AN OBJECTIVE STANDARD FOR HYPERSPECTRAL IMAGE QUALITY

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1. Introduction

What is spectral image "quality"? There is no objective definition, which is why there is no current standard. Image quality must be inferred from measurements of; spatial resolution, calibration accuracy, spectral resolution, signal to noise, contrast, bit error rate, dynamic range, sensor stability, geometric registration and other factors. (Schowengerdt, et al, 1974, Slater, 1980, Roger et al, 1996 & Meyer et al, 1993) While many aspects of sensor performance and image acquisition are measurable, a mathematical construction that incorporates these measurements into a quality rating is very difficult to derive. (Leachtenauer et al, 1997, Green et al, 1988, Smith et al, 1999, Halford et al, 1999, & Nill and Bouzas, 1992) This is because quality is a subjective concept and some of the system parameters affecting image quality interact in a non-linear manner (Leachtenauer et al, 1997). At this time, the sole spectral quality scale is the Multispectral Imagery Interpretability Rating Scale (MS IIRS) (IRARS, 1995). However, the MS IIRS remains a "work in progress" and is not used widely. The quality of multispectral and hyperspectral imagery has not yet been described in a parametric manner. The General Image Quality Equation (GIQE) parametrically evaluates single band images (Leachtenauer et al, 1997) and results in a value on the National Interpretability Rating Scale (NIIRS) (IRARS, 1996a & IRARS, 1996b). The GIQE could derive a NIIRS value for each band of a spectral image. In a similar manner, the noise estimates per band might be calculated (Roger et al, 1996). While repetition of gray-scale quality measures over multiple bands may be useful, it does not address <u>spectral</u> image quality.

In the context of this paper, hyperspectral image quality refers to the way a hyperspectral image works as a multivariate dataset. We define a high quality image as one that contains <u>separable</u> classes that are <u>spectrally very similar</u>. This study proposes a spectral similarity scale based on an objective methodology. It may be useful to compare and contrast this approach with the NIIRS (IRARS, 1996a & 1996b).

- Like the NIIRS, this definition inherently incorporates all factors antecedent to the image and concentrates on identifying the information potential of the image.
- Unlike the NIIRS levels, the proposed spectral similarity scale is a continuous scale founded on an objective methodology.

Two basic uses of a spectral similarity scale are:

- Assignment of a quality level to hyperspectral images. This would be fundamental to image resource management, as it would provide an objective indication of imagery information potential.
- Specification of the necessary image quality given the requirement that two spectra be resolved. Such spectra could derive from field spectroradiometer measurements.

This paper presents a spectral similarity scale and demonstrates its application as a standard for hyperspectral-image quality assessment. The work proceeds in two parts.

- The definition of the spectral similarity scale, its rationale and implementation. Several examples of spectra-pairs illustrate a variety of similarity values.
- Two examples will demonstrate the application of the spectral similarity scale as a hyperspectral quality measure.
    - The first application identifies and compares the image quality level of two AVIRIS images (NAS Moffett Field, 1992 & 1997) by comparing their ranks on the spectral similarity scale.
    - The second example identifies the image quality level required to identify nitrogen stress in corn. Similarity between spectra representing well-fertilized and nitrogen-stressed corn is determined on the spectral similarity scale. This value is considered the minimum image-quality level capable of revealing corn nitrogen stress. Subsequent comparison to the quality level of the two AVIRIS images and the nitrogen stress quality level indicate whether the images would have been capable of revealing corn nitrogen stress had it been in the image.

