Spectral Imaging Applications: Remote Sensing, Environmental Monitoring, Medicine, Military Operations, Factory Automation and Manufacturing.

Nahum Gat and Suresh Subramanian
Opto-Knowledge Systems, Inc. (OKSI)

Jacob Barhen
Oak Ridge National Laboratory

Nikzad "Benny" Toomarian
NASA Jet Propulsion Laboratory

ABSTRACT

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This paper reviews the activities at OKSI related to imaging spectroscopy presenting current and future applications of the technology. We discuss the development of several systems including hardware, signal processing, data classification algorithms and benchmarking techniques to determine algorithm performance. Signal processing for each application is tailored by incorporating the phenomenology appropriate to the process, into the algorithms. Pixel signatures are classified using techniques such as principal component analyses, generalized eigenvalue analysis and novel very fast neural network methods. The major hyperspectral imaging systems developed at OKSI include the Intelligent Missile Seeker (IMS) demonstration project for real-time target/decoy discrimination, and the Thermal InfraRed Imaging Spectrometer (TIRIS) for detection and tracking of toxic plumes and gases. In addition, systems for applications in medical photodiagnosis, manufacturing technology, and for crop monitoring are also under development.

Keywords: imaging spectroscopy, multispectral, hyperspectral, applications, sensors, algorithms, medical imaging, remote sensing, crop monitoring, machine vision, infrared, spectral unmixing, classification, phenomenology.

1 THE TECHNOLOGY

Imaging spectroscopy is a combination of several photonic technologies. It combines conventional imaging with spectroscopy and radiometry to produce images for which a spectral signature is associated with each spatial resolution element (pixel). Hence, data produced by a spectral imager constitute a 3-dimensional cube with 2 spatial and a third spectral dimension, as depicted in Fig. 1. Intensity values of the data cube can be converted, via proper calibration, to radiometric quantities that are related to the scene phenomenology. The position of spectral imaging relative to related technologies is shown in Fig. 2. The power of the technique is that the phenomenology provides a link to spatial and spectral analytical models, spectral libraries, etc., to support various applications.

It is obvious why the combination of imaging and spectroscopy is very attractive. In principle, one can improve image understanding by combining the best of two worlds: spatial and spectral analyses. The combined analysis may be considered as data fusion. Conventional color imagery

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touches upon the idea, except that conventional color imagery is based on very broad bands and the colors are achieved at the expense of spatial resolution.

Figure 1. AVIRIS Hyperspectral Image of Moffett Field, Mountain View, CA (Data Cube Composed of Individual Images Recorded at 244 Spectral Bands Between 0.4 to 2.4 μm , Each at about 10 nm spectral Bandwidth).

Figure 2. Relationship Among Radiometric, Spectrometric, and Imaging Techniques (After Elachi¹).

Since the recording media of imaging spectrometers conventionally is a 2-D matrix array (e.g., CCD), and since data produced by the sensors constitute a 3-D cube (2 spatial dimensions and a third spectral axis), these data cubes are built in a progressive manner, by (i) sequentially recording one full spatial image after another each at a different wavelength, or (ii) by sequentially

¹ Elachi, C. Introduction to the Physics and Techniques of Remote Sensing, Wiley Interscience, 1987.

recording one narrow (1 pixel wide, multiple pixels long) swath across the image after another with the corresponding spectral signature for each pixel in the swath as depicted in Fig. 3.

Figure 3. Some Remote Sensing Implementations of Multi- and Hyper-spectral Imagery [Systems *a* (using a few single detectors/filter combinations) and *b* (using a few linear array / filter combinations) are based on whiskbroom and pushbroom scanning techniques, respectively, for multispectral imagery; systems *c* (using a few linear arrays in a dispersive system) and *d* (using an area array in a dispersive system) are based on the same two scanning techniques for hyperspectral imagery].

Before getting into specific examples it is worth noting however, that multispectral techniques utilizing a small number (say, less than 10) of spectral bands were available since the deployment of Landsat in the 1960s. A question often asked is whether hyperspectral systems that utilize several tens or hundreds of bands are indeed better than multi-spectral systems. The answer is that often they are not. In that case, why all the interest in hyperspectral techniques? The reason that multispectral instruments and the bands they use are often tailored to a specific application. These bands may be therefore less than optimal or even completely unsuitable for other applications. On the other hand, hyperspectral systems have the advantage of providing data at high spectral resolution over a large number of bands, and may hence be used for a variety of applications. However, once the optimal bands have been determined for a specific application multi-spectral systems provide better solution since they are less expensive, produce smaller datasets, and have a greater greater signal to noise ratio (S/N). The examples that follow should be considered in the light of this idea.

