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Temporal Change Enhancement in Multispectral Images Remotely Sensed from Satellites

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ABSTRACT

The application of principal components analysis (PCA) to multispectral satellite images is a routine way to present the data in false-color composite images. These composite images include a very high percentage of available information and have no correlation between the displayed colors. PCA routines are included in commercial GIS software, and custom algorithms are in wide use. This paper describes an early application of a new, genetic algorithm based, PCA routine. Landsat data for an Idaho farm were evaluated for temporal changes using this new algorithm, and the eigenvalues consistently converged with excellent results.

Keywords: satellite images, multispectral, Landsat, genetic algorithm, temporal change, principal components analysis, PCA.

BACKGROUND

Each spectral band in a multiband data set contributes both exclusive and redundant information from a scene. The redundant information is that which is contributed by one or more of the other bands, and a measure of this redundancy is the interband correlation. It is often desirable to discard, or at least deemphasize, this redundant information prior to the evaluation of a scene. If an area on the ground reflects similarly in two or more bands, similar images of this area could be made from either of these redundant bands alone, or from a single combination of these bands, each weighted in some fashion. This reduction in dimensionality is desired since many bands are outside the range of human vision, and information contained in these bands must be displayed in false colors which humans can see. The process of PCA consolidates most of the information scattered throughout all the available bands into three or less new bands, which are made up of weighted contributions from each original band, and which have no correlation with each other. Having been consolidated into three new superbands, or principal components (PCs), most of the information from a scene may then be displayed in a single false-color composite.

a. PCA

Each spectral band in a Landsat data set contains measured values relating to the visible and infrared power received from the Earth. Brightness associated with a particular band can be considered as one measured dimension in a multidimensional coordinate system. Each axis in this system is assigned to a particular band. A pixel could then be represented by its displacement along each axis in this system, and be plotted according to its brightness in each band. A pixel having a certain value in one band would likely have a corresponding value in a correlated band.¹

If each of the n axes in this system were to be individually rotated, the axes in the transformed system could be oriented so that the interaxis correlation disappears. The first axis to be rotated can be oriented in n -space so that the image data projected onto it exhibit maximum variance. The second axis to be rotated is oriented in n -space to be orthogonal to the first, then rotated throughout this orthogonal $n-1$ space until the variance of the image data projected onto it reaches a peak. The third axis to be rotated is oriented to be orthogonal to the first two, then rotated throughout this orthogonal $n-2$

space until the variance of the image data projected onto it reaches a peak. This process continues until the last axis is set to be orthogonal to all the previous ones.

Each new axis is a linear transformation of the original set of axes, and each new variable associated with these new axes is a linear transformation of the original set of variables. The original variable could be the brightness in band 4. A transformed variable (PC) is a weighted combination of the brightness of all the bands. For example, the brightness of a pixel in the first PC includes a contribution from band 4 weighted according to the following:

$$w_{B4-PC1} = \cos \theta_{PC1} / \cos \theta_{B4}$$

where θ_{B4} is the angle between the pixel vector and the axis for band 4, and θ_{PC1} is the angle between the pixel vector and the axis of the first PC. While descriptions of vector rotation are useful in conveying what takes place in PCA, the actual process begins with the calculation of the covariance matrix of the n bands. Any off-diagonal nonzero value in this matrix represents some interband correlation, and the diagonalization of this matrix involves a transformation which can be used to eliminate this correlation through what has been described as axis rotation. The eigenvectors which result from this diagonalization become the new axes, and the associated eigenvalues represent the variances of the data projected onto these new axes. PCA is simply obtaining the eigenvectors of the multiband covariance matrix, then projecting the original data onto these eigenvectors.

b. Obtaining the Eigenvectors

Common methods to obtain the eigenvectors of a covariance matrix are described in the literature.² The new method presented herein involves the use of a genetic algorithm.³ Genetic algorithms as search engines have the advantage of being robust, i.e., they are not stalled at local peaks, neither do they "blow up" at singularities.⁴ Genetic algorithms are also tenacious – as long as the opportunity for further optimization exists in the search space, the algorithm will continue to progress through this space toward the optimum result.⁵

c. The Genetic Algorithm PCA

The genetic algorithm used³ involves the evolution of the transformation matrix used to diagonalize the covariance matrix. A more detailed description of this process will be available some time in the future.³ Further background on genetic algorithms can be found in the literature.^{4,5}

Application of the Genetic Algorithm PCA to a Scene for Temporal Change Enhancement

a. Data Used

The scene used was chosen for its relevance to some precision agriculture work we are involved in. A test bed farm a few miles southeast of Rexburg, Idaho, is the focus of this activity. Landsat Thematic Mapper (TM) data from three dates, July 2, 1984, May 2, 1992, and July 24, 1992, were used. Data spanning much shorter time intervals would make for a more interesting evaluation of temporal change, but such data were not available.

