Transform Methods for Remote Sensing Environmental Monitoring

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Abstract

Transform methods in signal and image processing generally speaking are easy to use and can play a number of useful roles in remote sensing environmental monitoring.
Examples are the pollution and forest fire monitoring. Transform methods offer effective procedures to derive the most important information for further processing or human interpretation and to extract important features for pattern classification. Most transform methods are used for image (or signal) enhancement and compression. However other transform methods are available for linear or nonlinear discrimination in the classification problems. In this paper we will examine the major transform methods which are useful for remote sensing especially for environmental monitoring problems. Many challenges to signal processing will be reviewed. Computer results are shown to illustrate some of the methods discussed.

Index Terms: transform methods, environmental monitoring, SAR image noise, component analysis, contextual image models.

1. INTRODUCTION

One unique feature in the remote sensing problems is that a significant amount of data are available, from which desired information must be extracted. Transform methods offer effective procedures for data representation, data compression and feature. extraction for pattern classification. In this paper the use of major transform methods in remote sensing will be examined non-mathematically.
Many mathematical details are in [1].[2][3]. These transforms generally involve linear operations. Let **x** be an n-dimensional input vector and **V** be the transformation matrix. The linear transform is $\mathbf{y} = \mathbf{V}\mathbf{x}$; $\mathbf{V} = [\, \mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n \,]$
For data representation

$$\hat{x} = \sum_{i=1}^{m} y_i v_i \qquad m \le n$$

In a non-linear transform, replace y_i by a function of y_i, $g_i(y_i)$. For data compression, **y** has a lower dimensionality.
In linear orthogonal transform, the vectors forming **V** are orthogonal. The optimal orthogonal transform in the minimum mean square error sense is the discrete Karhunen-Loeve transform (KLT). It has several equivalent names such as the empirical orthogonal function (EOF) and principal component analysis (PCA). For the purpose of pattern classification, such transforms can be useful as features. However the low mean square error does not guarantee the minimum probability of error typically used as classification performance measure. In fact the transforms for data representation are generally not the same as those for discrimination. We will examine other transforms such as the wavelet transform which has recently been used quite extensively in the remote sensing problems, and the independent component analysis (ICA) which was largely used in the blind source separation problems.
The advancement in signal processing provide many powerful transform and other techniques to deal with the environmental monitoring problems in remote sensing. Notably among the signal processing challenges is the complexity of noises that differ among different sensors and environments. Most signal processing methods are designed for additive noise situations. Mathematical modeling of noises is only partially successful. In general mathematical modeling of the remote sensing data is difficult. A good example is the speckle

noises that exist in synthetic aperture radar images. Though there are hundreds of papers on the subject, effective noise reduction is still problem dependent. The second challenge is the change detection. In environmental monitoring we need to assess the changes such as oil slick, pollution, damages of flood or fire, or even the seasonal variation of crop harvest. Just to take the difference or ratio of the images "before" and "after" an event such as flood or fire is not enough. An accurate assessment of the change requires a good pixel by pixel classification for images. Accurate pixel classification requires a high performance classifier which is not easy to come by. Ideally a simple signal processing procedure should be developed to give us the change detection results. The third challenge is the fusion of data from multisources or multisensors. The fused data is supposed to give us more information. Again a simple signal processing procedure is yet to be developed for effective data and sensor fusion. Another challenge is the subpixel detection and classification problem of target smaller than a pixel, since all sensors have their resolution limitation.

2. PCA and Component Analysis

The PCA transformation is based on the global covariance matrix. The traditional PCA attempts to maximize the data variances in the directions (components) of eigenvectors. The components are statistically uncorrelated and reduced rank reconstruction error is minimized. It does not guarantee however maximizing the signal to noise (SNR). The noise-adjusted PCA transform (NAPCA) attempts to make noise covariance to be identical in all directions, thus maximizing the SNR. For the projected PCA transform, the Wiener filtered data are projected onto the r-dimensional subspace of m eigenvectors of a modified covariance matrix ($r < m$) ([1] Chapter 11) The reconstruction of noise free data yields lower distortion (i.e. reconstruction error) than the PCA and NAPCA.

For discriminant analysis both inter-class and intra-class scatter matrices must be considered. There are a large number of papers on Linear Discriminant Analysis (LDA) but their use in remote sensing has been quite limited.

PCA may be considered as the most basic and most popular component analysis method. PCA only decorrelates the components of a vector. Nonlinear PCA attempts to use high-order statistics in PCA analysis. The independent component analysis (ICA) seeks for independent components which provide complimentary information of the data. ICA may use high-order statistical information. Its computation can now be more efficient by using fast ICA algorithms.

Among the other component analysis methods is the Hermite Transform. It is an image representation model that provides an efficient tool for image noise reduction and data fusion ([1] Chapter 24). The Gaussian derivative family exhibits a special kind of symmetries related to translation, rotation, and magnification and is particularly suitable for integration into Hermite transform for local orientation analysis. The SAR image noise reduction and fusion for multispectral and SAR images clearly demonstrated the important application of this unique approach.

