Digital Radiographic Image Denoising Via Wavelet-Based Hidden Markov Model Estimation

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This paper presents a technique for denoising digital radiographic images based upon the wavelet-domain Hidden Markov tree (HMT) model. The method uses the Anscombe's transformation to adjust the original image, corrupted by Poisson noise, to a Gaussian noise model. The image is then decomposed in different subbands of frequency and orientation responses using the dual-tree complex wavelet transform, and the HMT is used to model the marginal distribution of the wavelet coefficients. Two different correction functions were used to shrink the wavelet coefficients. Finally, the modified wavelet coefficients are transformed back into the original domain to get the denoised image. Fifteen radiographic images of extremities along with images of a hand, a line-pair, and contrast-detail phantoms were analyzed. Quantitative and qualitative assessment showed that the proposed algorithm outperforms the traditional Gaussian filter in terms of noise reduction, quality of details, and bone sharpness. In some images, the proposed algorithm introduced some undesirable artifacts near the edges.

KEY WORDS: Medical image denoising, digital radiography, wavelet denoising, hidden Markov model

Digital radiographic images acquired using an optically coupled charge-coupled device (CCD) detector can provide very high detective quantum efficiency (DQE) at low spatial frequencies but fall off at higher frequencies, requiring the use of sharpening algorithms. This inevitably boosts noise which can mask some features. This is often counteracted by using postprocessing sharpening algorithms which unfortunately increase the image noise. In order to minimize the amount of noise introduced in the image by sharpening algorithms, we have developed an algorithm to reduce the noise while keeping important details of the image.

General image denoising techniques based upon the traditional (orthogonal, maximally decimated)

discrete wavelet transform (DWT) have proved to provide the state-of-the-art in denoising performance, in terms of peak signal-to-noise ratio (PSNR), according to many papers presented in the literature.¹⁻³ The basic idea behind this image-denoising approach is to decompose the noisy image by using the wavelet transform, to shrink or keep (by applying a soft or hard thresholding technique) wavelet coefficients which are significant relative to a specific threshold value or the noise variance and to eliminate or suppress insignificant coefficients, as they are more likely related to the noise. The modified coefficients are then transformed back into the original domain in order to get the denoised image.

Despite the high PSNR values, most of these techniques have their visual performance degraded by the introduction of noticeable artifacts which may limit their use in denoising of medical images.⁴ The common cause of artifacts in the traditional wavelet-based denoising techniques is due to the pseudo-Gibbs phenomenon⁵ which is caused by the lack of translation invariance of the wavelet method. Shift variance results from

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the use of critical subsampling (decimation) in the DWT. Because of that, the wavelet coefficients are highly dependent on their location in the subsampling lattice⁶ which affects directly the discrimination of large/small wavelet coefficients, likely related to singularities/nonsingularities, respectively. Although this problem can be avoided by using the undecimated DWT, it is too computationally expensive.

The proposed method for denoising radiographic images, shown in Figure 1, starts by preprocessing the original image using the Anscombe's variance stabilizing transformation, which acts as if the data arose from a Gaussian white noise model.⁷ The image is then decomposed into different subbands of frequency and orientation responses using the overcomplete dual-tree complex wavelet transform (DT-CWT). By using the DT-CWT, the visual artifacts usually present in the image when using the traditional DWT are

significantly minimized,^{8,9} with the advantage of having a task that is still tractable in terms of computation time. The HMT model is used to capture the correlation among the wavelet coefficients by modeling their marginal distribution and thus improving the discrimination between noisy and singularity pixels in an image. Finally, the modified wavelet coefficients are transformed back into the original domain in order to get the denoised image. The efficacy of our method was demonstrated on both phantom and clinical digital radiographic images using quantitative and qualitative evaluation.

MATERIALS AND METHODS

Digital Radiographic System

The digital radiographic (DR) system used in our tests (referred to as XplorerTM system,¹⁰) is an optically coupled

Fig 1. Flow chart of the method proposed for denoising of digital radiographic images.

