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FILTERING TO REMOVE CLOUD COVER IN SATELLITE IMAGERY

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I. ABSTRACT

The possibility of filtering light cloud cover in satellite imagery to expose objects beneath the clouds is discussed. A model of the cloud distortion process is developed and a transformation is introduced which makes the signal and noise additive so that optimum linear filtering techniques can be applied. This homomorphic filtering can be done in the two dimensional image plane, or it can be extended to include the spectral dimension on multispectral data. This three dimensional filter is especially promising because clouds tend to follow a common spectral response. The noise statistics can either be estimated from a general cloud model or they can be derived from a multispectral classification program. Results from a computer simulation and from LANDSAT data are shown.

II. INTRODUCTION

Satellite multispectral scans of the earth's surface such as those obtained from LANDSAT are often corrupted by cloud formations. The usual reaction is to discard these images as useless. However, in some situations, the data of interest is temporary and a clear scan of the area cannot be obtained. The question arises as to whether it is possible to filter out the cloud cover thus exposing the earth's surface below the clouds.

In order to investigate the potential of such a technique, a model of the cloud distortion process has been developed. The "noise" effects of the cloud are not a strictly additive or multiplicative but a combination. Assuming the cloud cover is light enough so that some of the energy from the earth's surface passes through the cloud (in at least one spectral channel) a transformation can be developed which makes the signal and noise additive. Then optimum linear filtering techniques can be applied to separate signal and noise. An appropriate inverse transformation then returns the filtered signal to the picture domain.

To apply this filtering technique an estimate of the signal or the noise statistics must be made. Two techniques have been investigated. One involves using the LARSYS multispectral classification system. The other technique is to model a typical cloud cover pattern and use the statistics developed from this model as an universal set.

III. CLOUD DISTORTION MODEL AND FILTERING PROCEDURE

Assume that an image of the earth is produced when a light cloud cover exists over the region of interest as shown in Fig. 1.

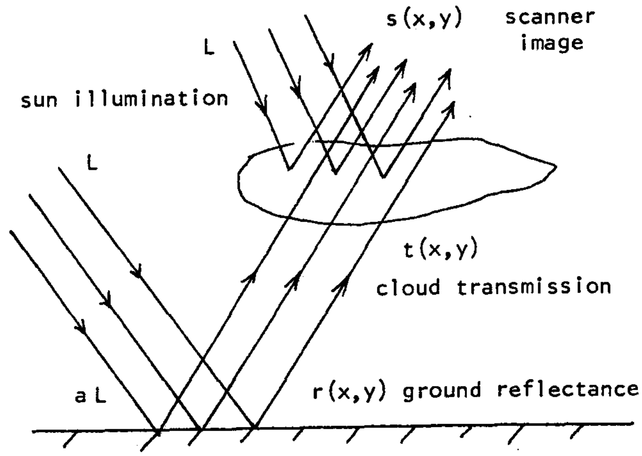


Figure 1. Satellite Scanner Image Components.

If we assume that the cloud reflection of sunlight plus the cloud transmission equals one (ignoring diffusion) and that the illumination is approximately constant on the earth's surface, then the received image at the scanner is

$$s(x,y) = a\,L\,r(x,y)t(x,y) + L[1 - t(x,y)] \leq L \tag{1}$$

where $r(x,y)$ is the signal and $t(x,y)$ is the noise. The values of $r(x,y)$, $t(x,y)$, and a (sunlight attenuation) range between 0 and 1.

A transformation is now performed by subtracting $s(x,y)$ from L and taking the logarithm:

$$\log[L - s(x,y)] = \log[t(x,y)] + \log[L - a\,L\,r(x,y)] \quad (2)$$

If the signal is now assumed to be $\log[L - a\,L\,r(x,y)]$ and the noise is assumed to be $\log[t(x,y)]$, then the signal and noise are additive and uncorrelated. Weiner linear filtering techniques can now be used to remove the noise.[1]

This method of converting a multiplicative process to an additive one and then applying linear filtering has been generalized and named homomorphic filtering.[2] In this case both multiplied terms (reflectance and transmission) are non-negative so that the simple logarithm is an effective transform.

