Medical Image Compression:
Study of the Influence of Noise on the JPEG 2000 Compression Performance

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Abstract

In this paper, the efficiency of the JPEG2000 scheme combined with a complementary denoising process is analyzed on simulated and real dental ortho-pantomographic images, where the simulation images are perturbed by Poisson noise. The case of dental radiography is investigated, because radiographic images are a combination between the relevant signal and a significant amount of acquisition noise, which is per definition not compressible. The noise behaves generally close to Poisson statistics, which generally affects the compression performance. The denoising process is supported by Monte Carlo noise modeling, which is introduced in the JPEG 2000 compression scheme to improve the compression efficiency of the medical images in terms of compression ratio and image quality. Fifty selected images are denoised and the compression ratio, using lossless and lossy JPEG 2000, is reported and evaluated.

1. Introduction

Trends in medical imaging are developing increasingly digital; meanwhile the amount of images captured per year is in the range of hundred petabytes[1] and still on the rise. Many compression techniques have been developed since the formalization of data compression by Shannon. Special fields are Teleradiology, Telemammography and Telepathology, where the full diagnostic information is transferred digitally. There are two types of compression - lossless and lossy -. Roughly speaking, a lossy scheme differs from a lossless in applying an additional quantization stage. This stage provides parameters to enable a balance between compression rate and induced artifacts [3].

Belbachir et al. [2] proposed a hybrid compression scheme by extending the wavelet transform (JPEG2000), adopting anisotropy and smooth boundaries, in applying the Contourlet transform for the processing of the fine detail scales. The scheme shows reduced artifacts in the image and it achieves better compression rate at larger (i.e. $\geq 1024^2$) images. Al-Shaykh [1] et al. studied the effect of noise on image compression using the JPEG lossy image processing standard, where it was found that at higher compression rates the coders filtered out most of the noise, but also degraded the image quality measured by **P**eak **S**ignal to **N**oise **R**atio (PSNR). Slone et al. [6] assessed twenty posteroanterior chest radiographs by five observers and concluded on one hand that lossless compression provides an inadequate reduction of the data amount, and on the other hand lossy compression artifacts may be detectable, but their presence does not affect diagnostic performance.

Therefore, compression schemes fall into three general categories: – Original data/lossless[2], as a gold/silver standard – Visually lossless[3], where the observer cannot detect any compression noise or artifacts – Diagnostically lossless[4], where artifacts are detectable but do not impact accuracy. In current clinical practice lossy schemes are not often being used, because of legal questions and regularity policies. New clinical testing can develop reasonable policies and acceptable standards for the use of lossy schemes.

Two main questions arise: – how much has noise influence on the compression performance? – and is it possible to increase compression efficiency by the application of an accurate denoising method?

In this paper, a different assessment for the investigation of compression efficiency of the JPEG2000 algorithm is given by noisy simulated and real dental **O**rtho-**P**an**T**omographic (OPT) images. The influence of the noise on the compression efficiency as a function of the signal dynamics is simulated, rather than shown by other assessments, the amount of noise is bound to the signal by a back-projection method. The approach can be exploited

[1] $1peta = 1000tera$

[2] up to 3:1 compression
[3] up to 16:1 compression
[4] compression limits not well determined

to every field of application, which utilizes an appropriate noise model. The qualities of the images are compared by means of the **M**ean **S**tructural **SIM**ilarity (MSSIM) index proposed by Wang et al. [8] and the usual PSNR.

The paper is organized as follows: in Section 2, preliminary notions on OPT images and JPEG2000 compression are given. The proposed image compression concept is described in Section 3. Section 4 focuses on the assessment of compression efficiency. In section 5, the conclusions and thoughts on further work are given.

2 Background

Within medical diagnostics alongside medical expertise intuitive decisions are often made solely, based on experience. Therefore, appropriate reconstruction methods have to be able to detect small, low contrast image details, frequently situated side by side, often hardly differing in gray-level-means, while maybe just exhibiting a slightly distinct variance. Herein an affinity to image compression is given, where similar objectives are considered.

