Multispectral classification algorithms and their application to thin section imagery

Kamil Zaniewski, Brandon University

Abstract: When working with soils or glacial sediments there frequently is a need to look at their microscopic-scale features. At the same time GIS is often perceived as applicable to macro scale studies founded on remotely sensed imagery or surveying data. But there is another side to GIS. Recent research results show that GIS applications are quite capable of dealing with micro-scale features. Images obtained from thin sections of glacial sediments were fully processed and analyzed using standard GIS techniques and produced quantified descriptions of the tested sediment samples. The key to this information lies in an effective application of multispectral classification algorithms. Classifications are used to accurately identify and segment imagery prior to any quantification procedure. It was found that in the highly complex visual space of glacial sediment thin sections, unsupervised classification methods are more effective in identifying micro-features.

Key words: micromorphology, multispectral classification, glacial sediments, image analysis

Introduction

Glacial micromorphology is still a new science - constantly and rapidly changing and growing. It is based partly on the body of work originating in soil science. A number of thin section description classifications have been created (Brewer 1964, 1976; Jongerius 1964; FitzPatrick 1984) but they are generally written with soil science in mind. This limits their usefulness to glacial sedimentologists. Van der Meer (1993) modified the standard soil classification system created by Brewer (1976) to better fit the growing needs of the new science. However, current micromorphological studies of glacial sediments are very often qualitative in nature. This unavoidably leads to a degree of ambiguity in description and interpretation. There were some attempts at making thin section descriptions more objective (FitzPatrick 1984, 1993) but these were limited to soil science and even then there is little consensus among researchers on which system works best. It may indeed be that each field of study, and even individual interest areas within each field, may require their own version of a classification system.

It is not the purpose of this paper to create such a system. Neither is it meant to restate the history or the principles of image analysis. Papers of this nature have already been written on the topics of image analysis in soil science (Mermut and Norton 1992; Terribile and FitzPatrick 1992). The purpose is rather to initiate the process of objective study of micromorphological features using the technique of image analysis. The long-term goal of this process is to create a comprehensive system to objectively describe thin sections of glacial sediments - likely a complimentary system to any qualitative method of classification presently existing or to be defined in the future.

To initiate this undertaking it is necessary to create a firm basis of feature identification in thin sections. A feature could be any object or objects of interest to the researcher. Void spaces, plasma, individual mineralogies, skeleton grains, staining patterns, and microstructures - these are but few examples of features of interest. It may prove impossible to devise a single method of feature identification for all of them at the same time. The principles used however, should stay the same and the classification method employed may also remain constant while some variables change based on the main topic of research. The result of such modifications should be an increase in the accuracy of the results of feature identification.

Previous Work

The basic concepts of multispectral image analysis form an integral part of most raster based Geographical Information Systems (GIS). GIS applications are generally used in large-scale studies of landscapes, natural resources management or social geography studies. As such they appear to have very little in common with image analysis of small-scale imagery such as thin sections of glacial sediments. However, previous work by the author showed that even the simplest of GIS programs are quite capable of dealing with very small coverages - both theoretically (Zaniewski 1994) and in simple practical applications (McCarthy and Zaniewski 2001).

For any application dealing with digital imagery, be it GIS or image analysis programs, it is necessary to define the various objects and to create topology for the images tested. The topology (or the information regarding the relationships between individual objects in a coverage) can be created following a translation of what is essentially a two-dimensional set of random values into a series of classes or objects. This can be achieved with the use of 'Athreshold' values. This is a very simple way of identifying the various features in digital imagery. Multispectral image classification methods tend to be more accurate and far more sophisticated in their assessment of the digital information. The use of multispectral image classification was developed for use in remote sensing to take advantage of available satellite imagery. The techniques and methods of such classifications are numerous and vary in their specific complexities, accuracies, applications and availability. A number of remote sensing textbooks include descriptions of some of the main techniques involved (Jensen 1996; Lillesand and Kiefer 2000). The use of multispectral image classification routines in thin section studies has been tried in soil science (Protz *et al*. 1992) and in glacial sediment studies (Hiemstra *et al*. in prep.)