2. The Spectral Similarity Scale

2.1 Definition

The image quality definition given above stressed that image classes be "spectrally very similar". How is that similarity judged? Two basic factors comprise vector difference: distance and shape. If there are others, they have not yet been explicitly identified. Euclidean distance primarily measures the distance between vectors using correlated variables. Correlation compares the shapes of vectors. For any pair of reflectance spectra, these two difference measures constitute a two-element vector called the "difference vector". The absolute magnitude of the difference vector is the "difference magnitude". The spectral similarity scale is comprised of difference magnitude values. By definition, the spectral similarity scale has a minimum of zero and a maximum of the square root of two. Small values on the similarity scale indicate similar spectra.

$$\text{Spectral Similarity} = \sqrt{{d_e}^2 + \hat{r}^2} \quad \text{(EQ 1)}$$

Where the quantities under the radical are defined by the following:

Euclidean Distance

This metric primarily measures the difference in magnitude between vectors. We define the Euclidean distance d_e for two vectors X and Y with Nb bands as:

$$d_e = \sqrt{\frac{1}{Nb}\sum_{i=1}^{Nb}(x_i - y_i)^2} \quad \text{(EQ 2)}$$

We have inserted the factor 1/Nb under the radical to remove the dependence on the number of bands. Thus this metric represents the average distance between the two vectors and it's range is between zero and one.

Correlation

The correlation coefficient squared r^2 is given by Equation 3. The mean value of vector X is μ_x and σ_x is the standard deviation. This metric compares the shapes of the vectors since subtracting the means removes any bias terms and dividing by the standard deviation removes gain factors. The range of this difference measure is between zero and one.

$$r^2 = \left(\frac{\frac{1}{Nb-1}\sum_{i=1}^{Nb}(x_i - \mu_x)(y_i - \mu_y)}{\sigma_x \sigma_y} \right)^2 \qquad \text{(EQ 3)}$$

Since we desire a metric where a large value means dissimilar vectors, we use as our metric:

$$\hat{r} = 1 - r^2 \qquad \text{(EQ4)}$$

Wavelength Regions used by the Spectral Similarity Scale are presented in Table 1. These were chosen to match the bands used by the 1997 AVIRIS image used in a later example.

Table 1. Wavelengths Utilized in This Study

Region	Wavelength Range, nm
Visible-Near Infrared	419-1264, 1523-1752
Short Wave Infrared	2089-2288

This table presents wavelength ranges of the 138 bands used by this study. The nominal bandwidth is 10nm.

2.2 Similarity Values for Example Spectra-pairs

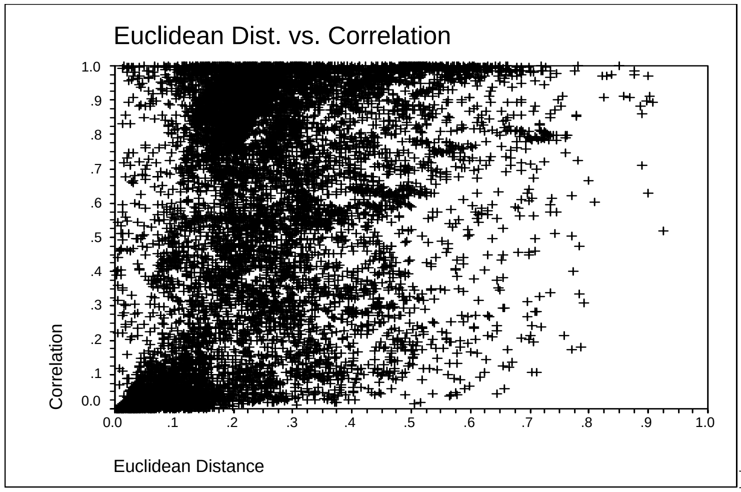
One hundred fifty spectra were obtained from three sources John Hopkins Univ., USGS Denver (Speclab) and the RESOURCE21 Spectral Library. These spectra were collected with different spectrometers. These came from the most comprehensive collection of high-resolution data available to us. These represent a variety of materials:

- **Construction materials:** asphalt (shingles & paving) , ceramics (brick & terra cotta), concrete, paint (olive green & black), tar paper, white rubberized coating and plate window glass.
- **Metal:** galvanized steel and aluminum.
- **Vegetation:** corn, cotton, soybean, wood (pine), quaking aspen, pinon pine, garrett saltbrush, juniper, sagebrush and grass (dry & green).
- **Rocks and Minerals:** basalt, albite gneiss, alkalic granite, dolomitic limestone, arkosic sandstone, bare soil and carbon black.

