EXhype: A tool for mineral classification using hyperspectral data

Ramesh Nityanand Adep *,1, Amba Shetty, H. Ramesh

Department of Applied Mechanics and Hydraulics, National Institute of Technology Karnataka, Surathkal, Karnataka 575025, India

Abstract

Various supervised classification algorithms have been developed to classify earth surface features using hyperspectral data. Each algorithm is modelled based on different human expertises. However, the performance of conventional algorithms is not satisfactory to map especially the minerals in view of their typical spectral responses. This study introduces a new expert system named ‘EXhype (Expert system for hyperspectral data classification)’ to map minerals. The system incorporates human expertise at several stages of its implementation: (i) to deal with intra-class variation; (ii) to identify absorption features; (iii) to discriminate spectra by considering absorption features, non-absorption features and by full spectra comparison; and (iv) finally takes a decision based on learning and by emphasizing most important features. It is developed using a knowledge base consisting of an Optimal Spectral Library, Segmented Upper Hull method, Spectral Angle Mapper (SAM) and Artificial Neural Network. The performance of the EXhype is compared with a traditional, most commonly used SAM algorithm using Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired over Cuprite, Nevada, USA. A virtual verification method is used to collect samples information for accuracy assessment. Further, a modified accuracy assessment method is used to get a real users accuracies in cases where only limited or desired classes are considered for classification. With the modified accuracy assessment method, SAM and EXhype yield an overall accuracy of 60.35% and 90.75% and the kappa coefficient of 0.51 and 0.89 respectively. It was also found that the virtual verification method allows to use most desired stratified random sampling method and eliminates all the difficulties associated with it. The experimental results show that EXhype is not only producing better accuracy compared to traditional SAM but, can also rightly classify the minerals. It is proficient in avoiding misclassification between target classes when applied on minerals.

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1. Introduction

The emergence of hyperspectral sensors enabled the acquisition of data with increased number of spectral bands and higher spectral resolution has certainly given significant impacts on our ability to map. High spectral information i.e. narrower bandwidth and contiguous spectral information facilitate to distinguish even the spectrally similar features and enabled to identify sub-class features such as different types of vegetation, mineral, soil and water, etc. To identify minerals, mostly absorption features are considered as a diagnostic characteristic. Absorption features indicate the presence of a particular mineral and the depth of absorption is a function of its grain size, absorption coefficient, and abundance (Clark et al., 2003). Available hyperspectral sensors can capture Electromagnetic Radiation in the region of visible to shortwave infrared. Thereby, in the reflectance curve, only two types of absorption features are visible electronic and vibrational absorption features (Clark, 1999).

Advances in data capturing have posed a challenge to researchers to classify the data more accurately. Advancement in image classification techniques has been happening in three different directions such as supervised, unsupervised and hybrid (i.e. combination of supervised and unsupervised). Recent years have witnessed an extensive use of supervised classification algorithms to classify minerals. Classification algorithms were improved by researchers from traditional algorithms such as Spectral Angle Mapper (SAM) (Kruse et al., 1993a); Spectral Information Divergence (SID) (Chang, 1999); Artificial Neural Network (ANN) (Paya et al., 1997) and Support Vector Machines (SVM) (Melgani and Bruzzone, 2004), etc., to hybrid combinations such as hybrid
similarity measures (Du et al., 2004; Naresh Kumar et al., 2011; Padma and Sanjeevi, 2014); Boosted Genetic Fuzzy Classifier (BGFC) (Stavrakoudis et al., 2011); Extended Spectral Angle Mapper (ESAM) (Li et al., 2014) and Support Vector Neural Networks (SVNN) (Lokman and Yilmaz, 2015), and went up to advance absorption feature oriented (Clark et al., 2003; Koerting et al., 2015; Mielke et al., 2016); spectral unmixing techniques (Tits et al., 2012; Zhu et al., 2014; Zhong et al., 2016) and machine learning concepts (Chen et al., 2014, 2015; Romero et al., 2016).

A close look into the developments has revealed that algorithms were incorporated with domain experts knowledge. The best examples are study of vegetation by indices (Sakamoto et al., 2011; Yu et al., 2014; Marshall and Thenkabail, 2015), feature matching techniques for mineral identification by Clark et al. (1990, 2003), Koerting et al. (2015), Mielke et al. (2016) and Optimal Spectral Library to deal with intra-class variation by Luc et al. (2005). In all the three cases, experts understood the behaviour of reflectance curve to their respective objective and then modelled the algorithms to classify features. It was also observed that researchers not only extracting more information from the reflectance curve but also from neighbourhood pixels to classify pixels accurately (Segl et al., 2003; Liu et al., 2015). Developed expert knowledge is translated into a computer–usable format and stored in the knowledge base (Huang and Jensen, 1997). Using such knowledge base, expert systems have been developed from time to time (Kruse et al., 1993b; Clark et al., 2003; Koerting et al., 2015; Mielke et al., 2016; Brossard et al., 2016). These expert systems have shown superior performance than the conventional algorithms. But with advancement in data i.e., in terms of spectral and spatial resolution, user’s desire more accuracy in mapping. Also, it has been seen that expert knowledge increased with time. The present study is mainly focused on to develop a new expert system by incorporating available expert knowledge to classify minerals.