CCD-based digital radiography unit. It uses a CsI scintillator as the primary x-ray conversion layer and couples the resulting light output to the CCD by a mirror-and-lens system. The 4×4 K CCD is cooled to 263 K resulting in a dark current rate of less than one electron per pixel per second. Images are digitized at 14 bits and subsequently reduced for display to 12 bits. The Nyquist resolution is 4.61 p/mm. System DQE is very high at low frequencies but falls off at higher frequencies, requiring the use of sharpening algorithms. This inevitably boosts noise which can mask some features, hence the current work on wavelet-based denoising.

Hand Phantom and Image Dataset

The hand phantom from Nuclear Associates (Carle Place, NY) illustrated in Figure 2(A) is composed of human skeletal parts embedded in anatomically accurate, tissue-equivalent material. The materials have the same absorption and secondary radiation-emitting characteristics as living tissue. According to Nuclear Associates, all bone marrow has been simulated with tissue-equivalent material, which permits critical detail study of bone structure and sharpness comparisons using x-rays. In this work, the phantom was used to determine the character-

Fig 2. (A) Phantom hand from Nuclear Associates. (B) Radiographic image obtained from the hand phantom with 60 kVp, 3.2 mAs, SID = 100 cm, small focal spot. (C) Clinical radiographic image used in this paper to illustrate the results of the proposed denoising algorithm. The selected box in (C) indicates the region area that will be zoomed in for the sake of better visualization of the details of the denoised images. (D-E) Radiographic images of the line-pair and contrast-detail phantoms, respectively, acquired with 70 kVp, 32 mAs.

istics of the image noise variance and the appropriate image set to be used in the training stage of the HMT model.

In order to assess the improvement in sharpness after denoising the images, a line-pair phantom from Nuclear Associates model 07-5388-1000 with 0.1-mm-thick lead strips and a maximum resolution of 5.0 line pairs per millimeter was used. Improvement in contrast was assessed using the CDRAD contrast detail digital radiography phantom with 225 target squares arranged in a 15×15 grid. In each square one or two holes are present. Holes increase in depth logarithmically in one direction and in diameter in the other direction ranging from 0.3 to 8 mm. The line connecting the central spots with the smallest visible diameter is the contrast detail curve. The phantom images were acquired with 70 kVp and 32 mAs.

A total of 15 single-view radiographic images of lower and upper extremities (hands, feet, wrists, and heels) were analyzed. All images were acquired using the same type of digital radiographic system, described in the "Digital Radiographic System" subsection, with $108 \mu\text{m}$ sampling interval and 14-bits gray-level quantization. The images used in this work were selected to characterize the best and worst quality images in terms of noise level.

Protocol for the Evaluation of Results

The proposed algorithm was evaluated quantitatively measuring the PSNR using digital radiographic images from the phantom illustrated in Figure 1(a) and qualitatively using a set of 15 clinical images.

The PSNR measure is defined as

$$PSNR = 10 \log_{10} \left(\frac{\max(x_{i,j})^2}{\frac{1}{N} \sum_{i,j} (I_{i,j} - \hat{I}_{i,j})^2} \right), \quad (1)$$

where $I_{i,j}$ and $\hat{I}_{i,j}$ are the original and denoised images, respectively. $x_{i,j}$ is the pixel value in the spatial location (i,j) of the original image, and N is the total number of pixels in the image. The PSNR is a scaled measure of the quality of a reconstructed or denoised image. Higher PSNR values indicate good quality resulting images.

The qualitative analysis was assessed according to the opinion of two expert imaging specialists (HA and CT) using a ranking table. All 15 single-view radiographic images were visually inspected on a 21-in. computer monitor. Image intensity histogram equalization¹¹ and image enhancement, using a standard unsharp-mask technique,¹² were used for the sake of better visualization of the denoising results. In addition, each processed image was visually compared to the same original image filtered using the Gaussian filter. The radius size of the Gaussian was changed during the analysis to provide the best tradeoff between sharpness of the bone details and noise reduction. Table 1 was filled out for all 15 images during the assessment of the algorithm.