These spectra do not represent all possible materials nor do they presume to represent the perfect spectra for the materials chosen. Rather, combinations of these spectra result in a nearly complete range of values on the spectral similarity scale.

A spline function was used to convert spectra obtained with an ASD field spectrometer, Becknic spectrometer and a Nicolet spectrometer to match the AVIRIS instrument during the 1997 overflights of NAS Moffett Field.

There are 11,175 combinations of two spectra given a population of 150. These spectra-pairs provide examples of various levels of similarity and the opportunity to examine the interaction of the two vector difference measures. Figure 1 shows the relationship between the two vector difference measures for all 11,175 spectra-pairs. Note the overall low correlation (R^2 = 0.16) this is a fundamental piece of evidence proving the necessity of both difference measures.



$R^2 = 0.160$

Figure 1. Vector Difference Measure Correlation

Note the overall lack of correlation between the difference measures for the 11,175 spectra-pairs. Euclidean distance and correlation describe the difference between pairs of spectra. These measure two basic factors of vector difference: "magnitude" and "shape."

Figure 2 presents several spectra-pairs as examples of different spectral similarity values. These graphs provide a qualitative sense of the meaning of various degrees of spectral similarity.

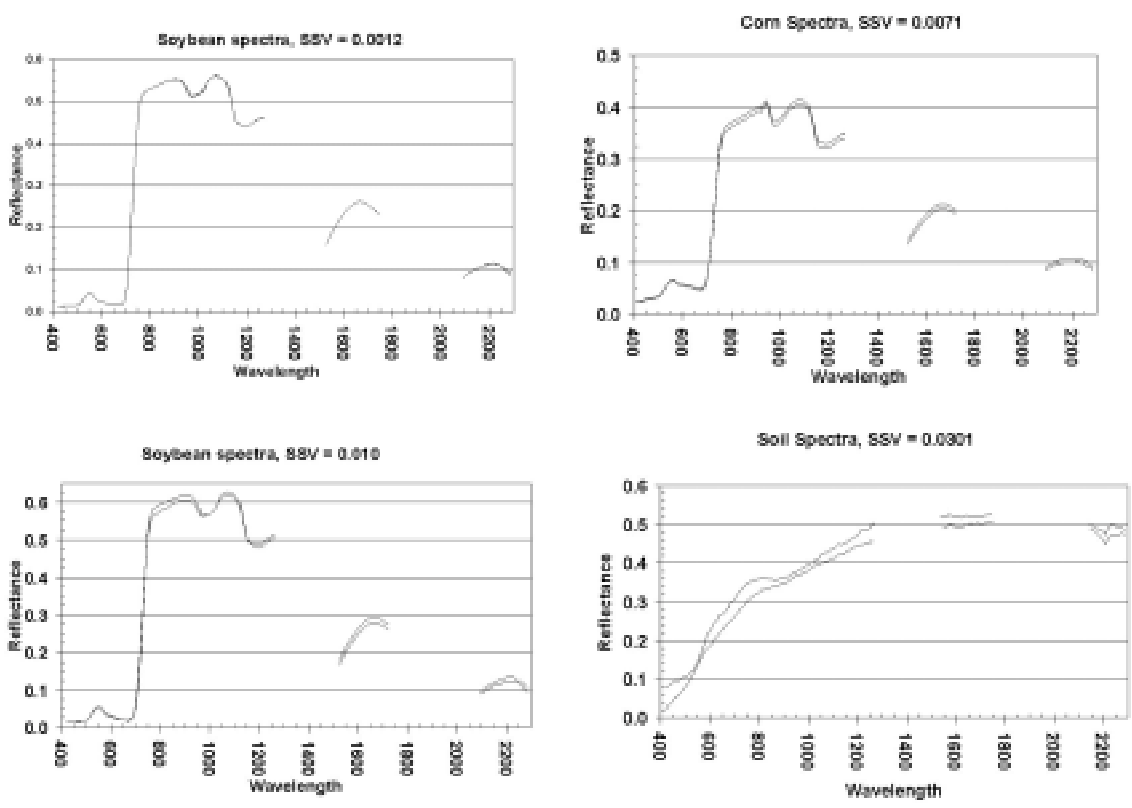


Figure 2a. Spectra Similarity Examples (Similar Spectra)

These graphs present four levels of high spectral similarity (0.0012, 0.007, 0.010 & 0.030). They provide a sense of the meaning of a similarity value. At very low levels of similarity, the spectra are highly correlated thus; the visible difference is primarily due to Euclidean distance.

