A Study on the Influence of Image Dynamics and Noise on the JPEG 2000 Compression Performance for Medical Images

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Abstract. This paper investigates a complementary compression concept to the JPEG 2000 standard for improving the compression efficiency of medical images, in terms of compression ratio and image quality, by introducing a denoising process before the application of the JPEG2000 compression. The case of dental radiography is assessed, where the JPEG 2000 compression standard is appropriately tuned to fit medical diagnosis demands to the compression ratio. Indeed, radiographic images are a combination between the relevant signal and the acquisition noise that is per definition not compressible. The noise behaves generally close to Poisson statistics, which generally affects the compression performance. In this paper, the efficiency of the JPEG2000 combined with a denoising process is analyzed on simulated and real dental ortho-pan-tomographic images. The test images are simulated using Poissonian statistics and a Monte Carlo noise modeling method. A hundred 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[3] and still on the rise. The aim of image compression is to reduce the amount of data to be coded by removing redundant information. Therefore, relevant information of diagnostic demand is selected in the image and the coding process is reorganized so that, on the one hand relevant information is emphasized, and on the other hand noise and non-meaningful data are dropped. To achieve this, one can focus on the region of interest; filter out noise; and quantize information accordingly to adaptive perceptual thresholds to satisfy constraints given by Weber-Fechner's law [7]. The law defines just noticeable differences (JND) that are mediated by medical expertise to prevent relevant information loss.

[3] $1 peta = 1000 tera$

1.1 Background

Compression have become a valuable technology by introducing the standards JPEG [15] and recently JPEG2000 [18] for widespread use. Special fields are Teleradiology, Telemammography and Telepathology, where the full diagnostic information is transferred digitally. Generally, a compression concept consists of a transform stage, a quantization stage and an entropy coder. Each of those stage can be tuned to satisfy the needs of the application at hand.

In general, two types of compression schemes - lossless and lossy - are known. The term lossless [6] means a reversible scheme that achieves modest compression rates by allowing exact reconstruction of the original image. Controversy, a lossy compression scheme is irreversible and cannot achieve exact reconstruction. 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.

To achieve visually lossless compression [14], a contrast sensitivity function (CSF), which is the visual ability to see objects that may not be outlined clearly or that do not stand out from their background, can be made adaptive to the human visual system (HVS) [11, 2] to regulate the quantization step-size and therefore to minimize the visibility of artifacts. Therefore, image quality can be classified into five general categories:

1. Original data, as a ”gold standard”.
2. Data lossless compressed, as a ”silver standard”; finite numerical precision causes small errors that are detectable mathematically.
3. Visually lossless, thus an observer cannot detect compression noise nor artifacts.
4. Diagnostically lossless, the artifacts are detectable but do not impact accuracy.
5. Artifacts put an substantially impact onto the diagnostic image content. The image gets useless from point of view of the medics’.

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. The performance of human observers can have additional impact on the assessment quality. The ideal observer approach (IOA) can be used for benchmarking, and represents a Bayesian method to perform detection tasks. Investigations show human performance limited by suboptimal sampling efficiency and by additive internal noise [8].

Many compression techniques have been developed since the formalization of data compression by Shannon. Clunie [6] tested seventeen lossless schemes with over three-thousand different images from multiple anatomical regions and came to the conclusion that newer lossless compression techniques perform better than older, and predictive schemes with statistical modeling and with transform based coding perform better than dictionary based coding. Belbachir et al. [3] 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 coefficients scales. This scheme shows less artifacts in the image and achieves better compression rate at high resolution (i.e. larger $\geq 1024^2$) medical 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 peak signal to noise ratio (PSNR). Slone et al. [17] 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. A recently published work [16] assessed JPEG competing with JPEG2000 schemes and came to the conclusion that JPEG could perform better than JPEG2000 for low compression rates. Herein, an open question arises in how one may compare the results from different investigations, concerning perceived image quality.

