ISIS; AN INFORMATION-EFFICIENT SPECTRAL IMAGING SYSTEM

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A specialized hyperspectral imager has been developed that preprocesses the spectra from an image before the light reaches the detectors. This "optical computer" does not allow the flexibility of digital post-processing. However, the processing is done in real time and the system can examine $\approx 2 \times 10^6$ scene pixels/sec. Therefore, outdoors it could search for pollutants, vegetation types, minerals, or man-made objects. On a high-speed production line it could identify defects in sheet products like plastic wrap or film, or on painted or plastic parts.

ISIS is a line scan imager. A spectrally dispersed slit image is projected on a Spatial Light Modulator. The SLM is programmed to take the inner product of the spectral intensity vector and a spectral basis vector. The SLM directs the positive and negative parts of the inner product to different linear detector arrays so the signal difference equals the inner product. We envision a system with one telescope and ≈ 4 SLMs.

INTRODUCTION

Different classes of materials can be separated from one-another because they have different reflectance spectra in the 0.5-μm to 2.4-μm spectral region. Figure 1a is an image of a scene containing soil, trees, and a tank. Figure 1b shows their spectra in the visible/near-IR[1] (0.45 μm ≤ λ ≤ 1.05 μm). A set of basis vectors, shown in Figure 1c, can be calculated for these spectra using spectral linear discriminant analysis[2]. These vectors, reminiscent of eigenvectors, would emphasize the differences between the spectra of the different material classes.

One can search for specific materials in an area by scanning it with a hyperspectral imager, processing the data, and comparing the results with known results. The data processing consists of taking the spectra from each image pixel and taking the inner product (dot product) of the pixel's spectra and each of the spectral basis vectors. The constants computed from the inner products can then be compared with known results. As an example, consider searching a scene (Fig. 1a) using two basis vectors. For each pixel of the scene, the two inner products have been taken and the results have been plotted, producing the scatter plot shown in Figure 1d. Note that the background and the material sought tend to cluster into three different areas, one of which is "interesting".

Most hyperspectral instruments use a line-scan-imager architecture. These instruments move an image of the scene across a slit. After passing through the slit, the spectra are

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dispersed perpendicular to the slit, and then the slit is reimaged on a two-dimensional detector array (e.g. a CCD). The coordinates on the detector array are x, measured along the length of the slit, and λ, the wavelength which varies in the perpendicular direction. Time multiplied by the velocity of the scan produces y, the other spatial coordinate.

Two typical airborne hyperspectral systems now in operation are HYDICE[3,4] and AVIRIS[5,6]. These systems collect 128 and 256 spectral bands respectively. They both record the data during each flight and then process it afterwards. This architecture is quite appropriate for aircraft-mounted systems.

However, this architecture is not nearly as logical for a satellite-borne hyperspectral imager if one needs to search large areas with high resolution. For example; if one wished to search a 100-km wide swath of land with a 10-m resolution, this implies that 7 million pixels must be processed per second. If there are 128 spectral channels, then there must be 900×10^6 A/D conversions per second. If 12-bit accuracy is required, the system must store 10^{10} bits/sec. If the desired swath length were 2000 km, then the system would have to store 3.2×10^{15} bits of data, and process it or send it to earth... This all sounds rather prohibitive.

We propose the ISIS architecture for this application because it reads about twenty-fold fewer spectral channels. Thus there are twenty-fold fewer detectors and A/D operations per second. Furthermore, the collected data can be process real-time, since only 3 arithmetic operations per pixel are required (per spectral basis vector). Therefore, uninteresting pixels can be ignored and only the useful data needs to be stored and/or sent to earth. In many applications, only a small percentage (2%?) of the data is interesting, so the required storage capacity is reduced by three orders of magnitude. The downlink capacity will also be reduced a thousand-fold. Remember that there is a price for this efficiency. One can only search for one (or a few) materials with this architecture. So if you know what you are looking for, the ISIS scheme will allow you to either reduce the amount of data handled, or to increase the number of pixels searched per orbit. If you don't know what will be found in the scene, a standard hyperspectral imager may be better.

