4-5-2010

Denoising of x-ray imagery with spatially-varying estimates of noise variance

Samuel Peter Kozaitis

Denoising of x-ray imagery with spatially-varying estimates of noise variance

S. P. Kozaitis
Department of Electrical and Computer Engineering
Florida Institute of Technology
150 W. University Blvd.
Melbourne, FL 32901
kozaitis@fit.edu

ABSTRACT

We described a way to use a block-matching 3-D denoising algorithm to reduce noise in x-ray imagery. We first filtered an image multiple times using different estimates of the noise variance. From a simple estimate of the denoised image, we then estimated the noise variance at each pixel of the image. Using this approach, we obtained improved results when compared to using a single value of estimate for the noise variance. Even a small number of quantization levels of the estimates of the noise showed improved results.

Keywords: block-matching, denoising, intensity-dependent noise, medical imagery

1 INTRODUCTION

Although many denoising methods have been developed for additive white Gaussian noise with a constant variance, such methods may not be optimum for medical imagery. Noise in medical imagery may not have a Gaussian distribution or a constant variance. For example, noise in MRI imagery was found to follow a Rician distribution and in x-ray imagery a Poisson distribution.[1,2] Noise in CT imagery was found to follow a nonstationary Gaussian distribution which is sometimes used to approximate noise in other medical imagery.[3] In spite of this, denoising methods have been used successfully to reduce noise in a variety of imagery. Many methods have been based on the wavelet transform which often compacts signals more efficiently than noise. Using thresholding based on different criteria, many approaches have been developed. For example, based on the assumptions of additive Gaussian white noise with zero mean and that white noise under any orthogonal transform is still white noise, a constant threshold can be used on wavelet coefficients to reduce noise.[4] Such an approach can tend to overly smooth signals, so a hybrid of this method and Stein's unbiased risk estimate was developed.[5] Another approach developed for imagery relies on data-driven parameters in a Bayesian framework by assuming wavelet coefficients in each subband can be described by a generalized Gaussain distribution.[6] A local adaptive algorithm using a bivariate shrinkage function based on the statistical dependence among wavelet coefficients has also proven successful.[7] Using third-order correlation coefficients of wavelet-signal correlations has also been useful to identify if a wavelet coefficient contains mostly noise.[8] Another successful approach is based on a statistical model of transform coefficients of an overcomplete mulitscale oriented basis where neighborhoods of coefficients at adjacent positions and scales are modeled as the product of two independent random variables.[9] Considering efficient transforms and manipulating their coefficients has led to some useful denoising algorithms.

Some recent approaches deal more with the spatial domain and have been even more successful. The non-local means algorithm performs a weighted average of the values of similar pixels, which is defined as the Euclidean distance between rectangular neighborhoods.[10] A more general similarity criterion has been proposed for this approach that depends on a noise distribution model.[11] Similarly, a non-local method for Rician noise reduction in magnetic resonance images has been proposed.[12] A different but very successful approach to denoising uses block-

Independent Component Analyses, Wavelets, Neural Networks, Biosystems, and Nanoengineering VIII, edited by Harold H. Szu, F. Jack Agee, Proc. of SPIE Vol. 7703, 77030V · © 2010 SPIE · CCC code: 0277-786X/10/$18 · doi: 10.1117/12.850791

matching of image regions. In this approach, similar non-local image patches are grouped together, and a 3-D transform of each group of patches is denoised.[13] We used this approach for denoising x-ray imagery and used a spatially-varying estimate of the noise variance. The variance is used to adjust the amount of denoising across the image. We describe our approach in the next section followed by results on x-ray imagery.

2 DENOISING OF MEDICAL IMAGERY

The block-matching 3-D (BM3D) approach relies on both local and non-local characteristics of an image by initially grouping similar patches or blocks in an image. Then, each group of blocks is represented by a sparse 3-D transform and a denoising is approach applied.[13] The image blocks can be square or adaptively-shaped. In addition, similar blocks can be found and an adaptively-shaped neighborhood can be extracted. A denoising method or Wiener filter is used on the 3-D spectrum to reduce noise, and then the 3-D data is inversely transformed. Finally, the estimated blocks are returned to their original locations. This method of grouping small image blocks is effective due to its sparse representation in the 3-D domain. Because of the small size of the image blocks, noise with a constant variance may be a valid assumption. However, we used different variances for different blocks.

