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DECISION SUPPORT IN HYPERSPECTRAL DATA ANALYSIS:

A PROCEDURAL DESIGN AND A CASE STUDY

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ABSTRACT

The distinguishing property of remotely sensed data is the multivariate information coupled with a two-dimensional pictorial representation. The analyst's interpretation of the image representation coupled with the spectral measurements on the pixel data is effectively a fusion of distinct data sources. This paper proposes remote sensing data analysis as a multi-source data fusion and presents a process model to guide the solution design. The paper illustrates the process with the analysis of airborne data collected over Washington D.C. in the generation of a detailed thematic map of the region.

Key words: Hyperspectral data, masking, segmentation, digital elevation map, data fusion.

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1. INTRODUCTION

The foundation of this paper is the proposition that effective multispectral image data analysis is an analyst driven placement of algorithms in which mathematical rigor, though of fundamental importance, is secondary to the analysis process design.

Multispectral remote sensing image data conveys information at the elemental level through the corresponding variations in the measured energy spectra, and at the composite level through the inter-pixel relationships. The subjective evaluations afforded by the image representation can be used as an interface between the human and the computer - thus supplementing mathematical analysis with the experience of the user analyst. This perspective can be developed into a procedural framework to initiate and guide the analysis of remote sensing data.

Section 2 of this paper discusses related research. It is claimed that the optimal engineering analysis is a data fusion where the human provides decision support in computer analysis. Section 2 proposes a process model substantiating this claim. Some guidelines for the design of a successful data analysis are presented. Section 3 executes the proposed strategy through a classification analysis of hyperspectral data collected for a flightline over Washington D.C.

2. INTERPRETING REMOTE SENSING DATA

If the input to the analysis is multispectral image data[1], and the output is knowledge - the key to a successful extraction of knowledge from the data is information provided by the analyst. As an example, hyperspectral analysis [1] depends extensively on the insights obtained from the visual representation of the data in image form. In this context, the analyst is considered a source of data, and the process of analysis is a data fusion. The phrase 'data fusion' has been interpreted differently in different research. For

[1] By multispectral image data is meant data gathered over a scene on a pixel by pixel basis to constitute an image in which measurements are made for each pixel in a few to perhaps several hundred individual regions of the electromagnetic spectrum.

the present discussion, the definition by [2] is highlighted below as being of greatest relevance -

> "... data fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources".

It should be noted that the ensuing discussion does not attempt a design of learning/intelligent algorithms. The emphasis lies on the recognition of the human-computer interaction and the development of a synergy to utilize the strengths of the respective channels.

2.1 Previous Work

In the context of remote sensing analysis, data fusion is probably most commonly encountered as sensor fusion - the combination of data from various scanner-sources over a given scene. It is believed that merging data from different sensors makes the analysis robust against sensor noise and algorithmic deficiencies. This paper extrapolates the notion of sensor-source to include the analyst as an integral part of the analysis process. The philosophy of this approach is well described in a work by Kushnier, et al [4] in the context of military strategizing. The authors state that the task of making tactical decisions in naval operations is too complex to be accomplished by humans alone or by computers alone, and present several examples in support of the statement. The paper highlights the division of responsibilities between person and machine with the proposition that the human uses judgment and native intuition to make decisions while the assessment of the situational physics is a highly mathematical endeavor best left to the computer. Also of note is the work of McKeown, et al [5] for cartographic feature extraction. The methodology and the principles guiding the analysis are similar to those of the case study elaborated in Section 3.

2.2 Principles of sensor fusion

Mathematical modeling on the computer serves a useful purpose, in that the system dynamics can be reduced to the manipulation of a few parameters. If applicable, the complexity of the ensuing analysis can be significantly reduced, and thus be

synthesized by the user into a suite of analysis-routines. In contrast, the factor invaluable to the successful application of laboratory models of terrestrial phenomena is the human ability to learn and to adapt the analysis to the peculiarities of the problem. Successful analysis is thus a balance between intuition and mathematics.

To maximize the benefit of human-machine interaction, this section identifies some basic principles to guide analysis.

Axiom 2.1: Human abilities are different from those of the computer.

Consider Table 2.1 below, adapted from [6].

Table 2.1: The human versus the computer in data analysis.

The human	The computer
· Can draw upon experience and adapt decisions to unusual phenomena. · Can reason inductively, and process hierarchically. · Can generalize from observations · Can generate output depending on subjective interpretation of task. · Is a source of data/information.	· Can perform repetitive pre-programmed actions. · Can process several items simultaneously. · Can implement the generalizations. · Generates output conforming to doctrines and performance indices based on a quantitative goal interpretation. · Has short response time, high speed of computation, and cheap data storage.

The conclusion drawn from Table 2.1 is that the inferential aspects of the analysis are best relegated to the human. The computer's abilities lie in the implementation of the schemes (of analyst design).

Axiom 2.2: The machine (in)validates the user's hypothesis.

In various applications, the output of the algorithm is a measure of belief in the hypothesis posed by the analyst. However, a poor output does not necessarily imply algorithmic deficiencies. Failure can be a result of the performance index being inadequate to the target task. An analysis is usually directed by the optimization of a user-

107 defined performance measure. Incompatibility between this measure and the objective is
108 unlikely to produce the desired results. In regard to analyses that seek a visual
109 interpretation of the data, this is an especially important (and often overlooked) issue.
110 Algorithms that process data through the optimization of mathematical criteria are often
111 sub-optimal in the sense that the output image is cluttered (or fuzzy or noisy) and is
112 visually unpleasing.
113
114 Axiom 2.3: Every analysis requires at least one revision.
115 The current level of technology precludes the possibility of an intelligent system
116 that operates independent of human input. Usually, analysis comprises various
117 algorithmic 'objects', selected from a suite of procedures, linked in the appropriate
118 sequence by the analyst. The optimal selection and ordering of these objects is often not
119 known. Occasionally, algorithm parameterization is also dependent on human input. It
120 may thus be concluded that almost any test run of the process is likely to produce results
121 that can be improved upon through experimentation. The sub-text to Axiom 2.3 is that no
122 practical engineering problem can be solved perfectly. The termination of analysis
123 depends largely on the tolerance level for errors, the available resources, and the
124 available time. It may also be inferred from Axiom 2.3 that, in the interest of effective
125 time utilization, it is desirable to have the analysis output in a readily interpretable form.
126
127 Definition 2.4: Data fusion is an interface that allows collaboration among data sources to
128 execute an analysis, enabling an assessment that is measurably superior to one in which
129 the sources are incorporated singly.
130
131 The above definition is an enhancement to the proposition of [2] under the belief
132 that definitions of the task and of the associated performance criterion are critical to the
133 analysis process.
134
135 **2.3 A Process Model**
136 It is believed that any data analysis has to be designed to the peculiarities of the
137 project at hand. In this sense, data analysis/mining/fusion is knowledge-based

