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ABSTRACT

We used a 3-D wavelet denoising method to reduce noise from multispectral imagery so that small objects may be more readily detected. Our approach exploits the correlation between bands typically present in multispectral imagery. Using our approach, the resulting image generally consists of a weighted sum of both spectral bands and spatial frequencies. We found that we could generally increase the SNR of a multispectral image more than if the spectral bands were processed independently.

Keywords: denoising, multispectral, three-dimensional wavelet transform, wavelet transform

INTRODUCTION

Detection of small objects in a noisy image is of significance in several applications.[1-3] Often, it is desired that an object be detected before it can be resolved to an extended object. An object may appear small because it is a large distance from a sensor such as an IR sensor, or the object is simply too small to be resolved as in some medical imagery. Because objects appear small they often contain little energy and are dominated by noise or clutter. They may not have shape characteristics so traditional methods of detection may not have the desired effect. Traditional methods of noise reduction may blur an image so that small objects are virtually eliminated. A method is needed to reduce the effects of noise in an image while preserving small objects.

Many signal detection methods work well when noise is not a factor. A robust noise reduction algorithm can make a large difference in a system overall performance. The underlying assumptions in many noise suppression methods are related to important details of an image being larger than a few pixels, or most of the pixels' neighbors representing the same structure. Therefore, many noise removing algorithms involve averaging or some sort of smoothing. Although these approaches have been useful, the underlying assumptions are not always valid for small objects and details are often blurred. Such an approach is limited when detecting small objects because the object is often blended into the background.

Recently, wavelet-based methods for noise reduction referred to as denoising have been introduced, and have showed success in removing noise from an image while preserving details.[4,5] Generally, denoising is the process of taking the wavelet transform of an image, thresholding the wavelet coefficients, and then taking the inverse wavelet transform. Furthermore, there are several ways to choose and implement the threshold.[6,7] Like the Fourier transform, the wavelet transform describes a function with basis functions. However, the basis functions of the wavelet transform, wavelets, are often more complicated than the basis functions of the Fouirer transform, sines and cosines. Furthermore, unlike the Fouirer transform the basis functions in the wavelet transform are localized in both the input and wavelet domain. This dual localization has some important consequences. One is that objects can often be represented quite sparsely in the wavelet domain. The denoising process works primarily because the wavelet transform compacts energy more efficiently than other transforms such as the Fourier transform.

A multispectral image usually contains more information than a conventional image that is the sum of spectral bands. A multispectral image can be thought of as a data cube where two of the coordinates are spatial and the third is wavelength. When processing a multispectral image, spectral bands may be selected, rejected or energy redistributed among them.[8] In this way bands may be identified that are potentially useful for object detection. The detection of small objects in the presence of noise complicates the problem because there is little energy associated with the objects. Because of the close spacing of spectral bands of multispectral imagery, there is often a large degree of correlation of an object from one band to the next. A method is needed that will exploit this correlation to reduce noise and automatically identify spectral bands or their sum so that object detection can be performed.

We used a three-dimensional (3-D) denoising method to reduce noise from multispectral imagery so that objects may be more readily detected. Our approach automatically exploits the correlation between bands typically present in multispectral imagery. Using our approach, the resulting image generally consisted of a weighted sum of both spectral bands and spatial frequencies.

In the next section we briefly described denoising of images using wavelets, and how denoising may be applied to multispectral imagery by considering each band separately in Sec. 2.2. We then described our 3-D denoising approach in Sec. 2.3. We tested our algorithm on images with a small object in the presence of noise and compared our method to denoising spectral bands independently. We varied the spectral content of our object and compared different performance measures to evaluate our approach.

2.0 MULTISPECTRAL DENOISING

We compared two methods of denoising multispectral imagery. We first described a method to denoise spectral bands independently. We used a conventional denoising algorithm that we applied to each spectral band independently, then summed the result for the final image. Next, we described our 3-D approach that exploited the correlation between bands.

