Statistical Characterization of Portal Images and Noise from Portal Imaging Systems

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Abstract In this paper, we consider the statistical characteristics of the so-called portal images, which are acquired prior to the radiotherapy treatment, as well as the noise that present the portal imaging systems, in order to analyze whether the well-known noise and image features in other image modalities, such as natural image, can be found in the portal imaging modality. The study is carried out in the spatial image domain, in the Fourier domain, and finally in the *wavelet* domain. The probability density of the noise in the spatial image domain, the power spectral densities of the image and noise, and the marginal, joint, and conditional statistical distributions of the *wavelet* coefficients are estimated. Moreover, the statistical dependencies between noise and signal are investigated. The obtained results are compared with practical and useful references, like the characteristics of the natural image and the white noise. Finally, we discuss the implication of the results obtained in several noise reduction methods that operate in the *wavelet* domain.

Keywords Portal images · Noise · Portal imaging systems

Introduction

The increasing relevance of imaging techniques in radiotherapy is evidenced by the fact that they are present in

different stages of the treatment process: simulation, planning, and testing prior to final treatment. The accuracy requirements that demand the radiation treatments are rising, because the current trend is aimed to increase the target volume dose, reducing at the same time the radiation dose over the healthy tissue surrounding the target. In order to ensure the accuracy with which the radiation dose is delivered to the various volumes, it is needed to reproduce, during treatment, the geometric conditions used for the treatment simulation.

One of the most widespread methods to guarantee consistency between the simulation conditions and the treatment conditions is to compare images directly acquired by means of the treatment beam (portal images) with synthetic images generated during the simulation phase (digitally reconstructed radiography). In both cases, a radiation beam is used to obtain a transmission image of the patient, similar to a radiography. By matching both images, one can determine if the geometric scenario of treatment agrees with that provided by the treatment simulation.

In addition to portal imaging, there are other methods designed for the purpose of verification prior to treatment, but among all those methods, the portal image has a feature that makes it unique: The treatment beam itself that gives rise to the image formation, so that the agreement between the patient positioning system and the treatment beam is inherent, and consequently no verification is required.

Nowadays, obtaining an image of adequate quality in radiation therapy using the radiation beam itself represents a major technological challenge. The portal image quality is intrinsically bounded by the low contrast and low spatial resolution caused by the use of radiation sources of high energy (photons with energies within the range of megaelectron volts). The limiting factor over the portal images contrast is the dominant type of the radiation–matter interactions at the energy levels used in radiotherapy. X-ray

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Fig. 1 A sample of the images used to investigate the statistical properties of the portal imaging. Above: images of the head (left) and chest (right). Below: images of the pelvis in anteroposterior (left) and lateral (right) projections

attenuation is dominated by the Compton effect, and the probability of Compton interactions is highly dependent on the electron density of the material, unlike what happens with the photoelectric effect, which shows a strong dependence on atomic number. Given that anatomic structures generally show small variations in the electron density; the contrast obtained for the energy levels of therapy is much lower than for the energy levels of diagnostic [1]. The radiation used in radiotherapy has a great ability to penetrate matter. This fact reduces the probability of interaction with the detector, resulting in a poor detection efficiency [2].

On the other hand, the secondary particles created in the detector have a high energy, resulting in a certain range of movement of these particles within the detector, thus leading to an impoverishment of the spatial resolution. Spatial resolution is also affected by the relatively large size of the focal spot of the beam. The relevance of portal imaging in radiotherapy treatments and its common use justify efforts to improve its inherent low quality.

The knowledge of the statistical properties of both image and noise is essential in order to develop suitable processing algorithms. This knowledge may reveal key differences between images and noise in denoising methods, or may guide the design of a priori distributions in Bayesian methods. In the field of medical imaging, wavelets have been used with denoising purposes since 1991 [3]. Moreover, they have also been applied

for image compression, tomographic reconstruction, image enhancement, registration, texture analysis, and segmentation (please refer to [4] for an exhaustive list of research works which use wavelets in different medical image processing scenarios). Since the beginning of the wavelet transform, it has been noticed that wavelet thresholding is of considerable interest in order to remove noise from signals and images. The outcome of this thresholding depends on the existing differences between the marginal distributions of the wavelet coefficients corresponding to signal and noise [5]. Alternative denoising methods which consider joint statistics of the subband coefficients have shown a better performance than those based on the marginal statistics of the wavelet coefficients [6, 7].

