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Image De-noising Using the New M.I.D.A.S.Filter

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ABSTRACT

The ever-present challenge faced by the signal processing analyst is to get more from the available data, whether it be exploiting the same data in new ways to garner new information, or simply to increase the confidence in existing qualitative metrics. Traditional techniques include filtering (to improve the signal to noise ratio of detected signals or images or to isolate and possibly remove interfering signals), feature detection/extraction (identifying key characteristics within the signal) and signal decomposition (identification of dominant signals of interest relative to noise terms). Current research by our team began with an emphasis on the filtering of signals of interest within the infrasound band but has been shown to also be effective in other applications including image processing. The Multi-band Isolation of Signals using Data-Adaptive Sub-banding (M.I.D.A.S.) filter begins with a wavelet pre-processing stage and follows with a spectral sub-banding stage for isolation of key signal content. The MIDAS filter is a coherent filter, so the filtering of a complex input produces a phase-preserved complex output. With many other infrasound and seismic data filtering tools such as the Pure State Filter, a real-valued input is required and thus no phase information can be extracted from the data set. A presented signal processing scenario where phase preservation is critical is image processing. A qualitative and quantitative assessment of image quality metrics suggests the MIDAS filter is effective at removing channel noise-type artifacts from images while preserving the phase information.

INTRODUCTION

The MIDAS filter was originally developed for application in the processing of infrasound and seismic signals of interest. In many cases these data sets are real-valued and are processed without regard for phase information. For many applications this is acceptable as the sensor systems are independent, isolated units. It is becoming increasingly common however, for the signal analyst to concern her/himself with channel-to-channel or sensor-to-sensor coherence between signals of interest. In this situation, the information contained within the phase of the signal(s) is relevant and the complete, complex representation of the sensor responses must be processed. The MIDAS filter is a phase-preserving filter in that it operates on complex input data, this capability separates it from existing infrasound processing tools such as the Pure State Filter [1,2]. One method to validate the performance of the filter is to apply it in the optical domain to the problem of image processing. Figure 1 below shows two examples of a test image used to demonstrate the filter. The raw, greyscale image shown on the left was used as a sample reference image and we applied random, gaussian white noise having pixel intensity consistent with white or black pixels. The figure on the right shows the resulting "noisy" image. This noisy image can then be processed with the MIDAS filter to remove the noise and subsequently evaluated using standard image quality metrics to determine the level of improvement.

Figure 1 Raw Image vs. Typical Noisy Image

This paper is organized as follows: Section II presents an overview of the image quality metrics used in this portion of the research to assess the effectivity of the MIDAS filter. Section III summarizes several test cases in which a certain class of noisy images were processed with the MIDAS filter and the results evaluated in a qualitative and quantitative sense. A common set of image quality assessment metrics is used to evaluate the results. Section IV presents conclusions and suggestions for future work.

I. ANALYSIS DISCUSSION

Evaluating the efficacy of the MIDAS filter when applied to image products is best done with both qualitative and quantitative methods. This is because the human eye is very good at discerning subtle structural, color, tonal and contrast distortions in an image but more subtle errors perhaps due to the image acquisition process, pre-processing or compression may only be brought out through numerical methods. This research makes use of both reference-based and non-reference-based image quality metrics. The Peak Signal-to-Noise Ratio (pSNR) and the Structural Similarity Index Measure (SSIM) are well established image quality metrics [3-7] that have seen numerous efforts to combine them to create a single, integrated metric [8,9]. The PSNR and SSIM metrics each require a distortion-free reference image from which to compute an error ratio, while the Perception-Based Image Quality Evaluator (PIQE) metric calculates the quality of an image based on distortions computed at the sub-scene, or neighborhood level within the image. This is done without the need for a reference image or any prior knowledge of the scene [10,11]. These non-reference-based image quality metrics are in direct contrast to popular neural network methods that require training data sets.

The peak signal-to-noise ratio is defined as:

$$pSNR = 10log_{10}\left(\frac{peakval^2}{MSE}\right) \tag{1}$$

where the peakval is the maximum pixel intensity in the image and MSE is the mean squared error between the test and reference signals.

