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KNOWLEDGE-BASED EVIDENTIAL REASONING ANALYSIS OF IMAGING SPECTROMETER DATA

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ABSTRACT Traditional classifier based on statistical theory can't be used to comprehensively deal with spectral indexes with different knowledge backgrounds and at different scales of measurement, and can't meet the needs of quantitatively analyzing Imaging Spectrometer data. This paper introduces the knowledge-based evidential reasoning analysis of Imaging Spectrometer data based on Dempster-Shafer Theory of Evidence. Testing results show that knowledge-based evidential reasoning analysis of Imaging Spectrometer data is a more effective approach of comprehensively and quantitatively analyzing spectral indexes with different knowledge backgrounds and at different scales of measurement. The accuracy of identifying ground objects with Imaging Spectrometer data can be effectively improved.

INTRODUCTION

Spectral behavior of object is a very complicated phenomenon. A single spectral index only is a description of spectral behavior of object in a certain aspect based on understanding of spectral characteristics of object to a certain extent. The description generally is ambiguous, inaccurate and incomplete to some extent. To completely describe and express the spectral behavior of an object, various spectral indexes of describing spectral characteristics of the object must be comprehensively utilized. Traditional classifier based on statistical theory can't be used to comprehensively deal with spectral indexes with different knowledge backgrounds and at different scales of measurement, and can't meet the needs of quantitatively analyzing Imaging Spectrometer data. E.g. maximum-likelihood algorithm and smallest distance classifier were neither designed nor intended to process data sets which possess higher dimensions (or number of bands, e.g. Imaging Spectrometer data), properties inappropriate for parametric statistical analyses and different scales of measurement (Peddle, 1995).

In currently practical applications, quantitative analysis algorithms of Imaging Spectrometer data generally utilize a single spectral index with a certain knowledge background, e.g. coding spectral absorption bands, matching wave shape of spectrum and spectral angle index. Accuracy of quantitatively identifying ground objects generally is poor and unreliable.

In recent years, evidential reasoning analysis of remote sensing and multi-source data based on D-S (Dempster-Shafer) Theory of Evidence received a increasing attention. Several testing results of previous studies (Gordon J. 1985, Moon W. M. 1990, Peddle 1995, Gong 1996) shown that evidential reasoning analysis is a full potential approach of comprehensively classifying data sets with different knowledge background and at different scales of measurement.

This paper introduces the knowledge-based evidential reasoning analysis of Imaging Spectrometer data based on Dempster-Shafer Theory of Evidence. Testing results show that knowledge-based evidential reasoning analysis of Imaging Spectrometer data is a more effective approach of comprehensively and quantitatively analyzing spectral indexes with different knowledge backgrounds and at different scales of measurement. The accuracy of identifying ground objects with Imaging Spectrometer data can be effectively improved.

THEORY OF EVIDENTIAL REASONGING ANALYSIS

D-S Theory of Evidence is a more effective approach of analyzing data sets which is inaccurate, uncertainty and ambiguous. A key aspect of the D-S Theory of Evidence is its ability to combine evidences extracted from multi-source data sets which often possesses different properties in the form of belief measure and plausibility measure by using the technique of orthogonal summation (denoted by $\oplus$). As an alternative approach to Bayesian theory, the D-S Theory of Evidence provides a powerful method for combining evidence into a decision using the concepts of evidential intervals and degrees of belief (Peddle, 1995).

Let a vector $X = (x_1, x_2, \cdots\cdots, x_n)$ denote a set of observations made at a particular position. X is a set of features or n pieces of evidence. Classification can be considered as a multi-valued mapping, $\Gamma: E \to 2^C$, E is the feature space, also called evidence space, $C = \{c_1, c_2, \cdots\cdots, c_k\}$ is the class space whose elements are mutually exclusive, 2^C is the set that contains all possible sets consisting of elements in C and the empty set Φ. In practical classification, $\Gamma: E \to 2^C$ is often simplified to: $\Gamma: E \to C$, because researcher's interests are only focused on the individual elements in C.