2.1 Ortho-pantomographic radiography

OPT is a technique where the entire dentition is projected onto a sensing device by means of the photons of a poly-energetic x-ray beam. The x-ray source and the detector are in opposition, rotating around the patients head, where the focus zone of the x-ray beam describes a planar curve, which is standardized for the human teeth and jaws.

2.2 JPEG2000

JPEG 2000 [7] may produce a lossless compressed image, which means, no data will be lost during compression and the entire data set can be recreated. Lossless compression ratios of 2:1 to 5:1 are possible. Visually lossless compression ratios can go much higher, theoretically to over 100:1, depending on the image characteristics.

3 OPT image reconstruction revisited for its use in advanced JPEG2000 Compression

Goebel et. al. have shown in [5] that the noise statistics of dental OPT images follow a mixture of two generalized Gamma distributions, where the one results from photon attenuation scatter (i.e. the absorbed photons) and the other from the photon scatter-glare (i.e. photons whose traveling paths have changed, and have not been absorbed) that is accountable to the noise contribution. They have also shown in [4] denoising, originated by an idea stemming from **B**lind **S**ource **S**eparation (BSS), where an image model is formed that utilizes a background image, which is a panoramic x-ray without patient; a Monte Carlo simulation of the x-ray source with inclusion of the modeling of the photon x-ray scatter by patients matter; and also the diagnostic x-ray image. A transmittance image T, calculated as the fraction of the diagnostic image and the background image corrects the inhomogeneous x-ray illumination and is used instead the usual diagnostic image. The fraction functional between two polynomials of degree 2 and 17, both fitting the vertical gray profile of the transmittance image, yields a correction matrix for avoiding low frequency and big contrast differences according to properties dictated by **H**uman **V**isual **S**ystem (HVS) for better perception.

The Monte Carlo simulation of the photon x-ray scatter yields a scatter glare distribution, which is used together with the likelihoods of the diagnostic image for scatter backprojection to achieve a Bayesian estimate of the image noise contribution. Then, the noise is modeled by the finite realization of a mixture of infinite Gaussian noise fields, having zero mean and varying variance, yielding the scatter glare noise estimate. The polynomial corrected transmittance image is then denoised by a new denoising approach, for the subtraction of the scatter glare noise estimates energy from that of the transmittance image using the wavelet domain. The underlying basic idea is that the transformed deterministic image content is represented by a set of a few stronger wavelet coefficients, whereas the noise is distributed across all coefficients at weak intensity. This decomposition property enables the subtraction of two random signals (i.e. the noise from the original image) by building the difference between the signal power values of both signals using their wavelet coefficients.

The main advantage of this approach is finally that it makes possible neglecting the inherence of the noise variance on the diagnostic image values. Thus, although the variance of the noise in radiography follows per definition the image value by some function, one can treat an acquired image $i(.)$ as an additive mixture from the diagnostic source image $s(.)$ contaminated by an independent noise function $n(.)$. Using the inverse BSS model yields the solution $\hat{s}(.) = i(.) - \widehat{\kappa}(s)$, with $\widehat{\kappa}(s) = \widetilde{\mathrm{N}}$, the noise estimate $\widetilde{N}$, which is generated by Bayesian backward scatter projection. The reconstructed estimate of the transmittance $\widetilde{T}$ getting reduced noise by preserving diagnostic detail.

The result of the noise estimation approach was used by Goebel et. al. in [4] for OPT image restoration. The approach was tested against classical wavelet hard- and soft-thresholding methods. It was shown that it performed substantially better than the former in terms of **M**odulation **T**ransfer **F**unction (MTF) and PSNR. Thus, within this paper, the denoising of the real radiographic images is supported by this modeling.

Table 1. Comparison of the compression results on five out of fifty real OPT images; showing the influence of the noise contribution on the compression performance.

