REMOVAL OF SALT-AND-PEPPER NOISE IN THEMIS INFRARED RADIANCE AND EMISSIVITY SPECTRAL DATA OF THE MARTIAN SURFACE

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ABSTRACT

The quality of false color images of THEMIS multispectral infrared data is significantly reduced by the presence of white noise. Presented here is the description of the algorithm developed for the removal of white noise from THEMIS data to produce higher quality false color imagery in radiance and emissivity without loss of spatial resolution. The algorithm utilizes inter-band correlations of surface features and principal component analysis techniques to separate noise from the radiation originating from the planet surface. This algorithm is a standard process available to users of THEMIS data for the production of false color imagery.

Index Terms – Salt-and-Pepper Noise Removal, THEMIS, Remote Sensing, Principle Component Analysis

1. INTRODUCTION

Electro-optical imaging systems are afflicted with a variety of noises, the origin and manifestation of which depend upon the design of their optical train, method of electronic control and readout, the physical means by which they acquire the signal, etc. Out of this variety of noises that may be present, the noise alternatively known as white noise, speckle or salt-and-pepper noise is ubiquitous [e.g. 1]. Compensation for this noise is accomplished by increasing signal-to-noise ratios (SNR) through methods such as signal pre-amplification or increasing integration. However, in cases where image analysis is performed close to the level of the noise to extract increasingly subtle signals from the data, white noise becomes a serious impediment to image interpretation. In multispectral data, false color images are often produced to visibly differentiate compositional variations in the scene. Additionally, colors are commonly stretched to exaggerate and emphasize these subtle spectral differences. One such stretch, the decorrelation stretch (DCS), is useful for multispectral data where differences between spectral bandpasses are minimal and other, gentler stretches yield little visible differentiation of regions [2]. In DCS images, white noise is amplified along with real color differences and may render the false color image too grainy and variegated to use. In Thermal Emission Imaging System (THEMIS, [3]) multispectral infrared data, decorrelation stretched false color images are significantly degraded due

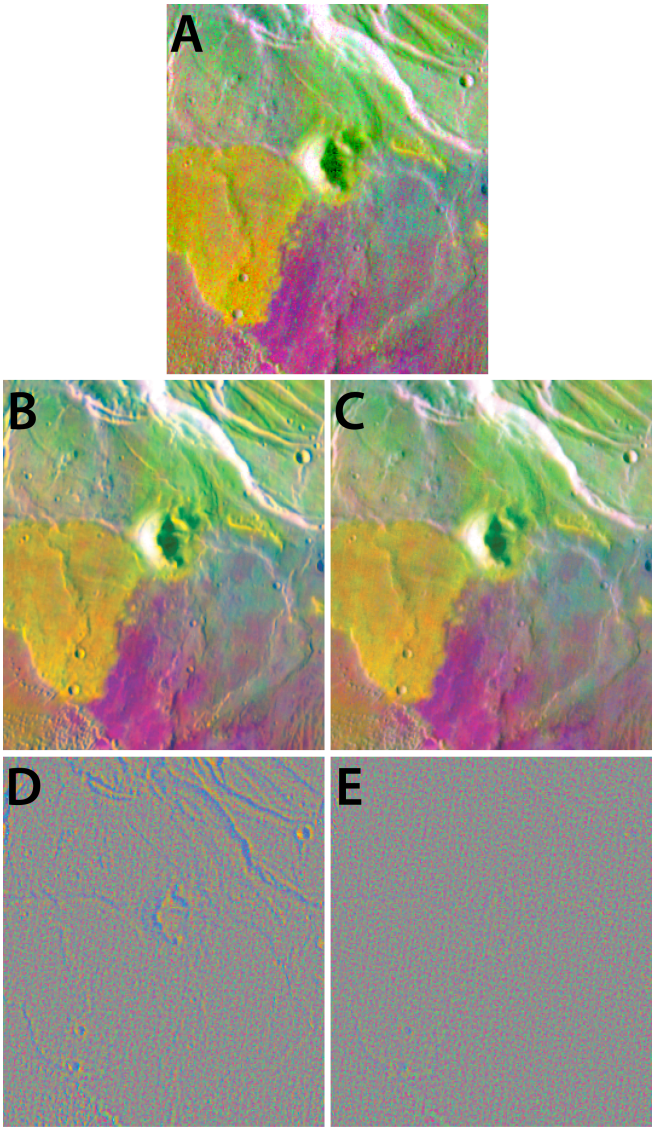

Figure 1. A section of THEMIS image I48021012, shown as a DCS of bands 8, 7, and 5. A) Original data. B) FFCS data. C) Final data. D) CN data. E) RN data. The visible spectral features in 1D are a direct result of spectral smearing. These remnant features are removed by using a PCA of Figure 1D and zeroing the first component. The reverse transformation to radiance data results in Figure 1E.

to white noise amplification. Presented here is an algorithm to remove white noise from multispectral data utilizing inter-band information. Although the following discussion uses THEMIS data for demonstrative purposes, the algorithm described may be applied to any multi- or hyper-spectral data set where differences between spectral bands are minimal.