ISIS ARCHITECTURES

ISIS is an imaging system containing a programmable spectral filter that can accentuate the spectral differences between the target and the background. It could be described as an optical computer that multiplies the spectra from the scene by a spectral basis vector before the photons reach the detectors. Figure 2 is a schematic showing the ISIS architecture. A telescope images a moving scene onto a slit. Light passing through the slit is dispersed perpendicular to the slit and then the slit is reimaged on an amplitude mask. The transmission of this mask is set equal to the spectral basis vector. Thus the transmission varies only in the spectral direction so each pixel along the slit length is treated the same. This mask passes the desired colors (appropriately attenuated) and

rejects the rest. Following the amplitude mask, the spectra are recombined and an image of the slit is created on a linear array of detectors.

The amplitude mask shown in Figure 2 can be programmed once which might be useful for some industrial applications where the selection of targets and the light level never change. However, for the remote sensing application a spatial light modulator (SLM) that could be reprogrammed would be far more useful. One possibility is shown in Figure 3, where the amplitude mask has been replaced with a liquid crystal SLM and a pair of polarizers. In this design, the first polarizer linearly polarizes the light from the scene. The liquid-crystal SLM must have a linear array of long, narrow windows that are individually addressable. Each liquid-crystal window rotates the polarization of the light in the narrow bandwidth impinging on it. A specified fraction of the light in each waveband can thereby pass the second polarizer (the analyzer) and will eventually reach the detector array.

Figure 1b shows two basis vectors $\varphi_2(\lambda)$ and $\varphi_3(\lambda)$ in a set, $\{\varphi_1(\lambda), \varphi_2(\lambda), \varphi_3(\lambda), \varphi_4(\lambda)...\}$. The first vector, $\varphi_1(\lambda)$, is usually similar to the solar spectrum and always positive. Hence it is not near as useful as the others are $(\varphi_2(\lambda), \varphi_3(\lambda), \varphi_4(\lambda)...)$ for discriminating between materials in the scene because it has relatively little structure. However, the other basis vectors are negative over parts of the spectrum, so they can't be accommodated with the simple ISIS architectures shown in Figures 2 and 3. However, using the double system shown in Figures 4a and 4b, basis vectors with negative parts can be accommodated. This is achieved as follows.

First the basis vector is separated into its positive and negative parts as shown in Figure 5.

$$\varphi_i(\lambda) = P_i(\lambda) - N_i(\lambda), \quad \text{for } i = 2 \& 3. \tag{1}$$

The two halves of $\varphi_i(\lambda)$ are coded into the two SLMs in Fig. 4a, which then take the two dot products of the basis vectors with the scene spectra;

$$A^+_i(x,t) = S(\lambda,x,t) \bullet P_i(\lambda)$$

and $\tag{2}$

$$A^-_i(x,t) = S(\lambda,x,t) \bullet N_i(\lambda)$$

Therefore the dot product of the whole basis vector and the scene spectrum is the difference between the two parts,

$$S(\lambda,x,t) \bullet \varphi_i(\lambda) = A^+_i(x,t) - A^-_i(x,t); \tag{3}$$

and they can be subtracted digitally. Note: The dot product can be normalized if the difference in (3) is divided by the sum of the two parts, $A^+_i(x,t) + A^-_i(x,t)$. This modification would reduce the effect of illumination brightness.

This led us to the (Fig. 4a) architecture that uses two liquid crystal SLMs. The two SLMs take the two halves of the dot product described by equations 2a and 2b. The system shown in Figure 4b was built from off-the shelf components, including a silicon-based detector array, a liquid crystal SLM, and lenses and prisms made for visible light operation. The optical train has very good image quality over a modest field of view, and for wavelengths between 0.45um and 1.05 um.

EXPERIMENTAL RESULTS

The prototype ISIS system (Figs. 4a & 4b) has been used to distinguish artificial from real ivy. Figure 6a is a photograph of the scene. Figure 6b shows the spectra and a spectral basis vector to find the artificial ivy. Figure 1c is the scene (Fig. 6a) as seen by the ISIS system. Figure 6d is a histogram of the pixels, where the small hump is the artificial ivy, and Figure 6e is the scene as seen by ISIS (Fig. 6c), and then thresholded. Admittedly this is a contrived example, but it does demonstrate the utility of the ISIS approach. Stallard and Gentry[7] will discuss these experiments in detail.