2. Procuring of knowledge for proposed Expert System

This section presents the review of various supervised classification algorithms to identify the qualities for proposed expert system and to construct a knowledge base for it.

Most commonly used supervised classification algorithms for classification of hyperspectral data which measure similarity between spectra are Euclidean Distance (ED) (Gower, 1985), Spectral Angle Mapper (SAM) (Kruse et al., 1993a), Mahalanobis Distance (MD) (Palacios-Orueta and Ustin, 1996), Spectral Information Divergence (SID) (Chang, 1999), Jeffries-Matusita Distance (JMD) (Richards and Richards, 1999), Spectral Correlation Angle (SCA) (De Carvalho and Meneses, 2000), etc. and their hybrid combinations SAM-SID (Du et al., 2003), SCA-SID (Naresh Kumar et al., 2011) and JMD-SAM (Padma and Sanjeevi, 2014). Each algorithm employs a different approach to discriminate the target and image spectra. For instance, ED computes the distance between two spectra, MD computes the statistical distance between a reference spectral vector and multivariate distribution of points, SAM treats spectra as two vectors and measures the angle between them and the SID measures the probability of spectral discrepancy (Shanmugam and Srinivasa Perumal, 2014). The limitation of these algorithms is that only one discrimination value is obtained, which is an average fit over the entire spectral range or a subset of the dataset that is used in classification. This single discrimination value may not be sufficient to discriminate targets especially when there is a subtle difference between their spectra.

For correct identification of the target, one should consider each salient feature of the spectrum in addition to overall spectrum. The salient feature can be an absorption feature and/or any other trend of the spectrum. Spectral Feature Fitting (SFF) proposed by Clark et al. (1990) considers only absorption features. To discriminate spectra, depth and shape of the absorption feature in target spectrum and image spectrum are compared. Only one absorption feature is considered and the user has to give a range of wavelengths within which a unique absorption feature exists for the chosen target spectrum. This technique was later modified as Multi-Range Spectral Feature Fitting (MRSFF) (Clark et al., 2003; Pan et al., 2013), where the absorption features at various wavelength ranges are considered for matching. Optional weights to each spectral range were also given to emphasize more important features. Both SFF and MRSFF use continuum removal method to separate absorption features from entire spectra and only absorption features were taken into account to find the discrimination between the target spectrum and image spectrum.

He and He (2011) introduced Weight Spectral Angle Mapper (WSAM) to improve the differentiability between similar minerals by setting a weight in the ‘difference range’ to reduce the similarity and to increase the discriminability. This method uses both absorption features and non-absorption features to compare spectra, but the adjustment of weights should be done manually.

The reflectance spectra of any land cover features vary within the class due to factors such as weather conditions, bidirectional reflectance distribution function effects, soil conditions, shadows, and phenological stage (Luc et al., 2005). Fig. 1 shows the variation of alunite mineral spectra in the Cuprite region. Even though such a variation exists in alunite, one can easily recognize all spectra as alunite. This variation of spectra is called intra-class variability (Luc et al., 2005). An Optimized Spectral Angle Mapper (OSAM) was proposed (Luc et al., 2005) to capture intra-class variability. Usually, a reference or target spectrum is taken as an average spectrum of each Region Of Interest (ROI). This implies a reference spectrum is unable to represent the spectral variability present within each ROI. OSAM contains an Optimal Spectral Library (OSL) which preserves the spectral variability present within each ROI. This library is called optimal because it contains all the spectra that can classify all pixels of a certain class correctly. All the image pixel spectra are classified using the reference spectra stored in the optimal spectral library to avoid misclassification due to intra-class variation. Finally, it has the same limitation as the traditional algorithms, being only one overall discrimination value.