Subjective quality ratings, utilizing usual mean opinion scale (MOS) statistics, built from averaging observations, done by medical experts considering compression artifacts, can prove lossy compression to be usable. Although, objective quality ratings, calculated by classical metrics, like the Peak Signal Noise Ratio (PSNR) or the Root Mean Square Error (RMSE) that can exactly determine any loss of signal, are not sufficient to predict differences between images as perceived by a human observer. Several CSFs [12] that are determined by a measure of the limit of visibility for low contrast patterns, were proposed (e.g. Campbell & Robson, Movshon, Barten, Daly, etc.).

Wang et al. [19] described the decomposition of the distortion between two images into a linear combination of components by the structural similarity index measure (SSIM), which separates out non-structural luminance and contrast distortions that are less important to the degradation impression of diagnostic information. Measures stemming from spatial autocorrelation[4], which consider the neighborhood relations between pixels, can cope better with the classification of artifacts, without affecting the diagnostic content [5].

However, in particular – questions are – how much has noise influence on the compression performance – is it possible to increase compression efficiency by the application of an accurate denoising method?

1.2 The Contribution of this Work

This work improves the compression performance by embedding a denoising process in the JPEG2000 compression scheme. The assessment for the investigation of compression efficiency of the JPEG2000 algorithm is performed on noisy simulated and real dental ortho-pan-tomographic (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, where the noise consists of a fraction of the signal by means of a back-projection method. The approach can be exploited to every field of application, which utilizes an appropriate noise model. The quality of the images are compared by means of a MSSIM algorithm proposed by Wang et al. [19] and the usual PSNR. Although the results are validated on radiographic medical images, this work can be extended to other medical images like mammograms, where compression is also

[4] i.e. Moran I statistics

of interest, and the dedicated noise model has to be deduced in the same way as it was performed for x-ray images.

The paper is organized as follows: in Section 2, the compression scheme JPEG2000; and OPT image reconstruction is revised as prerequisites. Section 3 focuses on the assessment of compression efficiency. In section 4, the conclusions and thoughts on prospective further work are given, and section 5 lists the bibliography references.

2 Preliminary Notions

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. With this in mind this paper is motivated.

2.1 Ortho-pantomographic radiography

This 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 jaw.

2.2 JPEG2000

JPEG 2000 may produce a lossless compressed image, which means, no data will be lost during compression and the entire data set can be recreated. Since 2001, JPEG2000 support is added to the standard of Digital Imaging and Communications in Medicine (DICOM).

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. JPEG2000 supports more than the 3 bands, like JPEG and other compression schema accept, and so it can easily handle hyper-spectral and multi-spectral imagery. Hyper-spectral imaging is the simultaneous acquisition of images in many narrow, contiguous, spectral bands. For example, most satellites today measure energy at many wavelengths, thus this is called multi spectral imaging.

Regions of Interest (ROI) allow greater image quality in the foreground, while other parts of a huge image may receive aggressive compression. That means, features of interest are maintained at source level of detail, and the rest of the image is only provided for contextual purpose. JPEG2000 specifies a 9/7 wavelet for ordinary lossy compression, and a 5/3 wavelet for lossless compression. The 8x8 blocking artifacts of JPEG compression are prevented by the allowance of pixel blocks of much higher size.

