

FOURIER FILTERING OF LANDSAT DATA FOR INFORMATION EXTRACTION IN SURVEYING AND MAPPING

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ABSTRACT

Various spatial filtering techniques have been developed to process digital Landsat data. This research aimed to filter the same digital data within the frequency domain, and involved the use of the Butterworth lowpass and highpass filters. The lowpass filter is used primarily for the reduction of noise whereas the highpass filter is used primarily for edge enhancement. The analysis of these two filters was based on a comparative approach, utilizing what had already been accomplished in the spatial domain. It was found that the Butterworth lowpass filter did an inferior job of reducing noise and keeping data distortions to a minimum than did the spatial filters. Also, the spatial filters clearly defined edges to greater detail than the highpass Butterworth filter. However these results only apply to the frequency filters used in this research. It cannot be inferred that all frequency techniques would be inferior to spatial filters.

INTRODUCTION

In the realm of general digital image processing, two-dimensional Fourier transforms are used for enhancement, compression, texture classification, smear removal, quality assessment, cross-correlation, and a host of other operations. In particular, the Fourier transform of an input image can be used to ascertain the spatial frequency content of that image. Other spatial filtering to modify an image or to analyze a spatial structure can often be performed conveniently in the frequency domain. The goal of restoration is to process a degraded image so that, in accordance with some criterion, it resembles as closely as possible some ideal image. Alternatively, the aim might be to enhance the details of the image to enable the maximum amount of information to be extracted from the image.

An example of this involves research into the extraction of surveying information, currently being undertaken in the Division of Surveying Engineering at The University of Calgary. A large amount of surveying and mapping information involves linear features, roads, railroads, cut lines, field boundaries, etc. In extracting these features from Landsat data, for example, the additional spatial component, represented by the linear element, can be used to assist in the delineation and interpretation process.

The work involves an analysis of a study area in the upper Kananaskis Valley of southwestern Alberta, located in part of the Rocky Mountains comprising a segment of the Calgary, Canada Landsat scene (see Figure 1). The test data set consisted of 600 by 600 pixels, from which a 256 by 256 pixel subset was taken. All the necessary corrections had already been applied to the original data to account for such things as haze correction, radiometric errors and sixth line banding. Then, the data were rectified to ground control using a second order polynomial, and nearest-neighbour resampling was carried out, based on a 50 by 50 m U.T.M. coordinate grid. As well, principal component analysis (PCA) had been performed, resulting in the first and second principal components containing 99 percent of the total original four band variance (Paine, 1984). These principal components were combined to produce a classified data set on which comparisons between the spatial and frequency domain filters were performed (Paine, 1983).

FREQUENCY FILTERING

The main difference between frequency filtering and spatial filtering is that the former is usually done in the global context, applied to the image or data set as a whole, whereas the latter is usually applied locally, to a sub-set of the data. Examples of spatial filters are the Means, Median, Mode, and Five-Nearest-Neighbours filters which act on the local 3 x 3 box of data, and the Minimum-Variance and Gradient filters, which act on a rotating 2 x 2 box of data (see Paine, 1986).

Frequency filtering involves spectral analysis using Fourier transforms. The Butterworth high and low pass frequency filters used in this research are global, linear filters. A linear filter is one which assumes no periodicity in the signal, and therefore can be more generally applied. There are several alternate linear filters that can be used within the frequency domain. Examples are:

- 1) Recursive Frequency-Domain filters,
- 2) Interpolating filters,
- 3) Wiener filters, and
- 4) Exponential filters.

Another approach to filtering is to use non-linear filters. Two of the more common non-linear filters are the Maximum-Entropy method (MEM) or the Maximum-Likelihood method (MLM). The MEM and MLM differ from conventional linear spectral analysis filters because they avoid the assumptions that the data set is periodic and that the data outside the record length are zero (Haykin et al, 1979). The MEM or the MLM show considerable promise for estimating the spectra, especially when the length of the data set is limited. However it should be noted that the computational effort involved with the non-linear filters is extensive and therefore they are not as widely used as the linear filters.

