

DER: Dynamic Evidential Reasoning applied to Hyperspectral Images Classification

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Abstract

This paper describes a new classification method (DER) based on evidential reasoning to which a series of modifications are added [1]. DER allows including new evidence for the classification process and defines a different decision rule. The evidential reasoning algorithm provides a means to combine evidence from different data sources. It is a supervised classification technique that uses a training samples set. This novel method (DER) offers a learning stage to introduce new evidence in case the classifier requires so. Moreover, it uses the plausibility measure in order to define the decision rule as a way to incorporate data-associated uncertainty. The proposed method is applied in order to classify crops in hyperspectral images of the area of Nebraska (USA). Some results obtained are presented in order to assess DER precision.

Key words: Hyperspectral analysis, Evidential reasoning, Crops classification.

1. INTRODUCTION

Technological advances currently allow obtaining hyperspectral images (continuing samples of spectrum wide intervals) with a data volume considerably higher in relation to the already obtained with multispectral images [2]. Hyperspectral sensors are remote sensing tools that combine the spatial presentation of an image sensor with a spectrometer analytical capacities. They can contain up to hundreds of spectral narrow-bands with a spectral resolution of the order of 10 nanometers or less [3]. Spectrometers produce a complete spectrum for all the pixels of the image. As a result of having a higher spectral resolution, it is possible to *identify* materials, whereas with broader-band sensors (e.g., Landsat Thematic Mapper TM), materials could only be *discriminated*.

However, these data are useful only if the methods capable of processing them properly are available; thus, the necessary information for a particular application will be obtained.

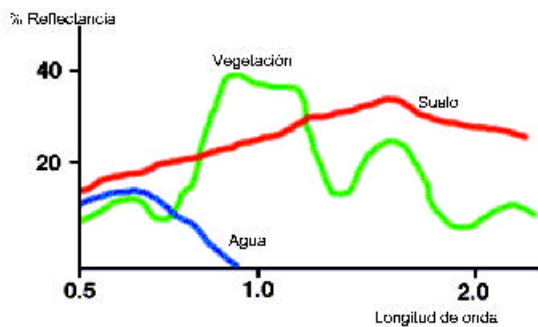
The classification methods to be applied for the hyperspectral image analysis must allow the combination of several data from different sources, and also of different nature. For instance, it could be necessary to combine spectral information with spatial information (as for example, texture features) [4] in order to achieve the classification of different crops such as soya, corn, etc.

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Curvas espectrales de distintos materiales



The study of cropped areas is an issue of special importance, not only for its scientific interest (searching for suitable classification methods), but also for its concern in relation to economic aspects. Being able to estimate the percentage of cropped areas for each type of crop in their growing stage can render the production estimate to be obtained. Furthermore, problems arising in certain areas can be detected (plagues or lack of irrigation) and thus fixed timely.

Green and healthy vegetation is characterized by having a reflectance spectral curve with peaks and valleys (**figure 1**).

Valleys in the visible portion of the spectrum are due to the pigments in the plant leaves. For example, chlorophyll absorbs in large extent the energy in the wavelength bands centered around 0.45 and 0.67 micrometers (visible blue and red). These colors are absorbed, while the visible part concentrated in the green is reflected to some extent (that is way most part of the vegetation is characterized by the green color of their leaves). If any plant is subject to some way of “stress” interrupting its normal development, it normally decreases or ceases its chlorophyll production. This causes less chlorophyll absorption in blue and red bands, and generally, reflectance in the red band increases in such a way that the plant turns yellow.

Peaks are due to high reflectance, between 0.7 and 1.3 micrometers (near infrared or Near IR) caused by the interaction with mesophilic cells of the leaves. The intensity of this reflectance is normally higher than that of inorganic materials, thus, in Near IR, the vegetation is described as shining.

These spectral variations ease precise detection, identification and monitoring of the vegetation on the surface.

Evidential reasoning is an alternative approach to the traditional classification methods based on Dempster-Shafer’s theory. This method has been used, for example, in the classification of woods and permanent snow and ice in Canada over multispectral images [5] [6].