Given two images (x,y) with pixel size (mxn), the mean squared error, MSE is defined as:

$$MSE(x,y) = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij} - y_{ij}\right)^2 \tag{2}$$

The structural similarity index measure is the summation of a luminance, contrast and structural term and is defined as [12-14]:

$$SSIM(x,y) = [l(x,y)^{\alpha}]\cdot\left[c(x,y)^{\beta}\right]\cdot[s(x,y)^{\gamma}] \tag{3}$$

where,

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{4}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{5}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{6}$$

which simplifies to:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{7}$$

Given images (x,y) in the above expressions: μ_x, μ_y, σ_x, σ_y represent the image means and standard deviations while σ_{xy} represents the cross-covariance for the images. The constants C_1, C_2, C_3 are present to prevent a zero denominator.

There are many different ways in which the desired “noise” contribution could be generated and added to the test image. In this experiment a simple speckled, or “salt-and-pepper” noise source was used. In this case each pixel in the image is assigned a random value from a standard, uniform probability distribution on the open interval, (0,1). The MATLAB function “imnoise” can readily perform this task while allowing the analyst to select a desired weighting function for the noise.

II. APPLICATION EXAMPLE

For this research, 10 modified realizations of the original image were produced, each having a unique, random noise overlay applied. This would be analogous to a sensor (camera) collecting multiple samples of the same scene with the random noise representing errors added to the data by the sensor and/or the data acquisition system. If we assume that the scene does not significantly change from one capture event to the next, then we can argue that the pixels that vary across time are noise and those that are persistent are valid image data.

The MIDAS filter works by interrogating each image on a pixel-wise basis. Each image in the ensemble is processed in succession in a "sliding-window" sense, while the filter algorithm develops a n-image pixel intensity history. This persistence function tends to reject pixel values that are varying from the ensemble mean. The length of the sliding window (number of images) is user selectable to accommodate dynamic scenes. Figure 2 below shows a typical progression of noise reduction with successive image realizations. (Image # at left of title and pSNR at right of title)

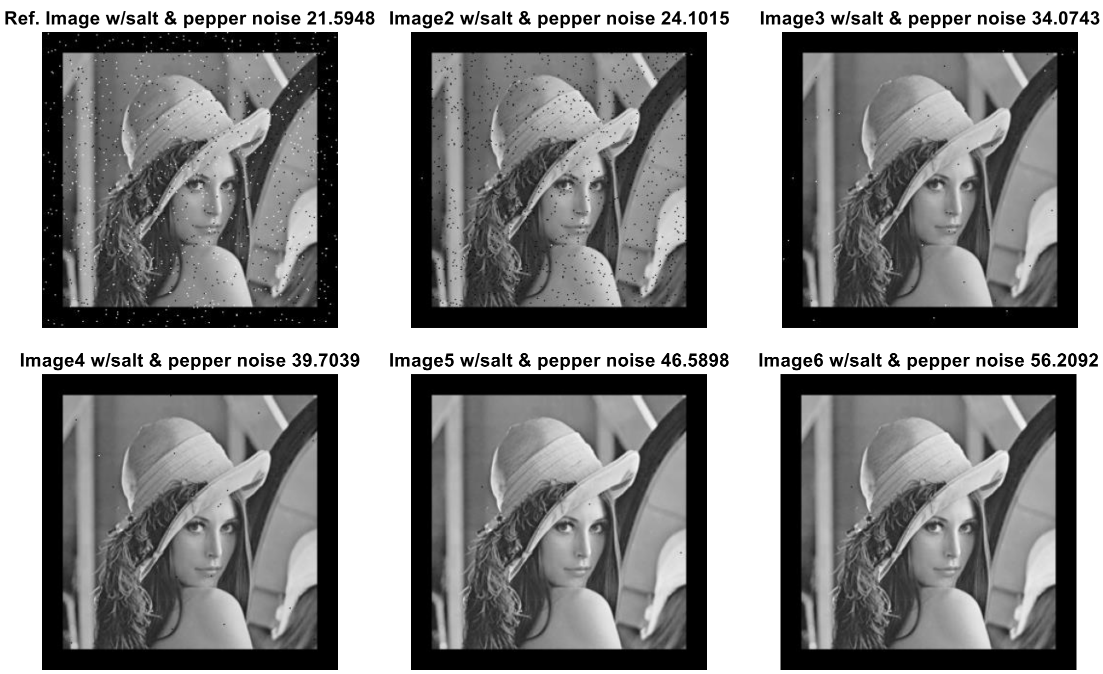

Figure 2 PSNR Assessment of Noise Reduction with Additional Realizations of Image

Figure 3 below shows a typical rate of SNR improvement as the number of additional realizations is increased.