Among other transforms is the S-transform. S-transform is an invertible time-frequency localization technique which combines elements of wavelet transform and short-time Fourier transform. 2-D S-transform was demonstrated for speckle noise removal of SAR images

3. WAVELET TRANSFORMS

There has been significant interest on the use of wavelet transforms in remote sensing ([2] Chapter 8). The 2-D Wavelet transforms have compared well with the discrete cosine transform for image compression. Wavelets provide a framework of multiresolution representation of the SAR image. One desirable characteristics of the wavelet transform is that the coefficients are nearly uncorrelated [20], i.e. the wavelet transformed image covariance matrix has off-diagonal terms nearly zero. Thus the wavelet coefficients are more effective than the original data as features. For each pixel in the subimages a feature vector can be constructed for classification. However pixel classification for image segmentation based on the 12-dimensional vector can be improved. It is also noted that fast algorithms are available for wavelet transform computations. Wavelet transforms are also useful for edge-preserving image smoothing in hyperspectral images and for detection of coastlines.

There are several choices of wavelet basis functions including the Morlet wavelet, Daubechet wavelet et al. Wavelet analysis has opened up many new information processing methods in remote sensing.

With the exception of perhaps the Haar transform, wavelet transforms do not follow the definition of linear transform, $\mathbf{y} = \mathbf{V}\mathbf{x}$, though the computation involved is a linear operation. A nonlinear, such the thresholding the large amplitude wavelet coefficient terms, can lead to improved image, i.e. reduction of noise.

4. CONTEXTUAL INFORMATION

One other important property of the remote sensing image is the rich contextual statistical information which must be described mathematically. The simplest form of contextual information perhaps is the co-occurrence statistics, which are very useful for image features. Formal contextual

models make use of the Markov random field and the 2-D time series analysis. The commonly used

Markov random field (see e.g. [4]) provides an estimate of each pixel based on the conditional Gaussian probability density of its neighboring pixels. The estimate however is not in a simple transform format. The autoregressive (AR) model can be set up as a transform and is computationally much simpler for one-dimensional pixel values. For a vector pixel constructed from a sequence of images, the AR model can be estimated efficiently by a new procedure developed by P. Ho [5].

5. COMPUTER RESULTS

To illustrate the transform methods, three sets of computer results are shown in this section. Fig. 1a shows a set of five channels among the nine original channels of SAR images. The nine channels include the nine pair combination among the three frequency bands (c,l,c bands) and three polarizations (hr, hv, vv). Fig. 1b shows the result of using an Independent Component Analysis method developed by us ([1] Chapter 20) that considerably removes the speckle noises. Another example is on the use of the second order AR model for extraction of water areas in the Lake Mulargias region in Italy [6]. Fig. 2a is the original image while Fig. 2b is the result of the image segmentation.

Although signal processing expert may consider the operations involved are fairly simple for each pixel, to process the entire image of say 512x512 require a lot of computations which can be a significant challenge for real time or near real time needs. To process vector image pixels for the entire image is even more computationally demanding. As a concluding remark, there are many opportunities and challenges in using signal processing for environmental monitoring which is a problem area of growing importance locally and globally. More talents in the signal processing community need to be directed toward solving remote sensing environmental monitoring problems.

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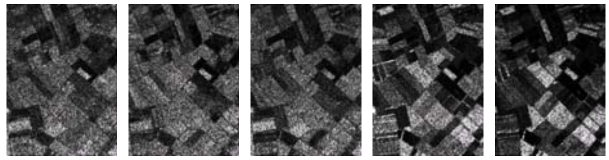


Fig. 1a   Five Channels of Original SAR Images

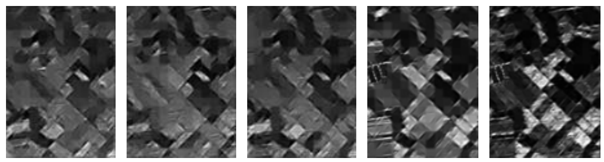
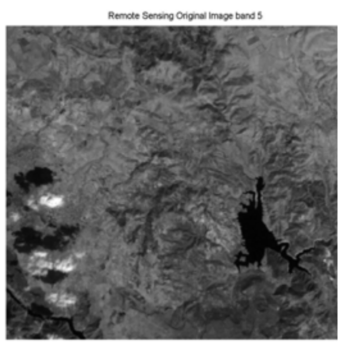


Fig. 1b   Restored Images with the Proposed Method



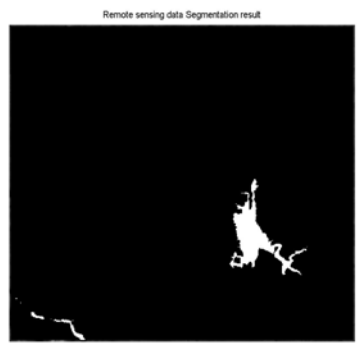


Fig. 2a Original image

Fig. 2b Segmented image