Mathematical theory of the evidence was suggested by Shafer (1976) as an extension and refinement of the Dempster’s combination Rule (1967).

The theory offers a general and heuristic basis for adding different amount of information - considered as pieces of evidence – of independent sources over a set of classes.

For a given pixel, the classification task is to assign the pixel to a member of a classes set. For it, a **support** measure and a **plausibility** measure are associated to each class of this set.

A decision rule may be to select the class with higher support [7][8]. Other option is to select the class with higher plausibility [9][10]. Authors like Peddle have opted for the support and plausibility sum [11]. In this paper, a different decision rule is suggested. It takes into account the class with higher support, and then analyzes in two stages whether to opt for such class or reject it - considering if the evidence is enough.

One of the questions introduced by the method is how evidence is derived from the sample data already obtained. Peddle suggests considering the distribution frequency as the support measure for a datum in a source and in a given class.

Dynamic evidential reasoning method proposes a way of incorporating new evidence in case the classifier requires so for improving its precision. The results of the classification are assessed, and if they are not “optimal”, sample data are added as new evidence. In order to determine the precision of the classification results, Khat error matrix and marker are applied [12]. This marker allows analyzing the error that took place in the classification. If the error surpasses the precision threshold (α), new evidence must be incorporated.

This method was applied in order to classify hyperspectral images of fields cropped with soya, sorghum and corn, for a specific stage of their development. The implementation allows working with an image interest area within which a category map is obtained as a result, including among themselves the “unknown”.

2. METHOD PRESENTATION (DER)

The evidential reasoning method, as mentioned above, computes the support measure for each data source and each class. Then, this support is combined in order to obtain a unique measure for each class; this is carried out by applying Dempster’s combination rule. Apart from the support measure, plausibility is calculated as well. Next, a definition for both is given [13].

Support:

Generally, it is a real number between 0 and 1, inclusive. It is said to be the mass or quantity of evidence in favor of a given class.

Plausibility:

Plausibility represents the mass or quantity of evidence not rejected by any class. In the context of a remote sensing classification, plausibility for class C_i can be computed as $1 - S(\neg C_i)$, where S is the evidential support and $\neg C_i$ is the complement C_i in the set of classes.

The real feasibility of a proposition is within the range of possible values in the interval occurring from the support measure and that of plausibility for class C_i , which is called **evidential interval**. The use of the evidential interval allows including in a decision rule both the support in favor of the class and the associated-uncertainty level.

Orthogonal Sum

The orthogonal sum of the evidence from two sources operates by sequentially multiplying the evidence for a given source class, by the evidence of each class of the following source (2.1). Then, a normalizing factor is applied (K) (2.2).

The orthogonal sum of two evidence vectors, m_1 and m_2 , is denoted by $m_1 \oplus m_2$.

$$m'(A_n) = K^{-1} \sum_{A_i \cap A_j = A_n} m_1(A_i) m_2(A_j) \quad (2.1)$$

$$K = 1 - \sum_{A_i \cap A_j = \phi} m_1(A_i) m_2(A_j) \quad (2.2)$$

The suggested decision rule consists in selecting the class that has the highest support. Then, the analysis of whether accepting or rejecting such class is carried out in two stages [14]. The first stage is known as Rejection Stage due to lack of evidence. In it, we study if the maximum support is zero or if the source quantity contributing with the evidence in favor of the class is lower than the source quantity threshold; in such case, the class to be assigned is the unknown. Otherwise, we pass into the second stage known as Rejection Stage due to ambiguity, where the plausibility measure and the distance between the support of the class of maximum support and the rest of the classes are analyzed. If the assessment of this stage shows that the maximum support class is to be rejected due to the lack of actual clarity for deciding, new measures are added in order to take the decision. An associated weight is incorporated to each class - source pair, indicating the importance of source information for the given class. A marker of the source quantity contributing with evidence in favor of each class is incorporated as well. In such case, the decision is:

(2.3) Class j corresponding to $\text{Max}(\text{total_weight}_j * (\text{ICF}_j + S_j))$ is selected with $1 \leq j \leq N$ where N is the total class.