An alternative method of filtering noise or smoothing a data set is by looking at the phase relationships between the Fourier coefficients at particular frequencies. The basis behind this method is to determine the coherency measure, which is the quantitative measure of the phase

agreement among the phases of various Fourier coefficients at a given frequency (Dave and Gazdag, 1984). The coherency measure assumes a value of unity if all of the Fourier coefficients of a given frequency are in phase, and a value of zero if their phases are randomly oriented (Dave and Gazdag, 1984). Thus it can be shown that the coherency measure attains a higher value for those frequencies that are less contaminated, and as a result the coherency measure is correlated more strongly with the signal component than with the noise component. The result, then, of multiplying the coherency measure with all of the Fourier coefficients will be an increased signal-noise ratio and thus a smoothing of the noise from the data set.

FILTERING TECHNIQUE

The first step when working with Butterworth filters in the frequency domain is to remove any trends that may occur in the data set. Trend removal is necessary in the Fourier analysis process and may be accomplished by fitting a surface through the data set and calculating the deviations from that surface (Davis, 1973). With this data set it was found sufficient to use a first order surface for this purpose.

The next step is to take into account the fact that the data set is defined by a finite interval. The Fourier transform is derived for a continuous function defined from minus infinity to plus infinity, or an infinite sampling interval. If the sample does not have an infinite sample interval, it will not satisfy the conditions necessary to recover completely an under-sampled function. This is known as aliasing. In order to get around this problem of aliasing, the finite sampling area can be represented by a function known as a window. A window and its Fourier transform are shown graphically in Figure 2. The window used in this research was the Hamming window. The circular pattern of the final data sets is due to the windowing process, because all outer corners of the 256 by 256 data set are damped down to zero (see Figure 3).

After windowing is completed, the next step is to decompose the data via a Fast Fourier Transform algorithm. The FFT is used because the data are sampled on a regular grid, allowing significant savings in computational time. Then, once the data set has been decomposed to the frequency domain, different filters can be applied to the data to try to remove random signals that can be attributed to noise. As well, filtering can be used to enhance the image.

The transfer function of the Butterworth filter of order N and cut-off frequency located at a distance D_0 from the origin is defined by (Gonzalez and Wintz, 1977):

$$H(u,v) = 1/(1 + 0.414 * (D(u,v) / D_0)^{2*N}) \quad (1)$$

where $H(u,v)$ transfer function,
 $D(u,v)$ distance from the point (u,v) to the origin
of the frequency plane,
N order of Butterworth filter used,
 D_0 distance to cut-off frequency.

The cut-off frequency defines the radii which encloses various percentages of the information that will be filtered. For low pass filtering, the frequencies inside the radius are referenced, for high pass filtering the reverse is true. The process of trying to decide what the cut-off radius should be is a difficult one, and is most easily done on a trial and error basis. The effect of the different cut-off frequencies is compared and the one that produces the best result, without losing or altering the data significantly, is chosen as the cut-off frequency to be used.

It should also be noted that since $H(u)$ has frequency components that extend to infinity, the convolution of these functions introduces distortions in the frequency-domain representation of a function that has been sampled and limited to a finite region (Gonzales and Wintz, 1977). This implies that, in general, it is impossible to completely recover a function that has been sampled in a finite region.

Finally, when the filtering process has been completed it is necessary to bring the data back to the spatial domain. This involves running the frequency data through several reversal algorithms, which include inverse FFT, inverse windowing and inverse trend. The filters can then be evaluated.

RESULTS OF FILTERING

In order to evaluate the filtered data sets, an unfiltered data set was used. Comparison was on the basis of:

- 1) Degree of generalization, which means that the image is smoothed so that areas become more homogeneous.
- 2) Degree of enhancement, where composite areas are created by merging discrete segments that are in close proximity. As well, linear features, such as edges and boundaries, are modified to become more distinct within the image.
- 3) Information distortion, which implies the movement of linear features or boundaries, the addition of erroneous information, or any significant loss of information.

The unfiltered classified data set shows both lack of generalization and boundary definition (see Figure 4). However this data set is considered distortion-free. Noise in the data can be regarded as masking the image, so the filtering process aims to produce a sharper image.