Noise Modeling and Anscombe's Transformation

In digital radiographic systems there are a variety of imaging noise sources, which originate from the different stages and elements of the system, such as x-ray source, scattered radiation, imaging screen, CCD camera, and electronic circuits among others. The dominant cause of noise, however, is due to the quantum fluctuations in the x-ray beam. In the present work, a preprocessing stage was applied to the acquired images to correct for the impulse noise, CCD dark current noise and pixel nonuniformity.

It is well known that the Poisson distribution can be used to model the arrival of photons and their expression by electron counts on CCD detectors.⁷ Unlike Gaussian noise, Poisson noise is proportional to the underlying signal intensity, which makes separating signal from noise a very difficult task. Besides, well-established methods for image denoising, including the HMT model,¹ are based upon the additive white Gaussian noise model. Therefore, in order to overcome this limitation, we have applied a variance stabilization (Anscombe's) transformation,⁷ described by

$$I_A(x,y) = 2\sqrt{I(x,y) + \frac{3}{8}}, \quad (2)$$

to the original noise image. $I(x,y)$ and $I_A(x,y)$ indicate the original and transformed images, respectively. The Anscombe's transformation acts as if the image data arose from a Gaussian

Table 1. Example of the rank options and image characteristics analyzed which were used by the two imaging specialists to assess the results of the proposed denoising algorithm

Image #	Image characteristics being assessed			
	Noise reduction	Lack of artifacts	Quality of details	Sharpness
Anatomy				
Soft tissue				
Bone details				

The images should be rated according to the following scores:

1. Excellent
2. Good
3. Average
4. Poor
5. Not acceptable

white noise model. More precisely, as the number of photon counts increases, the noise variance in a square-root image tends to a constant, independent of the signal intensity. The inverse Anscombe's transformation is easily obtained by manipulating Equation 2. In order to have a more tractable problem, in this work we are considering that the images are corrupted only by additive Poisson noise. Other sources of noise, including electronic noise normally present in digital radiographic systems, were not taken into account.

Dual-Tree Complex Wavelet

Compared with the DWT, the dual-tree complex wavelet transform is a very attractive technique for medical image denoising because it performs as well as the undecimated DWT, in the context of shift invariance, and with significantly lower computational cost.⁸

The nearly shift invariant property is obtained with a real biorthogonal transform having double the sampling rate at each scale and by computing parallel wavelet trees as illustrated in Figure 3, which are differently subsampled. The DT-CWT presents perfect shift invariance at level 1, and approximate shift invariance, beyond this level. The DT-CWT also presents limited redundancy in the representation (4:1 for the 2D case— independent of the number of scales), good directional selectivity (six oriented subbands: $\pm 15^\circ$, $\pm 45^\circ$, $\pm 75^\circ$), and it permits perfect image reconstruction.

Hidden Markov Tree Model in the Wavelet Domain

The HMT model, applied in the wavelet context,¹ is a statistical model that can be used to capture statistical

correlations between the magnitudes of wavelet coefficients across consecutive scales of resolution. The HMT works by modeling the following three important properties of the wavelet coefficients:

- **Non-Gaussian distribution:** The marginal distribution of the magnitude of the complex wavelet coefficients can be well modeled by using a mixture of two-state Rayleigh distributions. The choice for using the Rayleigh mixture model instead of the Gaussian mixture model was based upon the fact that the real and imaginary parts of the complex wavelet coefficients may be slightly correlated, and therefore only the magnitudes of the complex wavelet coefficients will present a nearly shift-invariant property, but not the phase.⁹
- **Persistency:** Large/small wavelet coefficients related to pixels in the image tend to propagate through scales of the quad trees. Therefore, a state variable is defined for each wavelet coefficient that associates the coefficient with one of the two Rayleigh marginal distributions [one with small (S) and the other with large (L) variance]. The HMT model is then constructed by connecting the state variables (L and S) across scales using the Expectation–Maximization (EM) algorithm. Figure 4 shows the 1D structure of the HMT model.
- **Clustering:** Adjacent wavelet coefficients of a particular large/small coefficient are very likely to share the same state (large/small).