The noise variance is an important parameter in the BM3D algorithm. It affects the amount of denoising in the individual groups of image blocks. Typically, a single value is used for an entire image. We produced a noisy image $f_n(x,y)$ from one without noise $f(x,y)$ according to

$$f_n(x,y) = f(x,y) + \beta f(x,y) n(x,y), \tag{1}$$

where $n(x,y)$ was a Gaussian-distributed noise image with variance β. Using Eq. (1) adds nonstationary Gaussian noise that is dependent on the value of the original image. When using a single threshold, we used the product of β and the mean value of the image as the estimate of the noise variance in an image. We also considered different values of the variance that was dependent on the local intensity of an image. For example, we filtered the noisy image with a 3 x 3 uniform filter and used the resulting image $g(x,y)$ for estimates of the local variance.

Using local estimates of the variances allowed the determination of the values in the denoised image. To determine the value of a particular pixel in the denoised image, we first filtered the noisy image using the BM3D approach multiple times with different values of variance. For example, if we considered n different values of the variance, we filtered the noisy image n times using a different estimate of the variance each time. The n estimates of the variance were $\sigma^2 = hs$, with $h = \{1, 2, \ldots n\}$ where

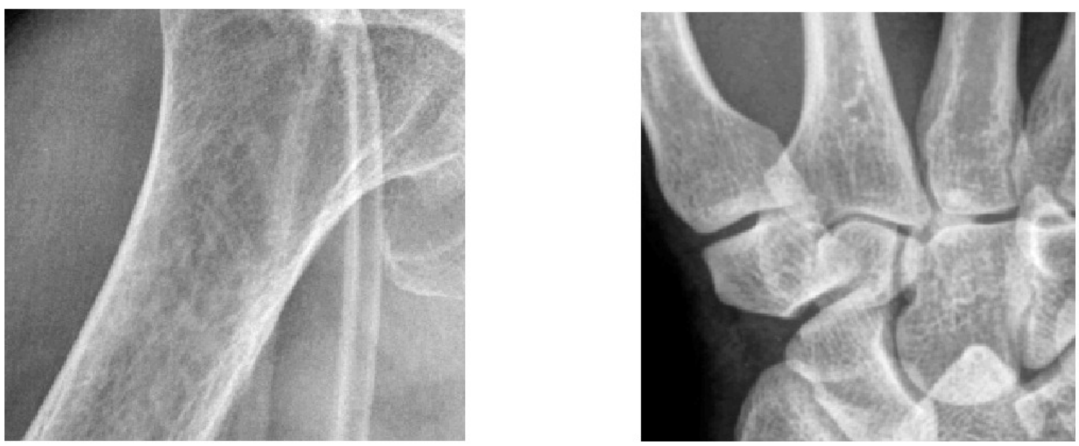
$$s = \beta L/n, \tag{2}$$

and L was the maximum value of noise-free image. The image $g(x,y)$ was quantized into n levels, and based on the quantized levels, the value of the denoised image at each (x,y) was chosen from one of the images filtered with the BM3D algorithm. This way a variance estimate was use for each pixel in $f_n(x,y)$.