Human ability to think, remember, and solve problems inspired many researchers to develop artificial models whose architecture are based on the way that the human brain performs computations (Hagan et al., 1996). A sub-class of artificial models called Artificial Neural Networks (ANN) were developed, which were simplified based on the biological learning process of the human brain (Paya et al., 1997). Many authors have used ANN to classify satellite images. Applications and limitations of ANN in remote sensing context were explained in several review papers such as (Paola and Schowengerdt, 1995; Kanellopoulos and Wilkinson, 1997; Kavzoglu and Mather, 2003; Mas and Flores, 2008). Use of ANN is not appreciable because most of the time bands were given as an input which increases the computational load and complexity in recognizing the pattern, in turn, reduces the performance. Present scenario has changed, a pre-processed information was fed to the neural network to classify satellite images (Chen et al., 2014, 2015; Romero et al., 2016).

The literature review has revealed that there is not a single algorithm:

1. To deal with intra-class variation;
2. To identify absorption features;
3. To discriminate spectra by considering absorption features as well as non-absorption features and also by full spectra comparison;
4. And finally to take a decision based upon the learning and by emphasizing most important features.
3. Data and methodology

3.1. Data

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data used in the study is shown in Fig. 2 was captured from ER-2 aircraft on August 8, 2011, at Cuprite, Nevada, USA. It is freely available from ENVI software provider. This scene comprises of a relatively large area (522 x 601 pixels and pixel size – 15.5 m x 15.5 m spot on the ground). AVIRIS collects spectra in 224 continuous spectral channels covering the wavelength range 0.38–2.5 μm with an approximate 10 nm spectral interval (Geng et al., 2013). This study area has excellent rock exposures, sparse vegetation, and dry climate. It is well understood mineralogically and many recent remote sensing studies of Cuprite have focused on instrument performance and spectral identification techniques (Plaza et al., 2009; Geng et al., 2013; Swayze et al., 2014; Zhong et al., 2016). Reference ground signatures of this site are available in the form of a U.S. Geological Survey (USGS) spectral library. These signatures were used to assess endmembers signature purity and to validate the results using virtual verification method (King and Clark, 2000).

3.2. Preprocessing

Preprocessing is required to correct a deficiency and remove flaws present in the data. Data available at the ENVI website was processed with Fast Line-of-sight Atmospheric Analysis of

Fig. 1. Spectral variation of alunite mineral collected from AVIRIS data, Cuprite.

Fig. 2. AVIRIS Cuprite scene with the band combination (R = band-29, G = band-20, B = band-12) and sampling locations shown were identified using n-Dimensional visualizer for collecting samples of Optimal Spectral Library (OSL). Target endmembers were extracted from OSL.
Hypercubes (FLAASH) to remove atmospheric effects. Also, bad bands due to water absorption and low SNR were removed. The following were identified as bad bands: 366–390 nm (bands 1–3), 1260–1560 nm (bands 98–128) and 1760–1960 nm (bands 148–170).

3.3. Endmember collection

Virtual verification method can be performed by examining the remote sensing data directly, if there is sufficient spatial and/or spectral resolution to positively identify objects in the image (King and Clark, 2000; Clark et al., 2003). Clark et al. (2003) stated using imaging spectroscopy data, with suitable spectral resolution, some specific minerals can be identified based on wavelength position and shape of characteristic absorption features. Fig. 3(B) shows a spectral plot of endmembers derived from AVIRIS data for alunite, buddingtonite, calcite, chlorite + muscovite and kaolinite. It can be seen that all spectra have electronic absorption features in the region of 400–1300 nm due to the presence of Fe-bearing minerals (Murphy and Monteiro, 2013; Swayze et al., 2014). But in the case of USGS library spectra as shown in Fig. 3(A), electronic absorption features are not found except for chlorite + muscovite spectrum where broad absorption feature in the region of 600–1650 nm is being due to \( \text{Fe}^{2+} \). The AVIRIS spectra have vibrational absorption features in the range of wavelength 1900–2400 nm and are found to be more similar to the USGS library spectra, which were used as the diagnostic characteristic by several researchers to identify alunite, buddingtonite, calcite, chlorite + muscovite and kaolinite in this Cuprite region (Clark, 1999; Clark et al., 2003; Swayze et al., 2014). All minerals were identified based on wavelength position and shape of characteristic absorption features. In addition, visually both ground and image spectra are comparable and shows more correlation. So, virtual verification method was used to assess the performance of the proposed algorithm for selected five minerals.