2.1 Denoising

We implemented a two-dimensional (2-D) denoising method by scaling an image, taking its wavelet transform, thresholding the wavelet coefficients, then taking the inverse wavelet transform. The scaling was performed my multiplying the image by a constant based on the estimated noise variance of the image. The noise variance was estimated by taking the median value of the wavelet coefficients at the smallest scale.[4]

After calculating the wavelet transform of the scaled image, the noisy wavelet transform coefficients are subjected to a soft or hard threshold. A hard threshold indicates that wavelet transform coefficients are retained only if their absolute value is greater than or equal to a threshold t, and is described as

$$\bar{W}f(a,b_x,b_y) = \begin{cases} Wf(a,b_x,b_y) & \text{if} \quad |Wf(a,b_x,b_y)| \geq t \\ 0 & \text{if} \quad |Wf(a,b_x,b_y)| < t, \end{cases} \tag{1}$$

where $Wf(a,b_x,b_y)$ is the wavelet transform of the image $f(x,y)$, a is the scale and $a > 0$, and b_x and b_y specify translations in two dimensions. A soft threshold is similar to the hard threshold, but "pulls" the values of the wavelet transform toward zero rather that simply retaining them. The soft threshold is described as

$$\bar{W}f(a,b_x,b_y) = \begin{cases} \mathrm{sgn}(Wf(a,b_x,b_y))(|Wf(a,b_x,b_y)| - t) & \text{if} \quad |Wf(a,b_x,b)| \geq t \\ 0 & \text{if} \quad |Wf(a,b_x,b_y)| < t, \end{cases} \tag{2}$$

where $\mathrm{sgn}(x)$ is the sign of x.

There are several ways to choose a threshold for denoising.[6,7] We chose a threshold that is, easy to implement, has been shown to work well for sparse data, and produces a good visual quality of a denoised signal. This threshold is described as[4]

$$t = (2\log(N))^{1/2}\,, \tag{3}$$

where N is the number of wavelet coefficients to be thresholded. After thresholding the inverse wavelet transform is performed on the thresholded coefficients followed by division of the scale factor.

The orthogonality of the wavelet transform transforms white noise into white noise. Therefore, due to the superior energy compaction of the wavelet transform, most of the coefficients in a noiseless wavelet transform are zero. The problem may then be thought of as separating a small number of large coefficients from a white noise background. This is accomplished using the thresholding process previously described.

2.2 Denoising bands independently using a 2-D algorithm

One way to process multispectral imagery is to consider the bands independently. The spectral bands may be processed using the same denoising algorithm as with a conventional image then summed to provide an output image. Each band will have its scale factor calculated independently. This method has the advantage of being straightforward but doesn't take into account any correlation between the data in the different bands.

2.3 Denoising bands using a 3-D algorithm

We considered the multispectral data as a 3-D data set. By performing the 3-D wavelet transform on the data we exploited the correlation between the different spectral bands. We wrote a multispectral image as a function of wavelength as $f_\lambda(x,y)$. The 3-D wavelet transform of the multispectral image was written as

$$Wf(a, a_\lambda, b_x, b_y, b_\lambda) = 2^{a/2} 2^{a_\lambda/2} \int\int\int f_\lambda(x,y)\, \psi(2^a x - b_x, 2^a y - b_y, 2^{a_\lambda}\lambda - b_\lambda)\, dx\, dy\, d\lambda, \tag{4}$$

where a_λ and b_λ are the scale and translation along the wavelength axis respectively. The scaling factor and threshold were chosen as before with Eqs. 1-3 extended to 3-D.

3.0 RESULTS

We compared our 3-D denoising results to those obtained by processing each band independently with a 2-D denoising algorithm. In addition, we compared our results to those obtained by a conventional sensor that does not distinguish between energy in different bands. For the conventional sensor the input was a single image that was the sum of several bands. In our experiments we used 256 x 256 pixel images that contained a 3 x 3 pixel Gaussian pulse with additive white noises shown in Fig. 1. We compared the input and output signal-to-noise ratios (SNRs) and the MSE of the object only (MSEo).

We compared the input and output SNRs using their ratio, the gain in decibels (dB). The output SNR was calculated by the ratio of the power contained in the image with only the object present and the power contained in the image with only the noise present. In this way we could measure the improvement of the SNR in an objective way. Because there was so much noise present, an increase in SNR may not indicate distortion of a small object. Therefore we calculated the MSEo, which was calculated from a 7 x 7 pixel area around the object. The region for the calculation of the MSEo was larger than the object because of the tendency of the denoising algorithms to broadened the signal when smaller scale coefficients of the wavelet transform are eliminated.