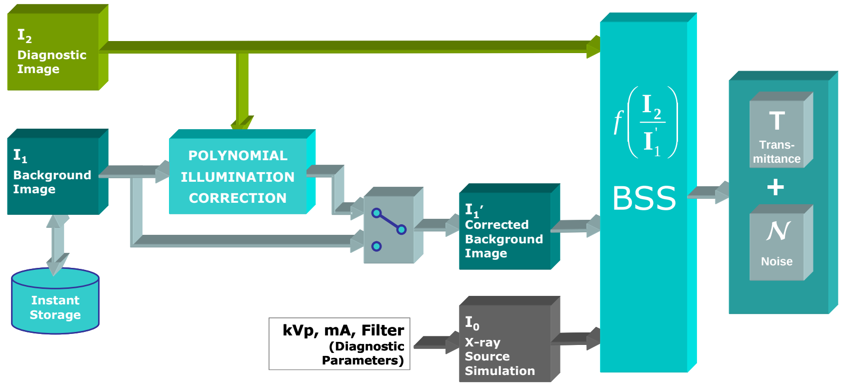

Fig. 1. The acquisition part of the approach, which is using three images, the diagnostic image I_2, a background image I_1, and a Monte Carlo simulation of the x-ray source image I_0. Non-linearities from the x-ray source can be compensated by polynomial illumination correction. The background image I_1 may be stored for instant use.

3 The Methodology: OPT image reconstruction revisited

Goebel et. al. have recently shown in [10] that the noise statistics of dental OPT images follow a mixture of two generalized Gamma distributions, rather than pure Poisson distributions, where one of them stems 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), which is accountable to the noise contribution. An image model $\boldsymbol{x} = \mathbf{A}\boldsymbol{s}$, was presented by adopting an idea stemming from blind source separation (BSS) [4][5], with $\boldsymbol{x}$ the observation vector, $\mathbf{A}$ the mixing matrix, and $\boldsymbol{s}$ the hidden original signal source vector. Utilizing an inverse BSS model, one may find a matrix $\mathbf{B} = \mathbf{A}^{-1}$, which reformulates to $\hat{\mathbf{s}} = \mathbf{B}\boldsymbol{x}$ that yields the solution $\hat{s} = i - \widehat{\kappa}(s)$, with i the image, and the noise estimate $\widehat{\kappa}(s) = \widetilde{\mathrm{N}}$. The noise estimate $\widetilde{\mathrm{N}}$ is generated by an empirical Bayesian backward scatter projection method.

Fig. 1 shows the acquisition part of the approach. This concept makes possible neglecting the inherent dependence 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. For example, if one is assuming a Poisson process the noise model can be written as: $i = s + \kappa(s)$, where i is the observed image, s is the ”source” signal without noise, and the noise function $\kappa(s) \propto \sqrt{s}$. In particular, in the denoising approach, the noise function is modeled by the Nakagami-m [13][6] distribution.

[5] BSS in general is the separation of a set of n statistically independent signals $\boldsymbol{s} = [s_1 \ldots s_n]$ from a set of m observed signals $\boldsymbol{x} = [x_1 \ldots x_m]$, tied together by a mixing matrix $\mathbf{A}$, leading to $\boldsymbol{x} = \mathbf{A}\boldsymbol{s}$

[6] A special type of Gamma distribution, successfully used by others to model scatter data.

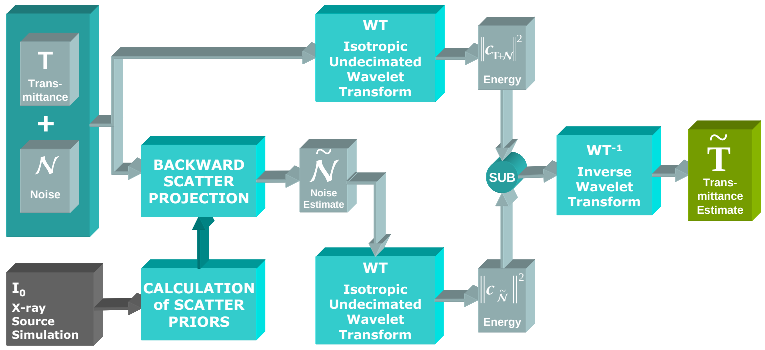

Fig. 2. The subtraction of the noise estimate $\widetilde{N}$ from the diagnostic image mixture by utilizing the conservation of energy within the wavelet space. The model exploits an empirical Bayesian approach for the auto-calculation of the backward scatter projection. The transform used is the isotropic undecimated a-trous wavelet transform.