2 APPLICATIONS

During the past few years OKSI designed and developed several imaging spectrometer systems for customized applications including algorithms for data processing. Examples that are discussed below include:

- The Thermal Infrared Imaging Spectrometer (TIRIS)
- The Intelligent Missile Seeker (IMS)
- Applications in agriculture, manufacturing and medicine
- Classification, detection, and subpixel unmixing algorithms

2.1 THERMAL INFRARED APPLICATIONS: Environmental Monitoring, Emergency Response & Plume Tracking, Battlefield Monitoring of CB Agents, Detection of Illicit Drug Manufacturing Byproducts, etc.

The objective is to detect the presence of target organic compounds in the atmosphere utilizing the longwave infrared (LWIR) which is the "finger print" spectral region of most organic compounds.

The sensor under development is the Thermal InfraRed Imaging Spectrometer (TIRIS), a 7.5 to 14.0 μm imaging spectrometer designed to demonstrate operations using uncooled optics for Dual Use applications (including military target detection and civilian applications). The environmental application is particularly attractive since with an imaging spectrometer, a toxic plume that is monitored can be simultaneously characterized spatially and spectrally, and the measurements can be registered to a map location via geographical information systems (GIS).

TIRIS is based on an Aerojet PATHS 64x20 Si:As focal plane array (FPA), indium bump multiplexed to a readout IC. The required FPA operating temperature of 10K is achieved by using a closed cycle helium cryo-cooler, selected for logistical reasons since TIRIS will be flown from various locations where liquid helium is not readily available. A prototype TIRIS sensor is shown in Fig. 4.

The sensor's field of view is divided into 20 spatial pixels while spectral signature data are collected in 64 bands at about 0.1 μm resolution. When airborne, full spatial/spectral image data cubes are generated in the pushbroom mode (Fig. 3d). Spectral dispersion is obtained by a combination of two means. First, a custom linearly variable filter (LVF) was designed and manufactured to match the FPA dimensions and pixel pitch. The LVF is placed about 0.2 mm from the FPA and it is cooled to the FPA temperature. A custom diffraction grating is also installed in the optical train with dispersion matched to the LVF spectral spread. The combination of grating/LVF produces a high optical efficiency. The grating as well as all other fore-optics function at room temperature. The nearfield thermal emissions from these components are suppressed by the LVF.

Custom electronics were built to operate the FPA and interface it to an image acquisition system. All the digital logic required to generate the necessary clocks and biases are loaded into an FPGA from an EPROM upon system power on. Data are read in 20 parallel channels and every three channels are multiplexed to a single A/D converter. Seven ADCs are used to digitize the data at

12-bits. Each data channel is then sequentially given access to a bus that is connected to a digital frame grabber in a desktop PC. A gray code is used to sequentially increment the rows from 1 to 64. Each row is read twice, once after incrementing the gray code, and a second time after a reset signal is applied to the row. The scheme allows using software implemented correlated double sampling or subtractive double sampling (CDS/SDS).

Figure 4. The TIRIS-I Sensor (OKSI/JPL Development - Sponsored by DARPA/SSDC).

The TIRIS prototype is currently undergoing spectral and radiometric characterization. Based on lessons learned, a second generation airborne TIRIS-II is under development using a Hughes HYWAYS 64x20 Si:As FPA.

Two models are used in the algorithmic approach to TIRIS data analysis. The first is a phenomenology model (forward solution) that simulates and predicts the sensor response for a better understanding of its operational parameters and limitations. It is a radiative transfer model that accounts for the terrain infrared characteristics, sky radiation, and the toxic plume parameters, as depicted in Fig. 5. A plume may be observed in absorption or emission depending on the temperature contrast with the background. Two spectral libraries, one of organic compounds and one of background materials, are used to model and predict the sensor response under a prescribed scenario. The model, developed in IDL, has a convenient GUI allowing the user to experiment with various parameters, Fig. 6.