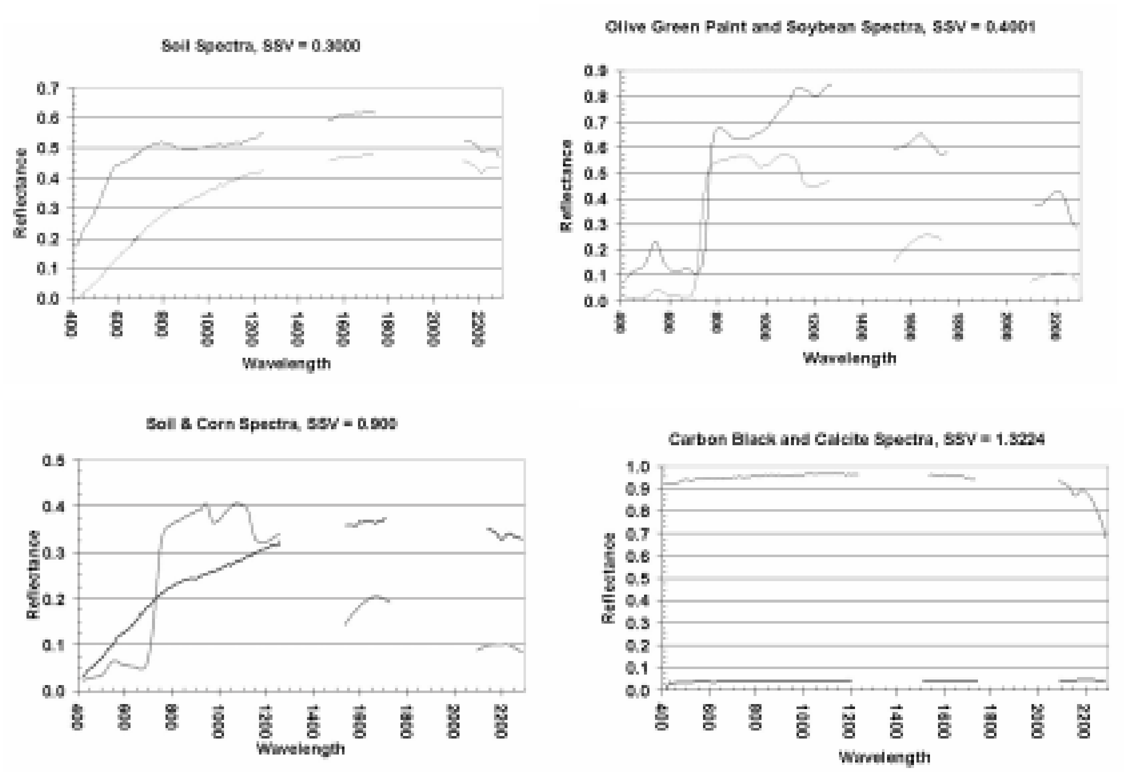


Figure 2b. Spectra Similarity Examples (Dissimilar Spectra)

These graphs present four levels of low spectral similarity (similarity = 0.300, 0.400, 0.900 & 1.322). As above, the intention is to provide a qualitative sense of the meaning of various similarity values. The last two graphs indicate special cases that provide further evidence for the use of both Euclidean distance and correlation. On the left (SSV=0.9) the spectra have a very low Euclidean distance between them and poor correlation. The other case is on the right (SSV=1.3) these spectra have high correlation and a very large Euclidean distance.

