HYPERSPECTRAL IMAGE ANALYSIS
USING HILBERT-HUANG TRANSFORM

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ABSTRACT: Hyperspectral images, which contain rich and fine spectral information, can improve land use/cover classification accuracy, while traditional statistics-based classifiers cannot be directly used on such images with limited training samples. The commonly used method to solve this problem is dimensionality reduction, and this can be done by feature extraction for hyperspectral images. There are two types of feature extraction methods. The first type is based on the statistical property of data, such as principal component transform (PCT), discriminant analysis feature extraction (DAFE) and decision boundary feature extraction (DBFE). The other type of feature extraction methods is based on time-frequency analysis. For example, it has been proven that wavelet-based feature extraction provide an appropriate and effective tool for spectral feature extraction. However, these methods have some disadvantages; for instance, it still needs adequate training samples, or it has to select the wavelet basis function in advance. Hilbert-Huang transform (HHT), consisting of empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA), is a relatively new adaptive time-frequency analysis tool, and has been used extensively in nonlinear and nonstationary data analysis. In this study, the HHT is implemented on the hyperspectral data for physically spectral analysis. The spectral features are then extracted based on the results of physically spectral analysis, so that we can get a small number of salient features, reduce the dimensionality of hyperspectral images and keep the accuracy of classification results. In our experiment, a real hyperspectral data set is used to test the effectiveness of HHT which was applied on feature extraction and classification. Finally, the results are also compared with other feature extraction methods.

1. INTRODUCTION

Imaging spectrometer, a technology which was developed in 1980's, can obtain hundreds of spectral bands simultaneously (Goetz *et al.*, 1985). The images acquired with spectrometers are called as hyperspectral images which not only reveal two-dimensional spatial information but also contain rich and fine spectral information. With these characteristics, they can be used to identify surface objects and improve land use/cover classification accuracies. In past three decades, hyperspectral images have been widely used in different fields such as mineral identification, vegetation mapping, and disaster investigation.

Due to the high dimensionality of hyperspectral data, image processing methods which have been effectively applied to multispectral data in the past are not as proper as to hyperspectral data. For example, it is ineffective when the traditional statistical classification methods are applied to hyperspectral images with limited training samples. In other words, the dimensionality increases with the number of bands, the number of training samples for classification should be increased as well (Hsu, 2007). This has been termed the "curse of dimensionality" by Bellman (1961). The commonly used method to solve "curse of dimensionality" is dimensionality reduction, which can be divided into two types: feature selection and feature extraction. For hyperspectral images, feature extraction is used to reduce the dimensionality more frequently (Hsu, 2003). Furthermore, there are two types of feature extraction methods. The first type is based on the statistical property of data. For instance, principal components transform (PCT) is the most commonly used and simple method. Although it concerns the distribution of whole data, some useful features for hyperspectral data will be neglected easily. Discriminant analysis feature extraction (DAFE) is to maximize the between-class scatter and minimize the within-class scatter. Although DAFE is an effective and practical algorithm, there are some disadvantages. First, the maximum number of feature is the number of class minus one. In order to get reliable parameters in DAFE, it needs enough training samples (Fukunaga, 1990; Lee and Landgrebe, 1993). Moreover, decision boundary feature extraction (DBFE), which was proposed by Lee and Landgrebe (1993), could find useful features by decision boundaries between different classes. It still needs adequate training samples to compute the decision boundaries. The other type of feature extraction methods is based on time-frequency analysis. For example, it has been proven that wavelet-based feature extraction provide an appropriate and effective tool for spectral feature extraction (Hsu, 2003). However, this method has some disadvantages; for instance, it has to select the wavelet basis function in advance, or it is not suitable for nonlinear data analysis.

Hilbert-Huang transform (HHT) is a relatively new adaptive time-frequency analysis tool. It combines empirical mode decomposition (EMD) and Hilbert spectral analysis (HSA), and has been used extensively in nonlinear and nonstationary data analysis. In this study, the HHT is implemented on the hyperspectral data for physically spectral analysis. The spectral features are then extracted based on the results of physically spectral analysis, so that we can get a small number of salient features, reduce the dimensionality of hyperspectral images and keep the accuracy of classification results. In our experiment, an AVIRIS data set is used to test the performance of the proposed HHT-based methods. Finally, the results are also compared with other feature extraction methods.

2. HILBERT-HUANG TRANSFORM

Hilbert-Huang transform (HHT), first proposed by Huang *et al.* (1998), is a valid time-frequency analysis tool for nonlinear and nonstationary data. The HHT which consists of empirical mode decomposition (EMD) and Hilbert spectral Analysis (HSA) will be described briefly in this section.

