MULTITEMPORAL RADAR-DATA: A SOLUTION TO THE DATA HANDLING AND PROCESSING PROBLEM WITH COMPRESSION TECHNIQUES

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ABSTRACT:

High compression rates of images containing a large rate of high frequent information can only be achieved by using lossy compression techniques. The Discrete Wavelet Transform (DWT) is presented and used to reduce the data volume of multitemporal RADAR data. At the same time as the data is compressed, the RADAR inherent speckle is removed. The suitability of the compressed and denoised data for image classification is tested. Compared with other techniques the presented method leads to significantly better classifications, especially at high compression rates, and for small homogenous areas. Owing to speckle removal the classification results are much better than those derived from the original data.

ZUSAMMENFASSUNG:

Hohe Kompressionsraten können in Bildern mit einem großen Anteil an hochfrequenter Bildinformation nur durch die Verwendung von verlustbehafteten Kompressionsverfahren erzielt werden. Die Diskrete Wavelet Transformation (DWT) wird kurz vorgestellt und zur Kompression von multitemporalen RADAR-Daten verwendet. Gleichzeitig mit der Kompression wird auch der RADAR-spezifische Speckle entfernt. Die komprimierten und entspeckelten Daten werden im Hinblick auf ihre Eignung zur Klassifikation von Landnutzungen getestet. Im Vergleich mit anderen Verfahren wird bei den erzielbaren hohen Kompressionsraten eine deutlich bessere Klassifikation, speziell bei kleinen homogenen Flächen, erreicht. Aufgrund der Speckle-Reduktion sind die Klassifikationsergebnisse viel besser als diejenigen, die aus den Originaldaten abgeleitet wurden.

1. INTRODUCTION

One main goal of processing remotly sensed data is to classify the data in order to derive thematic maps from it and to include those in Geographical Information Systems (GIS). The suitability of optical data for this purpose has been proven in many cases (e.g. Mausel et. al. 1990, Janssen & Middelkoop 1992), but clouds often hinder the use of optical data (e.g. Standley, 1997). Therefore a system, like the Synthetic Aperture Radar (SAR) which is more or less independent from atmospheric conditions, is an important data source.

In comparison with classifications based on optical data the classification of RADAR-data has various advantages and disadvantages. Main advantages are

- the independence of atmospheric conditions,
- the independence of illumination
- the penetration depth, which allows both an observation of volumetric and surface properties.

A detailed explanation of the advantages is given elsewhere (e.g. Ulaby et al. 1986). Disadvantages arise from

- the ambiguity of the signal interference patterns (speckle) and
- the single-band data as in the case of operational SAR-satellites as ERS or RADARSAT.

The latter one is not a real problem, as a multitemporal observation can be done easily. On the other hand multitemporal overlays lead to rapidly increasing data volume and may hinder efficient data processing. The ambiguity of the signal can be reduced in two ways: by regarding multi-temporal data or by the derivation of additional information such as textural features (Saurer & Triebfürst 1994). Once again, both solutions lead to increasing data volumes. In order to allow a proper data processing on personal and workstation computers or in the internet, the amount of data has to be treated as a problem for which compression techniques provide a solution.

Speckle filters are implemented in various image processing software packages, but an improvement of speckle reduction techniques is necessary to allow an automatic classification. Taking into account that speckle can be regarded as a stochastic process and not as information, it is obvious to treat the processes of data compression and speckle removal as one problem. Thus, an overview of compression techniques and the coding scheme used is given in chapter 2. In chapter 3 the integration of algorithms in a commercial GIS/remote sensing package is described. In chapter 4 an application is discussed briefly.

2. METHODICAL FRAME

For data compression lossless or lossy techniques are available. These methods are used for the reduction of redundancies in digital images. According to Gonzales & Woods 1992 three different redundancies are to be regarded.