3. Applications

3.1 Image Quality Assessment

Where does the image similarity value come from? The spectral image quality definition presented in the introduction stated that a high quality image contains separable classes that are spectrally very similar. Therefore, the task is finding the two image classes that have smallest similarity value. The process is as follows:

- Perform an unsupervised classification using the ISODATA algorithm with these parameters: 50 classes maximum, 5% change threshold, 100 pixels/class minimum and 3 iterations.
- Compute mean reflectance per class.
- Compute the similarity value for all combinations of two classes, analyze their distributions and identify the minimum value.

Unsupervised classification is appropriate because the actual material or mixes of materials in a class are unimportant to this process. There may be better clustering algorithms than ISODATA (ex. Ward's Minimum-variance) but that topic is not addressed here. Consistent results rely on a consistent procedure and these parameter values represent an example of a reasonable standard.

This example evaluates the spectral image quality of two AVIRIS images of NAS Moffett Field in 1992 and 1997 and these images represent data sets of different quality. Visual inspection revealed differences in band to band registration and noise levels. Image preprocessing consisted of atmospheric correction to reflectance (ATREM). The processing also included the removal of the saturated atmospheric water bands around 1.48 and 2.00 micrometers. Finally, a spline function (IDL) convolved the wavelengths of the 1992 image to match the 1997 bands (Table 1). This experiment demonstrates the similarity scale using 10nm bands centered on the wavelengths listed in Table 1.

The 1992 dataset produced 26 classes and 1997 produced 27. From a population of 26 classes, 325 class-pair combinations are possible. Each class-pair yielded a similarity value. Analysis focuses on two topics; the minimum similarity value per image and analysis of similarity value histograms. The minimum class-pair similarity values were 0.032 (1992) and 0.007 (1997). Study of the histograms reveals several items of interest. There are fewer "very similar" classes in the 1992 image compared to the 1997 image. Figure 3 presents the histograms of the similarity values for the two images. The 1992 data set has 17 class-pairs below 0.10 this is exceeded by the 1997 data which has 86. In addition, note that 40 class-pairs in the 1997 image have smaller similarity values than the smallest value in the 1992 image. These observations form the basis for judging the 1997 image to be of better quality than the 1992 image.

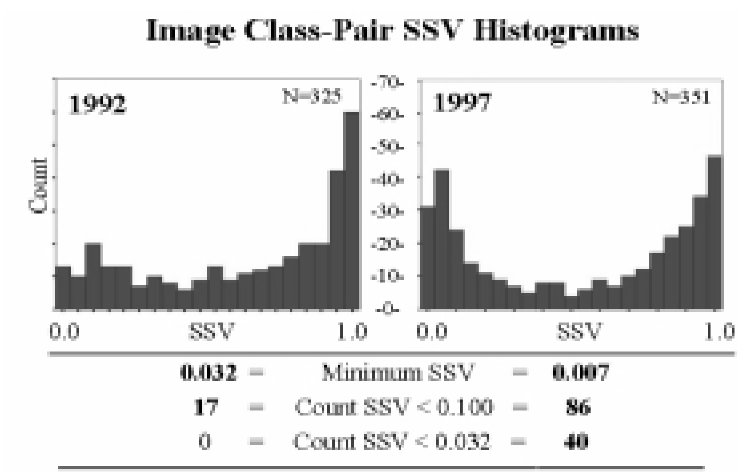


Figure 3. Image Class-Pair SSV Histograms

These two graphs present the histograms of the similarity values for both AVIRIS images. Note in the 1992 data the smaller number of class-pairs at the low end of the scale. Recall that low values of similarity represent similar spectra. Thus there are fewer class-pairs in the 1992 dataset that are "very similar" compared to the 1997 data.