engineering distinct from an algorithmic solution to a broad scientific problem. When designing such a data analysis project, the tasks can be divided into distinct modules that fundamentally remain unchanged, whatever the project objective. The process model of this section is an elaboration of these modules.

- TASK DEFINITION – We claim that every engineering problem can be designed to provide a useful solution provided the task is clearly defined and the measures of success are established at the onset. A rigorous task definition enables a judicious selection of the data sources, and a design of the analysis procedure. The measures of success limit the scope of the analysis.
- DATA SOURCES - The data sources, though restricted by availability, need to be assessed for their utility towards the task at hand, and for the presence of noise. Human interpretations and intervention are considered data sources essential to the process design. For instance, data sufficiently distinct from the general data population can alternately be considered outliers (noise) or data discoveries (information). The task of this module is to ensure the availability of adequate, appropriate and noise-free (within a user defined tolerance level) data for input to the analysis algorithms.
- DATA ANALYSIS – This module consists of a suite of algorithms required to perform analysis. Design considerations include procedural robustness and well-designed performance measures (Axiom 2.2).
- OUTPUT ASSESSMENT- The output of the analysis needs to be readily interpretable by the analyst (Axiom 2.1). A visually accessible output is especially desirable in remote sensing data analysis. The case study presented in the next section will demonstrate the value of image representations in remote sensing data analysis.
- TUNING - Finally, once the output has been assessed, the analyst proposes modifications (Axiom 2.3) and redoes the process.

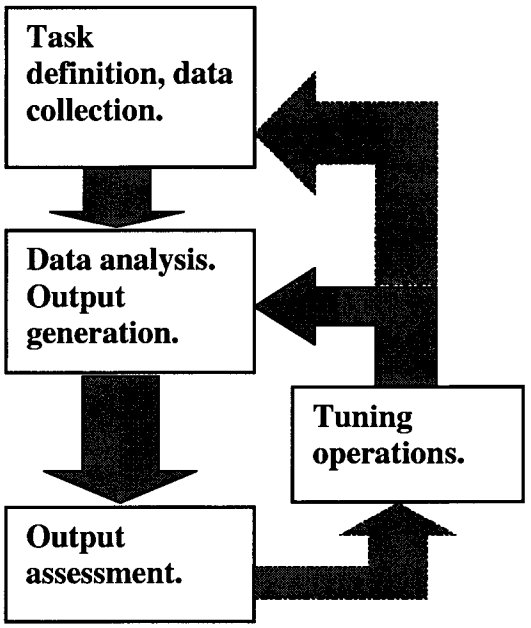

Fig. 2.1: Process model for data analysis.

3. A CASE STUDY - ANALYZING THE D.C. FLIGHTLINE

The HYDICE airborne scanner gathers data in each pixel over 210 channels (samples of the energy spectrum) between 0.4 and 2.4 μm. The data for this case study was collected using the HYDICE scanner on a flightline over Washington D.C. The spatial representation of this data is a region 1310 pixels × 265 pixels. The spectral data measures the energy reflected from the Earth's surface. It is a standard assumption that these elemental spectral measurements contain the information from which the corresponding terrain-type or land-usage can be identified. Under the belief that the scene comprises a definite set of scene-classes (such as water, grass, trees, road etc.), the data are processed and each element (pixel) is assigned a label from the set of scene-classes. A color representation of the output is known as a thematic map or a classification map, the colors used in the representation being mapped one-to-one with the set of scene-classes.

The process model of Section 3.2 is invoked to frame the project design and its execution.

- TASK DEFINITION - The analysis requires the classification of the spectral data into a set of scene-classes that, to the extent of the analyst's belief, spans the thematic content of the data. For the given data, it is concluded that the thematic content of the data is spanned by the class-set {ROOF, ROAD, SHADOW, TREE, GRASS, WATER, PATH}. The criteria for task completion are the following - a subjective evaluation of the thematic map, an evaluation of the thematic map for 'picture quality' (absence of clutter, speckle noise), and a quantitative comparison of the classification against regions identified by an independent observer as specific scene-types.
- DATA SOURCES - The primary source of data, other than the analyst, is the HYDICE scanner. An additional source of information is the Digital Elevation Map (DEM) of the scene.
- DATA ANALYSIS - The various modules available for this analysis are discussed individually in Section 3.1 - The analysis suite.
- OUTPUT ASSESSMENT - The output at each iteration of the analysis is a thematic map produced using MultiSpec [8].
- TUNING - The tuning process is dependent on the stage at which the output is assessed. If the output is deemed deficient in a certain aspect, the analysis will be modified appropriately and re-done.

A sequential scheme of modular design will be used in the analysis. Each stage in the analysis will be referred to as a node in the process-sequence. Human-computer interaction will be emphasized through the analysis, and the analysis at each node will depend on the subjective assessment of the output at the previous node. The quantitative assessment of the analysis will be presented in the synopsis, Section 3.2.12.

3.1 The Fusion Suite

The essential terminology of this analysis report is defined below.

3.1.1 Thematic map

The color two-dimensional composite of the classified data is known as a thematic map. The colors used in the representation being a one-to-one map from the set of scene-classes.

3.1.2 Maximum likelihood classification

The technique comprises the identification of training data - data representative of each of the classes in the set of scene-classes – followed by the construction of decision rules for the classification of the data. The analyst identifies a comprehensive set of scene-classes, and selects the training data. The algorithm assumes the spectral data are observations on parametrically describable processes whose parameters may be estimated using the training data. Mathematical details on the technique can be found in [9] [1] [3].