b. Preprocessing

The data from the latter two dates was previously corrected for satellite path inclination, but the data from July '84 were not corrected. Rotation using bicubic interpolation was applied to the July '84 data set to align it with the other data sets. A minor rescaling was also required to complete the registration of the July '84 data with the data from May and July '92. Since the focus was to be on a particular farm, spanning only a half mile, it was felt useful to try to improve the display of the 30-meter resolution data sets by magnifying them four times. Bicubic interpolation was used since it minimizes the amount of interpolation error, i.e., it minimizes the loss of an image's high spatial frequency components. Any interpolation

error introduced is likely correlated across all the bands, and relegated by the PCA to the lowest ranking PCs. The artifacts of the interpolation process will be visible in the low-ranking PCs.

c. First Approach: Applying PCA to Single Eighteen-Band Stack

Only the 30-m resolution TM bands were used, i.e., bands 1-5, and 7. This first approach was initiated by stacking all six bands from each date into a single eighteen-band file, then performing the PCA on this file.⁶ All eighteen PCs were saved and displayed. Features which are exclusively associated with one of the three dates were observed. Usable information was apparently available even in PCs ranked as low as ninth or tenth. The highest ranking PCs had the effect of emphasizing the more obvious scene detail, leaving the less obvious, and even obscure, detail to be clearly evident in the middle ranking PCs – those ranked from about fourth to seventh. However, the variation which was enhanced in this data configuration was a mixture of spectral variation and temporal variation – a mixture which placed no particular emphasis on the temporal variation. The steps in this first approach are summarized below:

- 1) Combine all bands from all dates into a single multispectral, multitemporal file.
- 2) Run a PCA on this combined file.

The second approach in this evaluation attempted to reconfigure the data in a way that would provide more opportunity for temporal variation enhancement.

d. Second Approach: Applying PCA to Single-Date PCs

The focus of the PCA is on the covariance matrix. A covariance matrix biased toward temporal variation can be obtained by first consolidating the six-band data from each date into PCs. The highest ranking PCs from each date are then combined into a superset. In the absence of temporal variation, a PC from one time would be completely correlated with its counterpart of another time, and have no correlation with the rest of the PCs in this superset. If a followup PCA were to be performed on this superset, temporal variation would have an exaggerated influence on the covariance matrix guiding the PCA. The resulting PCs should more effectively display the temporal change. PCAs were run on the data from each of the three dates, and then a follow-up PCA was performed on a file composed of the top three ranking PCs from each date. The resulting PCs were then displayed in a false-color composite which had significantly more detail than the one obtained using the first approach. The steps in this second approach are summarized below:

- 1) Run PCAs on files for each individual date.
- 2) Combine top ranking PCs from each date into a single superset.
- 3) Run a PCA on this superset.

e. Third Approach: Masking Off Areas to Restrict Algorithm to Farm

Since the primary interest is in the variation within a bounded area, the enhancement of variation should be restricted to this area. A mask was made to zero all pixels across all bands in areas outside of the farm's perimeter. The outline of this farm is that of a tilted semicircle, resulting from 180° pivot irrigation, with the pivot being close to railroad tracks running southwest to northeast. The PCA algorithm used in this evaluation³ was modified to recognize this form of masking, and ignore all zeroed pixels in the analysis. The data were configured and processed according to the second approach. The results were satisfying since even more detail was observed.

Finally, the data set from May '92 was removed from the evaluation, and this third approach was made solely on the data from July '84 and July '92. The farm fields were covered by bare soil in May '92, whereas they were fairly uniformly covered with vegetation in both July '84 and July '92 (see Figure 1, a and b). The similarity in ground cover for the two July dates made data from these dates more germane to a temporal change enhancement effort. Though these dates are separated by eight years, the perceived temporal change was far more subtle than that perceived in any comparisons involving the May

Figure 1

'92 data. Due to the lack of data separated by a short time interval, the apparently similar July data were used. The perception of similarity in ground cover was subsequently reinforced when overlays of data from each July date were made using both TM band 2 and TM band 4 (see Figure 1 c). Despite the apparent similarity in ground cover, this third approach led to a significant amount of detail being evident when false-color composite images were made from the resulting PCs (see Figure 1 d). The steps in this third approach are summarized below:

- 1) For each individual date file, mask or zero-out all pixels not within the area of interest.
- 2) Run PCAs on each of these masked files.
- 3) Combine top ranking PCs from each date into single superset, remask if necessary.
- 4) Run a PCA on this superset.

Conclusions

Effective temporal change enhancement of multispectral images using PCA is facilitated by first masking out all pixels not within the area of interest, then running PCAs on the image data from each individual date or acquisition time. The top ranking PCs from each acquisition time can then be combined in a single file, in which each acquisition time is represented by a small set of mutually orthogonal bands or PCs. Each set contains most of the information available from each acquisition time. When a PCA is then run on this combined file, the covariance matrix guiding the PCA is biased toward temporal variance in the data, and the enhancement of variance which results from this PCA is, in turn, an enhancement of temporal variance. The genetic-algorithm based PCA software used in this analysis³ consistently performed with excellent results.

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