1.1 White Noise Removal Techniques

In images with only a single band, removal of white noise is difficult and techniques are reliant on smoothing operations using low-pass filters where pixels are averaged together increasing SNR at the expense of lowered spatial resolution. In the ideal case, a flat-field image with no variability in the content of the scene, a low-pass filter will perfectly remove the high frequency corruption of white noise. However, low-pass filtering will blur sharp features in images with real content, smearing boundaries and degrading the spatial resolution of the image. Numerous variants of low-pass filtering of single-band images, in both image space and Fourier space, have been published [4]. Another method to reduce white noise in single band imagery is to average multiple images of identical spectral bandpass of an identical scene. This accomplishes the same result as time integration; signal is amplified while white noise remains constant in amplitude. Although this technique is highly successful in reducing the noise, the acquisition of multiple images or longer integration times may not be practical or possible, especially for spaceborne or airborne instruments.

Some spectral data permit a limited flexibility in separating white noise from target signal. In cases where intra-band variations are small, multiple spectral passes supply semi-identical images which can be used to similar effect as identical bandpass scene averaging. It is necessary to differentiate between real variations in content between scenes of different bandpass and speckle.

The goal of the algorithm presented in this work is to reduce the white noise in THEMIS radiance and emissivity data cubes in every band without a loss in spatial resolution. Radiance may be linearly, and thus reversibly, deconstructed into the component vectors of emissivity and temperature. THEMIS data for this work have been fully processed through the standard calibration and processing procedures [3, 5, 6].

1.2 Principal Component Analysis

Principal Component Analysis (PCA) is a powerful mathematical tool to quantitatively describe specific attributes of possibly correlated variables. PCA calculates the eigenvectors of a covariation matrix of N vectors producing another set of N vectors ordered by decreasing covariance [7]. The first principal component quantifies the largest similarity amongst the vector set. The second principal component performs the same operation on the residual after the first component is removed, and so on. There can only be as many components as there are original vectors.

The algorithm presented here utilizes PCA implicitly and explicitly. The algorithm works well on multispectral data sets where the first principal component is much larger than the subsequent components. In the case of multispectral images, this intuitively means that the smaller the differences between images of unique bandpasses the greater the efficacy of the algorithm in removing white noise and leaving real image content unaltered. Furthermore, the algorithm utilizes PCA on the separated speckle image to guarantee the purity of white noise once it has been separated from the real scene content.

2. METHOD

The technique is based upon the principle of rotating the data into some alternate image space where a low-pass filter may be applied and then transformed back to the original space where the filtering does not manifest as a reduction in spatial resolution. Furthermore, the algorithm utilizes knowledge about the statistical characteristics of speckle to aid in differentiating it from similarly high frequency, real information in the data.

The sum of the radiance of all sufficiently similar bands is computed and is called the Total Signal (TS). In THEMIS, the atmosphere is opaque in certain bands and the image is fundamentally different in content from those measuring the surface. These bands have been eliminated from the set on which the algorithm is applied. This algorithm is not very successful with datasets comprised solely of atmospheric observations because the algorithm benefits from the existence of strong surface features common in all bands and atmospheric data generally contains very few strong inter-band correlations.

The radiance data is transformed into Fractional Contribution Space (FCS) where each band is a divided by the TS to produce numbers between 0 and 1. FCS was chosen because it is a simple transformation, requires few processing resources and is easy to visualize and comprehend. Although this algorithm may be applied to any generalized multispectral or appropriately redundant data set, care must be taken in the calculation of the FCS. Several data sets, especially after advanced processing, may produce negative values and thus the sum does not equal the sum of the absolute value of the data.