3 RESULTS

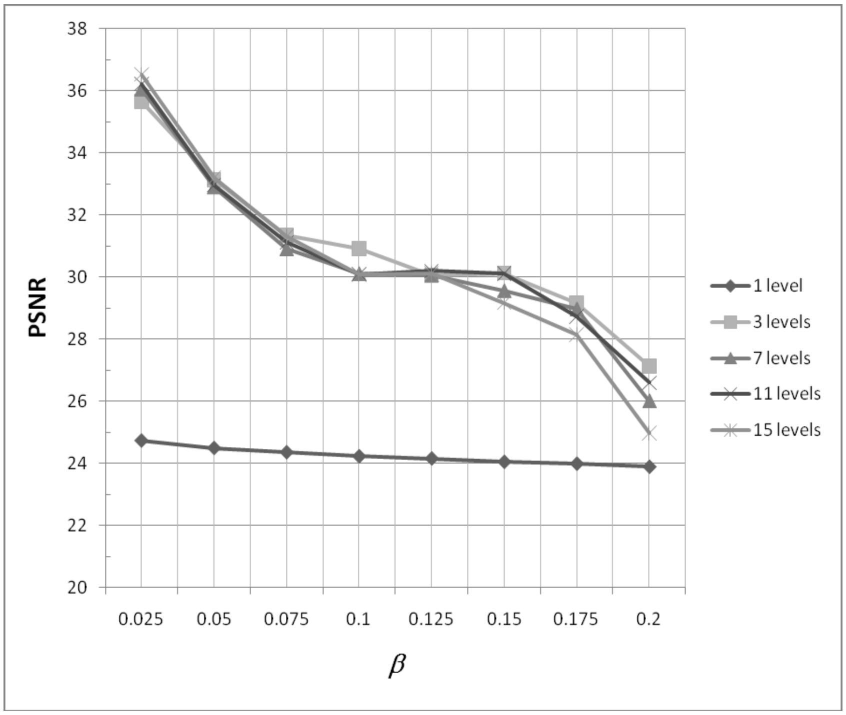
We used two different 256 x 256 pixel x-ray images shown in Fig. 1 in our experiments. In addition, we used a single value for the estimate of the variance as described earlier, as well as spatially-varying estimates based on the results of a low-pass filter. The estimates for the variance in this case were quantized to 3, 7, 11, and 15 levels. The input and output images were normalized to values between 0 and 1, and the peak signal-to-noise ratio

(PSNR) was used as a measure of performance. The PSNR was expressed in decibels as PSNR= 10log(1/MSE), where the MSE is the mean-squared error between $f(x,y)$ and the denoised output image. The PSRNR results as a function of β are shown in Fig. 2. For both images, the results show that the spatially-varying estimate of variance improved the PSNR for all values of β. In addition, the difference in PSNR values for most different levels of quantization of the variance estimates was small. At small values of β, the largest values of quantization gave the best results. However, this was not necessarily true as β increased. Furthermore, at small values of β, there were large differences between the PSNR for single and multiple-levels of quantization. As β increased, the difference became smaller. This is to be expected as eventually the images will become mostly noise and it will be difficult to reduce noise. Finally, as β increased the PSNR decreased only slightly, while the results for multiple levels showed a more profound decrease.

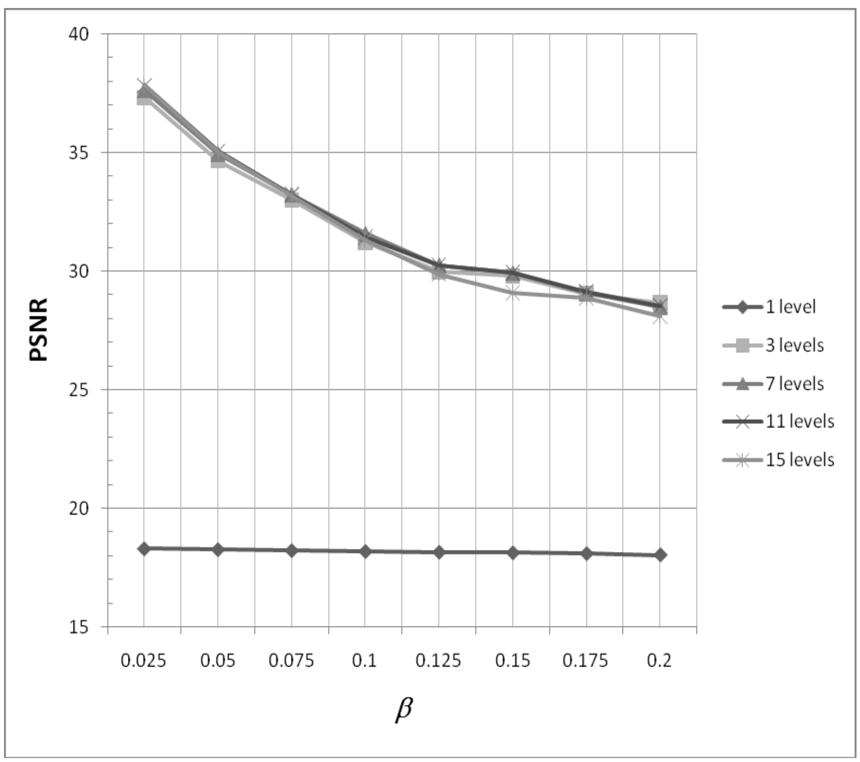


(a) (b)

Figure 1 Examples of x-ray images used in experiments.