CONCLUSIONS AND FUTURE WORK

A hyperspectral system architecture has been proposed that allow large areas to be searched with high resolution; rates of $\approx 7 \times 10^6$ pixels/s are anticipated. Furthermore, the computations can all be done essentially in real time. Therefore, only "interesting" data needs to be stored. ISIS could also be used to direct the attention of a standard hyperspectral system to the 'interesting" regions, and it could collect a full complement of spectral data.

A proof-of-principle ISIS system has been built using visible-light components. In a first set of tests, the ISIS system has been used to distinguish between plastic and natural vegetation. More realistic tests are planned, most under natural lighting conditions. If the near-term testing is encouraging, an ISIS will be constructed for a bandwidth that covers the visible and the short-wave IR (0.5 μm to 2.2 μm). We also anticipate the development of ISIS architectures that can take two or more dot products simultaneously, which would improve the differentiation between targets and background.

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ACKNOWLEDGEMENTS

Figure 1a. Photograph of scene. Source: HYDICE data provided by CMO/SITAC.
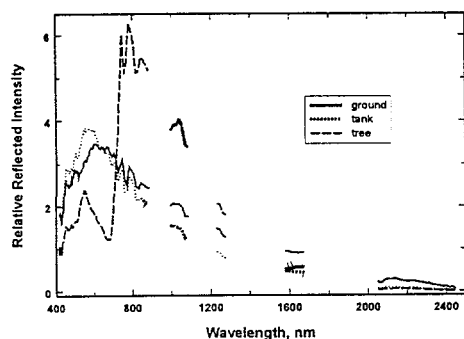
(b)
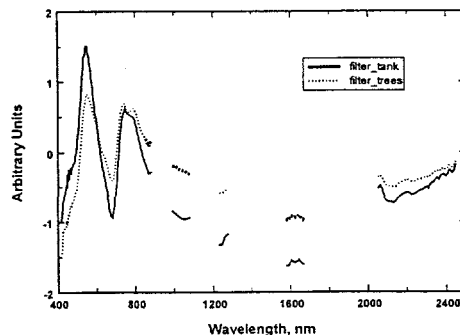
(c)