- inter pixel redundancy - the correlation between neighbouring pixels
- psycho-visual redundancy - the high frequent structures of an image, which have low influence on the visual impression of an observer
- coding redundancy - the coding depth of pixels which usually is determined by the minimum and maximum pixel values of the image (e. g. 8 bit, 16 bit data)

A reduction of all these redundancies allows high compression rates with the simultaneous conservation of image information. Lossless data compression techniques are limited to the reduction of the redundancies of type 1 and 3. Images with a large rate of high frequent information can only be compressed significantly by an acceptance of a certain loss of information.

Depending on the specific purpose, the rate of the allowed loss of information has to be determined.

2.1 Data Compression based on the Discrete Wavelet Transform (DWT)

The actual ISO-standard for image compression is given by the Joint Photographic Expert Group (JPEG). The methods used belong to the group of transform coding schemes and are based on Discrete Cosine Transforms (DCT). In general these techniques yield to the disappearance of small, sharp structures when high compression rates have to be achieved (Paola & Schoewengerdt 1995.). Applied to multimedia data this disappearance does not cause problems, as an observer can easily recognise the image contents without these sharp, high-frequent elements. For geoscientific data on the other hand, such small structures may be of high geoscientific interest and can not be neglected. Recalling the three types of redundancies (see above), it can be stated that the psycho-visual redundancy is reduced to a degree which is not acceptible.

Methods which allow a better preservation of sharp structures are compression schemes based on Discrete Wavelet Transforms (DWT). Therefore, these techniques suit the needs of geoscientific applications (Benz et al. 1996). Additionally, DWTs yield the best compression rates, which can actually be achieved and represent the state-of-the-art in image compression. Consequently, the new ISO-standard for image compression will take this fact into account (http://www.disc.org.uk/public/jpegnew.htm).
The DWT is a linear transform similar to the DCT, with other basic functions instead of cosines. Compared with cosine functions these basic functions, the wavelets, have some important advantages:

- There exist different kinds of wavelets - sharp and compact ones as Daubechies-wavelets or smooth and extended ones as Gabor-wavelets. Therefore, different spatial patterns can be treated with adequate functions.
- They are not infinitely periodic like cosine functions. This property allows the localisation of the function and a locally different frequency analysis as well as selective data access (cf. dark areas in Figure 1).

The wavelet transform can be realised as an iterated filtering process. This means, the input signal is first filtered (by convolution) with a highpass filter to separate the highest frequency parts of the signal and with a low-pass filter to separate all the lower frequencies. To retain the number of coefficients of the input signal, both output signals are decimated by two. The filters are called analysis filters and are part of a two-channel-filterbank. With the corresponding synthesis filters the input signal can be reconstructed. For each wavelet a corresponding filter bank exists and the coefficients

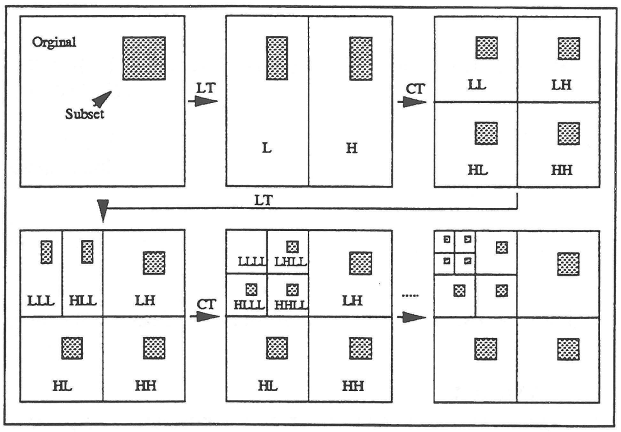

Figure 1: Scheme of the two-dimensional discrete wavelet transform (DWT) with three iterations (i.e. three frequency bands). One iteration step comprises a column transformation (CT) and a line transformation (LT), each consisting of a high (H) and low (L) pass filtering with subsequent downsampling by a factor of 2. The coefficients received by these two transformations represent the information contents of the image in the specific frequency band. The first iteration describes the highest frequencies of the image (level1).

of the highpass filter are dierived directly the wavelet function. After the input signal has been filtered once, the lowpass output signal can be filtered again with the same pair of filters. Now the high-frequency output represents frequencies which are not as high as the ones of the first filtering step (cf. Figure 1).