Each of these fractional components is then independently low-pass filtered with a NxN square box filter to remove speckle and produce the Filtered FCS (FFCS). Various filter kernel sizes and shapes can be applied to remove the contribution of high-frequency information. Generally, a uniform, square kernel size where N = 5 to 9 allows for greater than a 20x reduction of the amplitude of white noise spikes relative to the mean. This is sufficient for cosmetic restoration of the DCS images of THEMIS data and the later steps of the algorithm have an inherent flexibility capable of accommodating a wide range of kernel

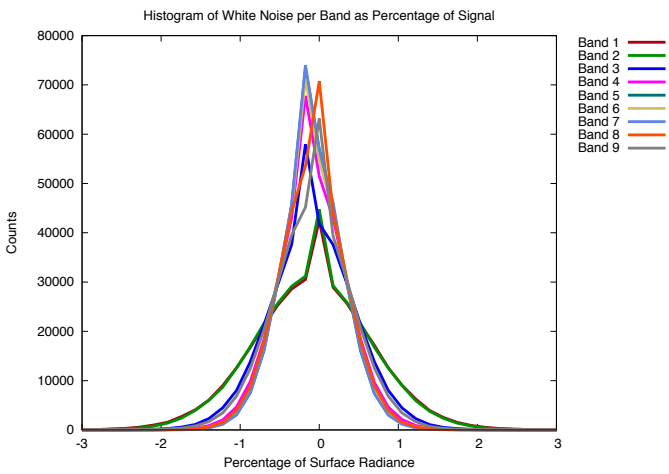

Figure 2: The white noise per band removed by the algorithm as a percentage of the average of the THEMIS infrared signal.

sizes. Of course, this low-pass filtering will remove real high-frequency information contained in the data along with speckle, but the vast majority of the surface signal is segregated from white noise. Because filtering will raise and lower values, oftentimes in the same direction in all bands, the FFCS is normalized to ensure the summation across all bands is unity.

The FFCS is then rotated back into radiance units by multiplication with the TS. The spatial resolution of the FFCS is not significantly degraded, as would have been the result of applying the low-pass filter directly to the radiance data. Instead, artifacts introduced as spectral differences can be observed on light/dark boundaries. The rotation into another space allowed for the retention of spatial resolution (i.e. the sum of signal across bands in any given pixel) at the cost of band-independent signal averages (or colors in stretched images).

The FFCS (Figure 1B) is then subtracted from the original radiance data to obtain Concentrated Noise (CN, Figure 1D) vectors, so called because the speckle is completely contained within these vectors and is mixed with only residual surface signal. The goal of the algorithm from this point forward is to confidently remove all valuable signal from the CN and thereby restore it to the "cleaned" data vector. The algorithm utilizes the fact that white noise will have a normal distribution centered on zero and will contain no inter-band correlations. To separate the speckle from high frequency signal removed erroneously from the data, a PCA is performed on the CN. The first component is dominated by spatially correlated information, which is derived solely from the surface data. Subsequent principle components are generally free of surface information and are therefore the principal components of speckle. The first component is set to zero and the remaining components are re-transformed into radiance space where only white noise remains which is called Reduced Noise (RN, Figure 1E). The RN is subsequently subtracted from the original data resulting in the white noise free data product (Figure 1C). A PCA performed on the RN yields a set of approximately equivalent eigenvalues and vectors that, when stretched for visual inspection, are all composed of unique white noise. The algorithm, by removing the first principal component of the CN will re-introduce a portion of the white noise but reduced by a factor of 1/N. The total reduction of the white noise in the original data can will consequently be (N-1)/N. The greater the number of bands available to the algorithm, the more efficient the removal of white noise will be.

3. RESULTS

The algorithm was developed to remove color speckle from thermal emission imagery in both radiance and emissivity space. This algorithm has been applied to tens of thousands of THEMIS images over the course of its development and has yielded high quality results (Figure 1) without the introduction of any significant image artifacts. After the application of this algorithm, small-scale surface differences are significantly easier to differentiate (Figure 1C) than in the original, unprocessed data (Figure 1A).

In an assessment of quantitative effects on the imagery, this algorithm was applied to the 9 surface-viewing bands of THEMIS imagery of Mars. In a study of four THEMIS images chosen for high spectral variability, we calculated the signal contribution of speckle extracted from surface data containing moderate geomorphological variation. The standard deviation of the distribution was approximately 1% for bands 1 and 2 and less than 0.5% for the other bands (Figures 2 and 3). In spectral radiance units for one case, this translates to speckle signal of amplitude $2e^{-6}$ for average surface radiance signal of $4e^{-4}$ (in band 4), corresponding to an average surface temperature of 260 K.