In the Theory of Evidence, a basic probability assignment (BPA) of C, denoted by m, is defined as:

$$m(A) = \sum_{f(x_i)=A} P(x_i) \tag{1}$$

where, f is the mapping function from a subspace of E to C, A is a subset of C, and $P(x_i)$ is the probability density of x_i in a subspace of E. Basic probability assignment is also referred as a mass function to distinguish it from the probability distribution in the theory of statistics. The value of m is lie in the range of 0 and 1, i.e. m: $C \to [0,1]$. A mass function has the following property:

$$\sum_{A \subset C} m(A) = 1 \qquad m(\Phi) = 0 \tag{2}$$

The probability distribution of C can be estimated by the mass function. Because the precise probability distribution of C may not be known exactly, in D-S Theory of Evidence, bounds of probability distribution are defined. The lower and upper probability of a subset B of C are denoted as B's belief measure Bel_m (B) and plausibility measure Pls_m (B), respectively. They can be determined from the mass function as follows:

$$Bel_m(B) = \sum_{A \subset B} m(A) \qquad Pls_m(B) = \sum_{A \cap B \neq \Phi} m(A) \tag{3}$$

Generally, Bel_m (B) $\neq \mathrm{Pls}_m$ (B), the true probability of B is between Bel_m (B) and Pls_m (B), i.e.

somewhere in the belief interval [Bel $_m$ (B), Pls $_m$ (B)]. In D-S Theory of Evidence, Bel $_m$ (B) indicates the amount of belief committed to B based on the given piece of evidence, while Pls $_m$ (B) represents the maximum extent to which the current evidence allows one to believe A.

In D-S Theory of Evidence, the combined mass function of two independent mass function m_1 and m_2 can be calculated by using Dempeter's rule of combination, denoted by $m_1 \oplus m_2$:

$$m_1 \oplus m_2(D) = \frac{\sum_{A_i \cap B_j = D} m_1(A_i) m_2(B_j)}{1 - \sum_{A_k \cap B_l \neq \Phi} m_1(A_k) m_2(B_l)} \tag{4}$$

where the combination operator "⊕" is called "orthogonal summation", D⊂C and D≠Φ, and $m_1 \oplus m_2(\Phi) = 0$. Using the orthogonal summation, the belief measure and plausibility measure in space C with additional sources of evidence can be updated in the same manner as we combine m_1 and m_2, i.e., treat $m_1 \oplus m_2$ as m_1 or m_2. According to Dempeter's rule of combination, "⊕" is commutative and associative, the order of applying the orthogonal summation dose not affect the final results.

EVIDENTIAL REASONING ANALYSIS OF IMAGING SPECTROMETER DATA

The key aspects of realizing knowledge-based evidential reasoning analysis of Imaging Spectrometer data are:

(1) effectively digging, expressing and measuring the researcher's knowledge/understanding of spectral behavior of object to form the independent evidence sources.

(2) Deriving evidence based on the representative information for the entire set of classes and determining belief measure and plausibility measure of the evidence value.

Evidence Source

In D-S Theory of Evidence, evidential reasoning analysis dose not set a strict limit to the knowledge backgrounds, the scales of measurements and distributions of the values of the evidence sources. Only requirement is that the evidence resources should be independent with each other, but D-S Theory of Evidence dose not give any definite explanation or definition to independence of evidence sources, and dose not develop the technique of evaluating and measuring the independence of evidence sources with each other. So, in currently practical applications of evidential reasoning analysis, all available evidence sources are used in entire reasoning process. As a alternative to the requirement, the techniques of decreasing statistical interrelationship are utilized, e.g., by using principal component analysis or statistical factor analysis to decrease the statistical interrelationship of evidence sources.

In practical applications of evidential reasoning analysis, an evidence source can be referred as a independent source if the distribution of evidence values of the evidence source can not be derived from other evidence sources by some inference processes or calculating processes. So, if two evidence sources are independent with each other in statistical senses, they also can be referred as independent with each other in evidential reasoning analysis. Two evidence sources, which are referred as independent with each other in evidential reasoning analysis maybe are not independent with each other in statistical sense.