With this model, the user can predict the sensor output under various operational conditions such as a specific mixture of plume component (or end-members that are selected from a library shown on the top-left of Fig. 6), environmental parameters such as ambient temperature, relative humidity, plume temperature, etc., as depicted on the right side of the figure. The top right corner of the screen allows selecting a specific sensor model that includes the spectroradiometric calibration of the sensor. Finally, corrections for atmospheric transmission are calculated externally using the MODTRAN² code. Once all such parameters have been specified, the model

²Bedrk, A., Bernstein, L.S. and Robertson, D.C. MODTRAN: A Moderate Resolution Model for LOWTRAN 7. AFGL Report GL-TR-89-0122, 1989

calculates and plots the sensor anticipated output in various user-selected formats on the bottom half of the screen.

Figure 5. Radiative Exchange Model for TIRIS Use in Detection of Gas Plumes.

Figure 6. User Interface, and Phenomenology Model for the Forward Solution (Sponsored by USAF Armstrong Labs).

The second model (inverse solution) uses the sensor output to determine the composition of toxic gas plume that create the observed signature. The inverse solution has two steps. First, the organic compounds library is scanned and reduced to a set of M potential end-members that contribute to the signature, based on detection probability and false alarm rate considerations. In the second step, an $M \times M$ matrix is constructed in which the M compounds selected in the first step are incorporated into M linear equations, in M spectral bands (M is typically much smaller than the number of sensor data bands). The system provides an exact solution to the problem rather than the traditional least squares approximation. The key to this approach is the proper selection of the M band.

The libraries used for the modeling include the EPA's most Hazardous Air Pollutants (HAPs) spectral library, and the NPIC spectral library of background materials. Other libraries can be incorporated to the model, and the model can be adapted to other sensors.

This is essentially a linear subpixel unmixing model that has applications to a wide variety of situations including (some are discussed in the sequel) medical, crop health monitoring, mineral prospecting, etc.

2.2 THE INTELLIGENT MISSILE SEEKER (IMS)

The purpose of this sensor was to explore the application of imaging spectroscopy for a real-time application, in an air-to-air or surface-to-air missile seeker.^{3,4} As infrared countermeasures and decoys grow more effective, air-to-air or SAM seekers must acquire more intelligence to discriminate between their target and the decoys. Over the years, in an attempt to foil the evolution of countermeasures, missile seekers evolved from a single "heat seeker" detector to ratio (two-band) seekers, three band seekers, and finally to imaging seekers. The original heat-seeker type devices utilized radiometric target signatures in a preselected spectral band to detect and track a target, while the later two or three bands seekers utilized more sophisticated spectroradiometric analysis to this end. Modern imaging seekers utilize spatial or geometric target characteristic. The question of course is whether the combination of imaging and spectroscopy can provide a more robust target identification and discrimination.

Since targets and decoys can be hot objects, the IMS imaging spectrometer concept evaluation sensor was built to collect radiation in the VNIR and MWIR. A schematic of the optical layout of the sensor is shown in Fig. 7. The sensor has a common 6" Cassegrain telescope with a dichroic beam splitter. The VNIR signals are reflected into a 256x256 CCD based imaging spectrometer operating from 500 to 1,000 nm, while the IR radiation is passed into a 160x120 InSb array operating between 2.5 to 5.0 μm . Both spectrometers have an adjustable width entrance

³ Gat, N., Barhen, J., Gulati, S., and Steiner, T.D., "The Intelligent Missile Seeker (IMS): Spectral, Spatial, and Temporal Domain-Based Target Identification and Discrimination: Part 1 - Sensor and Discrimination Algorithms," and "Part 2 - High Performance Intelligent Control System," Proc. 3rd Automatic Target Recognizor Systems & Technology Conf. GACIAC PR-93-01, Vol. 1, pp. 117-128, 129-139, 1993.

⁴ Gat, N., Barhen, J., Gulati, S., and Steiner, T.D., "Hyperspectral Imaging for Target/Decoy Discrimination: Sensor and Algorithms," Proc. Mtg. IRIS Specialty Group on Passive Sensors, IRIA Publication, 1994.

slit, that determines the spectral resolution of the sensor (which is not always determined by the number of pixels in the FPA along the dispersion direction).

To demonstrate the format of data recording, we show in Fig. 8 a "frame" of data captured during calibration process. The data represent spectral and spatial information along the x-y image coordinates, respectively. In this particular case, the field of view is a narrow swath that includes a point source Hg(Xe) lamp. The y-position determines the lamp elevation above the horizontal plane, while the x-position indicates the spectral signature of the source. To create a complete 3-D data cube, the field of view has to be scanned. The surface plot represents the relative intensity of the source at each wavelength and the spatial extent of the source.