4. DISCUSSION

At the point that the algorithm transforms the FFCS back into radiance units the colors of boundary pixels are clean of

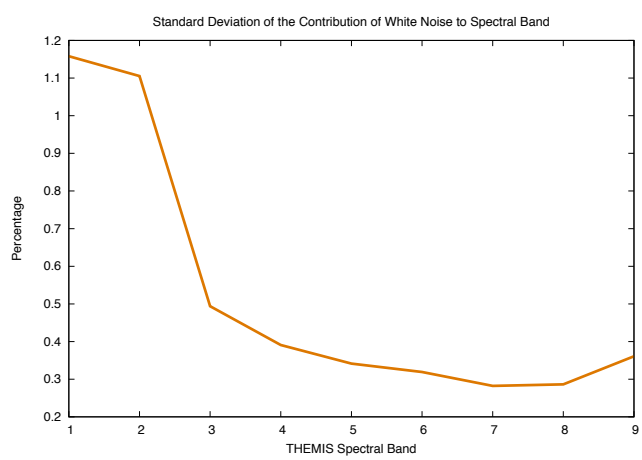

Figure 3: The standard deviation of the white noise removed by the algorithm per THEMIS band as a percentage of the average of the original data.

white noise but are no longer true to the local average of the unfiltered data. However, after the completion of the algorithm, the local averages on the scale of the low-pass filter kernel are identical between the cleaned and the original data. The residual white noise is reduced on average to 1/N times the amplitude of speckle in any individual band. This is due to the fact that white noise follows a normal distribution centered on zero and sums of multiple white noise images will yield the same distribution. This distribution, although having a greater extent in the wings, is divided by the number of bands and thus reduces outliers inverse-proportionally. Small events are likewise reduced in amplitude and the result is that the majority of the speckle occurrences are significantly damped.

The color change in light/dark boundary pixels is an expected side effect of rotating the radiance image into FCS. When a low-pass filter is applied to FCS data, the assumption is that any color change between adjacent pixels should be negligible. This is an incorrect assumption as geologic units often have very sharp boundaries (Figure 1), particularly at topographic barriers. However, because the algorithm deals with every band independently and requires the Total Signal to be constant, blurring of light/dark boundaries does not occur when FFCS data is rotated back into the original space. Instead, the low-pass filter leads to an offset in spectral character or color when viewed as a DCS image. This color offset is a notably less severe corruption of the data when compared with applying a low-pass filter directly to radiance data, as offsets are often comparable across bands. For example, if one pixel is adjacent to a pixel that is darker, averaging will cause signal depression in the first and elevation in the latter. Due to the nature of thermal radiation, the offset will almost certainly be comparable across all thermal bandpasses for the same pixel. After the re-normalization operation is performed across all bands to return the sum of FFCS to unity, the color offsets in each band retain their relative ratios. Since the primary goal is to remove color speckle from stretched color images; this operation is best done when hue is separated from saturation.

5. ERROR

The induced error of the algorithm depends upon the morphology of the surface of the planet. Errors were measured by comparing areal averages of data before and after the algorithm was applied. Over regions of negligible morphological variation, the algorithm has an insignificant effect on averages of areas greater than twice the smoothing filter used. In THEMIS data, ten regions selected for homogeneous surface composition and morphology showed differences of averages between the original data and post-algorithm to be less than 0.07% for areas the size of the low-pass filter kernel. The differences rapidly approach zero as area size increases. This demonstrates that the algorithm may be applied to calibrated data with bland surface targets without concern for increasing error.

The algorithm may induce errors across morphological or compositional boundaries. In general, in thermal infrared data, temperature boundaries produced by solar shadows are much greater in magnitude than compositional boundaries and offer a greater opportunity for the algorithm to induce error. Error was calculated on the six greatest temperature differentials found in a selection of 10 THEMIS images where error was detected. All six locations are at the edge of craters at the boundary between the face facing the sun and the interior wall of the crater in the shade. In all cases, the error was contained to one width of the low-pass filter from the boundary pixel.

6. CONCLUSIONS

The algorithm presented in this work successfully removes white or randomly distributed noise from multispectral THEMIS data and is a valuable tool in generating images for visual analysis. The algorithm retains much of the original spectral character of the data and allows for a significantly better assessment of small-scale spectrally distinct features. Furthermore, this algorithm has been applied to the more than twenty-five thousand THEMIS thermal infrared images without any major introduction of artifacts. These data are provided to the public as a browse product to quickly assess the spectral variability in images.

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