SQI: Source Quantity Index for class j

S_j : Support for class j

Total_weight_j: $\sum_{i=1}^M \text{weight}_{ij} / C_j$, where i is the sources contributing with evidence for class j $i = 1..N$
 $1 \leq j \leq M$ and

C is the quantity of sources contributing with evidence for class j .

On the other hand, DER presents a way of introducing new evidence to the classifier. Interest areas to be classified are established in the image and it is determined a priori which class they belong to. In order to train the classifier, the evidential reasoning method is applied by using the current knowledge basis, and then the results are assessed. In case Khat marker displays an error above the precision threshold in the classification, samples are introduced as new information for the system. If, otherwise, the indicator shows that the error does not surpass such threshold, the new evidence is not incorporated since it is unnecessary. This learning process carried out by the classifier is based on a supervised approach in which the user must have previous knowledge of the belonging of the sample to one of the categories.

Evidential reasoning provides is advantageous in several aspects. It allows analyzing the uncertainty level; working with information provided by different sources and of different nature; and also, it gives the possibility of using a large number of variables in the classification. This is indeed of special importance for the analysis of hyperspectral images.

The suggested modifications are aimed at improving the method in two ways:

- Allowing the incorporation of new evidence so that the classifier learns and renders more precise results.
- Using a decision rule that takes into account the plausibility, and does not risk itself for any class if it does not have enough evidence or if there is not enough clarity for such decision.

3. APPLICATION

The method is applied to hyperspectral image analysis of the area of Nebraska (USA), where three types of crops are meant to be recognized: soya, corn and sorghum, for a specific stage of their evolution. The images were acquired in August, 1998 by a *casi* sensor (Compact Airborne Spectrographic Imager) [15][16] with a pixel resolution of 1m, and it was provided by PRA company (Photon Research Associates, Albuquerque, USA) which carries out researches and developments for the analysis of “stress” and strength of vegetation.

For the training, samples are taken for each of the classes above-mentioned, and a class which does not belong to the vegetation (specifically, routes which appear in the images). From each of the samples, its spectral pattern and 4 statistics of first order are obtained in order to analyze the texture of the area (rank, standard deviation, skewness and average) [17], and in this way, spatial information is incorporated. These data are the ones which allow training the classifier in order to begin to work. From them, the support for each class and source is calculated. This information is combined by means of Dempster’s orthogonal sum at the time of classifying an unknown pixel.

If the incorporated evidence does not allow obtaining good results, and if new samples are available, it is possible to incorporate the information to the system as it was previously explained.

4. RESULTS

Next, some results obtained by DER method application in the described images are presented. The results are assessed by using the confusion matrix, general precision and Khat marker.

The method was tested running the learning process where it incorporated evidence for the classifier, obtaining an average percentage for the training samples sets of 96.85%.

Below, some results obtained for test sets different from the training ones are shown:

Table 4.1 – Matrix Class

Corn Class	Percentage assigned to Class:				
	Soya	Corn	Sorghum	Route	Desc.
Area 1. Total: 49 pixels	0 %	86 %	14 %	0 %	0 %
Area 2. Total: 28 pixels	0 %	89 %	10 %	0 %	0 %
Area 3. Total: 64 pixels	1.5 %	81 %	17 %	0 %	0 %
Area 4. Total: 30 pixels	0 %	90 %	10 %	0 %	0 %
Area 5. Total: 40 pixels	0 %	90 %	10 %	0 %	0 %
Area 6. Total: 100 pixels	2 %	88 %	10 %	0 %	0 %
Area 7. Total: 84 pixels	2 %	89 %	8 %	0 %	0 %
Area 8. Total: 10 pixels	0 %	100 %	0 %	0 %	0 %
Area 9. Total: 12 pixels	0 %	100 %	0 %	0 %	0 %
Area 10. Total: 25 pixels	4 %	80 %	16 %	0 %	0 %
Area 11. Total: 20 pixels	0 %	95 %	5 %	0 %	0 %
Area 12. Total: 8 pixels	0 %	87 %	12 %	0 %	0 %
Area 13. Total: 30 pixels	0 %	96 %	3 %	0 %	0 %