3.2 Image Quality Required by Spectral Task

Another application of the spectral similarity scale is the determination of the similarity value required for imagery that will separate specific spectra. For example, what similarity value is required for imagery that must capture nitrogen stress in corn? The similarity scale is the means for comparing these values with the assessment of imagery as discussed in the previous example. It is assumed that if the similarity value of a pair of spectra is larger than the minimum image-similarity value then, in general, the spectra could be separated. This assumption presumes supervised classification processes similar to the clustering algorithm used during image assessment. In this case, ISODATA which, does not use band covariance.

During the RESOURCE21 Alpha98 project, an ASD spectroradiometer measured corn spectra from plots subjected to various levels of nitrogen application. Within each collection date, the similarity between spectra from plots subjected to five levels of nitrogen application was calculated (Table 2). Examined over the growing season, these values give insight into the difficulty of separating the various treatment levels.

Table 2. Similarity Values Between Spectra of Nitrogen Stressed Corn

Diff. Mag. on 24 May 98					
	240	120	80	40	0
240	0				
120	0.0219	0			
80	0.0138	0.007	0		
40	0.0159	0.013	0.009	0	
0	0.024	0.031	0.026	0.018	0

Diff. Mag. on 31 May 98					
	240	120	80	40	0
240	0				
120	0.0122	0			
80	0.0126	0.004	0		
40	0.0081	0.008	0.006	0	
0	0.014	0.018	0.015	0.010	0

Diff. Mag. on 12 Jul 98					
	240	120	80	40	0
240	0				
120	0.0218	0			
80	0.0260	0.023	0		
40	0.0278	0.042	0.023	0	
0	0.087	0.098	0.080	0.050	0

Diff. Mag. on 19 Jul 98					
	240	120	80	40	0
240	0				
120	0.0068	0			
80	0.0154	0.010	0		
40	0.0155	0.012	0.009	0	
0	0.058	0.056	0.047	0.040	0

Diff. Mag. on 16 Aug 98					
	240	120	80	40	0
240	0				
120	0.0031	0			
80	0.0043	0.004	0		
40	0.0143	0.012	0.011	0	
0	0.035	0.031	0.033	0.022	0

Diff. Mag. on 30 Aug 98					
	240	120	80	40	0
240	0				
120	0.0045	0			
80	0.0091	0.005	0		
40	0.0233	0.018	0.013	0	
0	0.039	0.033	0.030	0.019	0

Diff. Mag. on 06 Sep 98					
	240	120	80	40	0
240	0				
120	0.0088	0			
80	0.0181	0.018	0		
40	0.0252	0.017	0.017	0	
0	0.041	0.034	0.020	0.020	0

Diff. Mag. on 04 Oct 98					
	240	120	80	40	0
240	0				
120	0.0144	0			
80	0.0107	0.009	0		
40	0.0118	0.005	0.005	0	
0	*	*	*	*	0

This table presents the spectral similarity values or "Diff Mag" between five levels of nitrogen application (lb./ac.) on eight dates of spectra collection.

The following two figures present the spectra and their respective similarity values for two different tasks. An "easy" task would be to separate 0 lb./ac from 240 lb./ac and a "hard" task would be to separate 120 lb./ac and 240 lb./ac. Figure 4a presents the two tasks on 31 May 98 which was very early in the growth cycle. Figure 4b is data from the same plots several weeks later in the season when the canopy is well developed. Note that, for the "easy" task the SSV has increased and that for the "hard" task the SSV has decreased.