In principle, various of bands of Imaging Spectrometer data, various of spectral indexes describing spectral behavior of object and other available data sources all can be referred as evidence sources in evidential reasoning analysis of Imaging Spectrometer data. Realization of evidential reasoning analysis can not be affected even if evidence sources are not independent with each other. Only the importance of some evidence sources with a certain knowledge background is objectively intensified in entire evidential reasoning analysis process. In the view of practical application, too many evidence sources will complicate the entire evidential reasoning analysis process, and the accuracy of classifying or identifying objects can not be effectively improved. Therefore, in evidential reasoning analysis of Imaging Spectrometer data, the reasonable and reliable evidence sources should be the set of data sources which are independent with each other, reliable and steady under various of conditions, with different knowledge background and effectively describing spectral behavior of object in a certain aspect.

Deriving Evidence

In evidential reasoning analysis, following requirements should be satisfied for the approach of determining the belief measure and plausibility measure of evidences (Peddle, 1995):

(1) Be free of the properties of data distribution, e.g., statistical assumptions and models.
(2) Be able to handle data set with different knowledge background and the scale of measurement.
(3) Be able to incorporate uncertainty into the analysis.
(4) Be able to determining evidence belief measure and plausibility measure for the evidence value which lie outside the numeric bounds of a training sample.

In our application, we used the approach based occurrence frequency of evidence values within training samples to determine the belief measure and plausibility measure for a piece of evidence. The approach is based on the fact that all training data have a frequency distribution, regardless of data type, knowledge background, the scale of measurement and statistical properties. The data acquired by Imaging Spectrometer and spectral indexes derived from Imaging Spectrometer data are satisfied with two basic premises for using this approach:

(1) Values found in training samples represent that class.
(2) The occurrence frequency of a specific value within the class training samples is an indicator of the magnitude of support for that class.

As the first step of this approach, the occurrence frequency distribution of training samples over the entire set of classes must be determined, i.e., determine frequency distribution for each evidence source over entire set of classes. Statistical distribution function can be used for the evidence source which possesses statistical distribution property. For i classes and k evidence sources, there are a total of $i \times k$ occurrence frequency distributions. For a piece of evidence P to be classified, the amount of belief measure in support of the class i can be determined as the occurrence frequency of P for class i in training samples which is lie in range [0, 1]. Uncertainty measure of P can be calculated by 1-sum of belief measures over entire set of classes. The sum of belief measures generally is less than 1. If the sum exceeds 1, the sum will be normalized to 1 based on the definition of basic probability assignment in D-S Theory of Evidence, and there will be no uncertainty measure.

Processing Evidence

The problem frequently met in evidential reasoning analysis is the value of evidence to be classified is absent in training samples over the entire set of classes. we will face the problem how to determine the basic probability assignment or belief measure and plausibility measure for the value of evidence in support of class label.

In our study, we used a interactive knowledge-based analysis for processing evidence. As the first step, the possible range of values of evidence must be determined, then the method of processing evidence is decided based on knowledge background and properties of values of the evidence resource. E.g., coding of spectral absorption bands has no any physical senses, so it is unsuitable to process the value of the evidence by interpolation or extension. In practical application, only method of processing evidence value for this kind of evidence source is determining amount of evidence in support of class label based on occurrence frequency distribution of occurrence in training samples over the entire set of classes, and the remainder is attributed to uncertainty measure.

For the evidence value which possesses a certain frequency distribution function, interpolation linear-weighted by distance is used to process the evidence value within the distribution range of the evidence values in the training samples, and extension is used for the evidence value which is out of the distribution range of the evidence values in the training samples to determine the belief measure and plausibility measure in support of class label for each possible evidence value over entire set of classes. This approach of processing the evidence value is based on two premises: (1) If a value i occurs in training samples for class C, then similar values are also indicative of that class. (2) Probability of the similar value represent class C increases with proximity to i (Peddle, 1995).

The second aspect of processing evidence is to assign weight to each evidence source according to the importance and reliability of the evidence source in classification decision based on expert's knowledge and understanding of each evidence source. In general, assignment of weight is completely determined by expert's understanding of ground objects to be identified and properties of evidence sources.

EXAMPLE APPLICATION

To illustrate the abilities of knowledge-based evidential reasoning analysis in comprehensively analyze various spectral indexes with different knowledge backgrounds and the scales of measurement, we select a Imaging Spectrometer data set for discrimination of rocks in Chongli area, Hebei province, China. This area has relative large area of outcrop uncovered by soil and vegetation.