Average percentage for corn class: 90.07 %

Table 4.2 – Route Class

Route Class	Percentage assigned to Class:				
	Soya	Corn	Sorghum	Route	Desc.
Area 1. Total: 38 pixels	0 %	0 %	0 %	100 %	0 %
Area 2. Total: 36 pixels	0 %	0 %	0 %	100 %	0 %
Area 3. Total: 75 pixels	1 %	0 %	0 %	98 %	0 %
Area 4. Total: 56 pixels	0 %	0 %	0 %	100 %	0 %
Area 5. Total: 56 pixels	0 %	0 %	0 %	100 %	0 %
Area 6. Total: 54 pixels	0 %	0 %	0 %	100 %	0 %
Area 7. Total: 32 pixels	0 %	0 %	0 %	100 %	0 %
Area 8. Total: 60 pixels	0 %	0 %	0 %	100 %	0 %
Area 9. Total: 40 pixels	0 %	0 %	0 %	100 %	0 %
Area 10. Total: 26 pixels	0 %	0 %	0 %	100 %	0 %
Area 11. Total: 33 pixels	0 %	0 %	0 %	100 %	0 %
Area 12. Total: 64 pixels	0 %	0 %	0 %	100 %	0 %
Area 13. Total: 68 pixels	0 %	0 %	0 %	100 %	0 %
Area 14. Total: 40 pixels	0 %	0 %	0 %	100 %	0 %

Average percentage for la Class Route: 99.85 %

Table 4.3 - Soya Class

Soya Class	Percentage assigned to Class:				
	Soya	Corn	Sorghum	Route	Desc.
Area 1. Total: 90 pixels	98 %	1 %	0 %	0 %	0 %
Area 2. Total: 84 pixels	98 %	1 %	0 %	0 %	0 %
Area 3. Total: 70 pixels	100 %	0 %	0 %	0 %	0 %
Area 4. Total: 120 pixels	98 %	1 %	0 %	0 %	0 %
Area 5. Total: 48 pixels	100 %	0 %	0 %	0 %	0 %
Area 6. Total: 63 pixels	100 %	0 %	0 %	0 %	0 %
Area 7. Total: 72 pixels	97 %	2 %	0 %	0 %	0 %
Area 8. Total: 32 pixels	90 %	6 %	3 %	0 %	0 %
Area 9. Total: 36 pixels	94 %	2 %	2 %	0 %	0 %
Area 10. Total: 63 pixels	89 %	9 %	1 %	0 %	0 %

Average percentage for Corn Class: 96.4 %

Table 4.4 - Sorghum Class

Class Sorghum	Percentage assigned to Class:				
	Soya	Corn	Sorghum	Route	Desc.
Area 1. Total: 255 pixels	0 %	2.7 %	97 %	0 %	0 %
Area 2. Total: 312 pixels	0.6 %	5 %	94 %	0 %	0 %
Area 3. Total: 70 pixels	1.4 %	0 %	98 %	0 %	0 %
Area 4. Total: 70 pixels	0 %	7 %	93 %	0 %	0 %
Area 5. Total: 72 pixels	1 %	19 %	79 %	0 %	0 %

Average percentage for Corn Class: 92.2 %

As it can be observed, the previous tables show an average percentage upper or equal to the 90 % for all the cases. As regards individual percentages for each area, it can be said that all of them are found above the 80 %.

In most of the conventional classifiers, it is difficult to incorporate as input a numerous quantity of variables – as it would be the case for processing hyperspectral images. Then, it is important to analyze acknowledged data before selecting the classification method to be used.

5. CONCLUSIONS

The suggested method has some advantages in relation to conventional classification methods; it is indeed of particular interest for the analysis of hyperspectral images. Like the evidential reasoning method presented by Peddle, it allows integrating several data of different nature. It is not necessary to presume a distribution of the data as it does happen with the maximum likelihood classifier which presupposes a “gaussian” distribution. [18][19]

Moreover, DER does not allow the knowledge basis to be static; instead of that, by means of a learning process, the possibility of incorporating new data to the system is given. It poses a different decision rule in which a more careful analysis of which class is to be chosen in order to assign it to the unknown class is carried out. The method already renders good results for the kind of problems which have been presented.