In order to follow the procedure outlined above, the sun illumination L must be estimated from the cloudy picture. Since a, $r(x,y)$, and $t(x,y)$ are all between 0 and 1, the maximum value of $s(x,y)$ cannot be greater than L (see Eq. 1). If the cloud transmission at any point is zero, the value of $s(x,y)$ at that point will be L. Therefore a reasonable value for L in a large image is the brightest point in the image. The original data is, therefore, processed by subtracting the intensity of each point from the maximum intensity in the picture. The logarithm is then taken of the inverted data. Now the signal and noise are additive. The filter function is

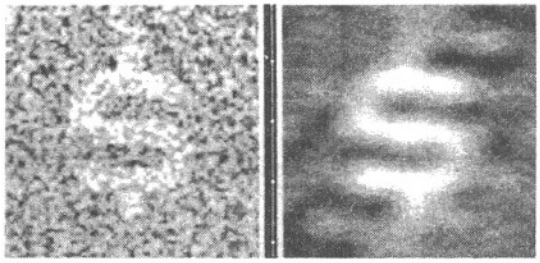
$$H(\mu,\nu) = \frac{S_{MP}(\mu,\nu)}{S_{PP}(\mu,\nu)} \quad (3)$$

where $S_{MP}(\mu,\nu)$ is the cross power spectrum between signal and signal-plus-noise and $S_{PP}(\mu,\nu)$ is the power spectrum of the signal-plus-noise. The two spatial frequency components are μ and ν. This is a non-causal filter which uses all the cloudy picture points to estimate each individual signal point.[1] In order to apply this filtering, an estimate must be made of $S_{MP}(\mu,\nu)$. This will be discussed in Section V.

IV. EXAMPLE OF HOMOMORPHIC FILTERING

An example of the ability of this filtering technique is now given to show its potential. A noisy picture is simulated using an original image $r(x,y)$ and a noise pattern $t(x,y)$ so that the output image $s(x,y)$ is formed by Eq. 1. Two-dimensional linear filtering is performed on $\log[L - s(x,y)]$ using known statistics of $r(x,y)$ and $t(x,y)$. The signal estimate is then obtained by exponentiating the filter output and inverting the grey levels. The complete process is shown in Fig. 2.

Results of several simulations using 64x64 pictures are shown. For comparison purposes, the mean and standard deviation of the noisy and filtered pictures are normalized so that $\mu=128$ and $\sigma=48$ on a display scale of 256. Fig. 3(a) is a noisy signal with L=15, $r(x,y) = 2/3$ in background and 4/5 in foreground, and $t(x,y)$ is white noise, uniformly distributed between 0.02 and 1.0. The filtered result is shown in Fig. 3(b).



(a) (b)

Figure 3. Computer Simulated Noisy Image (a) and Filtered Result (b). Signal and noise follow model in Eq. 1; L=15; $r(x,y) = 2/3$ to 4/5; $t(x,y)$ is uniformly distributed between 0.02 and 1.0. Filtering process is as shown in Figure 2.

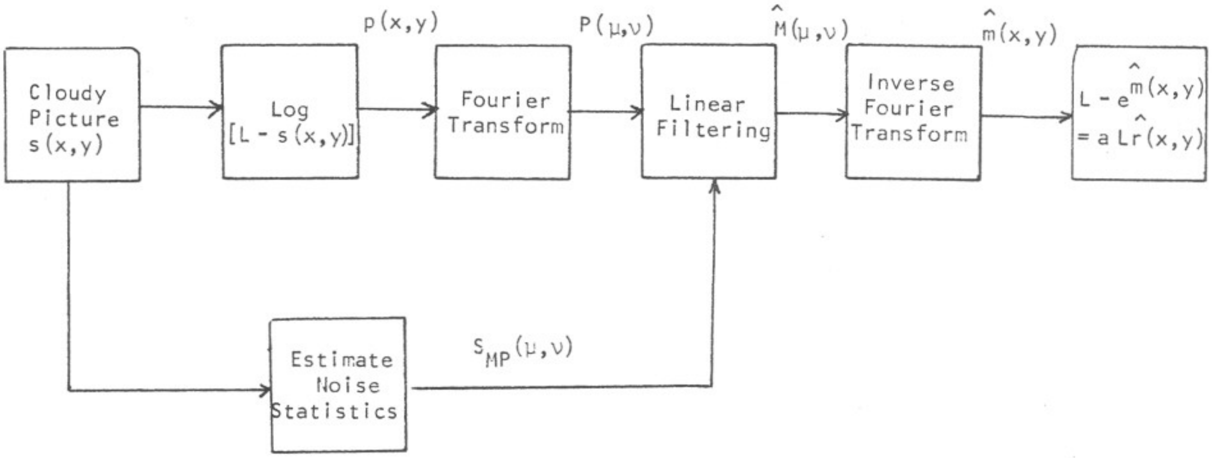
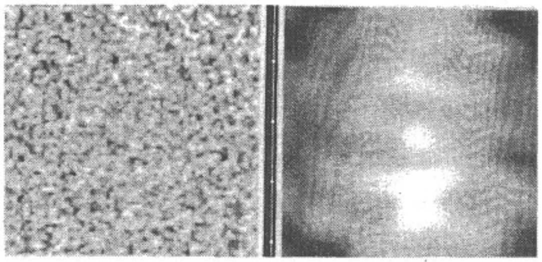