2.1 Empirical Mode Decomposition

Empirical mode decomposition (EMD) decomposes time-series data into a series of intrinsic mode functions (IMFs) adaptively. These IMFs include different regions of frequency, and each IMF has two properties (Huang, 2005):
(1) The number of extrema and the number of zero-crossing of an IMF must equal or differ at most by one.
(2) All the local maxima and minima of an IMF are symmetric with respect to zero.

The EMD consists of the following steps:
(1) First, identify all the local maxima and connect them by cubic spline function as the upper envelope for a signal, $x(t)$. Repeat the procedure for the local minima to generate the lower envelope.
(2) Compute the mean m_1 of the upper and lower envelopes, and let $x(t)$ minus m_1. We will get first proto-IMF (PIMF) component, h_1:

$$x(t) - m_1 = h_1 \tag{1}$$

The procedure which obtain IMF components is called sifting process.
(3) Proto-IMF, h_1, may not satisfy the definitions of IMF. Repeat the sifting process k times until the IMF meet the stoppage criteria.

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{2}$$

(4) As soon as the IMF component satisfy the criteria, we will get first IMF, c_1, and separate c_1 from $x(t)$.

$$x(t) - c_1 = r_1 \tag{3}$$

(5) Since the residue, r_1, still contains information with long periods, it is treated as the data and repeat the sifting process. The result is

$$\begin{gathered} r_1 - c_2 = r_2 \\ \cdots \\ r_{n-1} - c_n = r_n \end{gathered} \tag{4}$$

Finally, by Summing up equation (3) and (4), we obtain

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{5}$$

The EMD separates variations from the mean, and each IMF has its own physical meaning.

2.2 Hilbert Spectral Analysis

Having obtained the IMF components, we can apply the Hilbert transform to each IMF component and compute the instantaneous frequency. Then we can find the complex conjugate, $\hat{c}_i(t)$, of an IMF, $c_i(t)$, and have an analytic signal:

$$z_i(t) = c_i(t) + j\hat{c}_i(t) = a_i(t)e^{j\theta_i(t)} \tag{6}$$

$a_i(t)$ is the function of instantaneous amplitude, and $\theta_i(t)$ is the function of phase angle. As a consequence, we can express the original data as the real part, *RP*, in the following form:

$$X(t) = RP\sum_{i=1}^{n} a_i(t)e^{j\theta_i(t)} = RP\sum_{i=1}^{n} a_i(t)e^{j\int \omega_i(t)dt} \tag{7}$$

Therefore, the Hilbert spectrum can be defined as:

$$H(\omega,t) = RP\sum_{i=1}^{n} a_i(t)e^{j\int \omega_i(t)dt} \tag{8}$$

We can also define the marginal Hilbert spectrum as:

$$h(\omega) = \int_0^T H(\omega,t)dt \tag{9}$$

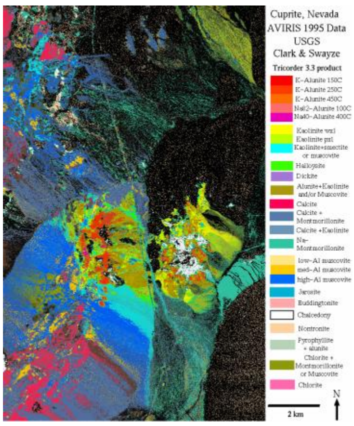
In summary, the HHT, consisting of EMD and HSA, can decompose data adaptively and compute instantaneous frequency by differentiation rather than convolution. HHT is a superior data analysis tool for nonlinear and nonstationary data.

3. HYPERSPECTRAL IMAGE FEATURE EXTRACTION USING HILBERT-HUANG TRANSFORM

3.1 Datasets Description

In this study, an AVIRIS data set is used to test the performance of using HHT on hyperspectral image feature extraction and classification. The AVIRIS data set shown in Figure 1(a) is the well-known Cuprite data set, which is a mineral region at Nevada. The image size of the test field is 350×350. The number of bands is 224. Figure 1(b) also shows a mineral map produced in 1995 by USGS. In this study, we choose 6 classes from this map (Table 1) for feature extraction and classification.