Minimum Noise Fraction (MNF) transformation, Pixel Purity Index (PPI) and n-Dimensional Visualizer were applied to collect spectra of each class from the image (Kruse et al., 2003a). Identification of spectra of each class was carried out using ENVI® 5.1 spectral analysis tool and by visual inspection using the USGS spectral library as a reference. A total of 117 sample spectra were collected. This includes 25 samples of alunite, 16 of buddingtonite, 33 of calcite, 26 of chlorite + muscovite and 17 of kaolinite. Endmember for each class was generated by taking the average of all the spectra of each class. Further, more details about collection methodology of samples are explained in Section 3.4.1

3.4. Proposed expert system

The proposed expert system is named as ‘EXhype (Expert system for hyperspectral data classification)’. It is incorporated with human expertise at several stages of it’s implementation: (i) to deal with intra-class variation; (ii) to identify absorption features; (iii) to discriminate spectra by considering absorption features as well as non-absorption features and also by full spectra comparison, and (iv) finally to take a decision based on the learning and by emphasizing most important features. Fig. 4 shows the working methodology of EXhype. To incorporate the desired expertise, EXhype is developed using a knowledge base consisting of Optimal Spectral Library (OSL) to deal with intra-class variation; the Segmented Upper Hull (SUH) method to segment spectrum and identify absorption and non-absorption features; SAM to discriminate spectra by considering spectrum completely as well as feature wise; by training the ANN with SAM discrimination value, EXhype is able to learn to give a response regarding pixels. EXhype follows binary classification technique, i.e. one against rest classification. It generates the rule image for each target class which contains belongingness of an image pixel to the target class and finally rule classifier is used to get the classified image. Detailed description of the components of the EXhype is presented in the following subsections.

3.4.1. Optimal spectral library

After collecting spectra from the n-Dimensional Visualizer in ENVI, the spectra of each class were examined in the spectral viewer where similar spectra were removed. The remaining spectra were stored in the spectral library, which is called an optimal spectral library. A number of samples of each class depend on the quality of data and the variation of that class in the image.

**Fig. 3.** (A) Ground spectra collected by the U.S. Geological Survey and (B) reflectance spectra of endmember derived from the AVIRIS Cuprite scene.
Fig. 2 shows the location of OSL samples. As mentioned previously, endmember of each class was extracted by taking the average of all the spectra of that class. To preserve intra-class variability, target endmember was compared with all the spectra in the library and those comparison values were given as a training data to ANN. Fig. 1 shows spectra of alunite class, collected from the spectral viewer and stored in the OSL.

### 3.4.2. Segmentation: Segmented Upper Hull algorithm

Target endmember spectrum was segmented using “Segmented Upper Hull” method (Clark and King, 1987) to identify the absorption features and non-absorption features in target spectrum. SUH was applied on target endmember to get continuum removed spectrum. Continuum tie points were collected (where data = 1.0 in the continuum removed spectrum) and using this continuum tie points, the target endmember was divided into segments. Continuum tie points were taken as starting point of each segment. Also, the end point of each segment was chosen such that, it is one band behind the starting point of the next segment. To keep sufficient length of the segment, a minimum of six bands per segment were considered. Fig. 5 shows plotting of tie points on alunite target spectrum and it shows only 9 tie points because other tie points were removed to keep the segments to be of sufficient length. Fig. 6 shows fully segmented alunite target endmember.

OSL spectra and satellite image pixels spectrum were also divided into the same number of segments and at the same position as it was performed in the target endmember spectrum. This was performed to compare the same region in both target spectrum and OSL or image pixel spectra. The position of each segment should be obtained from segmented target endmember. In Fig. 7 calcite was taken as library spectrum and it was segmented using the positions of each segment from target endmember, i.e., alunite in this case.

### 3.4.3. Spectral discrimination: Spectral Angle Mapper

The SAM algorithm discriminates two spectra by calculating the angle between them and treating them as vectors in space with dimensionality equal to the number of bands (Kruse et al., 1993a). More the spectral angle lesser will be the similarity. It is an easy and rapid method for discrimination. It is unaffected by solar intensity variation. It represses the influence of shading effects to give prominence to the target reflectance characteristics and it does not require any assumptions on the statistical distributions of input data in performing discrimination (Girouard et al., 2004). The angle between pixel spectrum X and a reference spectrum Y can be calculated using Eq. (1).

\[
\alpha = \cos^{-1} \left( \frac{\sum_{i=1}^{n} x_i y_i}{\left( \sum_{i=1}^{n} x_i^2 \right)^{1/2} \left( \sum_{i=1}^{n} y_i^2 \right)^{1/2}} \right) 
\]  

(1)

where
The target spectrum was compared with each optimal library spectrum using the SAM algorithm to get discrimination values. The comparison was performed on the individual segments as well as for the entire spectrum and obtained discrimination values were stored. The target spectrum was also compared with each image pixel spectrum in the same way as it was done for the library spectrum and obtained discrimination values were stored.