Methodology

Hardware and software:

The process of image classification and analysis involves a series of steps. The procedure begins with image capture. There are several methods of image acquisition. For this work images were obtained by a Leica DC200 digital camera mounted on a standard petrographic microscope (Leica Wild M420) capable of low magnifications (up to 10x). Imagery was imported and processed using a GIS program (TNT-Maps and Images Processing System) incorporating a number of multispectral classification options.

Image collection and preparation:

Each of the images captured for this project were stored as a TIFF format, 24bit RGB graphic file. This was done in order to accurately measure and record the spectral intensity of each image pixel for the three colour bands (red, green and blue). The use of 256-colour images (such as GIFs) should be avoided since the choice of values for each scanned pixel is random and the values do not reflect the intensity of colour. It is quite likely that two pixels with a slight variation in colour will be

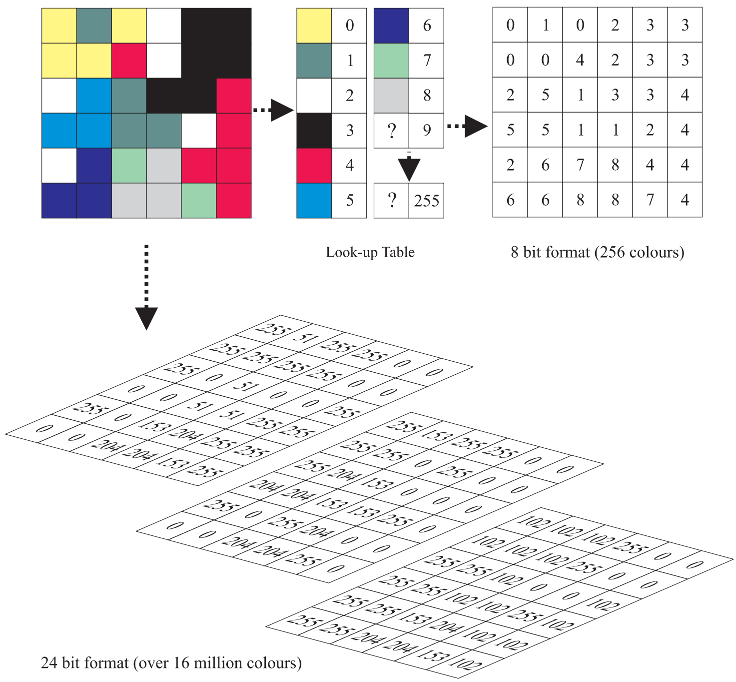

Figure 1: *Illustration of the difference between 256-colour and 24-bit colour data storage and display.*

represented as different values in a 256-colour image (Figure 1). Any analysis of such an image is likely to be impossible.

Images to be analysed were captured in sets of three. Every thin section was previewed and an area of interest was visually identified. Once the target area was selected it was photographed in plain light, under cross-polarized light and with a gypsum wedge in place - making sure that the thin section did not moved during the process. This was necessary in order to assure that the three images were showing the exact same location in the thin section. Each image was 1280 by 1024 pixels in size and was taken at the approximate magnification of x 10. Each pixel was calibrated to have the length and width of 5 microns.

The image capturing procedure was repeated four times - resulting in four sets of raw image data representing the selected coverage areas. The final result of image capturing was a series of pictures showing the same