3.1.3 Unsupervised binary segmentation

The unsupervised segmentation module used in this paper has been detailed in [7]. The input to the module comprises spectral data to be labeled from the set of scene classes, and the associated spatial locations of the data in the scene. The output is the labeling of the data into one of two scene classes. As an example, if a region in a scene is identified as vegetation, the technique can potentially separate the vegetation into two distinct categories – trees and lawn. The technique, as applied here, uses the masking scheme detailed in Section 3.1.6.

3.1.4 Digital Elevation Map (DEM)

The Digital Elevation Map of the scene is a two-dimensional pictorial representation of the scene elevation. The representation is quantitative for the computer and in shades of gray for the human. The lightness of a pixel's color is proportional to the elevation of the corresponding region in the scene. In Section 3.2.6, the DEM will be incorporated into the analysis to refine the identification of the rooftops in the flightline.

3.1.5 Decision tree (or graph) structure

As per Axiom 2.3, it is believed that an acceptable solution does not take the form of a single algorithm. The optimal scheme for engineering a solution to the problem comprises an assessment-analysis cycle repeated as many times as desired. The analysis algorithm at each stage can be modified as per the assessment of the previous stage. If the process modules are laid out in order of their occurrence, the proposed solution takes the

form of a directed graph. A representation of the solution is shown at the end of Section 3 in Figure 3.9.

3.1.6 Masking

Recall that the output of this analysis is to be a thematic map. At the end of each iteration of the analysis-assessment cycle, it may be discovered that data corresponding to some of the scene-classes have been accurately classified. This would correspond to certain regions in the scene that can now be spatially marked as distinct from the remainder of the data and excluded from further processing in the subsequent analysis-assessment cycles. A "masking" scheme excludes these data, and their labeling, from the scene. At the termination of the analysis on the unmasked data, the labels on the masked data can be recovered to complete the thematic map. Examples of the usage are in Section 3.2.3- Node 1 and Section 3.2.4 - Node 2.

3.1.7 Negative training

If the analyst has sufficient knowledge of the scene, he/she can conclude that a given scene-class is localized to a specific area. This implies that the set of scene-classes can be reduced outside the specified localization, and any data that are labeled from outside this reduced scene-class set need to be re-assigned labels. The ensuing analysis uses a simple re-labeling scheme - the scene-class of greatest frequency in the eight-point neighborhood of a given misclassified element is chosen as the new class-label. This process is termed "negative training", and its use has been illustrated in Section 3.2.7 - Node 5 and Section 3.2.8 - Nodes 6,7.

3.2 D.C. Flightline Analysis

3.2.1 Data cleaning

The 210 spectral channels[2] of data were individually examined for noise. Experience has shown that data can be corrupted for various reasons. Judgment on the data per spectral channel was made by visually examining the image representation for

the spectral response on each channel [8]. Histograms of some or all of the channels could also be constructed in order to look for additional types of distortion. Some causes for data corruption are listed below.

- Water absorption bands - an insufficient response over a given bandwidth. It can lead to an exaggerated sensitivity to sensor noise.
- Physical defects in scanner, such as scratches.
- Detector saturation due to unexpectedly light or dark scene objects.

Judgment on the analysis data was made by visually examining the output for each of the channels. In the present context, after excluding all such 'bad' data, 104 channels remained of the original 210: Channels 55-100, 108, 113-132, 135, 152-164, 173, 180-201. In the case of this data set, other types of distortion do exist, as is usually the case. As a result, it is desirable for the analysis algorithms to have a robustness such that such distortion have minimal negative effect.

3.2.2 Root Node - Statistical analysis

A three-color representation of the multispectral data using channels 60, 17 and 27 (data gathered at wavelengths 0.75μm, 0.46μm and 0.5μm respectively) is shown in Figure 3.1.

The foundation of this study is statistical hyperspectral analysis, as developed and refined over the years by various researchers [9] [10] [1]. Fittingly, the output at this stage is called the Root Node. The analysis for this stage stepped through the following path.

- A comprehensive set of scene-classes was identified - {ROOF, ROAD, SHADOW, TREE, GRASS, WATER, PATH}.
- Training data representative of each of the scene-classes was selected.
- The Discriminant Analysis Feature Extraction technique [1][9] was used to reduce the dimensionality of the data on a class-conditional basis.
- The method of maximum likelihood classification was used to classify the spectral data to generate the thematic map.

[2]The channel number, as in this usage, signifies a specific wavelength at which the spectrum of energy reflected from the Earth has been sampled. Correspondingly, the 210 channels for the HYDICE scanner are representative of samples at 210 distinct wavelengths.

In the selection of training data representative of each of the classes, it was realized that some of the scene-classes (ROOF and ROAD) are a cumulative of several spectrally distinct sub-classes. Consequently, the set of scene-classes was enlarged to {ROOF1, ROOF2, ROOF3, ROOF4, ROOF5, ROOF6, ROOF7, ROOF8, ROAD1, ROAD2, SHADOW, TREE, GRASS, WATER, PATH}. Figure 3.3 is a representation of the associated training data. The results of the classification are shown as a thematic map in Figure 3.4. In Figures 3.4, note that the sub-classes of ROOF, and those of ROAD, have been merged into their respective groups. Subsequent representations of the output shall also not distinguish among the sub-classes. Sections of Figure 3.4 are enlarged as Figures 3.4b-e, to highlight the errors that need to be rectified in subsequent iterations of the analysis.

Fig. 3.1: Three-color simulated color IR film representation of D.C. flightline.