According to the common principle of a transform coding process (cf. Figure 2) two or three steps are necessary for the compression of the data:

- wavelet transform
- quantisation
- entropy-encoding (optional)

Data compression is achieved by performing step 2, as most of the coefficients received in the wavelet transform are small (low information content) and can be set to zero. A further, optional compression can be achieved by a subsequent entropy-encoding (Gonzales & Woods, 1992), a process somewhat similar to the well known run-length-encoding.

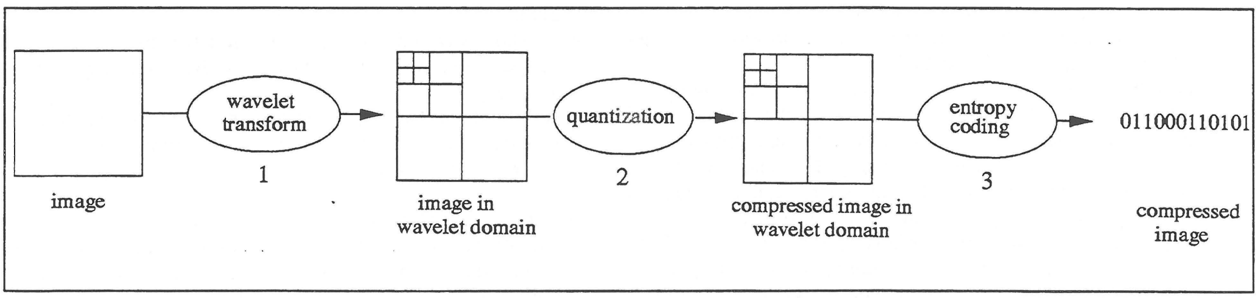

Figure 2: The three steps of a transform coding process: transformation, quantisation and encoding.

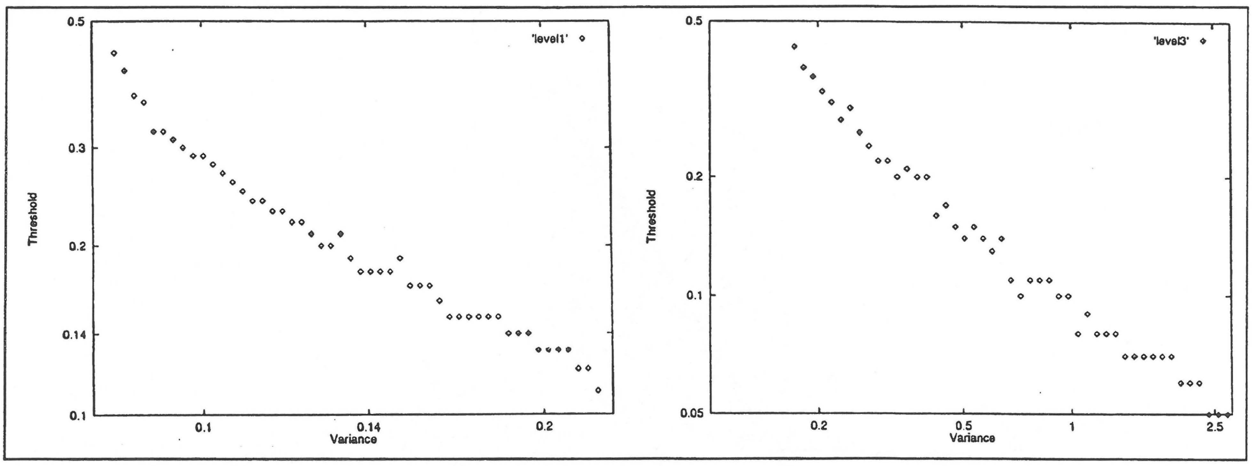

Figure 3: Dependence of optimal threshold and the variance of the wavelet coefficients. The examples shown are the results for two frequency bands ([a] level 1, [b] level 3).