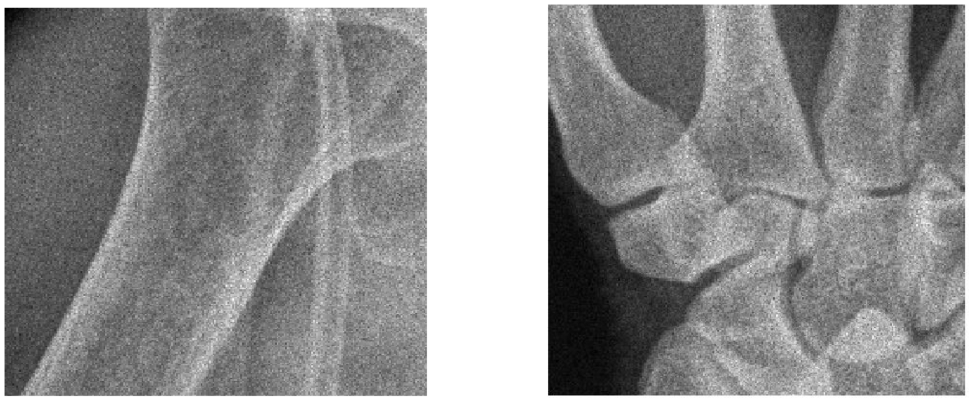


(a)

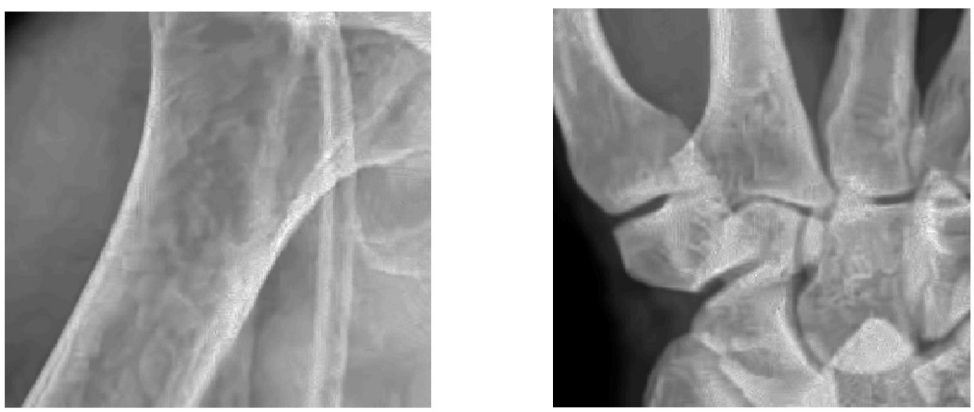


(b)

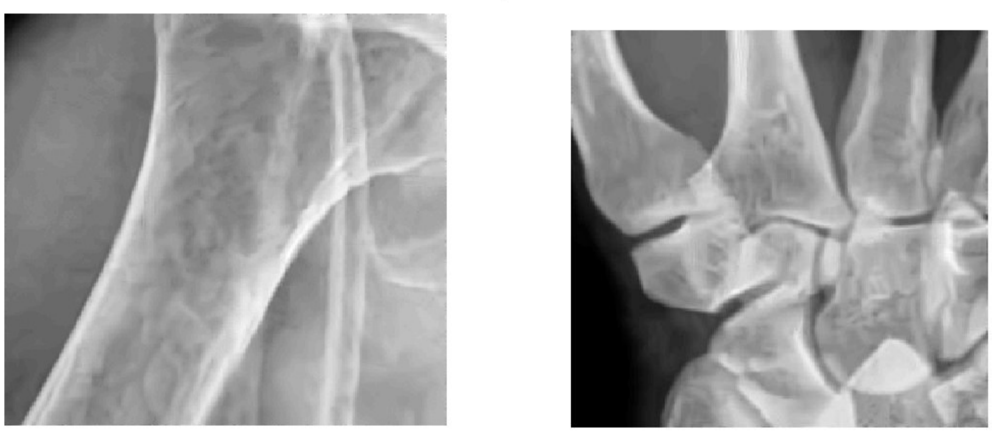
Figure 2 PSNR as a function of b for the variance quantized to various levels (a) results for Fig. 1(a) (b) results for Fig. 1(b).