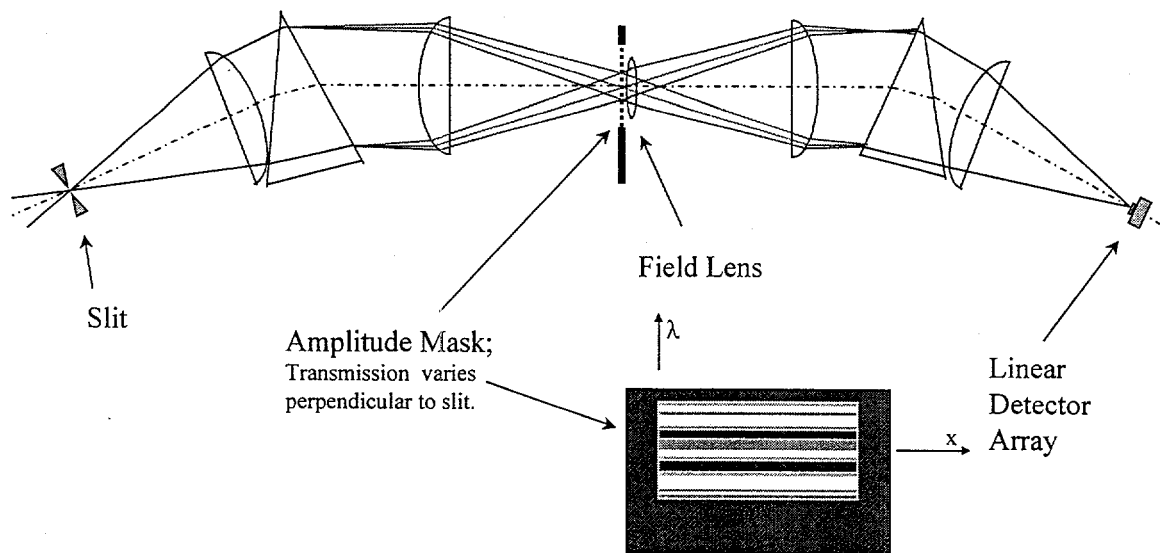**Figure 1b and 1c.** Reflectance spectra [Part (b)] and spectral basis vectors [Part (c)].
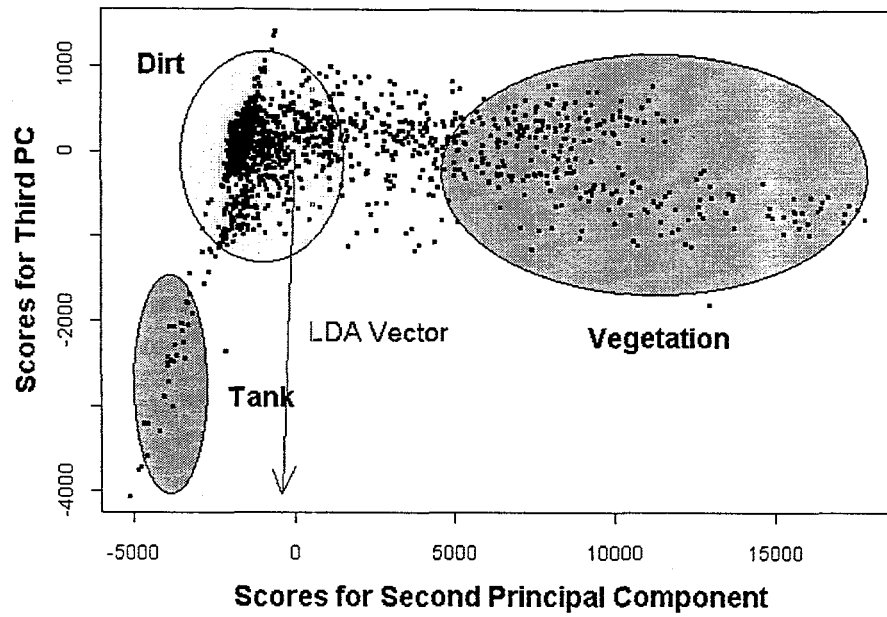
Figure 1d. Scatter diagram of data projected onto two principal components.
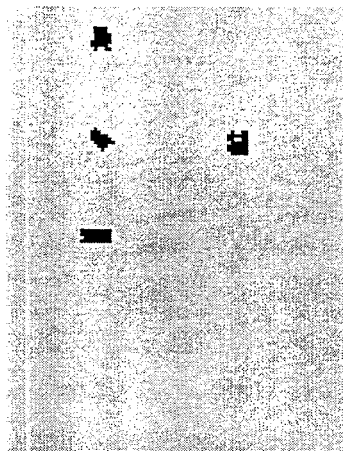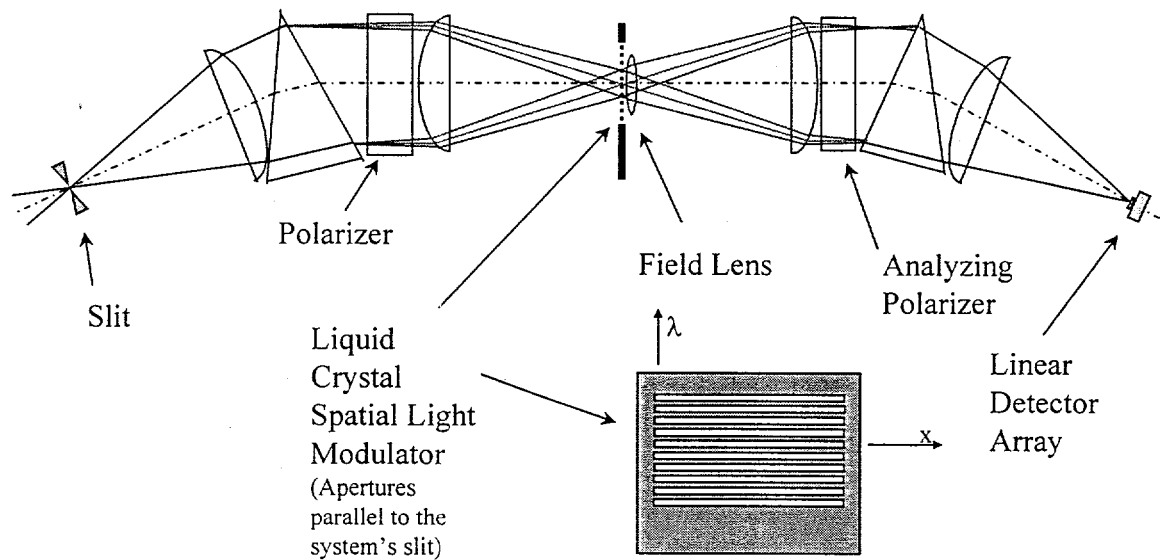

Figure 1e. Targets identified in the image of Figure 1a. Targets are shown in dark gray.