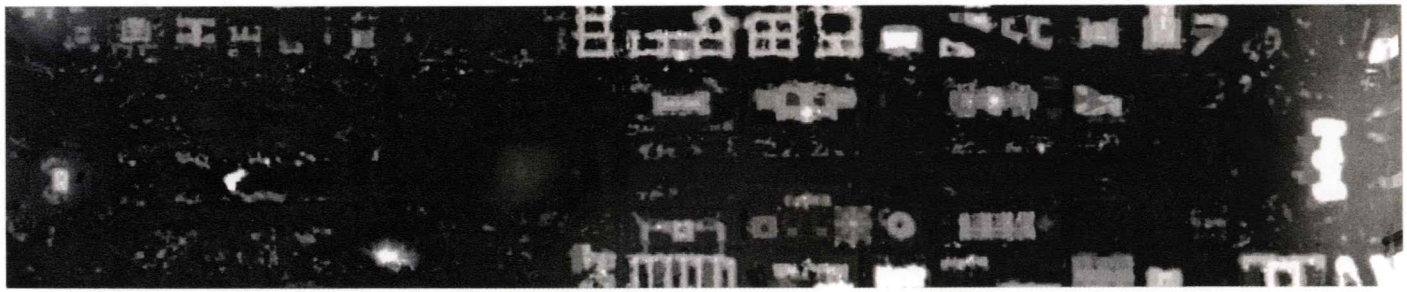

Fig. 3.2: Representation of the Digital Elevation Map. Note that the high elevation regions appear in a lighter shade of gray.

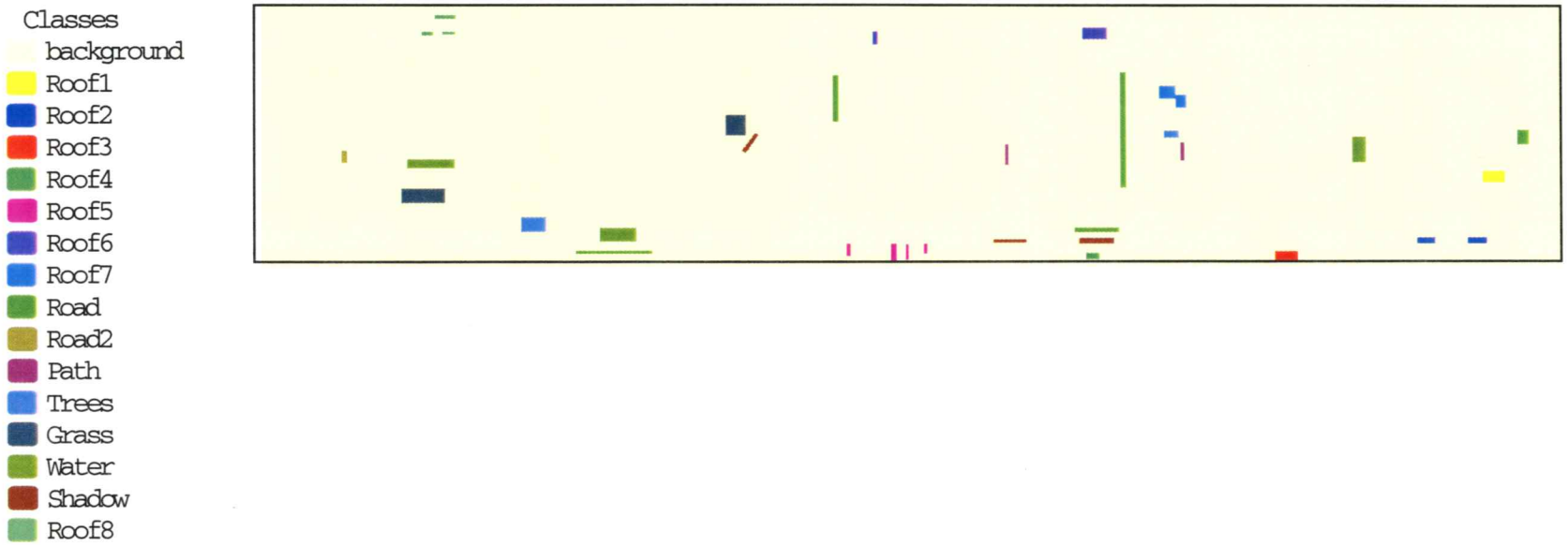

Fig. 3.3: Training data. Note that there are eight sub-classes to ROOF, and two sub-classes to ROAD.