There are many cases where the denoising methods take advantage of the underlying statistical characteristics of medical images. In the case of radiographic images, denoising methods using hidden Markov trees exploit the statistical properties of these images in the wavelet domain [8]. More recently, denoising methods based on the statistical properties of images and noise have shown a good performance when dealing with portal images [9]. Finally, it should be noted that denoising methods can also improve detectability in CT images by using total variation principles and curvelets [10].

The aim of this paper is to describe the statistics of the portal image and the noise generated in one of the portal imaging systems most widely deployed. The interest of this

work lies in the importance of such statistical studies in the development of image processing methods such as compression, denoising, and image restoration.

Materials and Methods

Imaging System

The portal imaging system studied is the Portal Vision aS500 from Varian Medical Systems. The aS500 is an amorphous Silicon flat panel detector with an *array* of 384×512 transistors. The pixel size is 0.784×0.784 mm, and the system contains a metal plate and a phosphor screen to convert the X-ray photons into photons in the visible spectrum. The transistors of the *array* transform these photons into an electrical signal. The radiation beams used have a nominal energy of 6MV and are produced by a linear accelerator Clinac 2100 DHX (Varian Medical Systems).

Portal Images

A total of 163 portal images, corresponding to different anatomical locations, were considered to determine the power spectral densities (also called power spectrum) and the *probability density functions* (*pdfs*). Figure 1 contains a sample of these images.

Noise Images

A process of averaging and subtraction of the mean is used to achieve noise images. To study the power spectrum and the *pdf* of noise, a series of uniform images were employed (see Fig. 2a). These images are obtained by irradiating a $30 \times 30 \times 15$ cm methacrylate phantom with a uniform beam. The average of 16 of these images is subtracted from each of them to compute 16 noise images (Fig. 2b).

In order to assess the statistical dependence between signal and noise, a procedure similar to the previously described one is followed but using a wedge phantom. This phantom provides an image with a wide dynamic range, representative of the analyzed portal images (see Fig. 3). In this study, the signal is represented by the average of the phantom images, and noise is represented by the difference between that average and one of the samples. The characteristics investigated are twofold: on one hand, the correlation between the noise mean value and the pixel value, and in other hand, the relationship between the noise variance and the pixel value in the image. This choice is intended to prove the hypothesis of independence between signal and image, a requirement commonly assumed in many image processing algorithms.

Fig. 2 Uniform image and noise image

It is worth noting that the analysis on the statistical dependence between noise and image makes use of two images algebraically related: The average of a series of images stands for the *signal* and, at the same time, appears in the difference calculated to estimate the *noise*. It is therefore necessary to show that this dependence between signal and noise, introduced by the proposed method, is small enough and does not mask the real one that we want to characterize. Starting from the Law of Large Numbers and assuming that every individual image of a set of N uniform images constitutes a realization of an independent and identically distributed stochastic process, the average of these images converges towards the mean or expected value of the stochastic process when N tends towards infinity; this mean coincides with the actual signal image (if the noise mean is assumed to be null), which is statistically independent from noise. In the case of a finite number N of samples, the larger is the N value, the lower is the statistical dependence between the computed average and each particular sample, thus becoming negligible.

Namely, the variance of the estimated noise $\hat{n}$ is related to the variance of actual noise n by

$$\sigma_{\hat{n}}^2 = \frac{N-1}{N} \sigma_n^2.$$

Statistical Characteristics Studied

The analysis of the statistical distributions of image and noise is motivated by the search for characteristics of the signal (anatomical information) at the image that do not appear in the noise. The description of these characteristics is the basis on which many methods of image processing and noise reduction are based. For instance, in Bayesian methods a major key is the choice of the a priori distribution for the signal present in the image. In this context, the knowledge of their statistical characteristics can be valuable information in order to make a more suitable selection of the aforementioned distribution.

The present work studies the power spectrum and the *pdfs* in the *wavelet* domain of both image and noise. The distribution of noise in the image domain is also revised. With regard to the mathematical representation of noise, a classical additive model is considered, that is, an image is given by the addition of a signal plus noise. Besides, assuming a sufficiently stable and uniform behavior of the portal imaging system, the signal and noise may be considered wide sense stationary random processes and the pixel intensity levels identically distributed in both cases. Thus, the power spectrum can be estimated from the two-dimensional spectra of a series of samples by averaging. Also, the *pdfs* can be estimated by normalizing the computed histograms. During the collection of individual spectra, Hamming windows are applied to minimize the distortion caused by the finite extent of the image [11], and, after that, the resulting two-dimensional spectra are radially weighted.

