About the impact of CCSDS-IDC compression on Image Quality

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Zusammenfassung: Zur Bewertung der Güte eines verlustbehafteten Bildkompressions-verfahrens werden häufig einfache Qualitätsmaße wie PSNR oder der besser an das menschliche Auge angepasste MSSIM-Index verwendet. Diese Qualitätsmaße quantifizieren den durch eine verlustbehaftete Kompression entstandenen Qualitätsverlust. Für die Fernerkundung eignen sich diese Verfahren jedoch nicht, da Fernerkundungsbilder zunehmend automatisch und mittlerweile weniger häufig durch den Menschen ausgewertet werden. Zur Bewertung der Bildqualität eines optischen Systems in der Fernerkundung werden u.a. die MTF und das SNR des Systems untersucht.

In dieser Arbeit wird der Einfluss aktueller verlustbehafteter Kompressionsverfahren mit Schwerpunkt auf dem Verfahren CCSDS-IDC auf die Bildqualität in untersucht. Werden die Bilddaten automatisch verarbeitet, so ist die Bildqualität letztlich hochgradig abhängig von den eingesetzten Algorithmen. Es wird gezeigt, dass eine verlustbehaftete Kompression selbst bei hohen Anforderungen an die Bildqualität möglich ist und diese Algorithmen bei geeigneter Wahl der Kompressionsparameter nicht negativ beeinflusst werden.

# Introduction

In spaceborne applications, there are challenging requirements on optical systems. In the last years, the spatial as well as the spectral resolution of the image data has increased, resulting in a tremendous increase in data rate. Besides this, there are requirements to image quality and constraints, resulting from the environment in which the system is to be used. An optical system for spaceborne application has to be highly reliable, low in power consumption as well as low in weight. The system also has to be radiation tolerant and able to operate in vacuum and in a high temperature range.

One major problem of satellite imagery is onboard storage and transmission of image data. This is caused by limited memory resources at the spacecraft as well as by limited download capacity and time to the ground station. So, it is necessary to compress image data. Depending on the requirements of the mission, lossless or lossy compression schemes can be used.

When using image compression, new problems arise. On a satellite we usually have very limited resources like space, time and power. A typical lossless image compression ratio is around 1:2 which is most often not sufficient. The loss of information, which comes due to the quantization stage in lossy compression, can be critical for some application, which results in a common assumption that lossy image compression is not appropriate for this particular application. This is almost always the case in scientific mission. On the other side, lossy compression suppresses noise in the image what can cause, that other algorithms run better Choong et al. [2006].

It is a fact, that lossy image compression introduces errors between the original image and the decompressed image. Depending on the compression ratio this might lead to visible distortions and artifacts (e.g. JPEG block artifacts) which results in degradation of the visual quality of the image. In applications where visualization for human beings is the main intention of producing images, the human visible system (HVS) has to be taken into account.

Correctly used, the term image quality describes the image degradation compared to an ideal image. On the way from the light source to the image, several components like the environment, the lenses or the electronics of the imaging system can introduce some amount of distortion. The term image quality is sometimes used wrongly. In the context of image compression, the performance of an image compression algorithm is evaluated with so called rate-distortion curves. Traditional distortion metrics used in the research field of image compression are mean square error (MSE) and peak signal-to-noise ratio (PSNR). As shown in Ponomarenko et al. [2010], these metrics have a weakness in predicting visual quality. In Wang et al. [2004] the structural similarity (SSIM) was presented, which uses luminance, contrast and structure comparisons to get a better visual quality prediction. In this context it should be noted, that possible noise of the original image most often is not taken into account. When using lossy image compression, knowledge about noise can be exploited to improve compression ratio.

In remote sensing, the HVS is not a good reference to determine image quality degradation because the main attention of producing images is often to process these automatically by algorithms. Furthermore, from the engineering point of view, determining the final image quality of the system or designing a system for a given image quality is a desired goal. A very useful tool for describing the image quality is the modulation transfer function (MTF), which relates input and output of a linear (imaging) system. Using the MTF has the advantage, that the overall system MTF can be determined as the product of the individual component MTFs. The general image quality equation (GIQE) is an empirical formula for predicting the image quality in terms of the National Imagery Interpretability Rating Scale (NIIRS) Irvine [1997]; Leachtenauer et al. [1997]; Thurman and Fienup [2008].