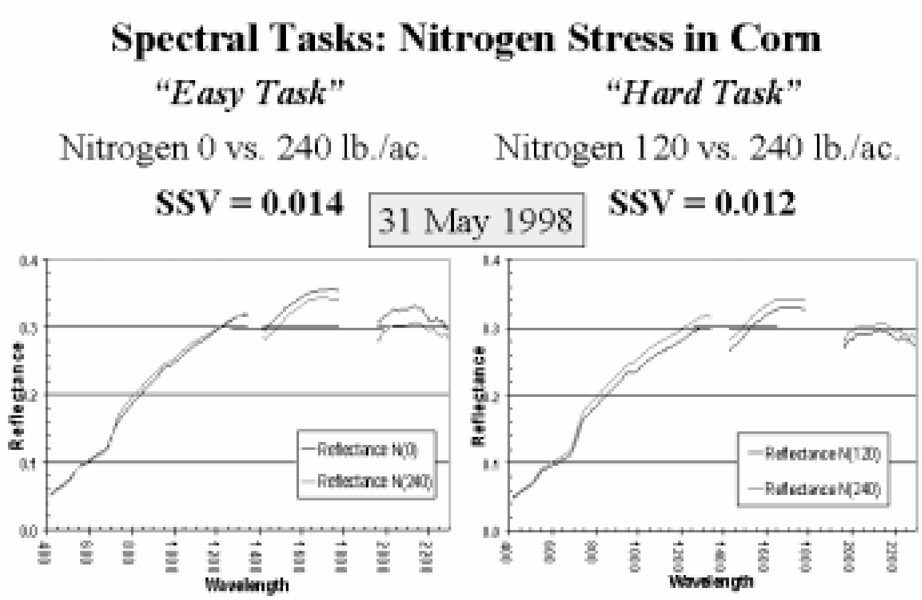


Figure 4a) Spectra and SSV's on May 31 1998 for an "Easy" and "Hard" Task

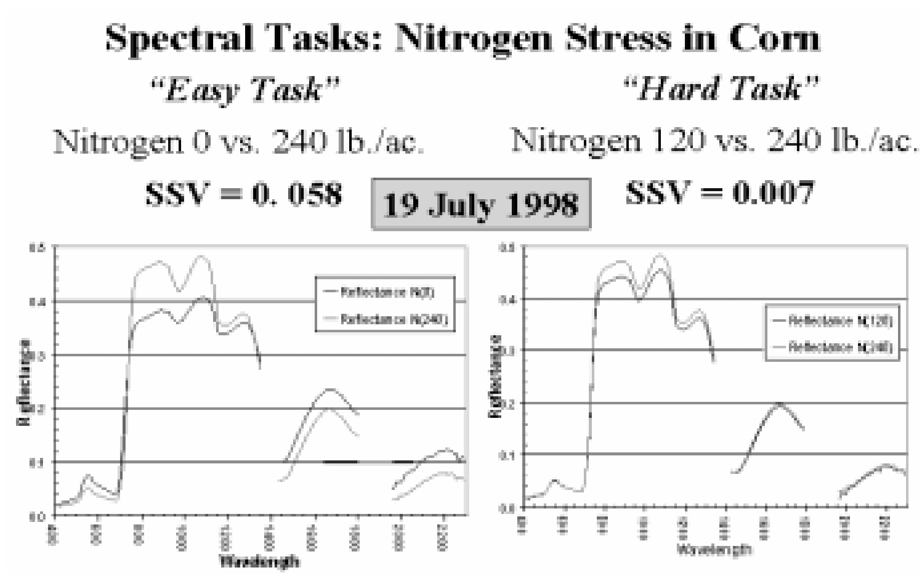


Figure 4b. Spectra and SSV's on July 19 1998 for an "Easy" and "Hard" Task

The next two figures present the similarity values for each task over time. The minimum image SSV from the previous example is included for context. Figure 5a indicates that once the canopy is well established the two treatments are easily separated and both images would be capable of the task. However, Figure 5b indicates the difficulty of the "hard task." The subtly of the task is lost in the image noise and the 1992 image seems not to have the potential to accomplish it. The 1997 image is better but this task presses beyond the limits of the image during the peak of the growing season. Given these results, it would be appropriate to evaluate a subset of the image limited to the cornfields. It is presumed that narrowing the contents of the dataset would result in a corresponding reduction in minimum similarity value.