3.4.4. Intelligent unit: Artificial Neural Network

In this expert system, ANN is used as an intelligent unit to take a decision based on training. ANN gives the degree of belongingness of a pixel to all targets. Pre-processed information was given to ANN to improve its performance, as it contains discrimination values of targets in terms of the full spectrum as well as individual segments instead of many hundreds of band information, thereby reducing the load on the neural network. The ANN was trained with input as discrimination values obtained from SAM when target spectrum was compared with each library spectra. The number of inputs equal to the number of segments in target endmember plus one (i.e. input of full spectra discrimination value). Fig. 9 shows the structure of ANN used in this expert system.

With the training data, ANN behaves as an expert system. Inter-neuron connection strengths, known as synaptic weights act as weights to the inputs of the neural network and are used to store the acquired knowledge. These weights were updated automatically with the training process. With the acquired knowledge neural network is able to deal with an intra-class variation of both target and non-target class since optimal spectral library contains both the spectra of target and non-target class. Hence, inputs of ANN contain discrimination values of target endmember with both the target and non-target class spectra to deal with intra-class variation. Furthermore, for all targets, AVIRIS spectra have diagnostic characteristic features in the region of 2000–2400 nm, in addition, there was a spectral variation due to Fe-bearing and other minerals in the region of 400–1200 nm. Since inputs to the neural network...
are discrimination values of the segments and full spectra, when training ANN, adjust the internal weights to emphasize inputs which give a better response.

The trained neural network was evaluated using the discrimination values of target endmember with each pixel spectrum obtained from the SAM. The response of ANN was used to generate rule image for the target endmember and it was stored. This rule image contains the response of ANN about belongingness of all pixels of satellite image to the target endmember category. The same procedure was repeated to generate rule images for each target endmember.

3.4.5. Final classified image: rule classifier

Rule classifier was applied on previously saved rule images to get the final classified image by giving optimum threshold to each class. The threshold for target classes was found by doing an iterative process of changing thresholds for each class and checking the overall accuracy value. Finally based on best overall accuracy value, the threshold for various classes were fixed.

3.5. Mapping method

SAM was used as a basis for to assessing the performance of the proposed EXhype classifier. SAM and EXhype were implemented in MATLAB®. A study by Kavzoglu and Mather (2003) was referred to decide structure and configurations of ANN. Their study has presented several heuristics proposed by different authors to find an optimum number of hidden nodes, initial weight range and a number of output nodes. Implementing the heuristics along with the revised combinations of latter, trial and error method was conducted to find structure and configurations of ANN. Finally, ANN model was selected based on best classification accuracy of OSL data. Table 1 shows the details of ANN model used in EXhype classifier. Table 2 represents its performance on the OSL data. Three layered feed-forward backpropagation neural network was used with output transfer function 'purelin' to get a response in fuzzy (i.e. degree of belongingness). EXhype adjust the input and hidden nodes of ANN based on a number of segments in the target endmember using relations given in Table 1. All other configuration of ANN remains same for all target endmember.

3.6. Sampling technique and accuracy assessment

Virtual verification method is used to extract information about the samples collected for accuracy assessment. It has been successfully applied by (Molan et al., 2014; Kumar et al., 2014). Both identified the samples by visually comparing with the USGS spectral library. Absorption band's number, strength, position, and shape were considered for visual interpretation of the spectra.

Stratified random sampling technique was adopted in this study, in which a minimum number of samples are selected randomly from each class. Congalton (1991) proposed that stratified random sampling is impractical because a collection of ground information at random locations is very difficult due to the difficulty of access; the temporal problems in collecting ground reference and satellite data lead to a mismatch between ground and satellite image data; and the cost of the project increases due to a collection of accuracy assessment data, late in the project instead of in conjunction with the training data collection. This is because...
sampling locations are only selected after the classification has been performed. All these limitations are eliminated when stratified random sampling is done using virtual verification method because the sample information is directly extracted from the image.

A modified method of accuracy assessment is used in this work which is based on the methodology adopted by Kruse et al. (2003b). Whenever researchers usually classified satellite images by considering only limited or interested classes and excluded the remaining classes, commission error due to other classes in interested classes was ignored. Therefore, the calculated user’s accuracies for interested classes may not be truly representative. Kruse et al. (2003b) also considered limited classes to assess the accuracy of Hyperion classified image using AVIRIS classified image as a ground truth information. To deal with commission error due to other classes, a column of ‘Unclassified category’ was added in the confusion matrix to get real user’s accuracy. In this study also, the same concept was adopted to get real user’s accuracies. But in consideration of ‘Unclassified category’, ‘Other’ label was added to represent other classes in confusion matrix. The modification has done because the ground truth information is available in the form of samples instead of classified map. The samples of other classes were identified using USGS spectral library as a reference and collected from all the regions in and around the interested or target classes. For this study, a total of 227 samples were collected, including 53 of alunite, 14 of buddingtonite, 39 of calcite, 37 of chlorite + muscovite, 24 of kaolinite and 60 of other classes. The overall accuracy value of the mapping was achieved by calculating the number of truly-classified pixels divided by the total number of involved pixels. The total number of involved pixels were calculated by summing the truly-classified pixels divided by the total number of pixels. The other classes pixel is unclassified, then it is considered as falsely classified and assigned a label of ‘other’. If the target classes pixel is unclassified then it is considered as falsely classified and assigned a label of ‘other’.