Figure 2. Homomorphic Filtering Process

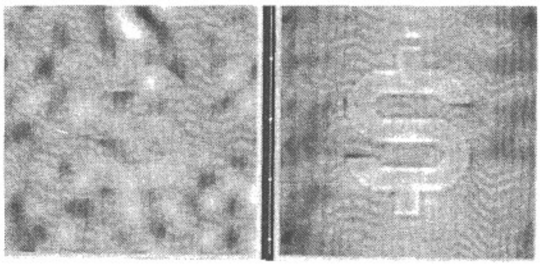
Fig. 4 shows another noisy picture and the filtered results with the signal level decreased to 23/30 in the background and 4/5 in the foreground.



(a) (b)

Figure 4. Computer Simulated Noisy Image (a) and Filtered Result (b). Same as Figure 3 except r(x,y) ranges from 0.767 to 0.800.

In Fig. 5(a) the same noise as used in Fig. 3(a) was low pass filtered before it was used. The signal edges (high frequencies) are retained in the filtered output because the noise has no components at these frequencies.



(a) (b)

Figure 5. Computer Simulated Noisy Image (a) and Filtered Result (b). Same as Figure 3 except t(x,y) is low pass filtered so that the maximum noise frequency is 8 cycles/picture width.

These simulation results give an idea of the maximum possible improvement because the model being used is exact and the noise statistics are known.

V. ESTIMATION OF NOISE STATISTICS IN CLOUDY PICTURES

A. Direct Method Using LARS Classifier

It is possible to quantify the presence of clouds in a multispectral image using the LARS classifier. This classifier processes multispectral data one point at a time classifying unknown data using training statistics developed from pre-classified data. The classifier compares the unknown data point with all the training classes and assigns it to one of them using the maximum likelihood rule. Detailed information about the classification algorithm can be found in LARS information notes.[3,4]

For training data we chose four classes of cloud and a class each of water and ground. Table 1 shows the six possible classes for each point and the estimated cloud transmission for each class.

Table 1. Cloud Training Classes

Class	Approximate Transmission
Full Cloud	0.1
Most Cloud	0.3
Half Cloud	0.5
Small Cloud	0.75
Water (No Cloud)	1.0
Ground (No Cloud)	1.0

The third channel of a 64x64 region of an original cloudy LANDSAT image is shown in Fig. 6.

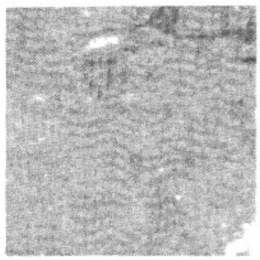


Figure 6. Third Channel for a 64x64 region of Cloudy LANDSAT Data.

The output of the classifier program for this data is shown in Fig. 7. The full cloud class appears

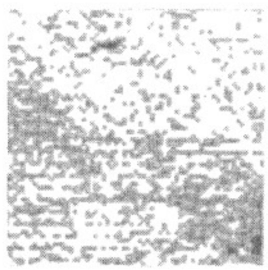


Figure 7. Classifier Output Using Region Shown in Figure 6. The full cloud class appears as the darkest points.

as the darkest points. This classification output allows the calculation of the noise statistics necessary for the filtering operation. This is done by taking the square of the magnitude of the two-dimensional Fast Fourier Transform[5] (FFT) of the logarithm of the classified image. This results in the estimated power spectrum of the noise $S_{NN}(\mu,\nu)$.