Figure 7: Optical Layout of VNIR and MWIR Imaging Spectrometers of the IMS Sensor, and a Photograph of the Assembly (Sponsored by USAF Wright Labs).

A MWIR signature of a passenger jet upon takeoff looking directly into the back of the plane is shown in Fig. 9. The signature closely matches the theoretical spectral distribution of a 1,100K source. The absorption of radiation in 2.7 and 4.3 μ m, due to H₂O and CO₂ in the atmosphere can be seen. Because of the presence of these gases in the engine plume, where the temperature is much higher than that of the surrounding atmosphere, the so called "red and blue spikes" (due to line broadening) are also seen.

The greatest challenge for the IMS application is the signal processing.⁵ Since the missile guidance and control system must be updated at about 50 Hz, the entire process of data acquisition and analysis must be repeated in less than 2 msec. One of the techniques developed for this purpose was termed "pseudo-signature." Basically, instead of analyzing large data sets corresponding to the complete spectral signature, only a subset or a pseudo-spectrum is analyzed. This

⁵ Gat, N., Barhen, J., Gulati, S., and Steiner, T.D., "Hyperspectral Air-to-Air Seeker," SPIE Vol. 2231, Algorithms for Multispectral and Hyperspectral Imagery, Pp. 127-135, 1994.

pseudo spectrum is a signature in a small number of bands (e.g., between 4 to 16 - depending on the complexity of the situation) that are created (i) by removing bands in which atmospheric transmission is poor (attempts to correct the data in those bands are impractical), and then (ii) by binning bands into a wide group (to improve signal to noise ratio). The latter does not require the use of the same number of binned bands per group, nor do the binned bands have to be contiguous. Such reduced size dataset can now be analyzed in real-time.

Hg(Xe), 1 order diffraction FOV: 4.5° down

Figure 8. Spatial / Spectral Calibration of IMS VNIR Sensor Using Hg(Xe) Source.

Figure 9. Signatures of an Airliner's Exhaust Plume Obtained via the MWIR Part of IMS.

The pseudo signatures are transformed into a domain in which maximum separation exists between the signatures of target and decoy. Target/decoy discrimination is accomplished in the transformed domain using for instance matched filters.

The IMS project proved the hypothesis that a multispectral seeker can be more robust than conventional seekers. It has also shown that with hyperspectral system, the bands can be dynamically configured for specific situation for optimized performance (for instance, day /night bands selection may be different since the sun glare and reflections off the background are not present).

Another side benefit of a multi- or hyper-spectral seeker is for target ranging. The ratio of the spectral signature at two bands; one in which atmospheric transmission is clear, and the other on the edge of a CO₂ absorption band (the amount of CO₂ in the atmosphere is pretty much a constant), depends on the range (attenuation caused by the CO₂), the wavelengths, and the object temperature. A solution can be found in a constraint least-squares sense to the target range.

2.3 OTHER APPLICATIONS

2.3.1 Crop Health Monitoring

Early detection of infestation in crops can lead to eradication using a local treatment. Such early detection by ground observers is impractical in very large fields. By the time infestation is detected, large areas have already been affected. Eradication at a late stage not only causes a large financial damage, but also requires aerial spraying and the use of chemicals that are harmful to the environment. Under a USDA program OKSI has developed a conceptual design of an airborne multispectral sensor comprising 4 digital video cameras each equipped with a wide band-pass filter. The spectral ranges are selected based on extensive ground measurements of healthy and infested crops. The system will be flown on a small plane.

The use of only a few bands is possible, as discussed earlier, when a system is designed for a specific target application. If more than a few bands were required, a more efficient method would have been some sort of scanning or staring imaging spectrometer as depicted in Fig. 3. In the present system, four cameras acquire an image and the data are simultaneously transmitted to a computer via a frame grabber. Using the PCI bus (32 bits wide bus running at 33 MHz; the specifications also allow 64 bit wide bus running at 66 MHz) and a DMA bus mastering mode, it is possible now to transmit data to the host memory at rates as high as 132 MBytes/sec in burst mode. For four 12-bits cameras, 512x512 pixels each, running at 10 MHz, the required transfer bandwidth is about 21 MBytes/sec, well within the PCI range. PCI frame grabbers that perform this function are less expensive than their predecessors that required large amount of data storage on board, and provided built-in expensive DSP functions.

An effective early detection technique requires in this case accurate subpixel unmixing analysis. A linear unmixing method was described earlier in connection with plumes containing gas mixtures. Such a linear technique is the first step in any analysis. Because of the specific conditions for radiative exchange, it is believed that non-linear effects may play a role in the measured signatures. Non-linear effects are caused by multiple scattering of photons off objects that have different spectral characteristics, as depicted in Fig. 10. Nonlinear analysis techniques are under development.