4. Results and discussion

EXhype is the hybrid combination of several algorithms such as SUH, SAM and ANN and uses OSL data to deal with intra-class variation. So its performance depends on how well the individual components can perform. The EXhype works in a stepwise manner to classify the targets. The performance of EXhype is explained with respect to each component in the paragraphs to follow:

OSL spectra were collected using n-Dimensional Visualizer where a cluster of each class spectra was observed. A total of 117 sample spectra were collected (Fig. 2). OSL spectra were used to generate target endmember for each class. All the target endmember were segmented (Alunite-10; Buddingtonite-6; Calcite-6; Chlorite + muscovite-3 and Kaolinite-11) using SUH to identify absorption features (Fig. 10). SUH is able to identify the vibrational

Table 1
Configurations and structure of ANN.

<table>
<thead>
<tr>
<th>Network type</th>
<th>Three layered feed-forward backpropagation neural network (Input layer, one hidden layer and output layer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input nodes</td>
<td>Number of segments + 1</td>
</tr>
<tr>
<td>Number of output nodes</td>
<td>1</td>
</tr>
<tr>
<td>Number of hidden nodes</td>
<td>Number of input nodes × 3 + 1</td>
</tr>
<tr>
<td>Initial weights range</td>
<td>([-0.15,0.15])</td>
</tr>
<tr>
<td>Training function</td>
<td>Scaled conjugate gradient backpropagation algorithm (trainscg).</td>
</tr>
<tr>
<td>Transfer functions</td>
<td>Hidden layer = tansig, Output layer = purelin</td>
</tr>
<tr>
<td>Sample size</td>
<td>Size of the Optimal Spectral Library</td>
</tr>
<tr>
<td>Sample size distribution</td>
<td>Samples are divided randomly. 60 percent for training, 20 percent for validation and 20 for percent testing.</td>
</tr>
</tbody>
</table>

Table 2
Performance of ANN model selected for EXhype on various endmembers.

<table>
<thead>
<tr>
<th>Target endmember</th>
<th>Classification accuracy on OSL data (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alunite</td>
<td>100</td>
</tr>
<tr>
<td>Buddingtonite</td>
<td>100</td>
</tr>
<tr>
<td>Calcite</td>
<td>100</td>
</tr>
<tr>
<td>Chlorite + muscovite</td>
<td>100</td>
</tr>
<tr>
<td>Kaolinite</td>
<td>100</td>
</tr>
</tbody>
</table>

Fig. 10. Segmented target endmembers using Segmented Upper Hull method.
diagnostic absorptions features in all target endmembers except for chlorite + muscovite, where the entire vibrational region is identified as a single segment. This could affect the performance of EXhype to classify chlorite + muscovite. SAM discrimination values of all the target endmember with OSL spectra are represented by box plots (Fig. 11) with respect to segment-wise as well as by full spectra comparison. There are two types of discrimination values: (i) comparison of target endmember with target class spectra and (ii) comparison of target endmember with non-target class spectra. If the distribution of discrimination values of target endmember with target class spectra are larger, it represents larger variation in target class spectra. If discrimination values of target endmember with target class spectra overlaps with discrimination values of target endmember with non-target class spectra then classification algorithm may not be able to rightly classify the target, which in turn produce commission and/or omission errors.

In the case of alunite and kaolinite (Fig. 11(A) and (E)) when full spectra were compared, the two whiskers are overlapping. This overlapping region creates a commission of non-target class pixels into target class. It can also be deduced from Table 3 accuracy assessment result where alunite and kaolinite were misclassified by SAM. Six pixels of kaolinite were classified as alunite and one pixel of alunite classified as kaolinite whereas EXhype classified accurately (Table 4). Because EXhype considered segments as well as full spectra but SAM considered only full spectra. In the case of alunite, segments 7–10 have higher clearance between two

Fig. 11. Discrimination values of SAM between target endmember and target class spectra or non-target class spectra. Discrimination value at ‘F’ in each box plot represents comparison of target endmember with target class spectra and non-target class spectra by considering full spectra.
whiskers and in the case of kaolinite, segments 9 and 10 have higher clearance. While training, ANN gave more weightage to these regions to classify alunite and kaolinite accurately. Thus, the segment-wise approach provides flexibility to EXhype to classify targets when there is subtle discrimination.