The HMT model is parameterized¹ by the conditional probability stating that the variable S_j is in state m given $S_{\rho(j)}$ is in state n , or, $\varepsilon_{j,\rho(j)}^{m,n} = p(S_j = m | S_{\rho(j)} = n)$ $m, n = 1, \dots, 2$. The state probability of the root J is indicated by $p_{S,J}(m) = p(S_j = m)$ and the Rayleigh mixture parameters as $\mu_{j,m}$ and $\sigma_{j,m}^2$. The value of $\mu_{j,m}$ is set to zero because the real and imaginary

Fig 3. Schematic of the dual-tree complex wavelet transform. (Figure provided by Dr. Kingsbury.⁸)

Fig 4. 1D tree structure graph for the dependencies of the Hidden Markov tree model. Three levels are illustrated. The trees for the two internal wavelet coefficients in level $J + 1$ are not shown for the sake of better visualization.

parts of the complex wavelet coefficients must have zero means (wavelets have zero gain at dc). $\sigma_{j,m}^2$ is the variance. The parameters, grouped into a vector $\theta = \{p_{SJ}(m), \varepsilon_{j,\rho(j)}^{m,n}, \sigma_{j,m}^2\}$, are determined by the EM algorithm proposed in Ref. 1. Herein, we assume that the complex wavelet coefficients w_j follow one of the two-state Rayleigh distributions as

$$f(w_{j,m} | \sigma_{j,m}^2) = \frac{w_{j,m}^2}{\sigma_{j,m}^2} \exp\left(-\frac{w_{j,m}^2}{2\sigma_{j,m}^2}\right), \quad m = 1, 2. \quad (3)$$

In order to have a more reliable and robust (not biased) parameter estimation, the HMT model was simplified by assuming that all the wavelet coefficients and state variables within a particular level of a subband have identical parent-child relationships. Therefore, each of the six image subbands obtained by using the DT-CWT was trained independently and hence presents its own set of parameters. The magnitude of the complex wavelet coefficients for each subband was modeled by the resulting mixture model

$$P(w_{j,m}) = \sum_{m=1,2} p_{SJ}(m) f(w_{j,m} | \sigma_{j,m}^2). \quad (4)$$

To take into account the dependencies among the wavelet coefficients of different scales, a tree graph representing a parent-child relationship is used (Figure 4). The transition of a specific wavelet coefficient j between two consecutive levels in the tree is specified by the conditional probability $\varepsilon_{j,\rho(j)}^{m,n}$. The algorithm for training the HMT model is provided in Ref. 1.

Training of the HMT Model

The main goal of the training stage is to find the correlation among the wavelet coefficients through the scales. Based upon experimental analysis and also in a practical laboratory experiment using the hand phantom object, we have verified that the best set of images to be used in the training stage of the

HMT model should have the lowest level of noise and present enough image structure.

To validate the above statement, the hand phantom was imaged with different radiation levels, according to the parameters kVp and mAs as indicated in Table 2, given a set of five images with different SNR values. The images were used in turn to train five models. The images were then processed and the PSNR was recorded for further evaluation. The results of the experiment are described in the “Results” section.

Selection of the clinical radiographic images used in the training of the HMT model was conducted by using a set of representative images (outside of the testing image set) of each anatomy being studied (hand, foot, wrist, and heel). A HMT model was estimated for each specific anatomy. The images were visually chosen based on the level of noise and amount of bone details. Images with lower level of noise and richer in bone details were given preference.

