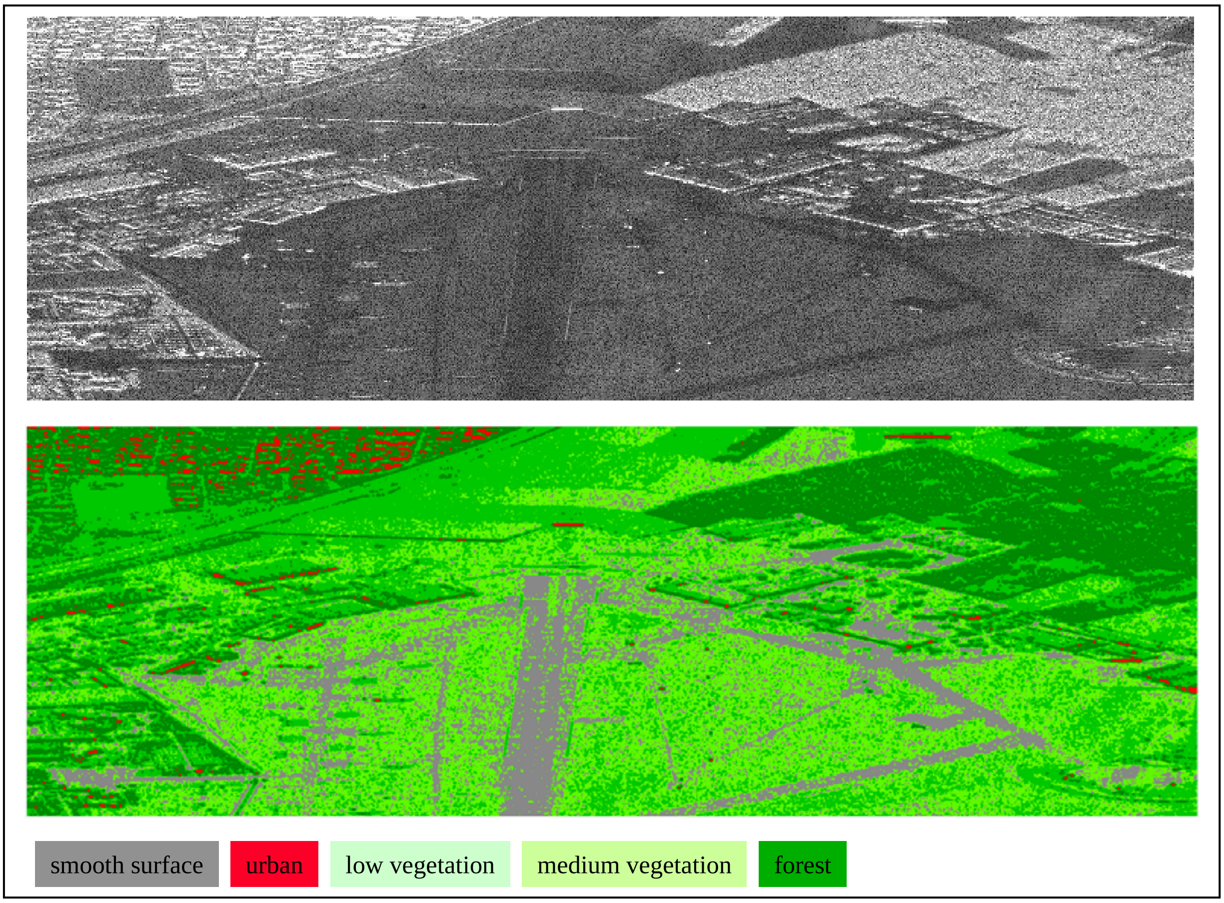


Figure 5: SAR intensity image and classification in basic classes