The performance of SAM is very poor to discriminate kaolinite from other classes due to less discrimination between them. Also, kaolinite spectra have large spectral variation in segments 1 and 2. This caused SAM to produce only 50% producer accuracy and 60% user accuracy. But in case of EXhype, producer and user accuracy values are 100% and 92.31% respectively. It has classified all pixels of kaolinite. Thus, EXhype was able to deal with the intra-class variation of kaolinite class.

From the box plot (Fig. 11(B) and (c)) it can be seen in the case of buddingtonite and calcite there is a clear difference between target class spectra and non-target class spectra. In this regards, both SAM and EXhype discriminated calcite and buddingtonite completely from other target classes. But most of the pixels of calcite and buddingtonite class were unidentified and there is a commission of other classes pixels. This could be, because of lesser discrimination of calcite and buddingtonite with other classes spectra. The performance of EXhype and SAM to map chlorite + muscovite is almost the same as can be seen from Tables 5 and 3, for the threshold value (i.e. degree of belongingness) of 0.95. But the overall accuracy of EXhype for such threshold is less. For the threshold of 0.98, EXhype produces best overall accuracy of 90.75% and kappa coefficient of 0.89. For the given threshold producer accuracy got reduced because chlorite + muscovite is divided only into three segments and it’s entire electronic as well as the vibrational region divided into one single segment, where all other classes are showing variation in those regions. Thus, the performance of EXhype merely depends on the performance of each of its components.

The overall classification accuracy of SAM and the EXhype are 60.35% (Table 3) and 90.75% (Table 4) and kappa coefficient of 0.51 and 0.89 respectively. EXhype confusion matrix (Table 4)

### Table 3
Confusion matrix for SAM classifier.

<table>
<thead>
<tr>
<th></th>
<th>Alunite</th>
<th>Buddingtonite</th>
<th>Calcite</th>
<th>Chlorite + muscovite</th>
<th>Kaolinite</th>
<th>Other</th>
<th>Row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alunite</td>
<td>44</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>4</td>
<td>54</td>
</tr>
<tr>
<td>Buddingtonite</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>Calcite</td>
<td>0</td>
<td>0</td>
<td>19</td>
<td>0</td>
<td>0</td>
<td>22</td>
<td>41</td>
</tr>
<tr>
<td>Chlorite + muscovite</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>37</td>
<td>0</td>
<td>8</td>
<td>45</td>
</tr>
<tr>
<td>Kaolinite</td>
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<td>0</td>
<td>0</td>
<td>12</td>
<td>0</td>
<td>6</td>
<td>17</td>
</tr>
<tr>
<td>Other</td>
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<td>6</td>
<td>20</td>
<td>0</td>
<td>6</td>
<td>17</td>
<td>57</td>
</tr>
<tr>
<td>Column total</td>
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<td>14</td>
<td>39</td>
<td>37</td>
<td>24</td>
<td>60</td>
<td>227</td>
</tr>
</tbody>
</table>

Overall Accuracy = 137/227 = 60.35%  
Kappa Coefficient = 0.51

### Table 4
Confusion matrix for EXhype classifier.

<table>
<thead>
<tr>
<th></th>
<th>Alunite</th>
<th>Buddingtonite</th>
<th>Calcite</th>
<th>Chlorite + muscovite</th>
<th>Kaolinite</th>
<th>Other</th>
<th>Row total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alunite</td>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>53</td>
</tr>
<tr>
<td>Buddingtonite</td>
<td>0</td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>26</td>
</tr>
<tr>
<td>Calcite</td>
<td>0</td>
<td>0</td>
<td>39</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>46</td>
</tr>
<tr>
<td>Chlorite + muscovite</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>32</td>
<td>0</td>
<td>2</td>
<td>34</td>
</tr>
<tr>
<td>Kaolinite</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>24</td>
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</tr>
<tr>
<td>Other</td>
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<td>1</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>49</td>
<td>59</td>
</tr>
<tr>
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<td>14</td>
<td>39</td>
<td>37</td>
<td>24</td>
<td>60</td>
<td>227</td>
</tr>
</tbody>
</table>

Overall Accuracy = 206/227 = 90.75%  
Kappa Coefficient = 0.89

### Table 5
Comparison of chlorite + muscovite classification results with respect to different degree of belongingness threshold value.