Noise variance estimation

Estimation of the noise variance is an important step in our image-denoising algorithm as it is used directly, along with the

Table 2. Parameters of the x-ray tube used in the experiment with the hand phantom shown in Fig. 2. In this experiment, the SID was set to 100 cm and the small focal spot was used. Except for the last set of parameters, the others are default values used in clinical application

Image	kVp	mAs	Type of patient usually applicable
1	60	2.5	Pediatric
2	60	3.2	Normal/medium
3	60	4.0	Large
4	60	20	Very high dose—NOT applicable

HMT parameters, in our wavelet-based filtering procedure. In the present work, the noise variance was estimated as

$$\sigma_n^2 = \sqrt{\sigma_{\text{real}}^2 \times \sigma_{\text{imaginary}}^2}, \quad (5)$$

where σ_{real}^2 and $\sigma_{\text{imaginary}}^2$ are, respectively, the noise variance of the real and imaginary parts of the wavelet coefficients computed by using the median absolute deviation (MAD,¹³) algorithm.

Denoising Using the HMT

The denoising procedure proposed in this work is composed of two shrinkage procedures: one is used for levels 1 and 2, and the other for the subsequent levels. The rationality of this strategy is related to the fact that the DT-CWT provides perfect shift invariance only at level 1, and approximate shift invariance for the other levels. Because of that, the capture of the inter-scale dependencies among the wavelet coefficients using the HMT model starts to become unreliable beyond level 2 or 3, due to the considerable image energy variation.

For the first two levels of decomposition, the conditional mean estimation of the noise-free wavelet coefficient was obtained using

$$\hat{w}_j = E[w_j|\theta] = \sum_j p(S_j = m|w_j, \theta) \frac{\sigma_{j,m}^2}{\sigma_{j,m}^2 + \sigma_n^2} w_j, \quad (6)$$

where $p(S_j = m|w_j, \theta)$ is the probability of state m given the noise wavelet coefficient w_j and the model parameters θ computed by the EM algorithm. σ_n^2 is the variance of the additive white Gaussian noise and $E[\cdot]$ is the expectation operator.

As the estimation of the subband variances $\sigma_{j,m}^2$ in the HMT model is performed using noise wavelet coefficients, their values are biased and should be corrected. The corrected estimation is then obtained by

$$\sigma_{j,m}^2 = \begin{cases} \sigma_{j,m}^2 - \sigma_n^2, & \text{if } \sigma_{j,m}^2 > \sigma_n^2 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

After level 2, a modified version of the soft-threshold procedure proposed in Ref. 14 was used to find the shrinkage factor

$$c_j = \frac{\text{sigm}[S(\|w_j\| - T)] - \text{sigm}[-S(\|w_j\| + T)]}{\text{sigm}\{S[\max(\|w_j\|) - T]\} - \text{sigm}\{-S[\max(\|w_j\|) + T]\}} \quad (8)$$

which is applied to the real and imaginary parts of the complex wavelet coefficient w_j . In the above equation, $\text{sigm}(y) = \frac{1}{1+e^{-y}}$ is the sigma function, S is an enhancement factor, and $T = \sigma_n/\beta$ is a threshold value. β is considered as a smoothing parameter. In the present work the default values of S and β were set to 1.3 and 0.9, respectively.

RESULTS AND DISCUSSIONS

Figure 5 shows the results of the experiment carried out to determine the relation between the

radiation dose and the algorithm performance, in terms of PSNR. The results were used to confirm that a high-quality image (the one obtained with a high x-ray dose, 60 kVp and 20 mAs) is in fact the best option to be used in the training of the HMT model. By analyzing the average PSNR values, we noticed that image 3 (obtained with 60 kVp and 4.0 mAs) provides the second best average result. The worst choice would be image 1, acquired with 60 kVp and 2.5 mAs. Despite the difference in the average values shown in Figure 5, and except for image 4, the PSNR values obtained by using different training images were very similar. The x-ray tube parameters used in the experiment are shown in Table 2.