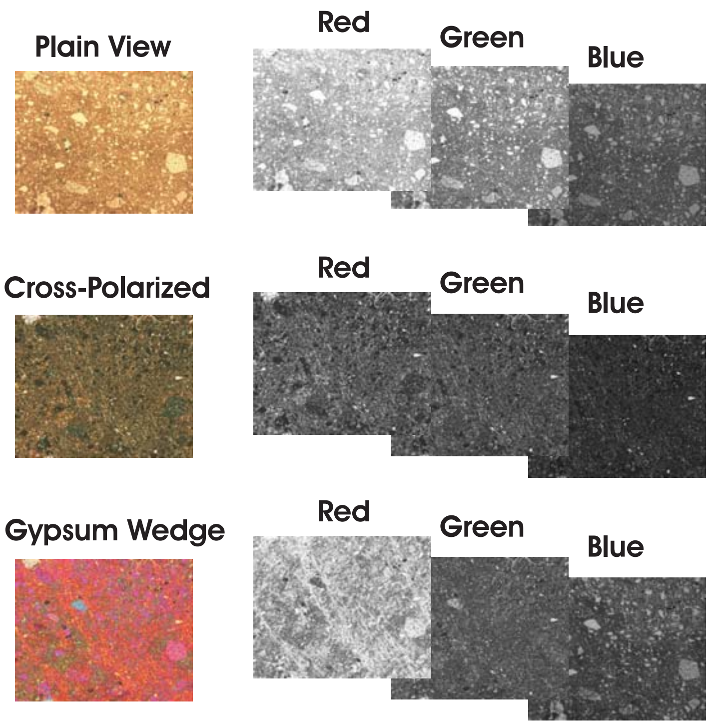

Figure 2: *Source images and their 9 colour 'bands'.*

part of a thin section under different viewing conditions. This is the micromorphology equivalent of remotely sensed images.

Importation:

The importation routine was performed by the GIS/image analysis program used in this project (TNT-MIPS). This program allows for a number of modifications to the original file as specified by the user. During the importation routine each of the three images for each coverage was divided into their colour bands (Figure 2). These were representing the red, green and blue spectrum bands of each digital image. For every one of the four coverages analysed there were now 9 individual spectral bands.

Spectral band selection:

Although the process of classification may be performed on all nine of the spectral bands (red, green and blue bands for plain, cross-polarized and gypsum wedge images) it is neither necessary nor practical. In fact it may be counterproductive and result in a longer procedural time without any substantial benefits in the form of increased accuracy. Multispectral classification algorithms are meant to identify features based on changes in their appearance (grey tone brightness) from image to image. Where differences between images are minimal (high correlation, data redundancy) the images will contribute little to the overall accuracy of the routine but will extend the time required to run the algorithm.

The number of spectral bands and their content may change from application to application. It is dependent on the spectral qualities of the material studied. This project looked at a small subset of the possible material types. This included: voids, plasma (material of colloidal size, i.e. <2¼m in diameter, which can also be referred to as sedimentary matrix) and mineral grains. A choice of 3 or 4 bands had to be made to maximize the effectiveness of the procedure. This is possible if the bands chosen represent spectral data of highest contrast between the different features of interest.

There are several criteria that could be used to select the four bands. The choice could be made based on prior knowledge or experience. If the objective of the project was to identify pore spaces (voids) then the use of UV illumination in combination with UV sensitive dye could produce an image with sufficient contrast between void and non-void pixels to satisfy the requirements of classification. This approach to band selection is however limited to the few situations where the variety of materials and the number of classes of interest are small.

An alternative approach is to use statistical correlation information. For each pair of images tested a correlation value was given, a line of best fit was calculated, and the correlation pattern was temporarily displayed on the screen. The objective of the tests was to identify 4 bands that were least alike. Once all 36 tests were performed a decision was made as to which set of image bands could be used most efficiently. The decision was based on the observed differences in correlation values with maximum variance being preferred. Table 1 shows the results of the correlation tests.

The following spectral bands were selected: the red bandwidth of the cross-polarized images (X_R), blue and red bandwidth of the plain light images (P_B and P_R) and the green bandwidth of the gypsum wedge superposition images (W_G). Even though some correlation values appear high, the correlation values for the remaining spectral bands justified their selection. For example, the correlation value for bands P_B and P_R is very high (0.80), however, the values for P_R and the remaining two bands (W_G,

Table 1: *Raster correlation values for sample R.745(1).*

	P_R	P_G	P_B	X_R	X_G	X_B	W_R	W_G	W_B
P_R									
P_G	0.89								
P_B	0.80	0.97							
X_R	0.20	0.10	0.06						
X_G	0.34	0.28	0.25	0.94					
X_B	0.40	0.39	0.37	0.82	0.92				
W_R	0.50	0.46	0.42	0.73	0.75	0.69			
W_G	0.35	0.25	0.21	0.74	0.75	0.67	0.71		
W_B	0.69	0.80	0.80	0.32	0.48	0.57	0.61	0.6	

X_R) are sufficiently low (0.20, 0.35) to justify the use of this spectral band. For some classification methods it may be necessary to limit this selection even further based on training site statistics.