We calculated performance measures for different levels of wavelet processing. The levels are a parameter a human operator might adjust when searching for an object or enhancing an image for better visual characteristics. The level of wavelet processing indicates how much of the wavelet transform was calculated. For example, one level of processing ($L=1$) indicates that wavelets at only the smallest scale were thresholded. Two levels of processing ($L=2$) indicates that wavelets at the smallest, and next smallest scale were thresholded. This may continue until the entire wavelet transform is subject to a threshold. For our images this occurs at level $L = 7$. We used wavelets often referred to as symmlets that are the least asymmetric compactly-supported wavelets with maximum number of vanishing moments with eight coefficients.[9] In all of our experiments we processed the images 10 times using independent noise samples and averaged the results.

We used the same input SNR in all images and used uncorrelated noise between bands for multispectral images. We considered three different spectral distributions of the object. We considered a multispectral image that contained four spectral bands and an object that appeared the same in all bands, an object that had a Gaussian spectral distribution, and an object that appeared in only one band.

3.1 Denoising images from conventional sensor

We considered an image that was the sum of spectral bands as from a conventional sensor. The image contained a single object with additive white noise with an input SNR of 0.0013. The results of denoising are shown in Table 1, where L=0 indicated that no denoising was performed. For L=1 the gain increased and the MSEo decreased. The results for L=1 are shown in Fig. 2. For L=2, the gain further increased; however, the MSEo increased to near the level in the original noisy image. Results for values greater than L=2 were not shown because the object was eliminated. Regardless of the spectral distribution of our object the results for the conventional sensor would be the same.

Table 1 Denoising images from conventional sensor

	L=0	L=1	L=2
Gain (dB)	0	5.69	6.20
MSEo	0.381	0.039	0.343

3.2 Denoising multispectral images of highly correlated object

We first considered multispectral images with an object that was highly correlated and appeared the same in all bands. The results are shown in Table 2 for the case of processing spectral bands independently. The results were similar to that of the conventional sensor in that the performance increased initially, but further processing eliminated the object.

The results of the 3-D algorithm are shown in Table 3 for the highly correlated object. In contrast to previous results the gain increased consistently as more wavelet levels were processed. In addition, the object was degraded as more wavelet levels were processed but not eliminated. The results for *L*=5 are shown in Fig. 5. In addition, a plot the center row of the images for *L*=1, 3, 5, and 7 are shown in Fig. 4. The results show the improvement of the SNR and the degradation of the object as *L* is increased.

Table 2 Denoising multispectral images with highly correlated object using 2-D algorithms

	L=0	L=1	L=2
Gain (dB)	0	5.70	6.22
MSEo	0.090	0.067	0.400

Table 3 Denoising multispectral images with highly correlated object using 3-D algorithm

	L=0	L=1	L=2	L=3	L=4	L=5	L=6	L=7
Gain (dB)	0	5.73	8.46	14.26	19.9	25.6	31.9	38.9
MSEo	0.097	0.069	0.123	0.148	0.142	0.155	0.154	0.160

3.3 Denoising multispectral images of object with Gaussian spectral distribution

We next considered multispectral images with an object that had a Gaussian spectral distribution. The object had an amplitude one-half of that of the center bands. The results are shown in Table 4 for the case of processing spectral bands independently. The results were similar to that of the highly-correlated object; however, the useful processing levels increased to *L*=2. Further processing generally eliminated the object.

The results of the 3-D algorithm are shown in Table 5. Similar to previous results for the 3-D algorithm, the gain increased consistently as more wavelet levels were processed. In addition, the object was degraded as more wavelet levels were processes. The object was present for more levels of processing than when using the 2-D algorithms.

Table 4 Denoising multispectral images with object with Gaussian spectral distribution using 2-D algorithms

	L=0	L=1	L=2	L=3
Gain (dB)	0	3.70	6.4	11.4
MSEo	0.100	0.066	0.280	0.411

Table 5 Denoising images with object with Gaussian spectral distribution using 3-D algorithm

	L=0	L=1	L=2	L=3	L=4	L=5	L=6
Gain (dB)	0	5.69	9.54	13.7	19.4	25.0	31.5
MSEo	0.112	0.062	0.212	0.320	0.337	0.413	0.385

3.3 Denoising multispectral images of uncorrelated object

We finally considered multispectral images with an object that existed only in a single band. For both types of processing the results were similar. The SNR increased as L increased as did the MSEo by a small amount. The MSEo was generally lower for this case because the energy was concentrated in one band. Even if the object appeared degraded, the remaining part of the image was much improved. Therefore, large gains of SNR were possible. Although comparable, the results for the 2-D algorithms appeared to be better.