Figure 6 shows the results of the two-state Rayleigh mixture model fitting the marginal distribution of the wavelet coefficients for the first four consecutive levels (1 to 4) of the image in Figure 2(C). Visual inspection indicates the good curve fitting provided by the Rayleigh function. Due to the high image energy concentration around magnitude 0.25 in Figure 6(A)–(B), application of a simple threshold technique to differentiate large/small values of wavelet coefficients, probably would not produce good results. Indeed, HMT-based denoising algorithms usually outperform standard thresholding techniques because the degree of coefficient shrinkage is determined based not only upon the value of the coefficient but also upon its relationship with its neighbors across scales (quad-tree relationship).

Figure 7 shows the line-pair phantom images denoised by using our proposed algorithm with

Fig 5. PSNR values resulting from the processing of the four phantom images acquired using different exposure levels. Each image was used in turn to train a HMT model. Afterwards, the estimated HMT models were used in the denoising algorithm. The PSNR average values from columns 1 to 4 in the attached table are 25.59, 22.64, 22.59, and 22.65, respectively.

Fig 6. Example of two-state Rayleigh mixture marginal distributions used to model the wavelet coefficients. The densities summation and the histograms of the wavelet coefficients are also shown. Plots were obtained for the first four levels (A-D); subbands with orientation 0° .

two levels of denoising and by using a Gaussian filter with radius size of two pixels. In the original image [Fig 2(D)], the sharpness of the edges can be visually assessed up to 3.4 or 3.7 lp/mm. In fact, visual inspection of this line-pair phantom image in a computer monitor can provide up to 4.6 lp/mm using the system described in the “Digital Radiographic System” subsection. However, a noticeable amount of quantum noise can be observed through the whole image. Figure 7(A) shows the processed image using our proposed algorithm. The amount of noise present in the original line-pair phantom image was reduced significantly. A noticeable improvement in sharpness can also be visually assessed which is confirmed by the high PSNR value (Table 3). In this case, visual differences between the small edges can be noticed only up to 3.1 lp/mm due to

the blurring effect caused by noise removal. Visible structured artifacts can be seen closer to the strong edges of the phantom. Because of the regular pattern characteristic of the artifacts introduced in the image, we argue that they may be acceptable in visual analysis of radiographic images providing a significant reduction in quantum noise and improvement in sharpness. The image resulting from the Gaussian filtering is shown in Figure 7(C). Although the noise level was considerably reduced without creating any visible artifact, all the small edge details were smoothed out. The visual differences between the edges can only be seen up to 2.2 or 2.5 lp/mm. In this case, the computed PSNR values were 32.23 and 31.58, respectively. Figures 7(B) and (D) show the image differences resulting from the subtraction of the original image and the denoised image.

Fig 8. Assessment of image contrast using contrast-detail curves. (A–C) Curves obtained using the proposed technique (with two, three, and four levels of denoising, respectively) and using Gaussian filter (with kernel sizes of 2, 3, and 4 pixels, respectively).

Fig 9. Radiographic hand image shown in Figure 2(C) denoised by using the proposed technique with different levels: (A) two levels, (B) three levels, and (C) four levels of denoising.

Comparing these two images, we can easily confirm that our proposed algorithm can keep much more of the fine details from the original image than the Gaussian smoothing method.

Modification in the visual contrast was also assessed by using the contrast-detail phantom image illustrated in Figure 2(E). The denoised images resulting from applying our proposed algorithm and the Gaussian smoothing to the contrast-detail phantom were visually evaluated and the respective contrast curves were obtained as illustrated in Figure 8(A)–(C). All three plots [Fig 8(A)–(C)] show a slight improvement in the image contrast using the proposed algorithm. Herein, we would like to mention that the proposed technique was not designed to improve the contrast of the image but only reduce the

quantum noise. We believe that introducing small changes in the algorithm can improve even more the image contrast. The best result in terms of contrast improvement was obtained by using the proposed technique with four levels of denoising [see Figure 8(C)].