Classification method testing and selection:

There are many methods of multispectral image classification. General remote sensing textbooks usually contain some explanation the most common algorithms, such as ‘Maximum Likelihood’ or ‘Parallelepiped’ (Lillesand and Kiefer 2000). These methods tend to vary in many respects. Two main types are supervised and unsupervised classification methods. These procedures can be further divided into more specific methods. Some techniques are faster but less accurate (e.g., ‘Minimum Distance to Means’ classifier which does not account for class variance) and their use tends to be limited to situations where spectral images fit a narrowly defined set of limitations – such as uniform class variances. Other methods may be more accurate but tend to require more processing time (required to calculate more comprehensive class definitions) and better quality data (higher overall signal-to-noise ratio) (e.g., ‘Minimum Distribution Angle’). The challenge is to decide which one best suits the purpose of thin section image analysis.

The variety of features and materials found in glacial sediment thin sections increase the complexity and difficulty of the multispectral classification. The requirements of an accurate supervised classification specify the need for a clearly defined set of training sites. Training sites are supposed to represent only one feature class (single material) and be spectrally homogenous. All of the different types of material should be defined or the algorithm may leave large portions of the image unclassified.

The alternative to this is to use an unsupervised classification method. This avoids the training site definition stage but includes complications unique to this group of classification techniques. To achieve accurate results with an unsupervised classification it is necessary to exaggerate the number of actual classes known to exist in each image. For example, if a known number of mineral types are 5 then in order to classify the sample field it is necessary to ask that at least 15 different classes be identified. This exaggeration allows the computer to identify new classes. These additional classes may include small areas of unique material left unobserved by the user (not an unlikely scenario when looking at thin sections of glacial sediments) or represent areas of the image where the mixing of skeleton grains, voids and plasma produced unique 'intermediate stage' 'fuzzy' classes. It is important to point out that a thin section image represents approximately 20 ¼m thickness of glacial sediment and not only its surface.

Unsupervised classification involving large numbers of classes can be a slow process. Furthermore, final classification routine does not label each spectral class, rather it is the user that has to identify the various class clusters and provide an appropriate attribute label. K-means method has been used effectively in pore studies (VandenBygaart *et al.* 1997) indicating that the unsupervised techniques have their place in sediment or soils-based studies.

To compare and evaluate effectiveness of the multispectral classification approach it was necessary to classify the same image using a variety of algorithms. Classification results were evaluated for accuracy and processing time. The image used to test the algorithms was selected to represent a typical glacial sediment thin section. It contained examples of a variety of skeleton grains, plasma, voids and plasmic fabric.

Results

Testing showed that the processing time might vary substantially. Table 2 lists the times obtained. It is important to note that the table only shows the time required to run the process. For supervised classifications actual processing time must include the creation of training sites. This tends to differ from image to image based on the variety of features contained in it. For example, when skeleton grain material consists of a large number of lithologies it becomes necessary to create a larger number

Table 2: *A summary of the classification techniques tested.*

Name	Type	Processing time	References
Simple One Pass Clustering	unsupervised	14 sec	Jensen (1996)
K Means	unsupervised	1min, 22 sec	Duda and Hart (1973); Schowengerdt (1997)
Fuzzy C Means	unsupervised	24min, 31 sec	Cannon *et al.* (1986); Schowengerdt (1997)
Minimum Distribution Angle	unsupervised	1min, 8sec	Paris and Kwong (1988)
ISODATA Classification	unsupervised	35 sec	Tou and Gonzalez (1974); Jensen (1996)
Self-organizing Neutral Network	unsupervised	1min, 55 sec	Schowengerdt (1997)
Adaptive Resonance	unsupervised	1min, 45 sec	Capenter and Grossberg (1988)
Minimum Distance to Means	supervised	13 sec	Jensen (1996); Lillesand and Keifer (2000)
Maximum Likelihood	supervised	19 sec	Lillesand and Kiefer (2000)
Stepwise Linear	supervised	10 sec	Johnston (1978)
Suits Maximum Relative	supervised	12 sec	Wagner and Suits (1980)

of training sites with an associated increase in preparation time. When using spectral signatures or spectral response patterns this preparation time may be minimized. However, the variety of material contained in glacial sediments will frequently require additional training site definition regardless of the pre-existing set of spectral definitions.