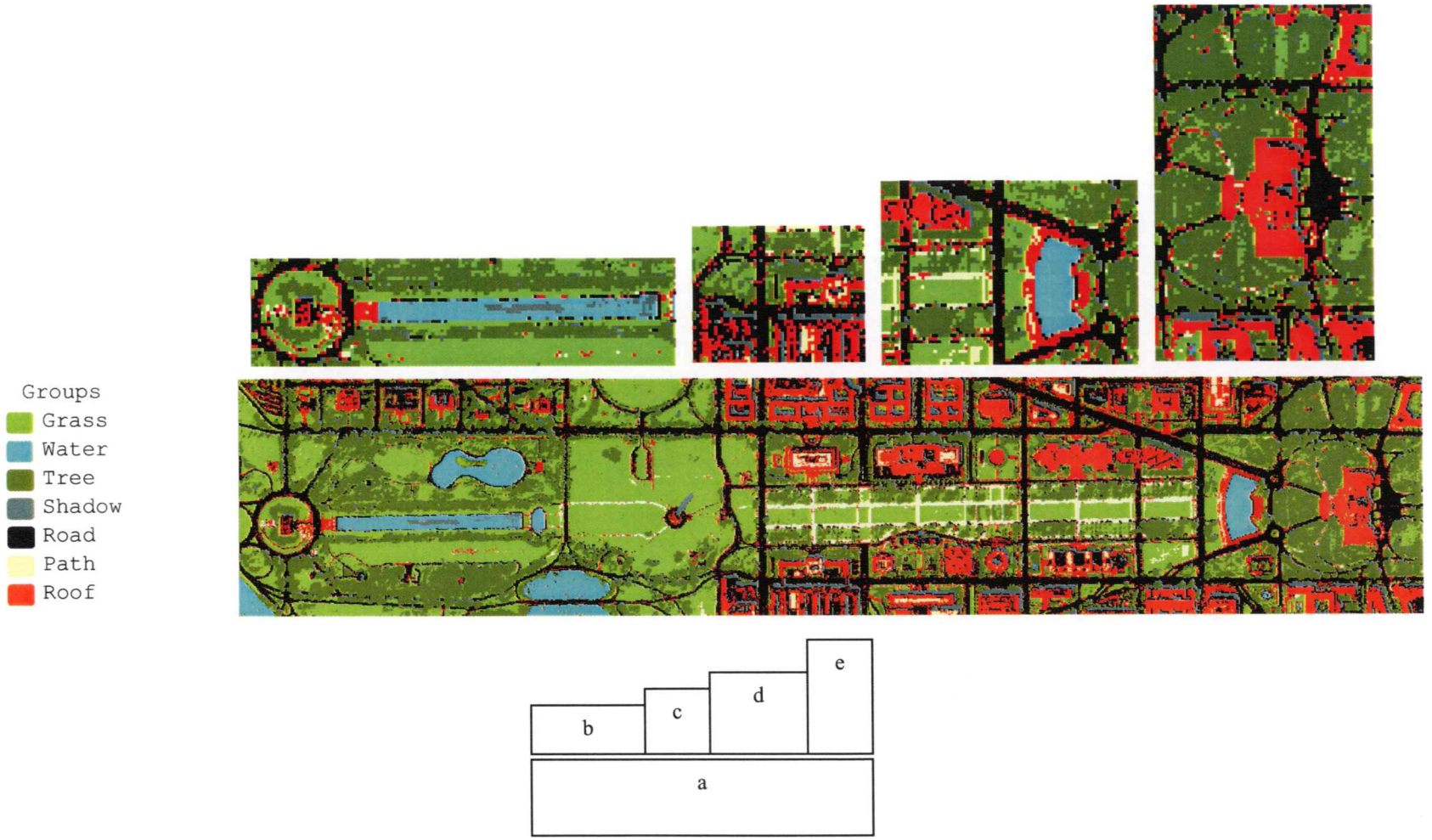

Fig. 3.4: a) The thematic map output from the maximum likelihood classification at the Root Node. b) Note that the analysis has identified 'SHADOW' in a water body. c) Note that clutter from ROAD and SHADOW corrupts ROOF identification. d) Note that class PATH clutters the middle of a lawn. e) Upon comparison with Figure 3.1, it is evident that the vegetation around the Capitol building has not been correctly separated.

The errors in classification are surmised to be a result of spectral similarities among various groups of scene classes, namely -

- ROAD, ROOF and PATH;
- WATER and SHADOW; and
- TREE and GRASS.

Other undesirable traits of the output include speckle classifications (such as isolated identifications of ROOF on roads because of traffic and debris). Since the multispectral data has been gathered at a high resolution, a visual assessment of the output is a reliable means to guide analysis. The quantitative assessment of the output is presented in Section 3.2.12.

3.2.3 Node 1 - Separating WATER + SHADOW

From the output at the Root Node, Figure 3.4b, it is evident that spectral separation between WATER and SHADOW can be problematic. This is a result of the energy absorption by water, which results in a spectral response that is similar (low in magnitude) to that of a SHADOW region.

Though there is confusion in separating WATER from SHADOW, the separation of these from other classes is accurate, and complete. Thus, the masking scheme of Section 3.1.5 is applicable to pull WATER+SHADOW from the remainder of the data, and is followed by the binary segmentation discussed in Section 3.1.2 to separate the masked data into WATER and SHADOW.

Several experiments with the above scheme were conducted. In each case, the separation of classes WATER and SHADOW was not clean (visually). Ultimately, the resolution of the deficiencies was postponed to a later stage (cf. Section 3.2.9 - Node 8).

3.2.4 Node 2 - Segmenting SHADOW

In general, SHADOW is a composite of sub-classes comprising various low energy responses on diverse materials. The objective of this stage was to separate the SHADOW class into its sub-classes. The data classified as SHADOW in Figure 3.4a were isolated by the masking process and the binary segmentation algorithm was applied. It was observed that one of the SHADOW sub-classes generated by the procedure correctly identified

water elements in the scene. This corresponded to the discovery of a new scene-class and was labeled WATER2. The experiment was repeated several times. In each case, the performance of the operation was mediocre (visual analysis). It was surmised that the assumption of the unimodal probability distribution for the SHADOW class, as used in the algorithm for the unsupervised segmentation [7], might be a poor modeling.

3.2.5 Node 3 - Separating GRASS and TREE

From the output at the Root Node, Figure 3.4e, it is evident that there are portions of the scene where there is confusion in classifying between GRASS and TREE. The data for classes TREE and GRASS are masked out from the remainder of the scene and the binary segmentation algorithm was applied to re-separate the merged classes into TREE and GRASS.

This stage is subsequently referred to as Node 3.

3.2.6 Node 4 - Extracting rooftops

One of the critical goals of this analysis is the extraction of roofs in the scene[3]. While the definition of a roof would generally imply "the cover of any building" [11], such a classification is complicated to implement via spectral analysis. There is an immense diversity in the materials used in constructing rooftops and in their condition, and consequently no single spectral response is representative of the class ROOF. At the Root Node, several spectral sub-classes of ROOF were identified and merged into one group at the end of the analysis. The elements identified as ROOF in Figure 3.4a can be masked from the remainder of the data. The masked output is represented as a black and white image in Figure 3.5.

Given multispectral data of the scene it is possible to achieve good separation between the composite class ROOF and other scene-classes. However, this is contingent upon the identification of a comprehensive list of ROOF sub-classes, and a well-executed selection of the respective training data. An alternate means for the analysis is proposed here based on the Digital Elevation Map (DEM) of the scene.

[3] The discussion of this section has also been published elsewhere [12].

Each pixel in the DEM is representative of the elevation of the area corresponding to the pixel on the ground. By definition, the information content of this data is directly relevant to the identification of rooftops in the scene. A grayscale representation of the DEM is shown in Figure 3.2. The lighter pixels in the image correspond to elements at higher elevations in the scene.

The DEM provides information on the rise in elevation of a given area-element in relation to its neighbor. The proposed solution took the following route.