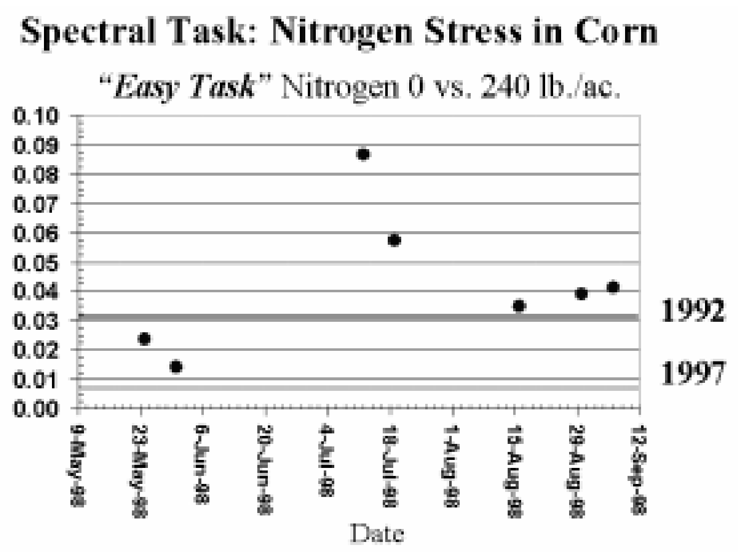


Figure 5a. Similarity Values of the "Easy Task" Over Time

This figure presents the similarity values between spectra from 240 and 0 nitrogen lb./acre plots. The minimum similarity values for the two images are included for reference. This graph suggests that the 1992 image has the capability to distinguish between high and low nitrogen plots after early July but not before. The 1997 image would seem to have the capability to differentiate these levels on all dates.

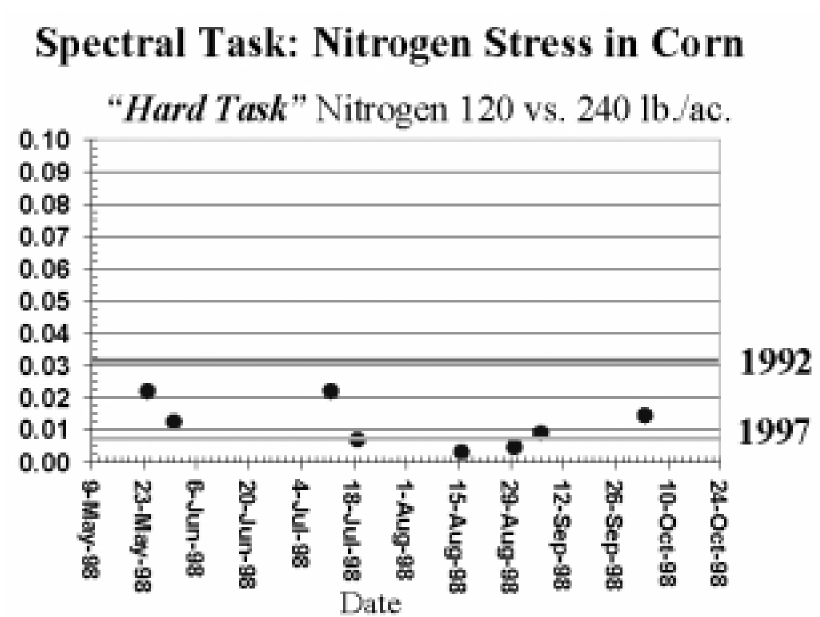


Figure 5b. Similarity Values of the "Hard Task" Over Time

This figure presents a more demanding example. In this graph, the two highest application rates are compared (120 & 240 lb. N/ac.). This graph suggests that the 1992 image is completely incapable of isolating the two treatment levels. On the other hand, the 1997 image shows more promise with the spectra pair similarity value being greater than the image minimum value on five of the eight collection dates.

4. Conclusions

Hyperspectral quality implies the ability to distinguish between similar spectra. These spectra-pairs can come from images or field radiometers. The spectral similarity scale presents an objective methodology capable of quantifying and summarizing the factors underlying the difference between spectra. Two measures of vector difference (Euclidean distance and correlation) combine into a similarity value. This scale can compare images or spectra for the purpose of image resource management, system specification, or suitability for a particular exploitation task. Additional effort is required to improve the foundation of the scale and demonstrate the relation between a similarity value for a spectral task and the minimum image-similarity value.

5. References

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