For unsupervised classification methods the additional processing time comes from post-processing of the classification results. Before the results can be evaluated for accuracy, care must be taken to reclassify the results accurately. This task must be performed every time an unsupervised algorithm is used. As can be seen from Table 2 most routines ran for less than 1 minute. Only the 'Fuzzy C Means' method took substantially more time.

Further evaluation was then performed visually to establish which classification methods came the closest to producing an effective rendition of the original image. This was done by comparing the characteristics of the original photo to those observed in the resultant class image. By concentrating on 'landmark' areas (such as boundaries between voids and plasma or plasma and skeleton grains) it was possible to note exceptional classification errors.

Overall most unsupervised classification methods produced good results. The exception was the 'Simple One Pass Clustering' algorithm which produced images of lesser quality. The best apparent agreement between the original photo and the classified results was obtained when the 'Minimum Distribution Angle' algorithm was employed.

All of the supervised classification results suffered from obvious errors where pixels were assigned into a wrong class or were left unclassified. Accuracy improved with progressive redefinition of the training sites.

However, it never achieved the quality of the unsupervised classifications results.

Discussion

Supervised classification methods should not be attempted for this type of analysis. The problem has to be traced to the inherent training site definition error encountered whenever imagery used shows a high degree of spatial variability. In transitional areas (contact zones) between voids and skeleton grains or voids and plasma the appearance of pixels will change gradually to represent the changing composition of the material. It is important to recognize that the thin section images are produced by illumination from below the sample (transmitted light). Every pixel in such an image is a product of the many different materials contained within the thickness of the section. Transitional areas will frequently exhibit a very high degree of spectral fuzziness – not fitting into any of the main material classes. Allowing a portion of the classified image to be left as unclassified will only solve some of the problems. Further problems may be encountered when training sites include areas not belonging to the right class. This can only be avoided by defining sites on pixel-to-pixel basis. This is a very slow and tedious process not practical when large numbers of thin sections are considered. The use of spectral keys (unique diagnostic spectral characteristics of a material) may be attempted but some caution is advised. Microscope settings must remain identical from sample to sample. Furthermore, spectral keys have to be redefined overtime in order to adjust for the changing brightness of the light bulb. New keys may have to be created to allow for inclusion of additional types of material not encountered previously.

Unsupervised classification algorithms showed many advantages over the supervised approach. No *a priori* knowledge is required. The computer does all the calculations necessary to identify groups of pixels similar in appearance. To complete the process it is necessary to reclassify the results so that they produce a more ordered appearance allowing for visual interpretation as well as conversion to vector based images, if necessary. Even when looking at a highly complex set of results (40 or 50 different classes) the time required to reassign pixels into voids, plasma and skeleton grains did not exceed that of the retraining procedures necessary for the supervised classifications.

A procedural time of over 20 minutes per application means that the 'Fuzzy C Means' algorithm should probably be considered too slow to be used on large numbers of images required to analyse even a single thin section. All other algorithms produced their results in less than 2 minutes leaving accuracy as the decisive factor. The problems encountered when using supervised classification methods, combined with their lower overall accuracy means that only unsupervised classification algorithms should be considered for use in thin section studies. Of all the methods tested, the 'Minimum Distribution Angle' showed best results and must therefore be recommended.

Conclusions

A classification routine, no matter how complete and accurate, should only be considered as a preliminary stage of image analysis. It is simply a first part of a longer procedure and it serves to provide rudimentary information as well as spatial definitions of some of the features contained in an image. For a micromorphologist this means that more studies are necessary if a more accurate means of data extraction are to be found. What is needed is a methodology of feature measurements better suited to micromorphology. For example, identification of all the quartz grains in an image must be followed by measurement of the grains identified. The measurements may involve simple area or diameter calculation for each grain. They may perhaps involve identification of shape characteristics or even the relationship between the grains and other material in the images. It is hoped that the use of this technique will result in a more accurate, certainly more objective, way of describing many of the micromorphological characteristics of glacial sediments. In order to reach this goal it is important to use the best available tools for obtaining the raw data. As such only some of the unsupervised classification methods appear to fulfil the basic requirements of speed and accuracy. Of these, the 'Minimum Distribution Angle' method shows most promise and is therefore recommended.

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