In order to estimate the *pdfs* of wavelet coefficients, the normalized histograms of such coefficients have to be computed previously. The decimated *Haar* transform is chosen, because this transformation has the minimal support among all the *Daubechies* wavelets. Also, *Daubechies* wavelets have a minimal support for a given number of vanishing moments. This aspect gives the *Daubechies* transforms the ability to compress the image information in a low number of coefficients, a very interesting property for image processing. By using a decimated *Haar* transformation, we ensure the conservation of energy in the transform domain, which is necessary for the comparison of image and noise histograms. However, in order to study the statistical dependencies between the wavelet coefficients, an undecimated wavelet transform is preferred, since it keeps constant the number of coefficients between scales. Both intra-band and inter-band statistical dependences are studied.

Fig. 3 **a** One image of a wedge phantom. **b** Average of 30 images of the wedge phantom. **c** Noise image. The noise image is obtained as the difference between the images in **(a)** and **(b)**

Fig. 4 Joint and conditional probability density functions between signal and noise in Fig. 3

Results

Statistical Dependences Between Signal and Noise

Figure 4 shows the joint and conditional *pdfs* of the noise image shown in Fig. 3c and the image representing the signal in Fig. 3b. The only remarkable statistical dependency is the increase in the noise variance as the signal increases. The relationship between the noise mean value and the pixel value can be seen in Fig. 5a, while Fig. 5b shows the relationship between the noise variance (divided by the pixel value) and the pixel value. In this latter figure, the proportionality between noise variance and signal can be noticed. Consequently, it follows that the signal-to-noise ratio is proportional to the signal.

Fig. 5 **a** Noise mean value versus pixel value. **b** Noise variance divided by the pixel value versus pixel value

Marginal Distribution of Noise in the Image Domain

The distribution of noise in the image domain is clearly Gaussian, as shown in Fig. 6.

Marginal Distributions in the Wavelet Domain for Portal Images and Noise

The comparison between the marginal *pdfs* of noise and image, in the wavelet domain, is shown in Fig. 7. This figure represents, on a logarithmic scale, the curves for the experimental *pdfs* of portal images (dashed) and noise (solid line). The coefficients in the first three scales for diagonal, vertical, and horizontal orientations are represented. It can be observed a decrease in the relative importance of noise with increasing scale.

Fig. 6 Normal probability plot for noise values in the image domain

The amplitude of the noise distribution decreases with respect to the amplitude of the image distribution as the scale increases.

The curves for the noise shows a parabolic shape across the different scales, which means that the Gaussian character remains in the transformed domain. On the other hand, the *pdfs* for portal images show large tails.

Statistical Dependence Between the Wavelet Subbands

This section presents the statistical dependencies between subbands in the wavelet decomposition for both image and noise. The results are presented for a particular

Fig. 7 Experimental probability density functions for the distribution of the wavelet coefficients. The first three scales of each orientation are presented for portal images (dashed) and noise (solid line)

orientation and scale; however, it was empirically verified that they are representative of all other relationships between subbands.

Figure 8 shows the joint and conditional probability density functions of the diagonal orientation subband (with scale 2) of the image in Fig. 1a and a spatially shifted version of it. The joint *pdf* shows no correlation between the subbands, but the conditional *pdf* shows another type of statistical dependence. Both for small displacements (one pixel in the horizontal direction and one pixel in the vertical direction) and for larger displacements (five pixels in each direction), the variance of the conditional distribution increases as the value of the conditioning variable increases. In other words, it is more likely to find detail coefficients of large amplitude in the surroundings of detail coefficients of large amplitude.

Figure 9 shows the joint and conditional *pdfs* between two subbands of the wavelet decomposition of the image in Fig. 1a. The *pdfs* show the statistical dependence between subbands with the same orientation but with different scale, and subbands with different orientation but with the same scale. As in the intra-band case, the *pdfs* do not show a correlation between the subbands, but they show the same type of statistical dependence: The variance of the conditional distribution depends on the value of the conditioning variable. Therefore, it is more likely to find detail coefficients of large amplitude in the neighborhood of other detail coefficients of large amplitude, even if both lie on different subbands.