For the sake of comparison, Figures 9 and 11 show examples of the radiographic hand image in Figure 2(C) denoised by using the proposed technique with different levels of denoising and the Gaussian filter with different kernel sizes. The granular appearance of the images in Figures 9(A) and 11(A) is typical of images corrupted by quantum noise. In these cases, the Gaussian filter and the proposed algorithm using two levels of

Fig 10. Radiographic hand image shown in Figure 2(C) denoised by using the isotropic Gaussian filter with different radius sizes: (A–C) radius sizes equal to 2, 3, and 4 pixels, respectively.

Fig 11. Image differences computed between the original and the denoised images using the proposed technique with different levels: (A) two levels, (B) three levels, and (C) four levels of denoising.

denoising were not efficient in removing the noise. A huge improvement in reducing the quantum noise, however, is demonstrated in Figures 9(B) and (C). The soft tissue is very clean and smooth compared to the results of the Gaussian filter in Figures 11(B) and (C). On the other hand, the amount of artifacts introduced close to the strong edges (especially in the boundaries of the metacarpals hand long bones) becomes more noticeable, compared to the results of the Gaussian filter. In general, the edge details are clearer and crisper in the images processed using the proposed technique and an improvement in the overall perceived image sharpness can also be noticed [see Figures 9(B) and (C) and Figures

11(B) and (C) for comparison]. The improvement in image sharpness is due to the fact that our proposed method treats differently soft tissue regions and regions presenting fine bone details. This fact can be noticed by comparing Figures 10(A)–(C) and 12(A)–(C). These image differences show that the proposed method can remove the noise without removing the small bone details from the image which are of great importance for diagnostic purposes.

The results obtained from the denoising of the 15 clinical digital radiographs were analyzed according to the protocol described in the “Protocol for the Evaluation of Results” subsection and are shown in Figure 13. In Figure 13(A),

Fig 12. Image differences computed between the original and the denoised images using the isotropic Gaussian filter with different radius sizes: (A–C) radius sizes equal to 2, 3, and 4 pixels, respectively.

Fig 13. Average results of the qualitative assessment of the proposed denoising algorithm performed by the two imaging specialists. The plots also provide a comparison with denoising using Gaussian filter. The assessment included analysis of noise reduction (A), analysis of artifacts (B), quality of details (C), and analysis of bone sharpness (D).

we can confirm the excellent performance of the algorithm, using two and four levels, in reducing the noise of both soft tissue and bone. As pointed out by the two specialists who analyzed the images, the algorithm was able to remove the quantum noise with great success. Despite the good performance in noise reduction, the proposed algorithm presented a poorer performance with regard to artifacts, when using four level of denoising, according to Figure 13(B). Artifacts are mostly caused by the pseudo-Gibbs phenomenon appearing near strong edges. This undesirable effect becomes predominant as the number of denoised scales increases. The proposed algorithm also scored well on overall quality of details after denoising, as can be seen in Figure 13(C). The bone sharpness was also preserved when compared to the Gaussian filter in Figure 13(D). Except for the presence of artifacts, the proposed denoising algorithm using four-level denoising presented better performance than the same method using two-level denoising or the Gaussian filter.

Finally, Table 3 shows the PSNR values computed for the phantoms and hand images. For all cases the proposed algorithm presented higher PSNR values compared to the Gaussian filter method.

CONCLUSION

In this paper, we present a method for denoising of digital radiographic images. Although the preliminary results have shown to be very promising, a more extensive evaluation of the algorithm should be carried out by a panel of radiologists. Also, investigation of directional response information provided by the DT-CWT and reduction of artifacts by using penalized reconstruction of the wavelet coefficients is under way. As the main idea of our proposed algorithm is based on modeling the wavelet coefficient associated with edges in an image, by reducing the noise level in the soft tissue while keeping the sharpness of the edges,

we expect an improvement in the detection of small bone fractures. Application to musculoskeletal images in which the noise level may not be the confounding factor in conspicuity of image features, but lack of adequate depiction of fine details, may benefit from the application of our proposed method.

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