The purpose of the paper is to get a better understanding of the impact of lossy image compressing using the CCSDS-IDC algorithm. The author currently works on a fast hardware implementation on a FPGA which is capable to compress data rates of 1 GByte/s and more. In future project, it is planned to integrate an image compression module directly on the sensor platform. So, it is absolutely necessary to predict the achievable image quality for given output data rates. CCSDS-IDC was chosen because of several aspects presented in section 4.1.

The paper is organized as follows. Section 2 gives a short overview of used visual quality metrics. Section 3 presents some basics of image quality and MTF measurement. In section 4, the CCSDS-IDC algorithm is presented in a very short term and the datasets are presented. In section 5, the results of the investigations are shown. Section 6 gives a short discussion on the results and outlook of this work.

# Visual Quality Assessment

The quality of an image compression algorithm is described with rate-distortion curves. These curves describe the dependency between bitrate (in bits per pixel, bpp) and the distortion of the reconstructed image in comparison with the original image. Most often, the mean square error (MSE) or peak signal-to-noise ratio (PSNR) are used. The definitions for these metrics are

and

where and denote the width and the height of the images and and is the dynamic range of the pixel values (for bit unsigned integer it is ). Although they are almost always used, MSE and PSNR produce not an adequate description of the visual quality. The problem is that different distortions can produce the same MSE or PSNR although they have very different visual quality Wang et al. [2004]. Structural similarity (SSIM) is a metric, which involves structural, luminance and contrast information in the images. There are a lot of other visual quality assessment metrics which were compared against a mean opinion score (MOS) VIF, VSNR or PSNR-HVS, just to name a few Ponomarenko et al. [2009]. All these metrics are full-reference metrics as they compare in undistorted with a distorted version of the image.

# Image Quality Assessment

Image quality is influenced by properties of the scene and by the image acquisition system. Some of the image quality factors are dynamic range, signal-to-noise ratio (SNR) and the modulation transfer function (MTF). Dynamic range is the information of the smallest and the highest possible value of a signal (or image). SNR is a measure that gives to relationship of the signal, usually containing the information, to the noise. The MTF describes the loss of contrast of the edges of an object compared to the contrast in the image.

Methods for the determination of the MTF are shown extensive in Burns [2009]. Image compression algorithms can be understood as a component of the overall imaging system Hadar et al. [2001]. However, they are typically neither linear, i.e. not all the output frequencies correspond with the same input frequencies due to the irreversible quantization, nor isoplanar, i.e. they are space-variant because they use some sort of blocking of image pixel or coefficients. In Hadar et al. [2001], lossy compression was assumed to be linear to solve that problem. Nevertheless, the MTF gained from compressed images must be carefully assessed, because image compression can introduce edges and artifacts.

The MTF can be determined by several methods presented in Blanc and Wald [2009]. The method used in this paper is based on edge targets. The edge spread function (ESF) is the systems response to a high dark-bright contrast edge. With the slanted edge algorithm used in Kohm [2004] it is possible to create a super resolution version of the ESF. The derivative of the ESF is the line spread function (LSF). The LSF is then normalized to 1. The Fourier transform of the LSF gives the MTF.

# Algorithms and Datasets

## Used Compression Algorithms

To compress images, the standards JPEG, JPEG2000, SPIHT Pearlman et al. [2004] and CCSDS-IDC CCSDS [2007] were used. Some of these compression algorithms have recently been used in space applications Yu et al. [2009]. There are a lot of other compression algorithms in the academic research are: e.g. EZW Shapiro [1993] or SPECK, just to name two. The standard CCSDS 122.0-B-1 is a recommendation of the Consultative Committee for Space Data Systems (CCSDS). It is a wavelet-based image compression algorithm and often just called CCSDS-IDC (image data compression, IDC). This standard can operate in lossless as well as in lossy mode. As denoted in CCSDS [2007], the standard differs from JPEG2000 in several aspects:

* it speciﬁcally targets high-rate instruments used on board of spacecraft;
* compression performance has been traded oﬀ against complexity, with particular emphasis on spacecraft applications;
* the lower complexity of the recommendation supports fast and low-power hardware implementation;
* it has a limited set of options, supporting its successful application without in-depth algorithm knowledge.