2.2 Denoising

Speckle in SAR images is due to interference of the various, independent scattering points. According to Goodman (1976) speckle in SAR images can be approximated with a multiplicative Gaussian noise. Taking the logarithm of the pixel intensities, this is similar to a simple additive white Gaussian noise. The goal is to minimise the effects of speckle in the SAR image, that means, the Gaussian noise has to be subtracted. Donoho and Johnstone (1994) developed a method for the reconstruction of a unknown signal from additive noise data. The main idea of this method is to denoise the data in the wavelet domain, as high and low frequent information can be separated easily. Due to the fact, that speckle is a high frequent pattern, the corresponding wavelet coefficients can be set to zero (hard thresholding). As this method leads to striking artefacts Donoho and Johnstone used the soft-thresholding, which reduces this effect:

$$f(w) = \begin{cases} w-t & \text{for } w > t \\ 0 & \text{for } -t \leq w \leq t \\ w+t & \text{for } w < -t \end{cases}$$

with w: wavelet coefficient
t: threshold value

Donoho and Johnstone chose a fix value of t, depending on the variance of the wavelet coefficients. Chang & Vetterli (1997) improved the method by choosing different threshold values for „edge“, „texture“ and „smooth“ regions. By extending the adaptive capability of the method a further improvement can be achieved. Therefore, we derived the dependencies between local variances and optimised threshold values. For the determination of the optimum 360 images were used. These images were overlaid with a noisy signal, which is similar to the ERS speckle. Comparing denoised and original images allows the determination of the optimal threshold (cf. Figure 3).

During the denoising process most of the wavelet coefficients in the higher frequency bands are set to 0, a prerequisite for the desired compression of the data volume.

2.3 Compression

The three steps of a transform coding process were mentioned above. Firstly the wavelet transform has to be undertaken. In the second step we quantise the wavelet coefficients by a scheme similar to the bit plane coding process described by Gonzales & Woods (1992). The efficiency of the bit plane coding is very high, as during the denoising about 90 to 95% of the wavelet coefficients were set to zero. In the third step an arithmetic coder (Moffat et al. 1995) is used. Combining the two methods compression rates of 25:1 to 50:1 can be achieved for SAR data.

3. SOFTWARE ASPECTS

3.1 Basic concepts of FREIKOM

In view of the necessity to compress geoscientific data the FREIKOM software (Freiburg compression module) was developed. FREIKOM is based on the DWT and implemented as a library of C-programs. It allows

- the compression of data with the conservation of relevant geoscientific structures (context-specific data compression),
- the combination of compression and other image processing functions as filtering, denoising, segmentation, and feature extraction

as described above. In contrast to the DCT or the Fourier transform the DWT enables the reconstruction (inverse transform) of an arbitrary subset of the image, for example the subset marked in Figure 1. Regarding the low frequency part of each iteration step (LL, LLLL, ... in Figure 1), a set of subsampled images at different scales is created. Therefore FREIKOM comprises two additional features:

- local access to compressed raster data, and
- the storage of the data at different scales with a smaller amount of disk capacity as needed for the original data.

3.2 Implementation of FREIKOM

Based on the disadvantages of RADAR-data which were pointed out in chapter one and which are partly common problems of geographic raster data handling, a software package for the compression of geoscientific data has been developed. This software was implemented in order to fulfill the following conditions:

- Accessibility: Users can use the software within their known image processing environment.
- Interoperability: The software provides clearly defined data interfaces to allow the interoperation with other software packages.