Stressing Plancherel's Theorem, the energy of the noise estimate is then subtracted from the noisy transmittance[7] image in the wavelet domain (see Fig. 2). The reconstructed estimate of the transmittance $\widetilde{T}$ getting reduced noise by preserving diagnostic details. The result of the noise estimation approach was used by Goebel et. al. in [9] 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 modulation transfer function (MTF) and signal to noise ratio (SNR). Within this paper, the denoising of the real radiographic images is supported by the model.

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. Fig. 3 shows one of the set of test patterns that are duplicated and perturbed by Poisson noise $\widetilde{N}$ to test the behavior of common noise simulation methods.

4 Experimental Results and Evaluation

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).

Fig. 4 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 show-

[7] The transmittance is calculated by the fraction $T = I_2/I_1$, as shown in Fig. 2

Table 1. Comparison of the compression ratio results for five out of fifty real OPT images considering lossless and lossy compression; showing the influence of original noise contribution; and denoised versions 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

ing 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 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

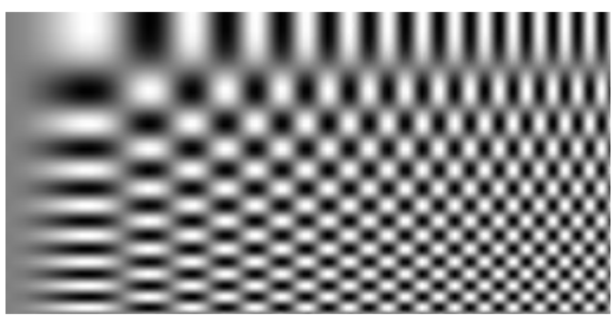

Fig. 3. A synthetic test pattern deployed by sine-wave gratings, which are optimally tuned to the HVS. The test images are perturbed by Poisson noise for the assessment.