Figure 10. Non-linear Mixing Model Based on Two Photon Reflections (A and B are Singly Reflected Photons, C Photons have Characteristics of A and B).

2.3.2 Advanced Manufacturing Technology

Another system currently under construction at OKSI is a stereoscopic hyperspectral camera system for use in advanced manufacturing technology lab of a large motor company. The system is based on two 12-bit cameras that are pixel-synchronized and read simultaneously into a computer via a frame grabber. The spectral bands are selected using liquid crystal tunable filters (LCTF) placed in front of each of the cameras, Fig. 11. The LCTFs are controlled via a computer and can be stepped through a series of wavelengths or randomly switched to any desirable wavelength.

Figure 11. LCTF-Based Hyperspectral Imaging Stereovision System.

There are many manufacturing processes that can take advantage of multi- or hyper-spectral data. These range from simple ones such as inspection of color and paint quality, detection of rust, or inspection of defects in thin film coatings. Another potential application is the on-line real-time inspection of weld quality. In this case the time evolution of spectroradiometric data can be translated to temperature maps and heat transfer processes in the welded parts. Heat flow maps can be correlated with good or cold welds. Real time detection of such defects can be used to correct the process before too many defective parts leave the production line.

2.3.3 Medical Applications

One of the more fascinating applications of imaging spectroscopy is a real-time system for use during surgery to delineate the regions of malignant cells. This application works in an active mode in which biological tissue is illuminated at wavelengths that causes the tissue to fluoresce. Typically this may include excitation in the UV or blue-green range of the spectrum and fluorescent at longer wavelengths. The fluorescence signatures of benign or malignant cells have been shown to sufficiently differ to allow discrimination.⁶ The problem then becomes one of detection of small signals embedded in a poor S/N and signal-to-background clutter conditions. In addition to tissue autofluorescence, other techniques are also being investigated including the use of photosensitizers⁷ and elastic scattering.⁸ Most of these methods, often referred to as optical biopsy, are based on non-imaging measurements but they could be extended, using the correct equipment, to multi- or hyperspectral imaging.

Another interesting study of utilizing hyperspectral techniques conducted by UCLA/JPL is related to functional mapping of the brain. The idea being to identify areas of the brain that perform specific functions without doing histopathology on every slice (Fig. 12).

Figure 12. Human Brain Data Cube⁹.

⁶ Alfano, A.A., *et-al* "Optical Spectroscopic Diagnosis of Cancer and Normal Breast Tissues," J. Opt. Soc. Am. B, Vol. 6, No. 5, Pp. 1015-1023, May 1989.

⁷ Frisoli, J.K. *et-al* "Medical Applications of Laser Induced Fluorescence: Pharmacokinetics of Photosensitisers," SPIE 1882, Optical Methods for Tumor Treatment and Detection: Mechanisms and Techniques in Photodynamic Therapy, II, 1993.

⁸ Bigio, I.J., *et-al*, "Optical Diagnostics Based on Elastic Scattering: An Update of Clinical Demonstration with the Optical Biopsy System," SPIE 2324, Optical Biopsy and Fluorescence Spectroscopy and Imaging, Pp. 46-54, 1994.

⁹ Courtesy of Dr. Greg Bearman, JPL, and Dr. Art Toga, UCLA.

2.3.4 Small Target Detection & Search and Rescue Operations

Often there is no need to identify a specific target, the need is only to detect the presence of a target of unknown *a priori* characteristics. Search and Rescue operation are an excellent example. In that case, a lost hiker in the mountains or a boat at sea must be rapidly detected. Rather than extensive analysis of a hyperspectral data cube, which is a time consuming process, a cursory technique based on "anomaly detection" has been devised. In anomaly detection an image is segmented into small subimages that are relatively homogeneous. The problem then becomes one of detecting pixels in the subimage region that are sufficiently "different" from their neighborhood. Since targets of interest may often be subpixel in size, the conventional approach would require performing complete subpixel unmixing, which is computationally expensive and require the use of extensive spectral libraries of all possible material in the image. The anomaly detection method removes the need for using extensive libraries of all potential end-members. It is designed to alert the operator to the presence of *suspect pixels*, for further investigation.