Figure 2. ISIS with an amplitude mask spatial light modulator (SLM).

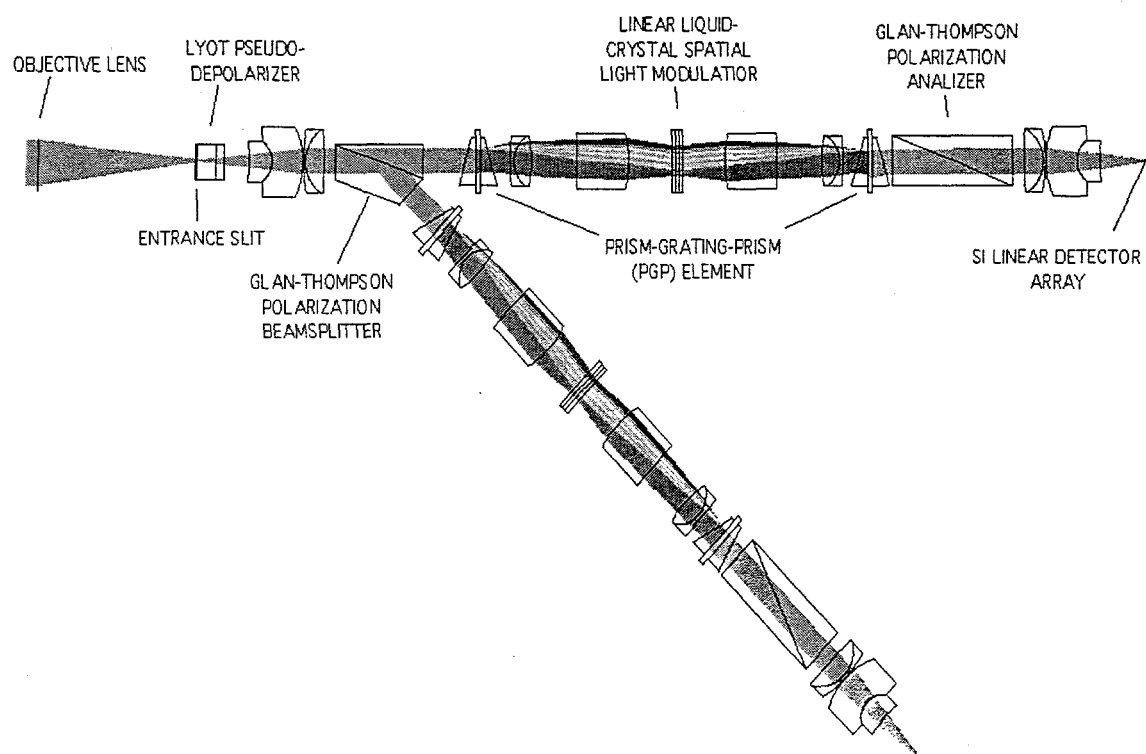

Figure 3. ISIS with a liquid-crystal SLM.
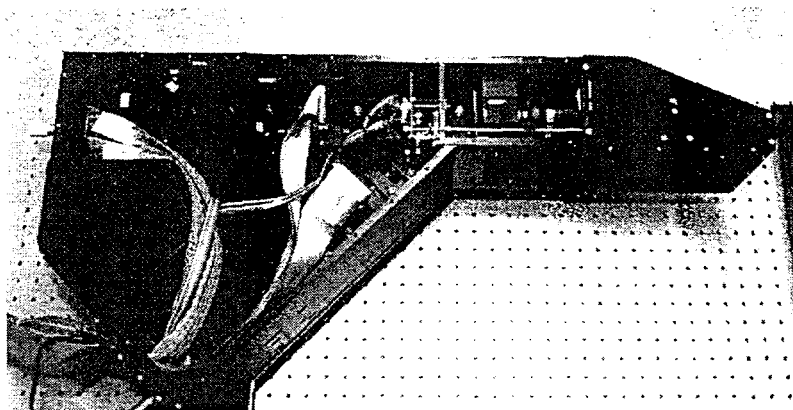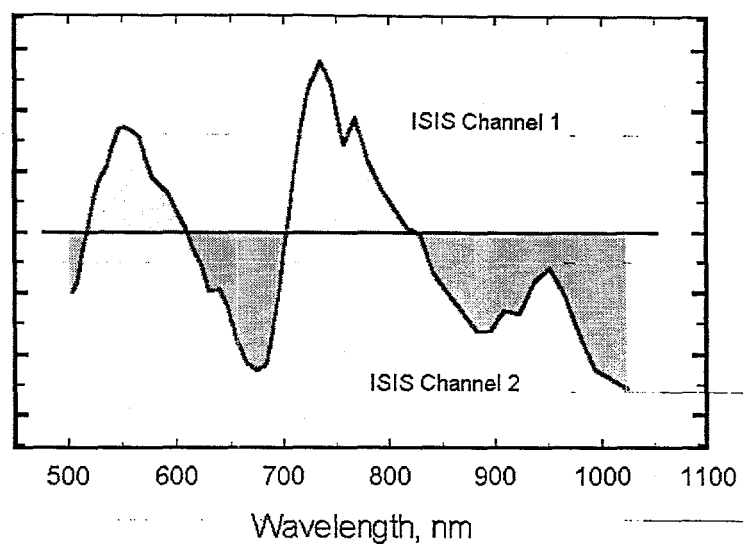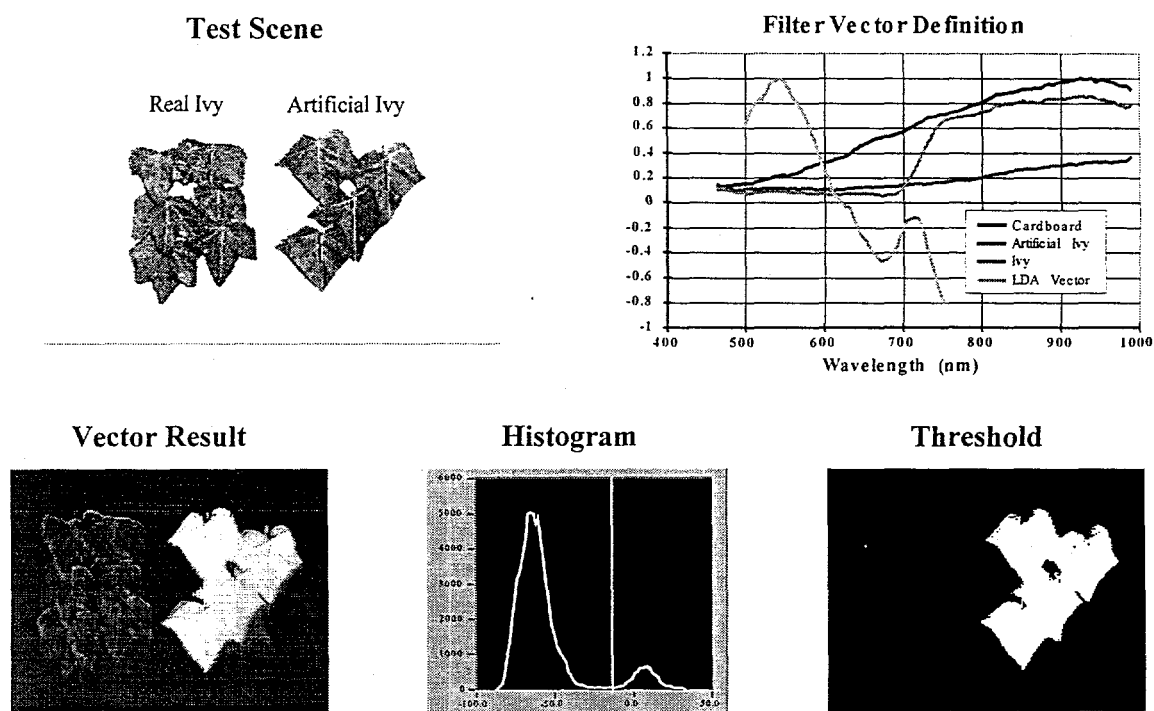
Figure 4a. ISIS experimental system.

Figure 4b. ISIS with cover removed.

Figure 5. Separation of the spectral basis vector into two non-negative parts, $\phi_i = P_i(\lambda) - N_i(\lambda)$.

Figure 6. Discrimination of real vs. artificial ivy.