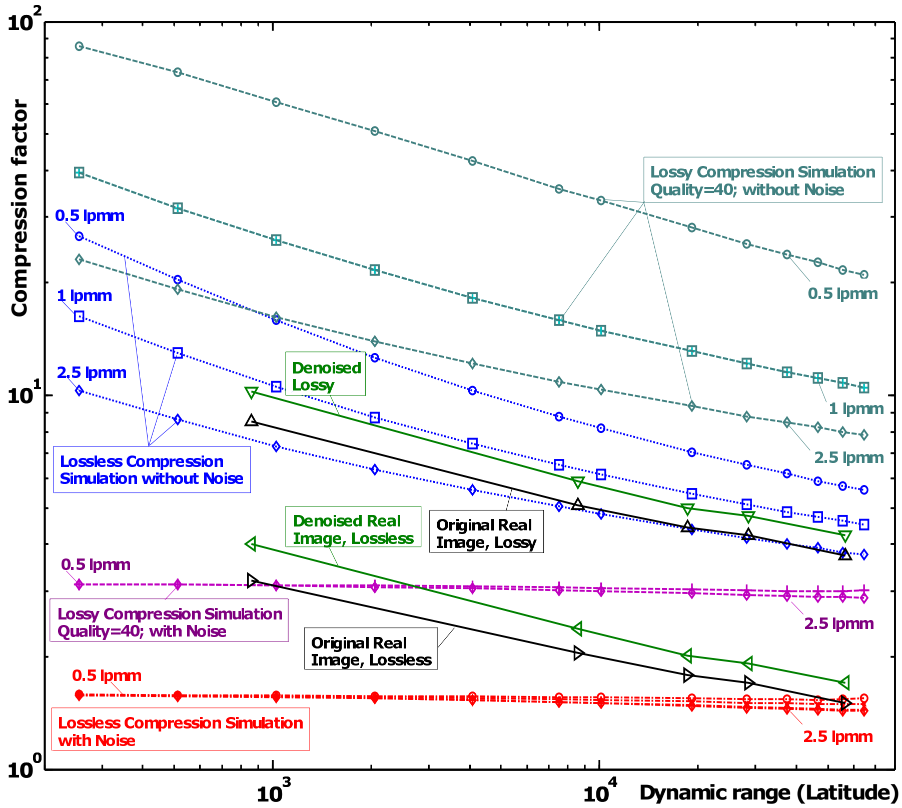

Fig. 4. The dependency of the compression factor on the dynamic range for smooth noisy images. There are four groups, each showing the three lines-per-millimeter frequencies 0.5, 1 and 2.5 lpmm, for lossless, lossy, lossless with noise and lossy with noise images. Additionally, results from the original real radiologic images of Table 1 are shown; performing closely to the noiseless simulation.

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 Conclusion and Outlook

This paper studied the improvment potential of the JPEG 2000 codec performance for medical images while including a denoising process. The additional denoising improved image quality; and the compression perfomance for ≈ 13%.

An improved compression, satisfying legal thoughts by aggressively using the ROI concept in JPEG2000 and a denoising step, seems to have potential for the compres-

Table 2. A comparison of the image quality by MSSIM and PSNR metrics for the real images.

Dyn. Range	Original MSSIM		PSNR	Denoised MSSIM		PSNR
	lossless	lossy	lossy	lossless	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

sion of radiographic images. The scheme can use a noise estimate, exploited by a Monte Carlo simulation for determination of an importance map– as shown in Fig. 5, proposed in [10] – that spatially defines the regions of interest for fidelity compression. The remainder of the image can be compressed more aggressively. In particular for dental use, the importance map can focus on the teeth and their surrounding neighborhoods that having fine detail, rather than other areas.

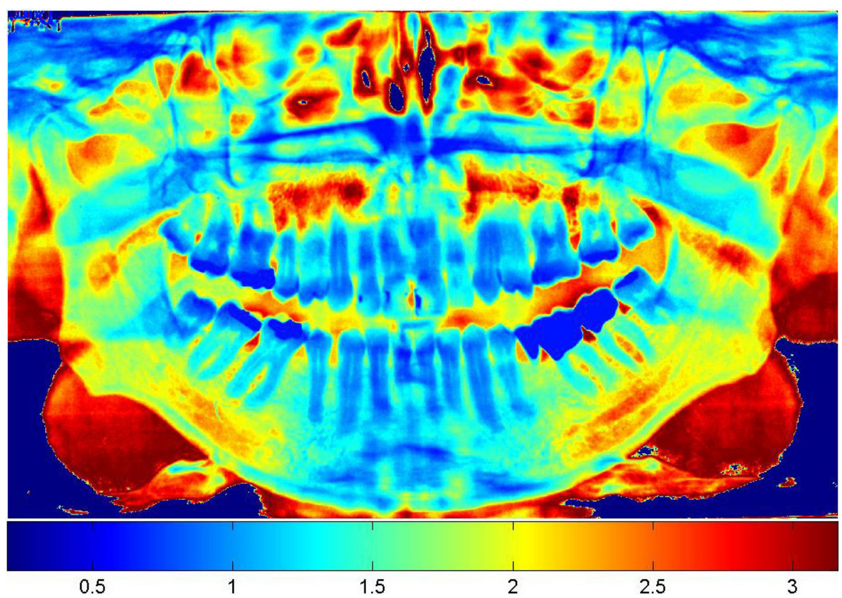

Fig. 5. The dedicated noise coherence factor $\xi(x, y)$ image. In the areas of interest, the factors are below 1, which causes softer denoising.

A combination of a recently proposed hybrid compression scheme by exploiting the Contourlet- and Wavelet-transform [3], may reduce artifacts for the lossy portion of the image furthermore.

As a perspective, this procedure will be validated for mammograms as compression is highly sollicited and the dedicated noise model should be deduced. It is also intended, as a next investigation focus, to improve the JPEG2000 compression, utilizing the hybrid contourlet/wavelet transform [3] and Monte Carlo noise modeling [10].

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