(a)

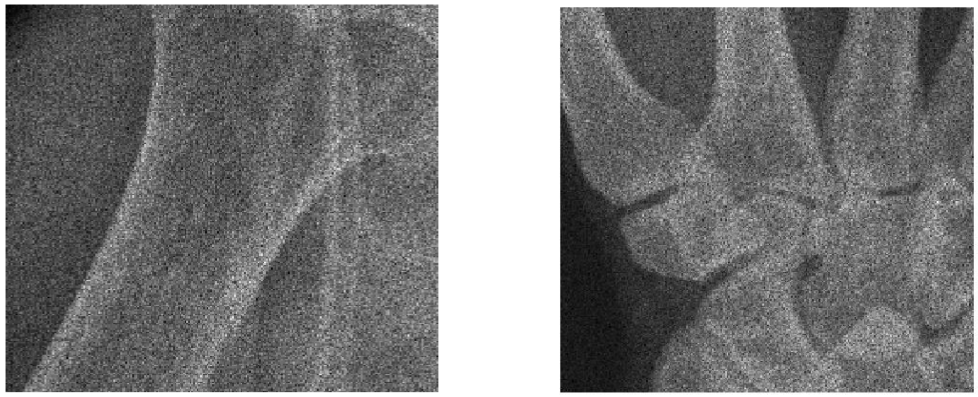


(b)

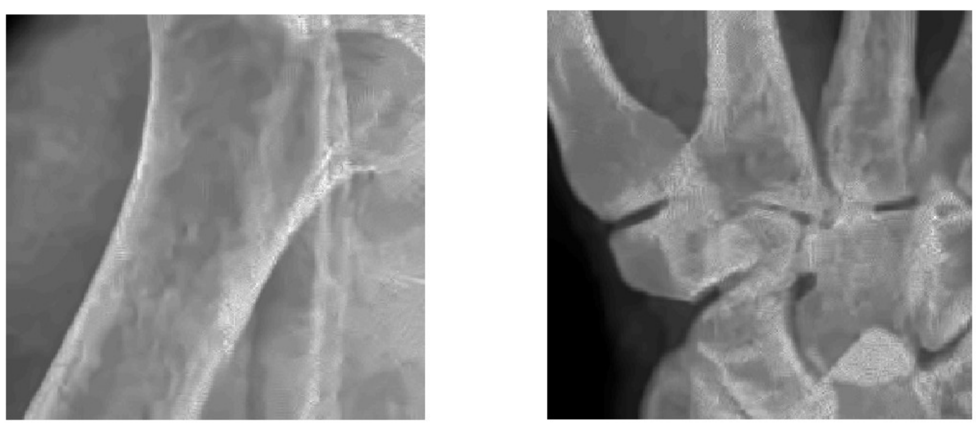


(c)