The cross power spectrum between signal and signal-plus-noise is then

$$S_{MP}(\mu,\nu) = S_{MM}(\mu,\nu) = S_{PP}(\mu,\nu) - S_{NN}(\mu,\nu) \qquad (4)$$

The above equation has assumed that signal and noise are uncorrelated, and that the mean of either the signal or noise is zero (which is not normally the case). Non-zero means result in the filtered output being off by a constant additive term (a multiplicative term after exponentiation) which can be corrected by normalizing the picture after filtering.

Each channel is then filtered by combining equations 3 and 4 resulting in

$$\hat{M}(\mu,\nu) = \frac{S_{PP}(\mu,\nu) - S_{NN}(\mu,\nu)}{S_{PP}(\mu,\nu)} P(\mu,\nu) \qquad (5)$$

where $P(\mu,\nu)$ is the 2-D FFT of the cloudy picture and $\hat{M}(\mu,\nu)$ is the filtered output, the estimate of the 2-D FFT of the signal. $\hat{M}(\mu,\nu)$ is then processed as shown in Fig. 2 to recover $\hat{r}(x,y)$ the estimate of the image beneath the clouds. Sample filtered output using this method and the data in Figs. 6 and 7 is shown in Fig. 8. Due to spectral similarities, concrete and clouds are easily confused by the classifier. It seems the noise statistics included the highway high frequencies in this example and thus the highway was filtered out along with the clouds.

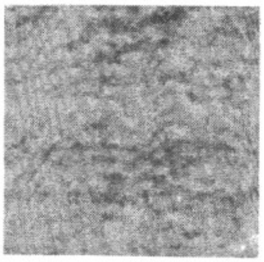


Figure 8. Filtered Output Using Data in Figures 6 and 7.

B. Indirect Estimation of Noise Statistics

It may prove impractical to use a multispectral classification program to find the noise statistics. Instead it may be possible to use a generalized cloud power spectrum, derived by averaging many sample spectrums together. This is easiest done by using data taken over water where the reflection $r(x,y)$ is almost constant. In this case, Eq. 2 reduces to

$$\log[L - s(x,y)] = \log[t(x,y)] + K \qquad (6)$$

where K is a constant, and the power spectrum obtained is that of the noise except for the d.c. (0,0) frequency point.

This power spectrum should be circularly symmetric since clouds have no preferred orientation and should consist mainly of low spatial frequency components since clouds are relatively large and smooth functions compared to ground reflectance. Some care must be taken to normalize the power spectrum before it is used in Eq. 5, so that $\hat{M}(\mu,\nu)$ remains positive.

VI. THREE DIMENSIONAL FILTERING

The real potential in the cloud filtering process is in incorporating a third dimension, the spectral channels, forming a three dimensional reflection $r(x,y,z)$ and cloud transmission $t(x,y,z)$. The linear filter thus employed is three dimensional, $H(\mu,\nu,\rho)$ using three frequencies (two spatial and one spectral). Although there are only four points in the spectral dimension for LANDSAT data, the method has good promise, because most clouds follow the same response in the spectral dimension: cloud transmission increases with wavelength in a predictable fashion. When this information is incorporated into the filter (by means of the 3-D power spectrum), image variations which have the cloud spectral response are filtered out and image variations which do not follow the expected response of clouds in the spectral dimension are left in. The three dimensional filter, therefore, tends to reject all variations that are low frequency in the spatial dimensions and follow the cloud spectral response in the third dimension.

The equation used for three-dimensional filtering is identical to Eq. 5, except each term contains three frequency variables. The 3-D noise power estimate can be obtained by averaging the 3-D power spectrum of several regions of similar clouds taken over water (or any other constant reflective surface). This method will have even greater potential for multispectral data with more than 4 spectral channels.

VII. CONCLUSIONS

Two and three dimensional filtering of multispectral data to remove light cloud cover is a distinct possibility. In computer simulated noisy situations, the filtering results are good. Insufficient LANDSAT data has been processed to arrive at conclusive results as to the utility of such techniques. The model of cloud distortion of images needs to be refined based on the results of filtering using the simple model presented. It may be necessary to consider convolutional effects of cloud cover as well as multiplicative effects. The change in multispectral classification accuracy after filtering may be a suitable measure of the performance of such homomorphic filters.

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