Lowpass Butterworth filters at 99, 95 and 90 percent energy level are displayed in Figures 5, 6 and 7, respectively. The 99 percent filter shows little generalization or enhancement compared to the unfiltered data set. Also there is little distortion of information. On the other hand, the 90 percent filter shows much generalization and smoothing, to the extent that some information is lost and erroneous information added. The lowpass Butterworth filter at 95 percent gives optimum results. This filter does a very good job of removing the noise from the image, showing that it has good generalization properties. As well, there is good enhancement resulting from merging of new areas. Boundaries and linear features have become more discrete, however

there is some addition of information, implying distortion along boundaries. It is clear that the Butterworth filter with a 95 percent energy level gives the best overall representation.

The 95 percent Butterworth lowpass filter can be compared with the Minimum-Variance spatial filter used by Paine (1986), which is displayed in Figure 8. Both the spectral and spatial filters have good enhancement properties and generalize the data very well. Also, noise reduction is good in both cases. The major difference between these two methods is the superior boundary definition of the spatial filter. Also, the 95 percent lowpass filter tends to add information to the image.

Of the three energy levels used (90, 95, 99 percent) in the Butterworth highpass filter to try to enhance edges, the 95 percent level did the best job of defining the edges or linear features (see Figure 9). The 90 percent level caused the edges to thicken to the point where they were not clearly definable. On the other hand, the 99 percent level filter did not define the edges well enough.

The 95 percent Butterworth highpass filter can be compared with the Gradient filter used by Paine (1986) for edge enhancement (see Figure 10). In comparison, the 95 percent highpass filter performed rather poorly. The noise in the highpass filter masked the edges, whereas the spatial technique highlighted the edges very well and edge information can easily be extracted from that image.

CONCLUSIONS

The aim of this research was to utilize filtering techniques in the frequency domain in order to evaluate their usefulness for information extraction in surveying and mapping. It was found that the filters used were adequate, however not as good as spatial filters. Some explanations as to the apparent poorer performance of the Butterworth filters could be:

- 1) Errors were known to exist because of the prior classification process, and
- 2) The Butterworth filter is basically a global filtering technique as opposed to a local or regional spatial filter.

With a global type filter each pixel is being treated the same, in that a cut-off radius is chosen and the same degree of filtering is applied universally. With the local filter, each pixel is treated separately and is dependant upon the pixels immediately surrounding it. In this way each pixel is changed according to a majority rules type of philosophy. This implies that any partial errors introduced by the classification process will be taken care of, because these errors will be locally restricted and will not be propagated.

This research, however, did not cover the complete spectrum of filters that may be employed in the frequency domain. A logical extension would be to investigate frequency domain filters that act more like the local filters used in the spatial domain. These might give a more accurate representation of the data set. As well, one could begin to

look at power spectrum plots and select the frequencies that contain the majority of the information in the data sets. Also, by utilizing bandlimited filters it may be possible to get more acceptable results.

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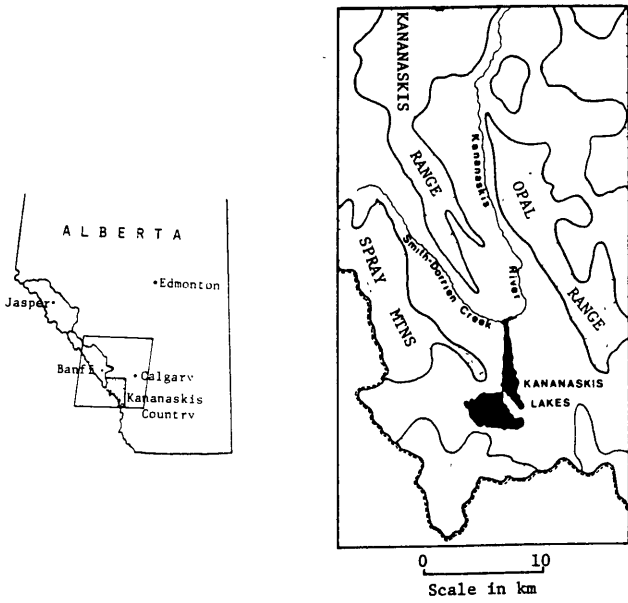