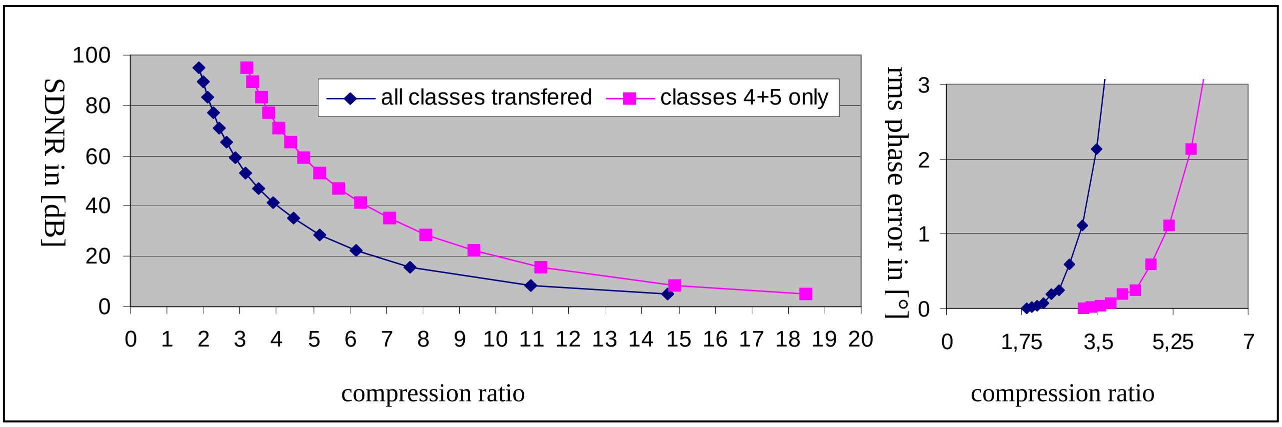
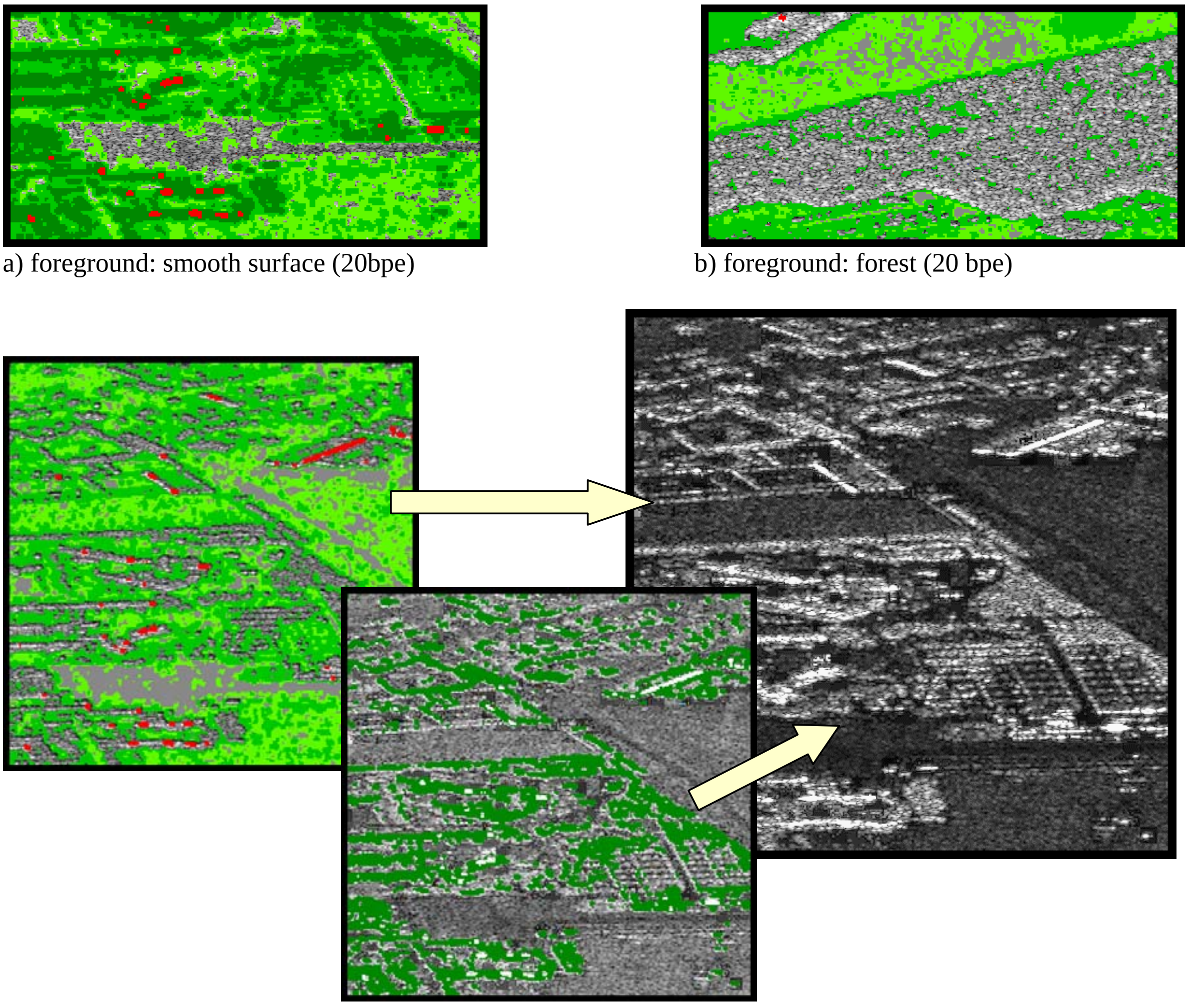