2.4 CLASSIFICATION TECHNIQUES

Supervised classification of multi- and hyper-spectral imagery is a robust technique that can be applied in almost all the fields that were discussed above. Customarily objects' signatures are presented in the feature-space which in our case is an N -dimensional space where N is the number of spectral bands, Fig. 13. Classification algorithms have emerged from, and primarily based on statistical techniques, including clustering algorithms. In contrast, neural network (NN) based classification may have the advantages that (i) they are distribution-free, (ii) they are non-linear, and (iii) they do not require a phenomenology based model to describe the data distribution, but can learn by example. In spite of these potential advantages, NN are not often used in hyperspectral image classification. The reasons are (a) the inordinately long training time associated with backpropagation type algorithms training on large data sets, and (b) the dependence of the final results on the starting parameters assigned to the NN weights. The latter problem is related to the fact that the NN training algorithms often get trapped in local minima as opposed to establishing global minimization of the error function. OKSI has addressed some of this issues with excellent results.

- i. A technique based on the Generalized Eigenvalue Problem (GEP^{10,11}) was developed for transforming hyperspectral data to a domain in which maximum separability exists between signature classes (Fig. 13-C) -- reducing the dimensionality of data sets by better than an order of magnitude, and improving classification performance. The dimensionality of the problem is determined by the number of non-zero eigenvalues of the transformation matrix, which in turn depends on the number of primary classes in the image (as opposed to the original data that have the dimensionality equal to the number of spectral bands of the sensor). This technique can also serve as a basis for lossless (or lossy) data compression for use in hyperspectral data transmission across networks or telemetry from satellites.

¹⁰Therrien, C. Discrete Random Signal and Statistical Signal Processing, Prentice Hall, New Jersey, 1992.

¹¹Richards, J. A. Remote Sensing and Digital Image Analysis, Springer Verlag, 1995.

- ii. A subnetwork technique was devised for performing hyperspectral image classification (in the transformed domain). Analogous to matched filters, each subnetwork is trained to identify one class and reject all other existing classes -- a process that significantly speeds up and improves classification performance, and is fully amenable to parallel processing with no additional programming overhead!
- iii. A novel world-class NN training paradigm based on alternating direction singular value decomposition (AD-SVD)¹² was developed and demonstrated, reducing training time for large data sets and large number of input nodes, to a fraction of a second. The AD-SVD allow determining the synaptic weights of the NN typically in a single pass. A similar backpropagation network required 10 to 15 minutes training.
- iv. A recurrent NN with enhanced learning algorithm has been adapted based on prior work at JPL, to address hyperspectral analysis. This fully connected network, configured as a system of subnetworks was shown to perform very well on the benchmarking datasets, opening the way to use hyperspectral data in dynamical, time-dependent applications such as monitoring seasonal change, deforestation, soil erosion, etc.
- v. A special hyperspectral classification benchmarking technique was developed, based on "synthetic signatures" and various "noise" and "clutter" models. The use of synthetic signatures provided the utmost certainty in validating results (which practically is impossible with remotely sensed imagery due to the lack of sufficient and reliable ground truth).
- vi. Performance benchmarking was established for statistical classification methods including: maximum likelihood, minimum distance, parallelepiped, and spectral angle mapper, as well as common feed-forward error backpropagation architecture, recurrent networks (with enhanced learning techniques), and the new AD-SVD network.
- vii. Work was conducted addressing subpixel spectral unmixing, in which the dominant component in an unknown mixture is identified based on classification algorithms.

Figure 13. Signatures in the Spectral (Physical) Domain (A); in the Feature Domain (B); Transformed for Maximum Separability (C). (Work Sponsored by U.S. DOC and NASA GSFC)

¹²A Milestone Paper under preparation (contact the authors for details)

3 SUMMARY

As hyperspectral imaging techniques evolve and penetrate new disciplines, their primary contribution will be in the development of new applications and the selection of optimal spectral band parameters (bands position and widths). In most cases, practical operational considerations (sensor cost, data volume, data processing costs, etc.) will favor the use of multi-spectral systems. Hyperspectral sensors will find use in general purpose instruments such as spaceborne systems that provide data to a broad range of end-users (agriculture, mineralogy, etc.). It will be the value-added data provider, or the end-users' responsibility to extract the useful data and reject the voluminous data that not only does not contribute to the application, but may cause enormous confusion.

3.1 WWW RESOURCES

A current list of imaging spectroscopy related resources on the Web is maintained by OKSI at URL <http://www.techexpo.com/WWW/opto-knowledge>.