The compressor typically consists of two parts: a discrete wavelet transform (DWT) module and the bit-plane encoder, which is an entropy coding stage. To have a well understood code basis, the encoder and the decoder was implemented in C++. For all tests, the encoder was set to frame mode, which means, that the whole images were compressed in a single segment. The wavelet was set to the lossy bi-orthogonal CDF 9/7 wavelet. Quality control was achieved by setting segment size to the desired ﬁle size.

## Datasets

To investigate in the impact of image compression on image noise, Gaussian noise images with certain variance and mean were generated. In the case of compression on noisy images, Gaussian noise was added to images with a certain variance, but zero mean. For this paper, noise was added to the recently used image “Lena” and the image “Marstest” taken from CCSDS [2007]. To investigate in the impact of image compression on feature matching, test images “boat” and “graf” of the university Leuven Leuven [2007] were used. The datasets contain several images taken from different perspectives and transformation matrices to project the images on each other. For the investigation in the impact of image compression on stereo matching, images from the Middlebury Stereo Vision Page Scharstein and Szeliski [2002] were used. For stereo-matching, the StereoSGBM matching implementation in OpenCV was used. To determine the MTF, tools and test charts from Burns [2009] and the recently used image “boat” were used.

# Results

## Impact of compression on noise

A ﬁrst investigation on the impact of compression was done on Gaussian noise images with and. A similar research was done in Ponomarenko et al. [2010] were the authors corrupted the test image Lena by Gaussian noise (see also subsection 5.2). Depending upon compression algorithm, the compression ratio can be varied by compression rate (CR) or by a quality factor. In the case of JPEG, the compression rate is controlled by a quality factor in the range. Modern algorithms like JPEG2000, SPIHT and CCSDS-IDC support to select a desired bitrate. Figure 1 shows the results. As expected, at low bitrates, all compression algorithms produce images with low noise variance due to the fact, that lossy image compression has low-pass characteristics. One can see, that these rate-noise-curves have an overshoot between 2 and 3 bpp, what can be explained by signal over- and undershoot at high frequencies and in turn, this increases the dynamic range of the image. It is also obvious, that the SPIHT and the CCSDS-IDC algorithm have a similar curve except they have a small spatial shift. This can be explained by the fact, that both algorithms use the bi-orthogonal CDF 9/7 wavelet and a similar hierarchical coding scheme.

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Figure 1: The noise variance before compression and after decompression for (left) and (right).

## Impact of compression on noisy images

In order to investigate the impact of lossy image compression on noisy images, the images Lena and Marstest (, noise free) were corrupted by Gaussian noise with and as it was done Ponomarenko et al. [2010]. The resulting image is which contains additive Gaussian noise. The image is now compressed and then decompressed to image.

Figure 2 shows the results. One can see that for noisy images with known noise characteristics there is some optimal bitrate which in this case is for at around 0.35 bpp and for at around 0.2 bpp. For the image Marstest, results look some diﬀerent. For there is clear maximum of the PSNR curve, but there is an optimal bitrate at around 0.75 bpp whereas the optimal bitrate for is at around 0.4 bpp. These results show that there is a dependency between image noise and optimal compression bitrate. The higher the image noise is, the lower is the optimal bitrate for the tested images. Unlike in Ponomarenko et al. [2010], the PSNR value of the rate-distortion curve of the noise-free image is always higher or equal to the corresponding value in the curve of the noisy image. Furthermore the results show that the dependency between image noise and optimal bitrate also depends on the image scene. In the case of image Lena there is a clear maximum of the PSNR curves whereas in the image Marstest there is no such point.

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Figure 2: Dependency between bitrate and for the image Lena (left) and Marstest (right).

## Impact of compression on feature matching

Features are often used to match a current image against another image (or images) to ﬁnd corresponding image points. With these correspondences it might be possible to detect and track objects, to reconstruct the stereo information of two cameras or to orientate images to each other. It is conceivable that image features are matched against features derived from compressed images. In order to investigate the impact of image compression on feature matching, scenes from the database Leuven where used. The database contains eight scenes each including 6 images and 5 transformation matrices from the ﬁrst to every other image of the scene.