Figure 6: Performance FLECS extended by adaptability to image contents



a) foreground: smooth surface (20bpe)

b) foreground: forest (20 bpe)

c) foreground (smooth surface and forest): 20bpe, background: 1 bpe

Figure 7: Image content dependent compression and transmission, a) and b) only foreground elements are reconstructed, c) both background and foreground are reconstructed but with different reconstruction quality and data rate

4 DISCUSSION

In this paper we showed a general approach for adaptive data compression serving the needs of system design and user requirements. The resulting compression ratio and performance are not yet optimized. This is either subject of an operational implementation or future studies:

- Adding entropy coding to compress the classification map and the quantized coefficients will reduce the data rate without additional loss. The technology is state of the art and can be implemented in operational design
- As Shapiro et al [15] show, successive approximation quantization instead of simple bit plane transmission leads to reduced quantization distortion.
- More iterations of wavelet and decomposition in wavelet packets promise significant improvements. A better energy compaction is possible and the energy concentrated in medium frequency bands can be extracted. Due to the rapid development of technology, (e.g. CWIC described by Schaefer et al. [14]) implementation even onboard the satellite can be envisaged and can be therefore considered for STEP 1 compression. Integration in our module is in progress and results will be shown in following publications.
- Main advantage out of this finer decomposition will be achieved, if a vector quantizer or trellis-coded vector quantizer [9] exchanges the linear quantizer. It will allow fractions of bits per sample, it is more effective than the scalar quantizer in partitioning the data space and makes a better adaptation to the statistics of wavelet coefficients of high resolution

SAR images possible (compare also studies from Antonini et al [2]).

- An interesting research topic in future will be a class dependent quantization. We expect significant improvements, because the detected basic classes are characterized by their statistic. The better the quantizer is adapted to a statistic, the better the results will be. For each class there will be a optimized quantizer. The selection of the decoder at the client can be based on the classification map. No additional header will be necessary. Up to now, problems are still the large heterogeneity within one class which requires further partitioning into small blocks. Pre-classification has to be optimized with respect to data compression.

5 CONCLUSION

Synthetic Aperture Radar provides information for the remote sensing community, which is complementary to optical sensors. However, data rate and amount of data exceed the capacity of usual data links and storage devices by far. SAR data compression is necessary to ensure efficient use of acquired data and processed images.

Here, we proposed a two-step data compression:

- First a nearly lossless compression at the sensor, which does not influence any application but at least triplicates the amount of transmittable data.
- Second, an image content adaptive compression which accommodates the user requirements. Either a homogeneous distortion is realized or only relevant partitions or classes of the data set are transmitted to reduce the data rate significantly.

The presented results are neither optimized in terms of image reconstruction quality nor in terms of minimum compression ratio. The aim of this study was to show the ability and the possible gain by splitting data compression in image independent and image dependent compression. The additional computational requirements for edge detection and classification are only moderate and can be easily performed on the ground station server network. No expensive space qualified hardware is necessary and no additional computational power is required at the client. The suggested algorithms for edge detection and classification base on fuzzy systems, which possess a high robustness for slightly varying parameters.

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