- It was assumed that all the rooftops in the flightline are contained in the classes ROAD, PATH, ROOF and SHADOW identified at the Root Node. The first step in the process was a masking operation on the four classes, excluding the remainder of the scene in the thematic map (and associated HYDICE data) from subsequent analysis.
- Rooftop identification followed via a thresholding operation on the elevations of all data elements identified above. The procedure was designed as a Boolean-type operation in which all data (identified as one of the four classes listed above) below a certain elevation were said to be at ground level; the filtered data were thus identified as building-rooftops.
- Since there was some amount of variation in scene elevation, the elevation threshold had to be locally determined. This was accomplished by partitioning the scene into several zones. The zones were defined as regions of relatively unchanging terrain elevation and the elevation threshold for each zone was obtained independently. This scheme is detailed in [12].

The result of the ROOF identification operation is shown in Figure 3.6. Data that had previously been identified with this class, but was not retained after the analysis of this stage was assigned the class ROOF-RESIDUE.

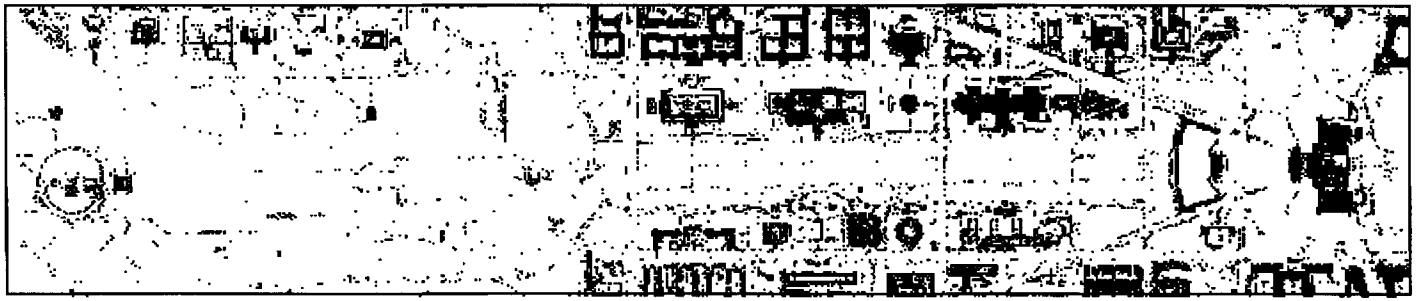

Fig. 3.5: Scene class ROOF isolated from the remainder of the thematic map of Figure 3.4a using the masking operation.

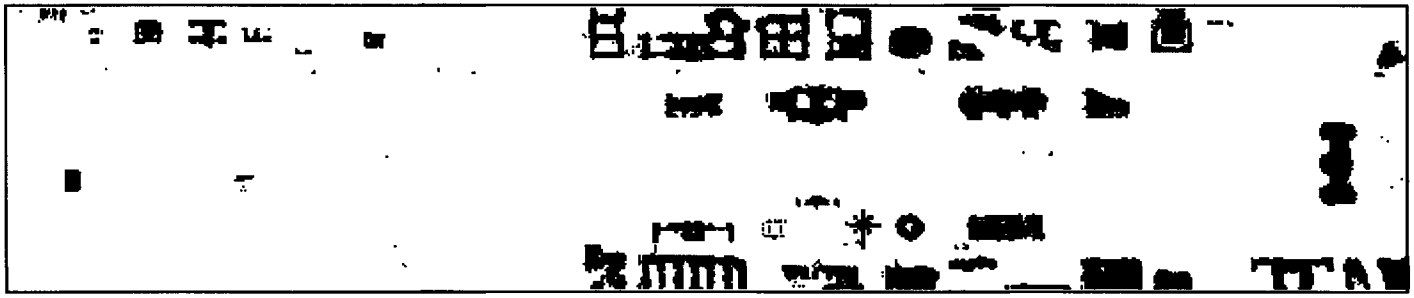

Fig. 3.6: The output of the operation at Node 4 isolates the ROOF class based on a filtering operation on the scene elevations.

3.2.7 Node 5 - Negative training on PATH

It is evident from Figure 3.4 that speckle misclassification compromises the quality of the output. One way to overcome such errors is to forego the use of the spectral data completely in subsequent processing. The reason for this proposition is that spectral information need not necessarily reflect the target objective. For instance, spectral data on roads is 'corrupted' by presence of cars etc. While the statistical spectral classification is true to the data, the returned output is likely cluttered with speckle noise. To counter such problems, the analyst can make the judgment that a given scene-class is restricted to a certain portion of the scene and perform the "negative training" operation sketched earlier. In this case, the scene-class PATH was isolated to a small strip restricted to the center of the flightline for application of the operation, and all other PATH classifications outside this strip were re-assigned. The analysts based this decision on a visual inspection of Figures 3.1 and 3.4.

3.2.8 Node 6 - Negative training on WATER2, WATER

It was desired to remove all classifications of WATER or WATER2 that are erroneous from the classification map. It was an analyst decision to restrict WATER/WATER2 classification spatially, to the three large water bodies that could be visually identified in Figure 3.1. The Negative Training module could then be used to clear the remainder of the scene of clutter associated with WATER classification.

3.2.9 Node 7 - Re-assigning SHADOW (spectral method)

It has been noted that distinguishing the class SHADOW from the remainder of the data is a difficult task. The original motive for identifying SHADOW in the data was to explain the low energy in the spectral readings over various portions of the image. Failure to do so had resulted in a poor statistical classification of the data. At this stage however, it was concluded that the class SHADOW was non-informative, and had to be removed from the set of scene classes. The maximum likelihood classification module was used to re-assign labels to all data that had been previously classified as SHADOW. The training data for the module were the remainder of the data in the scene, labeled as per the classification map at Node 1.

3.2.10 Node 8 - Negative training on classes WATER + WATER2

As expected, because of the high spectral similarity (low magnitude of response) between the class SHADOW and WATER, most of the re-assigned data in Node 7 got classified as WATER. The negative training operation was applied, as at Node 6, to remove the occurrences of water classification outside the regions pre-defined by the analyst as water bodies.

3.2.11 Node 8b - Reassigning class SHADOW (spatial scheme)

Instead of the scheme used at Nodes 7 and 8, it could have been preferred that the re-assignment of the SHADOW pixels was done via a voting scheme on the labels of the respective eight point neighborhoods. This technique would have negated the need for Node 7, the negative training on WATER. It was discovered that the outputs at Nodes 8, 8b were very similar – both by subjective evaluation and by quantitative measurement. The output in Figure 3.7 corresponds to that obtained at Node 8.