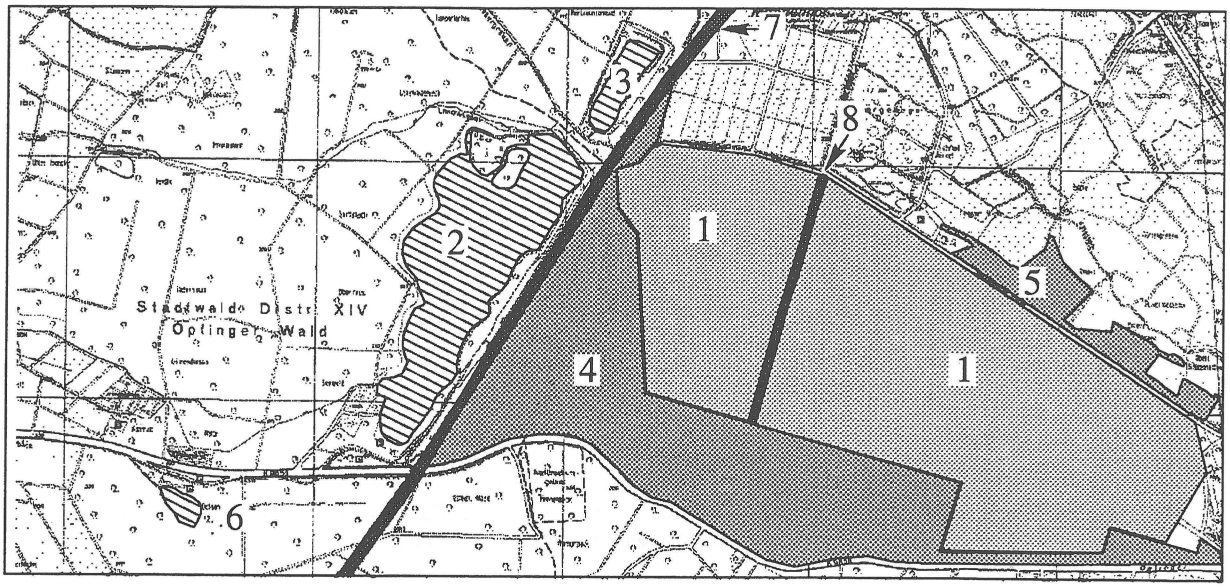

Figure 4: Topographic map of a subset of the test site. Areas and features discussed in the text are marked with numbers.

- Use of available resources: Graphical user interfaces, data access routines and corresponding libraries should be used to allow efficient software development.
- Integration into a GIS environment: Users should be able to deal with georeferenced data and to carry out GIS specific analysis methods.

As a consequence the software was integrated in a widespread GIS/remote sensing package. Comparing five different software packages it was decided to integrate the FREIKOM-package in Erdas/Imagine, Version 8.3, as it has some crucial advantages: This software is wide-spread, has a block-based data structure, provides voluminous C-libraries and allows a fast development of GUIs with the aid of a powerful macro-language.

4. APPLICATIONS

The development of the techniques described above was driven by the intention to map properties of the snow cover for huge areas in the vicinity of the Antartic Peninsula. These properties are an important factor for the observation of climatic change in this region. Up to now mapping is restricted to some small areas. In principle, the use of RADAR data contributes to the solution of the problem. But some problems are connected with the RADAR data itself. Speckle, topographic effects and data volumes, especially for multi-temporal data, do not allow an automatic classification. Therefore, data compression is absolutely necessary. For the development and the test of the suitability of the compression techniques a well-known test site in the surroundings of Freiburg in south-western Germany has been chosen. Preliminary results could be derived from this test site (cf. Figure 4). Therefore, a georeferenced multi-temporal dataset consisting of three ERS-scenes and, as reference, a landuse map derived from aerial mapping have been used. The ERS data were processed in different manners. After the processing the resulting datasets were classified using a supervised classificator:

1. The multi-temporal dataset was built-up (Figure 6 a,b).
2. The multi-temporal ERS-data was denoised with a Frost filter of 9·9 pixels size (Figure 6 c,d).
3. The multi-temporal ERS-data was denoised with the wavelet-based method described in this paper (Figure 6 e,f). The filter used was Daubechies-4-tap.
4. The Frost filtered image (see 2) was compressed at various rates, using the JPEG method realised in Erdas/Imagine 8.3 (Figure 6 g,h). The image shown is compressed at a rate of 26:1. A rate of 48:1, as for the Wavelet filtered data, leads to a result, which can not be used.
5. The Wavelet filtered image was compressed at various rates using the techniques presented in this paper (Figure 6 i,k). The image shown is compressed at a rate of 48:1.