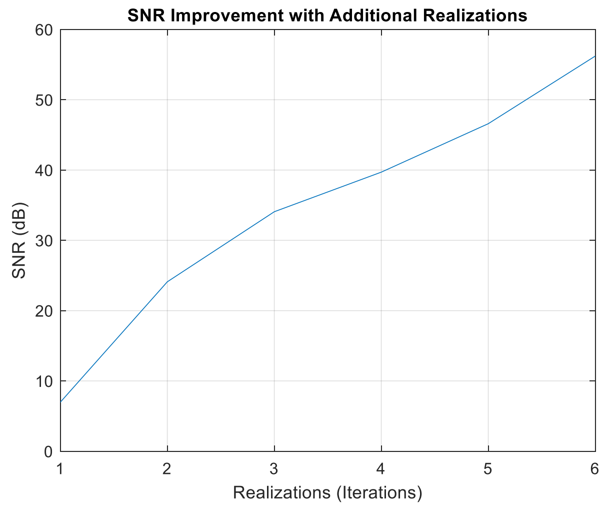

Figure 3 Noise Reduction with Increasing Image Count

Similar to the Signal-to-Noise Ratio metric, the Structural Similarity Index Measure (SSIM) is an image quality figure of merit that is based on the subjective assessment of the test image relative to a distortion free reference image. The SSIM metric has the dual benefit of not only a quantitative score in the global value metric provided, but also a qualitative measure in the form of the quality map of the image. This quality map identifies localized structure differences relative to the reference image.

For evaluating the MIDAS filter using the SSIM metric, a similar approach was used to that of the PSNR metric above. A series of noisy images were created and the SSIM metric was used to evaluate the progressive improvement of the filter as successive realizations of the image were processed. Figure 4 below shows the SSIM score and spatial image map for several of the realizations. (Image # at left of image title and pSNR for upper row, and SSIM score at right of title for lower row).

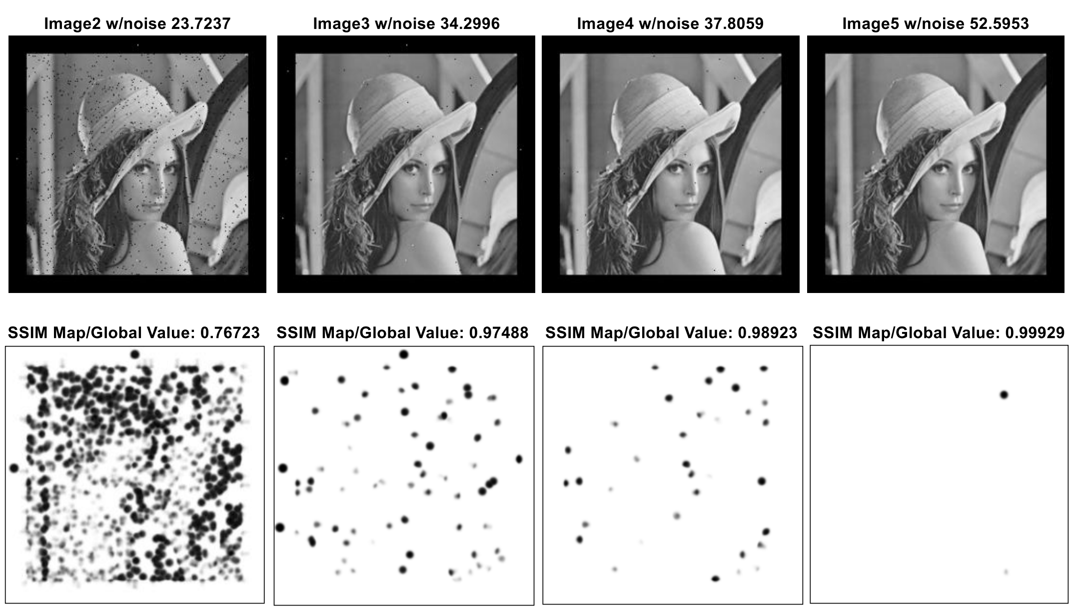

Figure 4 SSIM Assessment of Noise Reduction with Additional Realizations of Image

As Figure 4 indicates, increasing realizations of the test image (increased MIDAS filter iterations) reduces the residual noise in the image. In this example, the final image SNR was 52.59 dB. In conjunction with the SNR metric, the quality map shows continuous improvement with additional realizations. In this case the final quality score achieved for the global map was 0.99929, with 1.0 being the target value.