For each test scene, sift Lowe [2004] features ware calculated the first image of the dataset. Then, images 2 − 6 were compressed by CCSDS-IDC at diﬀerent compression rates. After decompression, again sift features were calculated and matched against the features from the ﬁrst image. With the transform matrix it is possible to decide whether a matching is good or bad: For each matching, the point in the first image is transformed to the position in the second image. Then, the distance from this position to the position of the matching feature was calculated. If the distance is higher than a threshold, the matching was set to bad. A threshold of 10 pixels was chosen for these tests.

Figure 3 shows the results. One can see that on both plots, there are very different percentages of wrong matches for the different images. For the scene “boat” on the right side, the rotation and zoom of the scene increase from image 2 to 6. This leads to a higher percentage of wrong matches. The upper curves show a high percentage of wrong matches at all bitrates, which is caused by high perspective distortions between the images. According to the compression rate, one can see that there is a rise in wrong matches below 1 bpp for both scenes.

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Figure 3: The percentage of erroneous sift feature matches in dependence of the compression rate for the scene wall (left) and for the scene boat (right).

## Impact of compression on stereo-matching

Beside feature matching, stereo-matching algorithms are used more and more in the interpretation of remote sensing images. The datasets from the Middlebury Stereo Vision Page Scharstein and Szeliski [2002] and the StereoSGBM matching implementation in OpenCV were used. The database contains four image pairs (cones, teddy, tsukuba and venus), the corresponding ground truth and three masks which are needed for stereo-matching evaluation. For these tests, the mask “all” was chosen containing all pixels including half occluded pixels. Because the OpenCV implementation of StereoSGBM cannot calculate disparities for all pixels, some more pixels were excluded from error calculation. To measure the matching error, the percentage proportion of faulty pixels in the disparity map was determined with the mask. See Scharstein and Szeliski [2002] for more details on this calculation.

Figure 4 shows the results. The blue curves describe the percentage of erroneous disparity values. The red lines show the error value when no compression was used. One can see that at 4 bpp there is almost no error for all images. The matching error rises at around 2-2.5 bpp. At 1 bpp, the matching error is around 5 % higher than without compression. At 0.5 bpp, it is around as twice as high as without compression. At around 0.25 bpp, stereo-matching the number of bad matches increases dramatically.

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Figure 4: The matching error in dependence of the compression bitrate chosen for both images. The horizontal red lines show the matching error without compression. The evaluation database contains four images: cones (top left), teddy (top right), tsukuba (bottom left) and venus (bottom right).

## Impact of compression on image MTF

To determine the MTF, tools and test charts from Burns [2009] and the image “boat” were used. The tool sfrmat3 uses the slanted edge method Kohm [2004]. Two images were chosen for evaluation. Regions of interest for MTF determination were selected for both images. In the image “ISO DSC 300 mono”, this area in and and for the image “boat”, the area is in and. The compression ratios were 0.5 bpp and 1 bpp for the testchart, and 1 bpp and 2 bpp for the boat image. Figure 5 shows the results. One can see that for 1 bpp, the MTF of the Testchart, and for 2 bpp, the MTF of the boat are nearly unaﬀected. When increasing the compression ratios, both MTF curves degrade. But because of the non-linearity of the image compression, results must be interpreted with caution. The dependence of MTF and compression rate was also investigated with other bitrates and the MTF curves, which are not shown in this paper, show, that the MTF is stable at higher bitrates than 2 bpp for the boat image and 1 bpp for the testchart.

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Figure 5: The MTF before compression and after decompression on the same region of interest. The top curves show the MTF curves for the testchart at 0.5 bpp (left) and 1 bpp (right). The bottom curves show the MTF curves for the boat image at 1 bpp (left) and 2 bpp (right).

# Discussion and Outlook

In this paper, the impact of lossy image compression with CCSDS-IDC on image quality was investigated on selected examples. The results have shown that a compression ratio of 1:4 (2 bpp bitrate for 8 bit images) has almost no impact on the quality of the results. For the author, this study is not yet complete and there are many more relationships to be examined. Furthermore, the already obtained results will be examined in the future and must be proofed with more images. The complexity of the image scene is another topic which has to be included in this investigation. The influence of the selected wavelet on the application performance and MTF measurements is also an interesting and part of the author’s current research.

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