The verification of the classification results is quite difficult. Thus, a combined qualitative and quantitative approach was used. Hereby three questions have to be answered:

- What is the overall accuracy?
- How well are small features classified?
- How well are large homogenous areas classified?

The overall accuracy for the original image and the uncompressed Frost filtered image is significantly worse than the other results (Table 5).

Table 5: Overall classification results

Image	correctly classified pixels [%]
original multi-temporal data	46,2
Frost-filtered image, uncompressed,	73,9
Wavelet-filtered image, uncompressed	86,9
Frost-filtered image, compressed 26:1	86,6
Wavelet-filtered image, compressed 48:1	86,8

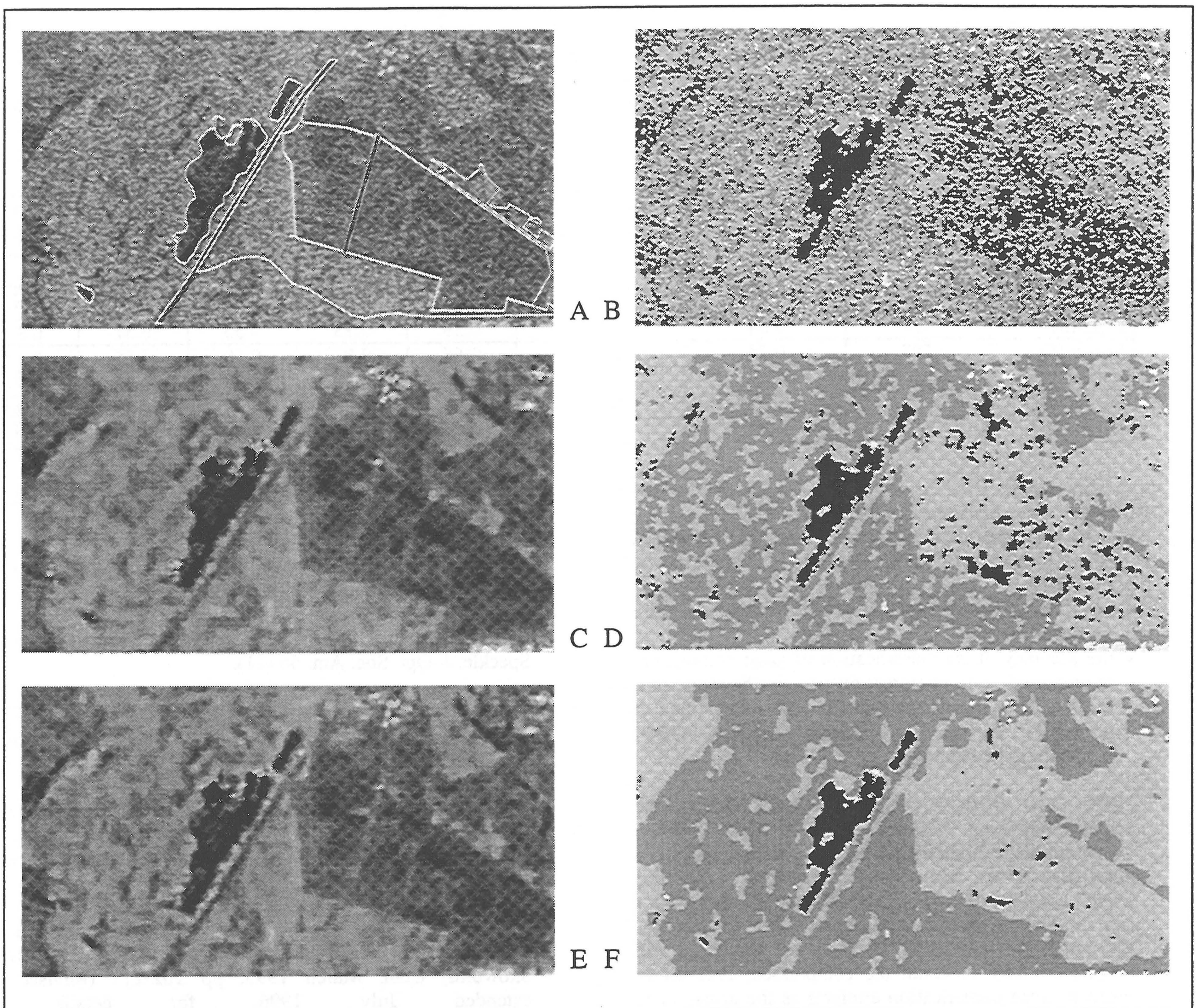

Figure 6: Classification results of the original and denoised SAR images.
In (A) the border lines of the areas from Figure 4 are overlaid.

Table 7: Comparison of classification results of multi-temporal SAR-data after denoising and compression. The percentage given is the percentage of correctly classified pixels. The numbers in column 1 refer to the areas in Figure 4. The lines of the table are sorted according to the size of the corresponding areas. With high compression rates applied, the classification of small homogenous areas becomes worse. Nevertheless, the differences in preserving these areas for the method presented in this paper (Wavelet-filtered, bit-plane and arithmetic compression) and a common method (Frost-filtered, compressed with JPEG method) are obvious.

object	area [pixel]	Frost-filtered, uncompressed [%]	Wavelet-filtered, uncompressed [%]	Frost filtered, compressed with JPEG		Wavelet -filtered, compressed with bit plane and arithmetic coder]		
				26:1 [%]	48:1 [%]	26:1 [%]	48:1 [%]	92:1 [%]
Lake (6)	59	0.12	0.14	0.07	0.01	0.14	0.07	0.03
Lake (3)	191	0.64	0.60	0.59	0.13	0.55	0.51	0.37
Forest (5)	747	0.55	0.68	0.66	0.83	0.59	0.56	0.50