As an alternative to the PNSR and the SSIM, the Perception Based Image Quality Evaluator (PIQE) metric is an image quality assessment tool that is purely based on the input image [15]. No reference image is needed for this metric. The PIQE metric computes statistics based on localized evaluations of distortions within the test image. Figure 5 below shows the progression of noise reduction in the test images with additional realizations. As with the examples above, the pSNR score for each filtered image is shown in the image title, while the PIQE score for each image is plotted below the images.

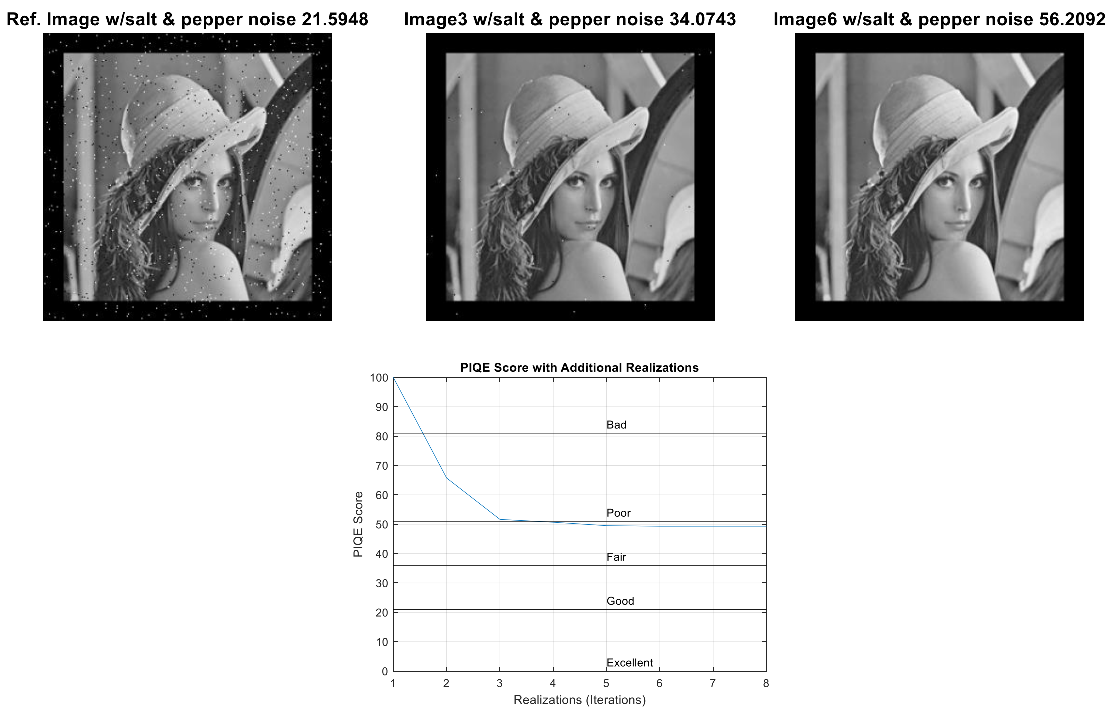

Figure 5 PIQE Assessment of Noise Reduction with Additional Realizations of Image

The PIQE metric assigns the image quality score based on preset threshold values. Lower scores for this metric indicate better filter results, with scores in the mid-ranges being common. Very high contrast images and/or images having low spatial variance generally achieve lower (better) PIQE scores.

III. CONCLUSION

The MIDAS filter has been extended beyond its original development objectives to include complex signal processing capability. While this capability enhances support within the objective infrasound and seismic domains, it also facilitates an unexpected application across other domains up to and including the optical range where image products may be considered. Here, the MIDAS filter works on channel and sensor noise and thus can operate in a complimentary manner with other optical filter products that work directly on noise sources in the image plane. A representative image processing problem of white noise removal was used to validate the MIDAS filter. Qualitative and quantitative image quality figures of merit were used to demonstrate the effectiveness of the MIDAS filter on the test imagery. The ability of the filter to significantly reduce the noise within the test images and still be able to reconstruct the images demonstrates that the filter does not significantly distort the incoming phase information. This research focused on a particular type of noise distribution. Future efforts may investigate alternative noise distributions.

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