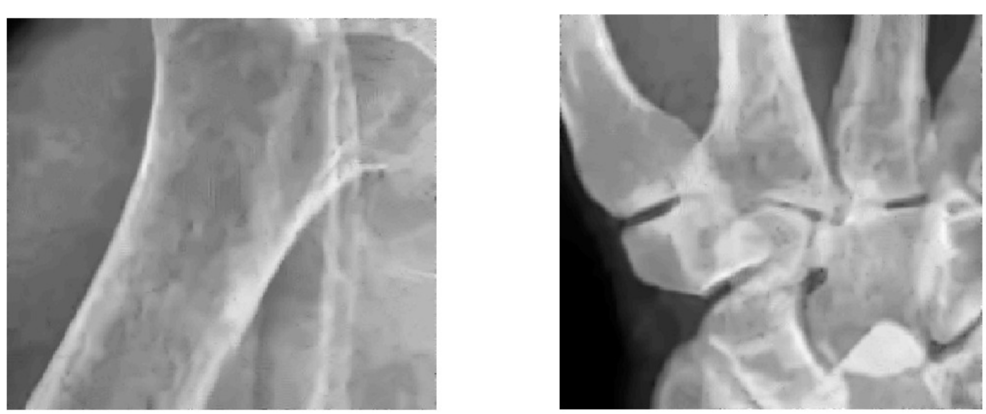
Figure 3 Results of denoising experiments for images in Fig. 1 (a) noisy images with $\beta = 0.1$ (b) denoised results using a single value of variance (c) denoised results using seven levels of variance that are spatially-varying.



(a)



(b)



(c)

Figure 4 Results of denoising experiments for images in Fig. 1 (a) noisy images with $\beta = 02$ (b) denoised results using a single value of variance (c) denoised results using seven levels of variance that are spatially-varying.

4 CONCLUSION

We found that using multiple estimates of the noise variance led to improved performance of removing noise from x-ray imagery using a block-matching 3-D algorithm. The variances were primarily based on intensity values and even simple estimates showed improved results when compared to using a single value. Using a small number of levels, such as three, improved results significantly. Larger values of quantization did not show much improved performance. However, a better estimate for the true intensity value in an image may improve results.

5 REFERENCES

[1] H. Gudbjartsson, and S. Patz, "The Rician distribution of noisy MRI data," *Magn. Reson. Med*., 34, 910-914 (1994).

[2] P. Gravel, G. Beaudoin, and J. A. DeGuise, "A method for modeling noise in medical images," *IEEE Trans. Med. Imag*., 23, 1221-1232 (2004).

[3] T. Lei, and W. Sewchand, "Statistical approach to X-ray CT imaging and its applications in image analysis – Part I: Statistical analysis of X-ray CT imaging," *IEEE Trans. Med. Imag*., 11, (1992).

[4] D. L. Donoho, and I. M. Johnstone,."Ideal spatial adaptiation via wavelet shrinkage," *Biometrika.*, 81, 425-455 (1994).

[5] D. L. Donoho and I. M. Johnstone, "Adapting to Unknown Smoothness via Wavelet Shrinkage," *J. Amer. Stat.Assoc.*, 90(432), 1200–1224 (1995).

[6] S. G. Chang, B. Yu, and M. Vetterli, "Adaptive wavelet thresholding for image denoising and compression," *IEEE Trans. Image Proc*., 9(9), (2000).

[7] L. Sendur, and I. W. Selesnick "Bivariate shrinkage with local variance estimation," *IEEE Sig. Proc. Lett*., 9(12), (2002).

[8] S. P. Kozaitis, and S. Kim, "Denoising using higher-order statistics," in *Independent Component Analysis, Wavelets, and Neural Networks*, T. Bell, M. V. Wickerhauser, H. H. Szu, Eds., Proc. SPIE 5102, paper 6 (2003).

[9] J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, "Image denoising using scale mixture of Gaussians in the wavelet domain," *IEEE Trans. Imag. Proc*., 12(11), 1338-1351 (2003).

[10] A. Buades, B. Coll, and J. Morel, "A non-local algorithm for image denoising," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2005*, 2, (2005).

[11] C. A. Deladalle, L. Denis, and F. Tupin, "Iterative weighted maximum likelihood denoising with probalistic patch-based weights," *IEEE Trans. Image Proc*., 18(12), (2009).

[12] L. He, and R. Greenshields, "A nonlocal maximum likelihood estimation method for Rician noise reduction in MR images," *IEEE Trans. Med. Imag.*, 28(2), (2009).

[13] K. A. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian,."Image denoising by sparse 3D transform-domain collaborative filtering," *IEEE Trans. on Imag. Proc.*, 16(8), 2080 – 2095 (2007).