The results obtained in the case of noise were very different. Figure 10 shows the joint and conditional *pdfs*

Fig. 8 Joint and conditional probability density functions for a subband of the wavelet decomposition of the head image in Fig. 1a and the same subband after shifting

for subbands with different scales or different orientations of a noise image. In this figure, no statistical dependences can be appreciated; the results are similar to those expected in the case of white noise. Hence, the noise of portal imaging systems does not show the statistical dependences that are found in other imaging modalities [12] or those found in portal images, which were shown above.

Some statistical characteristics found in the distributions of the image, not present in the noise, reveal important differences in the statistical nature of signal and noise. The

results state that the differences between natural image and white noise are also found between portal images and the noise of portal imaging systems. Historically, these typical differences have allowed the development of efficient methods for noise reduction. In particular, the differences in the shape of the marginal distributions of the wavelet coefficients explains the high performance of noise reduction methods based on thresholding and coefficient contraction [5, 13, 14]. Moreover, the use of a priori probability functions, which reproduce the statistical relationships found between the wavelet subbands, has allowed the design of

Fig. 9 Joint and conditional probability density functions for subbands with different orientation or different scale in the wavelet decomposition of the head image in Fig. 1a

Bayesian methods for image restoration [7] which are recognized among the most efficient at present.

Image and Noise Power Spectra

Figure 11 shows the average power spectra of the portal images analyzed and the average power spectra of noise images.

The noise power spectrum is nearly flat in the decade corresponding to the higher resolution. On the other hand, the portal images spectrum is well approximated by a straight line on the logarithmic representation.

Discussion and Conclusions

As shown in Fig. 4, the noise does not show any correlation with the signal in images, but the noise variance is found to be proportional to the signal amplitude. This feature is expected of a Poisson distribution; we must not forget that the production of photons in the target and the interaction of the particles in the detector are Poisson processes. Furthermore, given the high number of particles and their low probability of interaction, the Poisson distribution can be approximated by a Gaussian distribution.

The Gaussian nature of the distribution of noise in the spatial domain justifies the use of noise reduction methods based on minimizing the Stein's unbiased estimator [15] as has been done in the case of natural images [16–18].

Noise in portal imaging systems resembles the Gaussian white noise. Moreover, this Gaussian behavior holds for

Fig. 11 Power spectra of portal images and noise

noise in the transform domain and represents the first major difference with the case of portal images (see Fig. 7). For portal images, the distribution of the coefficients in the wavelet domain has larger tails than for the noise and is sharper in the vicinity of the distribution center. The importance of the detail coefficients of large amplitude in the image distribution is due to irregularities in the image such as corners, edges, or spikes. The differences found between the distributions of portal images and noise in the portal imaging systems is similar to those found between natural images and Gaussian white noise. Therefore, it is expected that the noise reduction methods based on thresholding of

Fig. 10 Joint (*top row*) and conditional (*bottom row*) probability density functions of two adjacent scales (*left column*) and two different orientations (*right column*) of a noise image

coefficients, very efficient in the case of natural images, are also efficient in the case of portal images.

Figure 10 shows that noise does not present any statistical dependences between scales or orientations. By contrast, in the case of portal images, certain statistical dependences appear (Figs. 8 and 9); the presence of a high amplitude coefficient in a given position increases the likelihood of finding other high amplitude coefficients in the neighborhood of that position. Note that the idea of neighborhood of a coefficient is being used in a wide sense here, because it also considers and includes the spatial surroundings in other scales and other orientations. The aforementioned statistical dependences are also present in natural images and have been investigated [6, 19] for developing Bayesian methods of noise reduction [7].

The noise spectrum is nearly flat in the region of high and medium frequencies (see Fig. 11). In the case of portal images, the average spectrum can be approximated by a straight line in the logarithmic representation, which implies that the spectrum follows a power law $f^{-\alpha}$, where f stands for frequency. The measured slope of this straight line in the logarithmic representation is $\alpha \approx 3.1$. In natural images, the spectrum also follows a power law [20–22], but in this case, $\alpha \approx 2$. As a consequence of this behavior, the energy is equally distributed in octaves, thus leading to a kind of spatial invariance in which objects can appear with equal probability at any scale. In the case of portal imaging, this invariance is lost, since a negative exponent of amplitude greater than two concentrates the image energy in the first octaves of the spectrum. One explanation may be found in the importance of objects such as bony structures or air cavities, taking into account that these relatively large objects concentrate the image contrast. Another explanation is the limited spatial resolution of portal imaging systems.

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