Table 5 Denoising multispectral images with uncorrelated using 2-D algorithms

	L=0	L=1	L=2	L=3	L=4	L=5	L=6	L=7
Gain (dB)	0	5.70	10.8	15.6	21.3	27.1	33.3	39.5
MSEo	0.100	0.036	0.039	0.059	0.063	0.073	0.072	0.073

Table 6 Denoising images with uncorrelated using 3-D algorithm

	L=0	L=1	L=2	L=3	L=4	L=5	L=6	L=7
Gain (dB)	0	5.69	9.86	14.2	19.8	25.6	31.0	37.8
MSEo	0.115	0.037	0.115	0.144	0.149	0.152	0.161	0.155

4.0 CONCLUSION

We used a 3-D denoising method to reduce noise from multispectral imagery so that small objects may be more readily detected. Our approach exploits the correlation between bands typically present in multispectral imagery. Using our approach, the resulting image generally consists of a weighted sum of both spectral bands and spatial frequencies. We found that we could generally increase the SNR of an multispectral image more than if the spectral bands were processed independently.

5.0 ACKNOWLEDGMENTS

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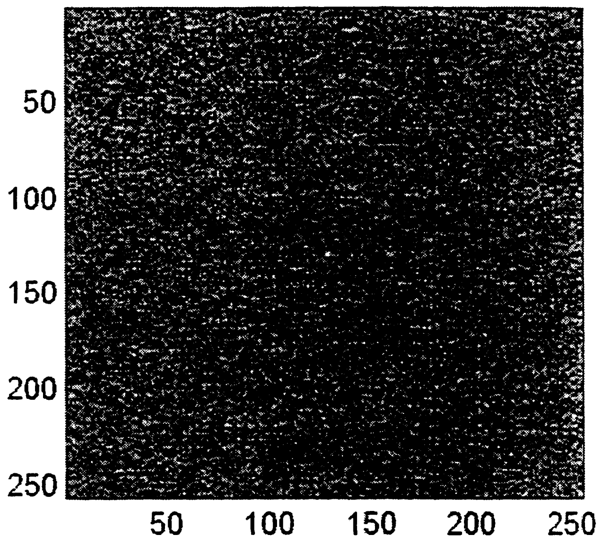

Figure 1 Noisy image with 3 x 3 pixel Gaussian pulse in center, SNR = 0.0013.

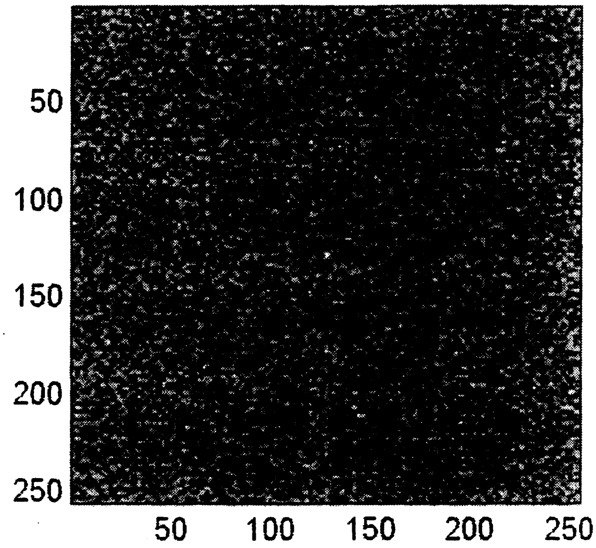

Figure 2 Denoised version of Fig. 1 using conventional 2-D denoising method with L =1.

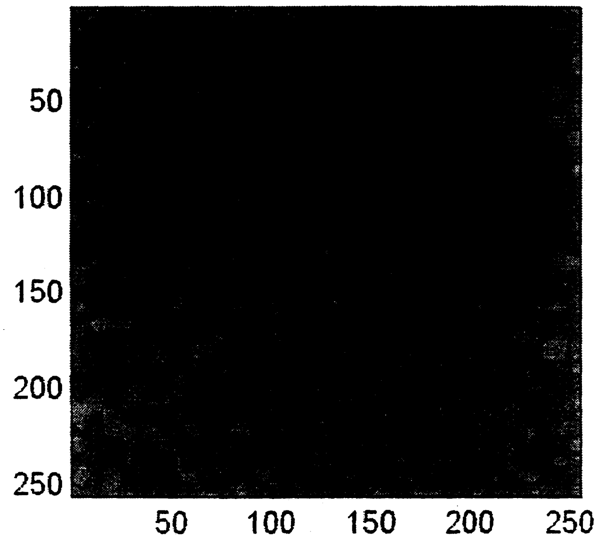

Figure 3 Denoised version of Fig. 1 using 3-D denoising method with L =5.