Fig. 3.7: Thematic map generated at Node 8 of the analysis, used as final output.

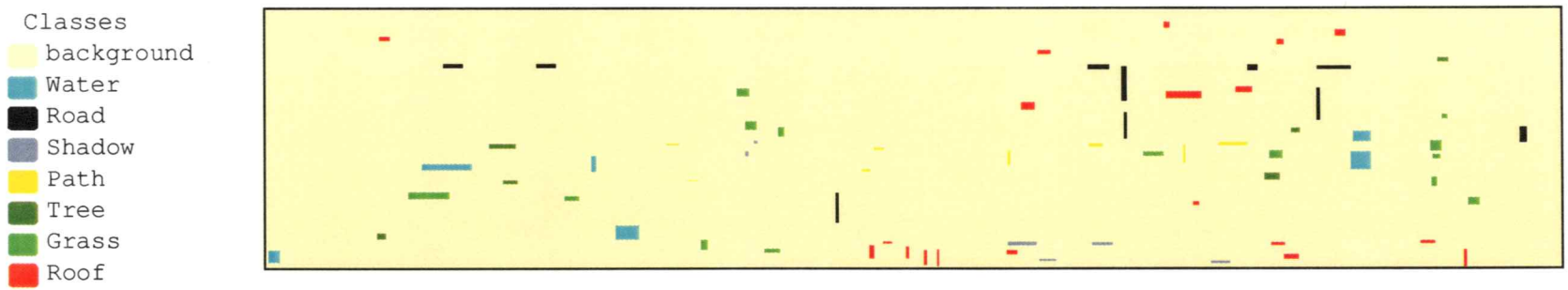

Fig. 3.8: Representation of test data used in assessing performance of classification analysis [13].

3.2.12 Synopsis

The output shown in Figure 3.7 passed the criteria for subjective evaluations – absence of clutter, verification by regional expert for absence of logical aberrations in classifications. A quantitative assessment of this output was carried out against the test data identified in Figure 3.8. These test data were gathered by a researcher [13] independent of the analysis presented here, as representative samples of each scene-class in the flightline. The output in Figure 3.7 could thus be compared to the samples identified in Figure 3.8 to evaluate the accuracy of the analysis. The classification performance at Node 8 is tabulated in Table 3.1 for each of the scene-classes. For comparison, Table 3.1 also lists the classification performance at the Root Node.

Table 3.1: A quantitative assessment of classification outputs at Root Node and Node 8.

Scene-class	Number of test samples	Root Node		Node 8	
		Identified number	% accuracy	Identified number	% accuracy
ROAD	1 056	1 018	96.40	1 016	96.21
WATER	1 566	1 456	92.98	1 556	99.36
PATH	261	246	94.25	238	91.19
TREE	450	429	95.33	428	95.11
GRASS	1 378	1 029	74.67	1 270	92.16
ROOF	1 192	974	81.71	1 059	88.84[4]
All classes	5 903	5 152	87.28	5 622	94.31

The analysis procedure can be summarized by the representation shown in Figure 3.9. It is implicit that the output at a terminal node in the directed graph is retained for the final output without further processing.

[4] The scene-class ROOF, has been characterized in the functional sense in Node 8. If scene-class ROOF-RESIDUE is merged with ROOF, the number of pixels in Node 8 correctly identified as 'roof' is 1 174, and the overall classification accuracy improves to 97.19%.