The evidence sources consist of 5 spectral indexes with different knowledge background and the scale of measurement: a band of Imaging Spectrometer data set (1.671~ 1.702 μm), coding of spectral absorption bands extracted from Imaging Spectrometer data set (2.114 to 2.398 μm), ratio of band 54 (2.146~ 2.242 μm) to band 56 (2.210~ 2.242 μm) of Imaging Spectrometer data set, the depth of absorption band centered at 2.178~ 2.210 μm and a spectral angle index.

To establish class space and determine the belief measure and plausibility measure of the evidences in support of class label, following training samples data sets were selected based on the geology map of this area: (1) Sandy gravel, (2) Sub-sandy soil, (3) Tuff breccia, (4) Quartz schist (a), (5) Quartz schist (b), (6) Quartz schist (c), (7) meta-anorthosite , (8) Granite.

Table 1 shows the classification accuracy of training samples obtained by evidential reasoning analysis. The Tuff breccia, the Granite and different Quartz schists are effectively identified with better classification accuracy. Because the area of outcrop of meta-anorthosite is relative small and there is a relatively serious disturbance of soil and vegetation, some training samples of meta-anorthosite are lack of typical representative of the class. The training samples of Class 1 and Class 2 are almost confused in classification, because the training samples of two classes all consist of identical sandy gravel and subsoil though they are divided into different geological units in geology map of this area.

Table 1. Classification Results of Samples Obtained by Evidential Reasoning Analysis

Class	1	2	3	4	5	6	7	8
Accuracy (%)	97.5	23.2	89.5	86.3	88.1	83.8	70.3	93.1

Fig 1 is the distribution map of rocks in this area obtained by evidential reasoning analysis. Fig 2 is the map of rocks in this area obtained by supervised cluster classifier using 27 bands of Imaging Spectrometer data set as input. Comparing with the geology map of this area, the classification result obtained by evidential reasoning analysis is apparently better than by supervised cluster classifier. The distribution range of rocks in classification map obtained by evidential reasoning analysis is identical with geology map of this area.

CONCLUSION

The knowledge-based evidential reasoning analysis has stronger abilities to comprehensively analyze spectral indexes with different knowledge backgrounds and scales of measurement, and is an effective approach of quantitatively analyzing Imaging Spectrometer data. The accuracy of identifying ground objects by using Imaging Spectrometer data based on spectral behavior of ground objects can be greatly improved. The testing results also shown that the classification effectiveness by the knowledge-based evidential reasoning analysis is highly correlative with the representative of selected training samples and objective effectiveness of evidence sources to extract representative information of ground objects to be identified.

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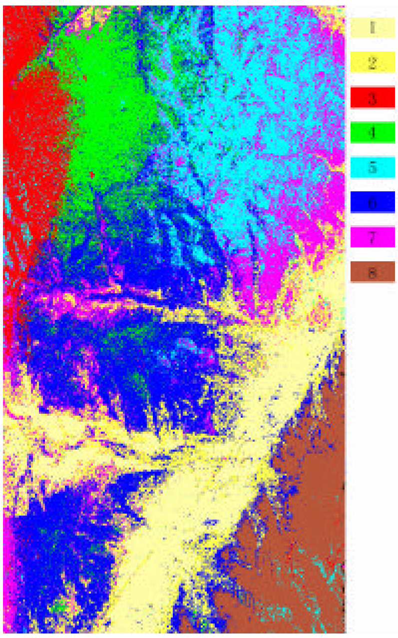

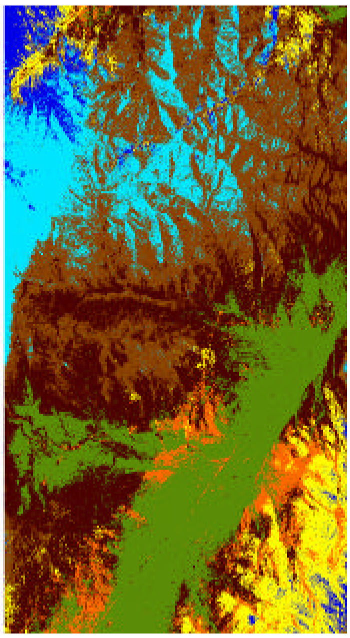

Fig 1 (left): Distribution of rocks obtained by evidential reasoning analysis

Fig 2 (right): Distribution of rocks obtained by supervised cluster classifier