Figure 1: The Kananaskis Valley in Alberta

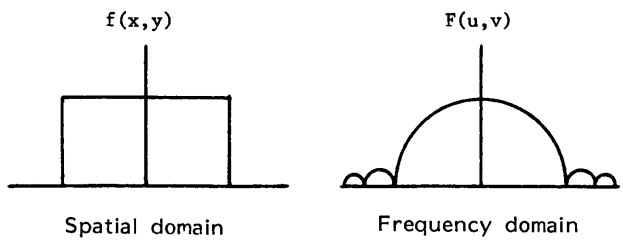


Figure 2: Window function and its Fourier Transform

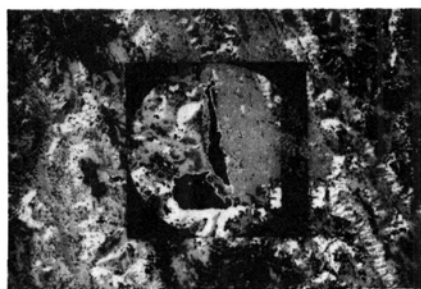


Figure 3: Circular pattern of Hamming window

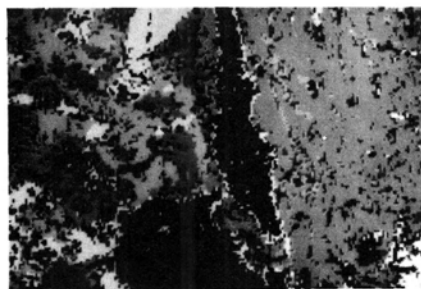


Figure 4: Unfiltered classified data set

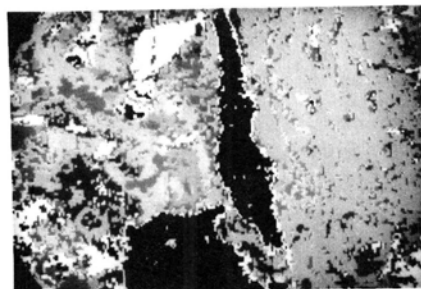


Figure 5: Lowpass Butterworth filter (99 percent)

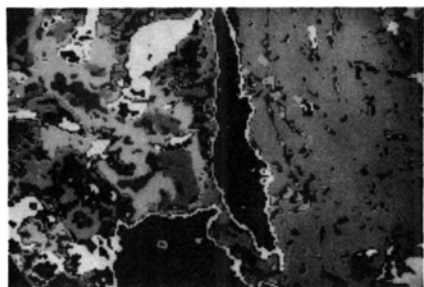


Figure 6: Lowpass Butterworth filter (95 percent)

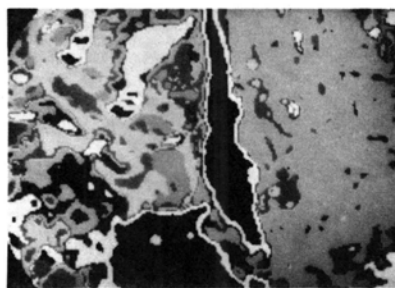


Figure 7: Lowpass Butterworth filter (90 percent)

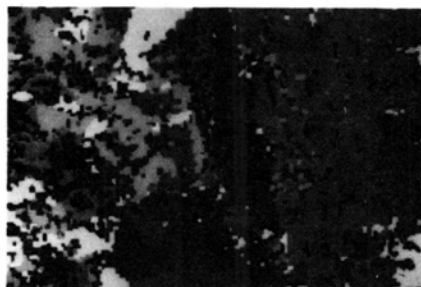


Figure 8: Minimum-Variance spatial filter

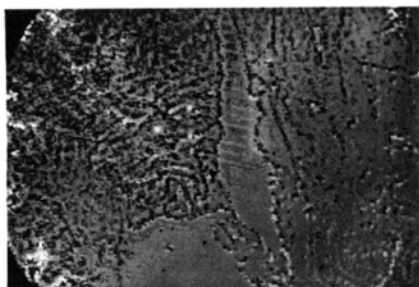


Figure 9: Highpass Butterworth filter (95 percent)

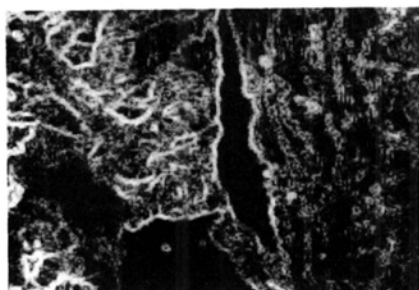


Figure 10: Gradient spatial filter