		Compression of the Original Images					Compression of the Denoised Version of the Images				
			Lossless		Lossy Q=40			Lossless		Lossy Q=40	
Image	Dyn. Range 1:N	Original TIFF Size in Bytes	Ratio	Compressed Size in Bytes	Ratio	Compressed Size in Bytes	Original TIFF Size in Bytes	Ratio	Compressed Size in Bytes	Ratio	Compressed Size in Bytes
Im1	859	5953770	3,19	1865511	8,53	697955	5554802	4,02	1381881	10,23	542991
Im2	8598	5956778	2,04	2913467	5,08	1171541	5541896	2,36	2347144	5,87	944041
Im3	18598	5956926	1,78	3346022	4,42	1346354	5551302	2,01	2759379	5,01	1109115
Im4	28598	5957118	1,70	3504326	4,34	1409780	5553742	1,92	2894115	4,77	1164495
Im5	56553	5958622	1,50	3968786	3,73	1596354	5551738	1,70	3264450	4,23	1311882

4 Experimental Results and Evaluation

Since early stages of the HVS are optimally ”tuned” to sine-wave gratings, synthetic test patterns are often used in tests of acuity. Therefore, the assessment deploys sine-wave gratings as test images with smooth increasing frequencies from 0.10 lines per mm (lpmm) to the upper bound frequencies of 0.5, 1 and 2.5 lpmm. The set of test patterns is duplicated and perturbed by Poisson noise $\widetilde{N}$ to test the behavior of usual noise simulation. One-hundred test images per set, with logarithmic amplitude stepping from set to set were generated to study the influence of changing dynamic range, resolution and scatter noise onto the compression factors. Thus, six sets of test images were generated: – an original set – an original set with Poisson noise added – and then – a copy of both sets compressed by lossless compression – and again – another copy of both sets compressed by lossy compression (Q=40).

Figure 1 shows the simulation results of the dependency of the compression factor on the dynamic range for the smooth, noisy images. There are four groups, each showing the three lines-per-millimeter frequencies 0.5, 1 and 2.5 lpmm, for lossless, lossy, lossless with noise and lossy with noise. Additionally, results stemming from a set of original real radiologic images, listed in Table 1, are shown. The results are plotted for five real image examples, with different dynamic ranges 1:N.

In the noise free cases, the graphs from the simulation results show a nearly linear behavior between logarithmic dynamic range and logarithmic compression factors. The lines-per-mm frequency produces a practically parallel shift of the curves. The noise added cases behave nearly constant, regardless of the dynamic value. Compared this to the graphs of the real diagnostic images, there is found a different behavior – the real images compete like the simulation images, without noise, in both, the lossless and the lossy cases. Therefore, the usual method of just adding noise, bound by some function (e.g. Poisson) on the image values, seems not accurate enough. Unfortunately, the denoising of the real diagnostic images does not bring a big advantage in compression performance alone. Table 2 compares the quality measures achieved. The denoised images perform better in both metrics', the PSNR and MSSIM. Therefore, utilizing the denoising method, one achieves higher compression together with better image quality. The higher the dynamic of the image, the more there is a limitation stemming from the quantization stage of the compression. Therefore, the dynamic range of the image should not be spread by extra contrast enhancement prior to compression.

5 Conclusions and Outlook

This paper studied the improvement potential of the JPEG 2000 codec performance on medical images by including a denoising process. The additional denoising improved image quality and the compression performance by $\approx 13\%$. A new compression scheme satisfying legal thoughts, by aggressively using the ROI concept in JPEG2000 and an additional denoising step, seems to have potential for the compression of radiographic images. A noise estimate exploited by Monte Carlo simulation [5] determines an importance map that spatially defines the regions of interest for fidelity compression. The remainder of

Table 2. Images quality by MSSIM and PSNR.