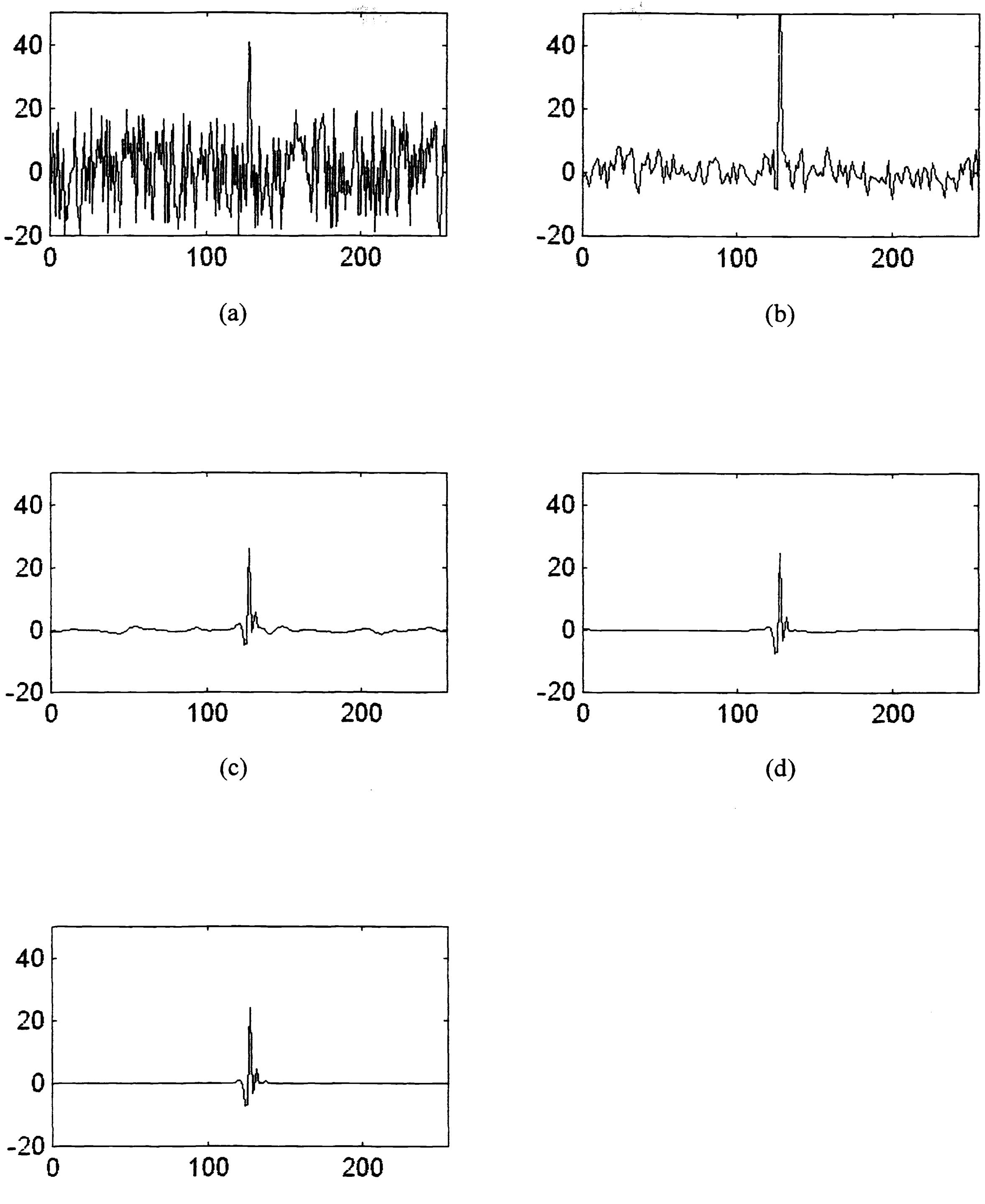

Figure 4 1-D slice through center row of images processed with 3-D algorithm (a) no processing (b) $L = 1$, (c) $L = 3$ (d) $L = 5$ (e) $L = 7$