(a) False image



(b) Mineral map in Cuprite (USGS Spectroscopy Lab, 1998)

Figure 1. An AVIRIS data set of Cuprite

Table 1. The 6 chosen classes

Class names
Alunite
Kaolinite
Muscovite
Calcite
Montmorillonite
Kaolinite+Semectite or Muscovite

3.2 Feature Extraction Using Hilbert-Huang Transform

According to the characteristics of time-frequency analysis of HHT, the HHT will be applied to spectral curves of each pixel in hyperspectral image. First of all, Hilbert-Huang transform is implemented on a spectral curve. The instantaneous frequency and amplitude of each component will be calculated. Then Hilbert spectrum is formed by using instantaneous frequency and amplitude. The residual information is also considered in this spectrum. After that, the M largest values in the Hilbert spectrum are selected as the important features of the spectral curve for classification. These features are sorted by the bands where the feature is located. If more than two features have same location of bands, sort the features according to their frequency. Finally, the extracted features are used as the inputs for classification. Maximum likelihood classifier is used in this study. The procedure of feature extraction using Hilbert-Huang transform is illustrated in Figure 2.

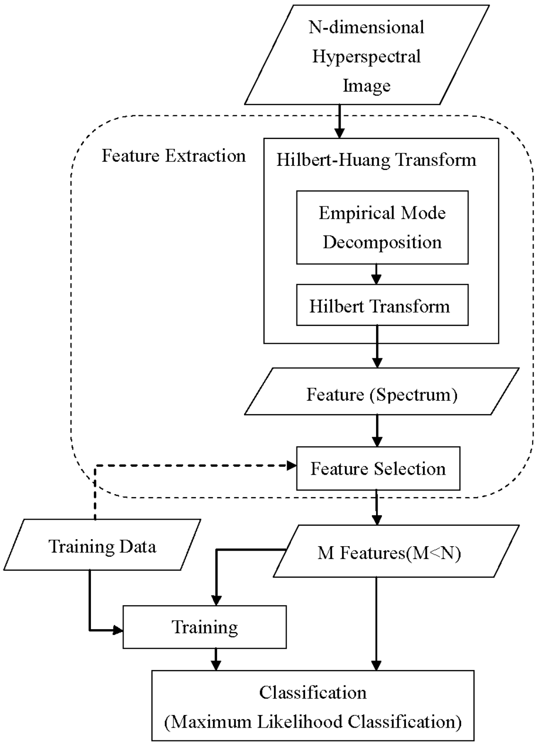


Figure 2. The flow chart of feature extraction using Hilbert-Huang transform

4. EXPERIMENTS

There are two experiments in this study. The first experiment is to compare the performance between unsupervised and supervised HHT-based feature extraction. In experiment II, the HHT-based feature extraction methods are compared with other feature extraction methods mentioned in section 1.

4.1 Experiment I: Comparison of Classification Results between Unsupervised and Supervised HHT-based Feature extraction

The purpose of the experiment is to test the performance of unsupervised feature extraction method which mentioned in section 3.2. In addition, the features of supervised HHT-based feature extraction are selected by computing Bhattacharyya distances from the features extracted by unsupervised HHT-based methods. The classification accuracies are calculated for various numbers of features by HHT-based methods.

Figure 3 shows the classification accuracies with different HHT-based feature extraction methods. We can find that both unsupervised and supervised HHT-based methods have good classification accuracies. The classification results both conform to Hughes phenomenon that accuracy increases at first and then accuracy decline when the number of features increases with constant number of training samples. Compared with unsupervised HHT-based method, supervised HHT-based method can improve classification accuracy apparently. Supervised HHT-based feature extraction can achieve better classification accuracy (91%) with nine features, whereas unsupervised HHT-based method has lower accuracy (76.33%) with five features. Therefore, supervised HHT-based method can have better results by calculating the separability of different classes with training samples than unsupervised HHT-based method.

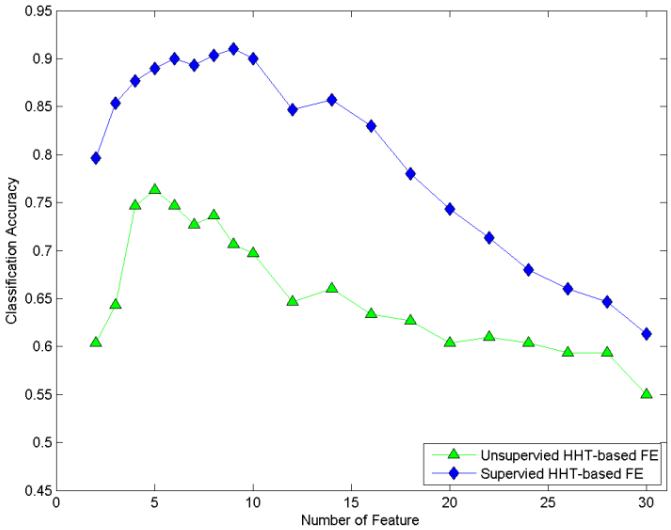


Figure 3. Comparison of classification accuracies between HHT-based methods

4.2 Experiment II: Comparison of Classification Results Using Different Feature Extraction Methods

In experiment II, the purpose is that compare the performance using HHT-based methods with other feature extraction methods. The classification accuracies with different methods are showed in Figure 4. First of all, the classification accuracies of all these method are conformed to Hughes phenomenon, but the results of PCT is the worst. Secondly, the results of DAFE, DBFE and supervised HHT-based methods are similar and better than other methods. Nevertheless, the maximum number of features of DAFE is only L-1 where the number of classes in this experiment is L = 5. Next, the results of nonlinear WFE and unsupervised HHT-based method are similar. After all, the classification accuracies of supervised HHT-based method are more stable than other methods when number of features is more than twenty-four.