Dyn.	Original MSSIM		PSNR	Denois. MSSIM		PSNR
Range	lossl.	lossy	lossy	lossl.	lossy	lossy
859	1,00	1,00000	95,43	1,00	1,00000	101,01
8598	1,00	0,99997	79,12	1,00	0,99999	82,89
18598	1,00	0,99992	74,62	1,00	0,99996	77,57
28598	1,00	0,99982	71,11	1,00	0,99993	74,66
56553	1,00	0,99966	68,04	1,00	0,99981	69,94

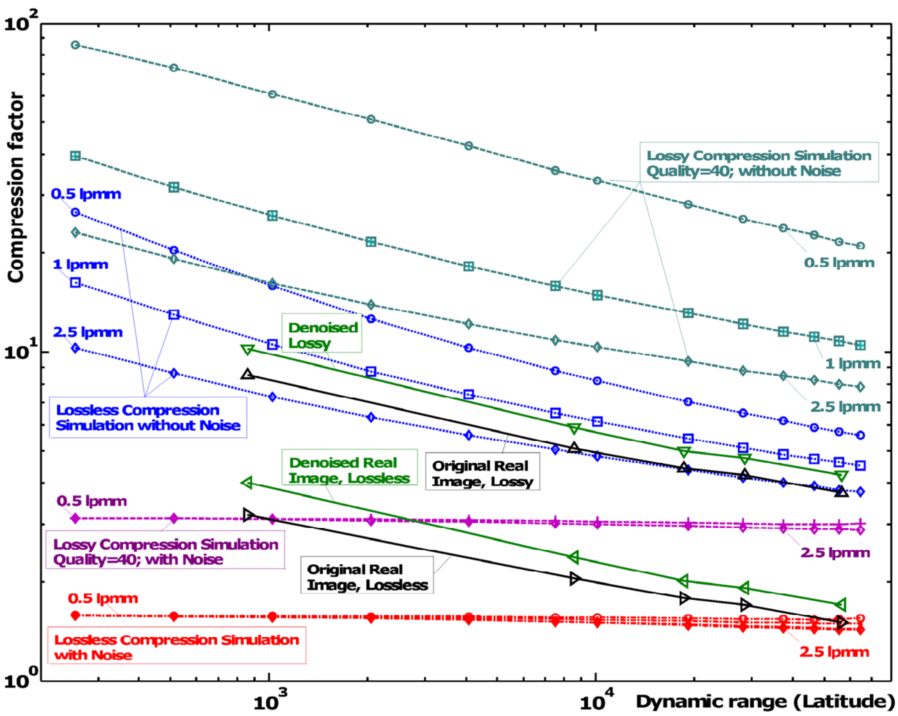

Figure 1. The dependency of the compression factor on the dynamic range for smooth noisy images. There are four groups, each showing the three lines-per-millimeter frequencies 0.5, 1 and 2.5 lpmm, for lossless, lossy, lossless with noise and lossy with noise images (see also Table 1).

the image can be compressed more aggressively. A combination of a recently proposed hybrid compression scheme by exploiting the Contourlet- and Wavelet-transform [2], may reduce artifacts for the lossy portion of the image furthermore. Based on the results of the work in this paper, an advanced JPEG2000 method (see Figure 2) with the aforementioned extensions will be the next focus of work.

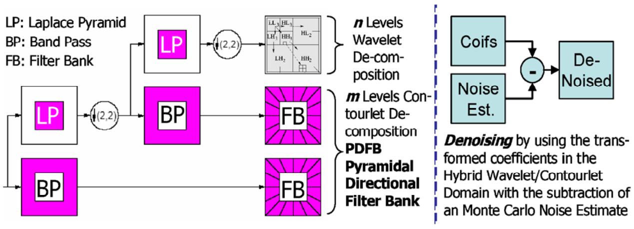

Figure 2. The concluded hybrid approach will use the Contourlet transform for the first decomposition levels and the biorthogonal wavelet transform for the lower resolution levels. The ROI and the denoising approach will be extended to the hybrid scheme.

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