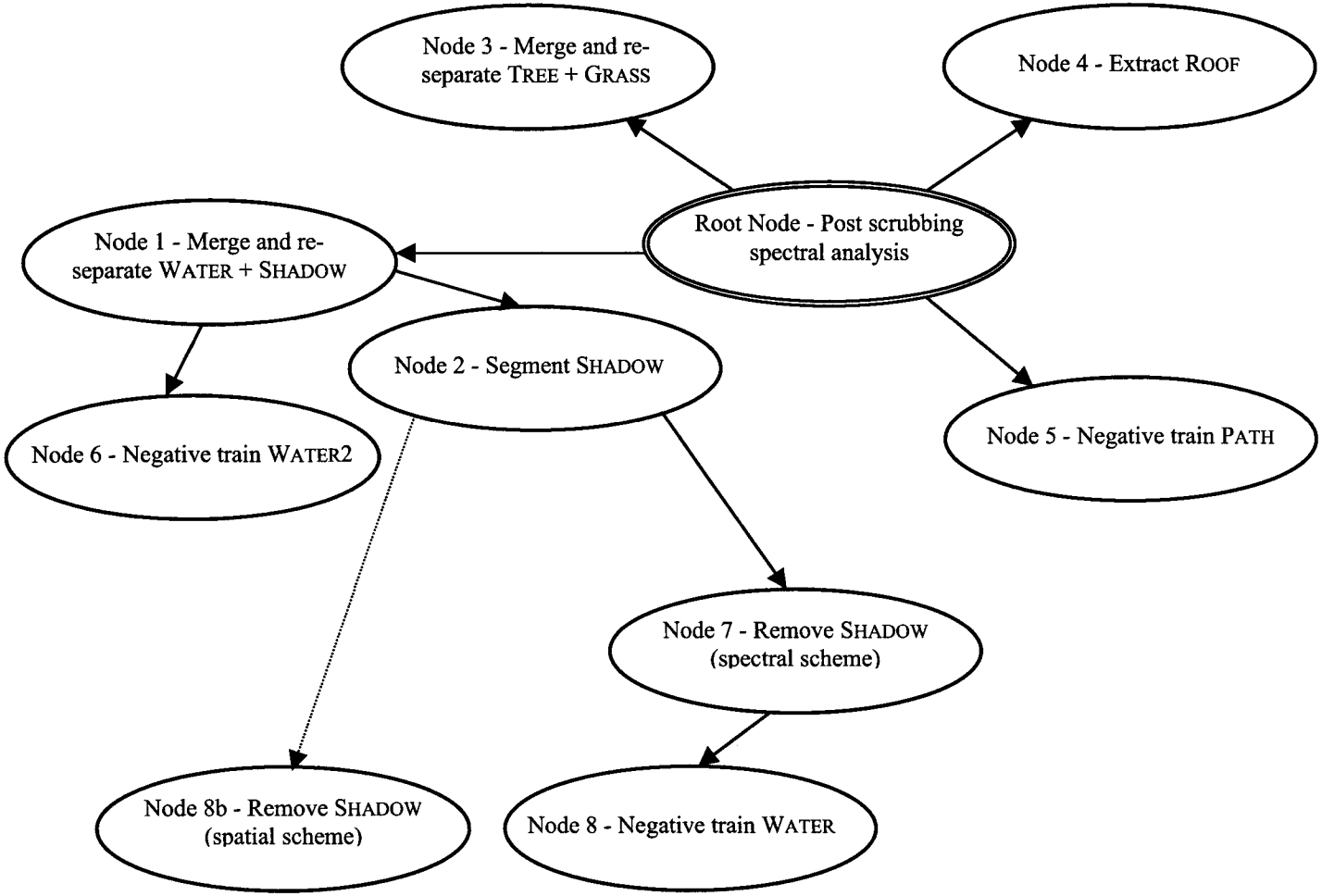

Fig. 3.9: Graph representation of the D.C. data analysis.

Some general conclusions of this study are listed below:

- A hierarchical scheme of analysis can be useful, especially if used to isolate problematic data for post-processing independent of the remainder of the data.
- The removal of clutter from the classification output can often be handled without reliance on the spectral data.
- When setting the design goals for the analysis, scene-classes can be decided based on function, or based on composition. For example, in this analysis, the Root Node identified eight distinct materials used in constructing roofs. However, the goal focused on the identification of roofs according to usage, and the final output showed ROOF and ROOF-RESIDUE (the data that were spectrally similar to ROOF, but were functionally distinct).

4. DISCUSSION

The innate capability for discrimination between very subtle classes by means of hyperspectral data is very great. However, to achieve this potential with high accuracy requires a very precise description of the classes desired. This means that, because of the higher data dimensionality, the size of training sets for the various classes must be large and must be quite representative of the scene-classes that the analyst has in mind. Thus one direction to proceed in improving the results obtained at the root node would be to augment the training sets used. The technique illustrated here provides an alternative to that procedure in allowing the analyst to achieve an adequately precise version of the thematic map in mind. Which methodology would be best would depend on the circumstances of the particular problem.

A drawback of the approach presented here is that the methodology for the solution is not strictly repeatable, since it is unlikely to be as effective, in the exact same form, in any other project. It can be countered that, while a scientific solution to a given class of problems seeks robustness and broad applicability, practical concerns demand a certain level of customization to the solution for every distinct project. It is evident that the procedure followed in this analysis is not unique. It is a moot point if, and how, superior results can be obtained using an alternate scheme. Whatever the chosen design,

it is believed that the axioms of data fusion proposed in Section 2 and used throughout the case study of Section 3, would be equally applicable.

This study is distinct from several contemporary works in remote sensing research in that the analysis is conducted as if for an engineering project rather than for an ill-posed mathematical problem with an uncertain solution. The emphasis is on innovation, as per the needs of the problem, with procedural guidance obtained from visual inspection of the output.

BIBLIOGRAPHY

[1] D. A. Landgrebe, "Information extraction principles and methods for multispectral and hyperspectral image data", in *Information Processing for Remote Sensing*, C. H. Chen, Ed. New Jersey: World Scientific Publishing Co., 2000. Also available from http://dynamo.ecn.purdue.edu/~landgreb/publications.html

[2] L. Wald, "A European proposal for terms of reference in data fusion", *International Archives of Photogrammetry & Remote Sensing*, vol. XXXII, part 7, pp. 651-654, 1998.

[3] X. Jia, J. A. Richards, W. Gessner (Editor) and D. E. Ricken (Editor), *Remote Sensing Digital Image Analysis: An Introduction*, 3rd ed. Berlin: Springer Verlag, 1999.

[4] S. D. Kushnier, C. H. Heithecker, J. A. Ballas and D. C. McFarlane, "Situation assessment through collaborative human-computer interaction", *Naval Engineers Journal*, vol. 108, no. 4, pp. 41-51, July 1996.

[5] D. M. McKeown, Jr. , S. D. Cochran, S. J. Ford, J. C. McGlone, J. A. Shufelt and D. A. Yocum, "Fusion of HYDICE hyperspectral data with panchromatic imagery for cartographic feature extraction", *IEEE Transactions on Geoscience & Remote Sensing*, vol. 37, no. 3, pp. 1261-1277, May 1999.

[6] B. Schniederman, *Designing the User Interface: Strategies for Effective Human-Computer Interaction*, 2nd ed., Reading MA: Addison-Wesley, 1992.

[7] V. Madhok, "Spectral-spatial analysis of remote sensing data: An image model and a procedural design", Ph.D. dissertation, School of Electrical and Computer Engineering, Purdue University, August 1999. Available from http://dynamo.ecn.purdue.edu/~landgreb/publications.html

[8] L. Biehl, and David Landgrebe, "MultiSpec - A Tool for Multispectral-Hyperspectral Image Data Analysis", 13th Pecora Symposium, Sioux Falls, SD, August 20-22, 1996. See also http://dynamo.ecn.purdue.edu/~biehl/MultiSpec/

[9] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, San Diego CA: Academic Press Inc., 1990.

[10] C. Lee and D. A. Landgrebe, "Analyzing high-dimensional multispectral data", *IEEE Transactions on Geoscience & Remote Sensing*, vol. 31, no. 3, pp. 792-800, July 1993. Also available from http://dynamo.ecn.purdue.edu/~landgreb/publications.html

[11] *Webster's Ninth New Collegiate Dictionary*, Springfield MA: Merriam-Webster, 1993.

[12] V. Madhok and D. Landgrebe, "Supplementing Hyperspectral Data with Digital Elevation", *Proceedings of the International Geoscience & Remote Sensing Symposium (IGARSS)*, June 28 - July 2, 1999. Also available from http://dynamo.ecn.purdue.edu/~landgreb/publications.html

[13] Y. Zheng, private communication.