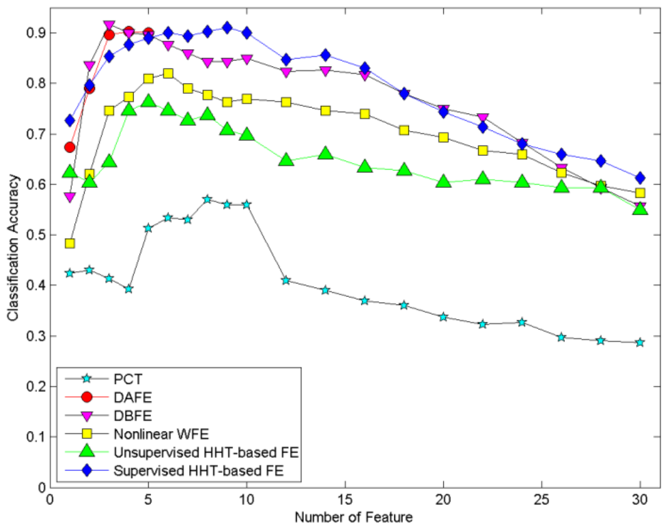


Figure 4. Comparison of classification accuracies using different methods

5. CONCLUSION

In this study, two feature extraction methods using Hilbert-Huang transform were proposed to extract useful features for hyperspectral image classification. The experiment results show that HHT-based feature extraction methods are an effective tool. According to the experiment results, the classification accuracies of supervised HHT-based feature extraction are similar with DAFE and DBFE. Furthermore, the results of unsupervised

HHT-based method are similar with nonlinear wavelet-based feature extraction. By extracting features form Hilbert spectrum, we can not only reduce the dimensionality of hyperspectral image but also get a small number of salient features for classification. Therefore, Hilbert-Huang transform is an appropriate tool for hyperspectral image analysis.

In the future, the effectiveness of HHT-based methods still has room for improvement. In addition, the objects identified in the experiments are mainly the minerals. It is another object to investigate that the HHT-based feature extraction methods proposed in this study are suitable for other kind of material objects such as metropolitan area or vegetation area.

REFERENCE

AVIRIS Airborne Visible/Infrared Imaging Spectrometer, 2011. AVIRIS Data - Ordering Free AVIRIS Standard Data Products, URL: http://aviris.jpl.nasa.gov/data/free_data.html, (last data accessed：2011/07/14).

Bellman, R., 1961. Adaptive Control Processes: A Guided Tour: Princeton University Press.

Fukunaga, K., 1990. Introduction to Statistical Pattern Recognition, Second edition, San Diego: Academic Press, Inc.

Goetz, A. F. H., G. Vane, J. E. Solomon, and B. N. Rock, 1985. Imaging Spectrometry for Earth Remote Sensing, Science, 228:1147-1153.

Hsu, P.-H., 2003. Spectral Feature Extraction of Hyperspectral Images using Wavelet Transform, National Chen Kung University, Tainan, Taiwan, R.O.C.

Hsu, P.-H., 2007. Feature extraction of hyperspectral images using wavelet and matching pursuit, ISPRS Journal of Photogrammetry and Remote Sensing, 62(2):78-92.

Huang, N. E., Z. Shen, S.R. Long, M. C. Wu, H. H. Shin, Q. Zheng, N.-C. Yen, C. C. Tung, and H. H. Liu, 1998. The empirical mode decomposition method and the Hilbert spectrum for non-stationary time series analysis, Proc R. Soc. London, A454: 903-995.

Huang, N. E., 2005. Introduction to Hilbert-Huang Transform and Some Recent Developments. The Hilbert-Huang Transform in Engineering, Taylor & Francis Group, LLC, Boca Raton, pp.1-23.

USGS Spectroscopy Lab, 1998. Imaging Spectroscopy Material Maps: Cuprite Introduction, URL: http://speclab.cr.usgs.gov/map.intro.html, (last data accessed：2011/07/14).