Lake (2)	1854	0.73	0.70	0.70	0.37	0.72	0.72	0.71
Forest (4)	8786	0.70	0.88	0.87	0.98	0.87	0.88	0.89
Grass (1)	9050	0.87	0.97	0.98	0.91	0.99	0.99	0.98

Considering the classification results for different features with different sizes (cf. Table 7), it is obvious that

- with high compression rates applied, the classification of small homogenous areas becomes worse (areas 6,3,5 in Figure 4)
- small homogenous areas are preserved best with the method presented here
- the accuracy of the classification of large homogenous areas is preserved up to compression rates in the range of 50:1 for the combined Frost-filtered and JPEG-compressed data and up to 100:1 for the data processed according to the method presented in this paper

Upon closer examination of the images and the classified datasets additional information can be deduced. The classes which appear in Figure 5 are water (black), forest (dark grey), grass (light grey), and urban areas (white). According to the overall statistics the classifications derived from the original and the Frost-filtered data are not satisfactory (Figure 5 b,d). The other three classifications show no significant differences (Figure 5 f,h,k). In detail the compressed, Frost-filtered data result in some classification artefacts as the urban areas within the forest (Figure 5h, within area 4 from Figure 4). Small, linear objects as roads (objects no. 7, 8 in Figure 4) can not be classified, but remain visible in the denoised data and even in the compressed data.

5. CONCLUSIONS

Denoising and compression of RADAR data improves the results of a classification derived from this data. The method described in this paper leads - at higher compression rates (up to 100:1) - to similar accuracies of the classification results as standard denoising and compression techniques realised in a commercial image processing system.

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