<table>
<thead>
<tr>
<th>SR. no.</th>
<th>Threshold</th>
<th>Producer accuracy (%)</th>
<th>User accuracy (%)</th>
<th>Overall accuracy (%)</th>
<th>Overall kappa coefficient</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>0.95</td>
<td>100.00</td>
<td>82.22</td>
<td>90.31</td>
<td>0.88</td>
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<tr>
<td>2</td>
<td>0.96</td>
<td>94.99</td>
<td>89.87</td>
<td>87.87</td>
<td>0.87</td>
</tr>
<tr>
<td>3</td>
<td>0.97</td>
<td>91.89</td>
<td>85.00</td>
<td>89.75</td>
<td>0.87</td>
</tr>
<tr>
<td>4</td>
<td>0.98</td>
<td>86.49</td>
<td>94.12</td>
<td>90.75</td>
<td>0.89</td>
</tr>
<tr>
<td>5</td>
<td>0.99</td>
<td>81.08</td>
<td>96.77</td>
<td>90.31</td>
<td>0.88</td>
</tr>
</tbody>
</table>
showed that there was no misclassification between the target classes. The commission errors which were present due to other classes could be because EXhype was not trained for such cases. Kaolinite and calcite were poorly classified by the SAM algorithm. In case of calcite, many pixels were unclassified and many pixels of other classes were identified as calcite. Kaolinite was also misclassified in a similar manner as calcite. Besides, some of the kaolinite mineral pixels were also classified as alunite. Even though alunite and kaolinite have similar spectra, as can be seen from Fig. 3, EXhype discriminated both targets but SAM failed to discriminate completely. The performance of both algorithms was better in case of chlorite + muscovite. Overall SAM algorithm did not classify many target class pixels and poorly discriminated similar targets, whereas EXhype showed excellent performance. It can also be deduced from Figs. 12 and 13, where in case of SAM classified image both kaolinite and alunite regions are overlapping. Furthermore, many of the alunite, kaolinite, calcite and buddingtonite pixels, which were mapped by the EXhype were not mapped by the SAM.

4.1. Time complexity analysis of the EXhype

The EXhype is built upon pre-existing algorithms and for it to work requires the complete functioning of the underlying components. It means that the efficiency of the EXhype, just like its accuracy, is a culmination of the components’ efficiency. It can also be inferred from Big-O analysis, worst case time for the proposed EXhype was found to be $O(pk + lks)$ and for SAM $O(p)$ respectively, where

\[ P = \text{Number of pixels} \]
\[ k = \text{Number of segments per endmember} \]
As shown in Fig. 14, the computational time of the standalone SAM algorithm is lesser than the EXhype, of which it is a component. In case of EXhype, more computational time is coming at the cost of better extraction of pixel information. In order to find computational taken by the two algorithms, they were tested on the MATLAB R2015a platform, Processor - Intel(R) Core(TM) i7-4770 CPU 3.40 GHz, Installed memory (RAM) - 8 GB and Operating System - Windows 8.1 Pro.

5. Conclusion

This study has arrayed and discussed the concepts, limitations and modifications of various algorithms. It has also discerned that, various algorithms employ different human expertise to interpret imaging spectrometer data. To develop a prominent expert system, its knowledge base should contain complete domain expert knowledge.

In this study, a new expert system is developed to classify minerals by incorporating human expertise into a single expert system named ‘EXhype’. EXhype is developed using a knowledge base including the Optimal spectral library, Segmented Upper Hull method, SAM and ANN. It enhanced the classification accuracy by dealing with intra-class variation; analysing spectra completely and individually by considering absorption features as well as non-absorption features. Then it finally took decisions based on the learning and by emphasizing most important features. The experimental results showed that EXhype was more proficient than traditional SAM algorithm and avoids misclassification between target classes when applied to minerals. EXhype was also proved to be successful in discriminating spectrally similar targets.

The computational time taken by EXhype is more than SAM; it is coming at the cost of improved accuracy and it was found that time for execution is quite reasonable. The algorithm was primarily developed to improve classification accuracy especially of minerals and not from a computational efficiency viewpoint.

This study came out with a novel way, to give input to the neural network instead of full band information. To calculate real user’s accuracies when limited classes are considered for classification, a modified accuracy assessment method was used in this study. This was done to estimate a real user’s accuracy values by including other classes in the confusion matrix, which in turn produces a more qualitative overall accuracy value. It was also inferred that the virtual verification method allows the utilization of stratified random sampling method and eliminates all the difficulties associated with it.

The expert perceives information about spectra differently in a different context and after processing the information arrives at a decision to solve the problem. EXhype replicates the same process. It is a known fact that different similarity measure algorithms work better for different conditions. As the EXhype can be modified to incorporate any of the available similarity algorithms, it is an intelligent and dynamic tool, that can be used for various situations.

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References