6. REFERENCES

- [1] D. Peddle. “MERCURY \oplus : An Evidential Reasoning Image Classifier”. *Computers & Geosciences*, vol. 21, No.10, pp. 1163-1176. 1995.
- [2] Jensen. “Introductory Digital Image Processing. A remote sensing perspective”, 2da Edition, Prentice Hall. 1996
- [3] A. F. H. Goetz , and V. Srivastava, "Mineralogical mapping in the Cuprite Mining District, Nevada", in Proceedings of the Airborne Imaging Spectrometer Data Analysis Workshop, JPL Publication 85-41, Jet Propulsion Laboratory, Pasadena, CA, pp. 22-29. 1985
- [4] T. M. Lillesand, R. W. Kiefer. "Remote Sensing and Image Interpretation", 3rd Edition, John Wiley. 1994.
- [5] D. Peddle, and S. Franklin. “Multisource evidential classification of surface cover and frozen ground”. *International Journal R. S.*, vol. 13- No. 17. 1992
- [6] D. Peddle, and S. Franklin. “Classification of Permafrost Active Layer Depth from Remotely Sensed and Topographic Evidence”, *Remote Sensing Environment*, vol. 44, No.1, pp. 67-80. 1993.
- [7] T. Lee, J. Richards, and P. Swain. “Probabilistic and Evidential Approaches for Multi-source Data Analysis”, *IEEE Transactions on Geoscience and Remote Sensing*, vol. 25, No. 3, pp. 283-292. 1987
- [8] G. Wilkinson, and J. Megier. “Evidential Reasoning in a Pixel Classification Hierarchy – A Potential Method for Integrating Image Classifiers and Expert System Rules Based on Geographic Context”, *International Journal of Remote Sensing*, vol. 11, No.10, pp. 1963-1968. 1990
- [9] H. Kim, and P. Swain. “A Method for Classification of Multisource Data Using Interval- Valued Probabilities and its Applications to Hiris Data”, in *Proceedings of a Workshop on Multisource Data Integration in Remote Sensing*, NASA Conference Publication 3099, pp. 75-81. 1990.

- [10] A. Srinivasan, and J. Richards. "Knowledge-based Techniques for Multi-source Classification", *International Journal of Remote Sensing*, vol.11, No.3, pp.505-525. 1990.
- [11] D. Peddle. "Knowledge Formulation for Supervised Evidential Classification". *Photogrammetric Engineering & Remote Sensing*, vol.61, No.4., pp. 409-417. 1995.
- [12] D. Peddle. "An Empirical comparison of evidential reasoning, linear discriminant analysis, and maximum likelihood algorithms for alpine land cover classification". *Canadian Journal of Remote Sensing*, vol.19, No.1. 1993.
- [13] Anger C.D., Mah, S., Babey, S.K. "Technological enhancements to the compact airborne spectrographic imager (casi)." In *Proceedings of the First International Airborne Remote Sensing Conference and Exhibition*. Strasbourg, France. Vol. II, pp. 205-213. 1994.
- [14] Sanz C., "DER (Dynamic Evidential Reasoning), applied to the classification of hyperspectral images". International Geoscience and Remote Sensing Symposium (IGARSS 2001 – IEEE), July, 2001. ISBN: 0-7803-7033-3
- [15] Babey, S.K., Anger, C.D. "Compact airborne spectrographic imager (casi): A progress review." In *Proceedings of the SPIE Conference*. Orlando, Florida. SPIE Vol. 1937, pp. 152-163. 1993.
- [16] R. G. Congalton, K. Green. "Assessing the Accuracy of Remotely Sensed Data: Principles and Practices". Lewis Publishers. 1997.
- [17] Jensen. "Introductory Digital Image Processing. A remote sensing perspective". 2da edition. Prentice Hall. 1996.
- [18] "Remote Sensing Digital Image Analysis: An Introduction". J. A. Richards, X. Jia. Springer-Verlag New York, Incorporated. 1999.