Photonics and Imaging Technology

Hyperspectral Imaging - teaching robots to see

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Hyperspectral imaging is an exciting and promising technology that is rapidly becoming very popular. When combined with real-time classification software and robotic actuators, hyperspectral imaging has the capability to revolutionize machine vision, enabling robots to perform complex tasks previously limited to humans. Although a few hurdles remain before hyperspectral systems become fully commercialized, the potential benefits are significant for both research and industry.

Hyperspectral imaging is the measuring of high-resolution spectral data at every pixel in a two-dimensional image. Standard cameras provides three spectral data points at each pixel: red, green, and blue (RGB). The viewer's brain inputs the mixture of these colors and interprets them as a unique color, although in reality a materials' reflectance spectrum is a continuous curve consisting of an infinite number of wavelengths. In contrast to RGB, hyperspectral imaging measures hundreds of spectral data points at each pixel, delivering a near-continuous reflectance curve. Figure 1 shows an RGB image from aerial hyperspectral data of a farm, along with reflectance spectra from three regions in the scene.

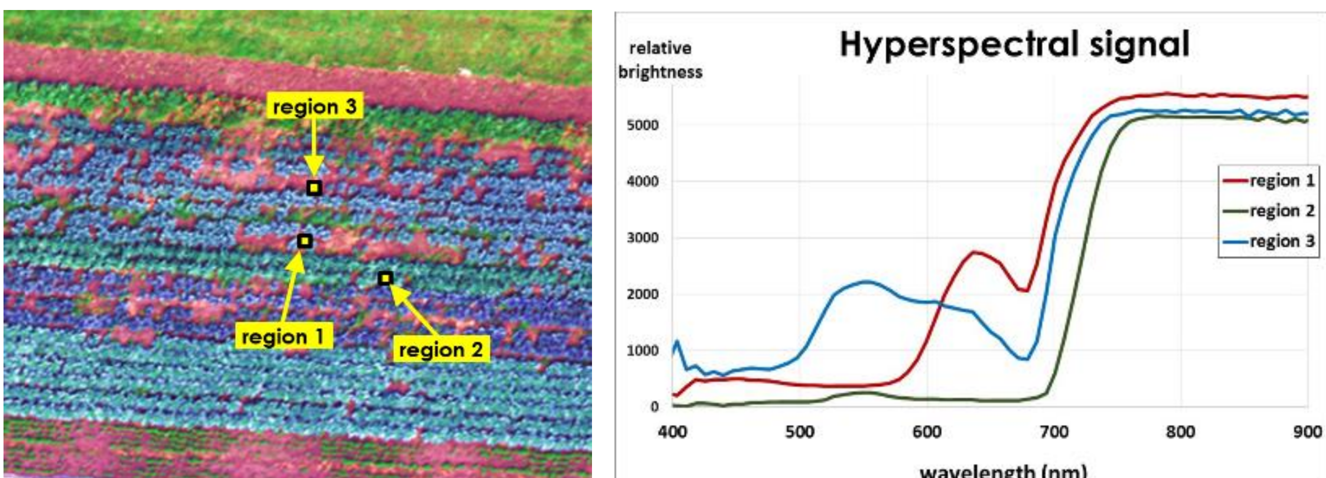

Figure 1. RGB image of hyperspectral data of a farm (left), and reflectance spectra from the specified regions (right).

Hyperspectral imaging is a form of spectroscopy. A standard spectrometer provides only one "pixel" per measurement – there is no imaging. "Multispectral" imaging refers to a camera with each pixel delivering a few spectral data points, typically between four and twelve. The term "hyperspectral" refers to very many spectral data points (typically 200 to 500) producing a near continuous spectrum at each pixel. Designing and manufacturing hyperspectral cameras is significantly more complex than for point spectrometers, as focusing all wavelengths across an entire image plane while minimizing distortions is a difficult optical problem.

Figure 2 shows the same data from Figure 1, but reduced to a multispectral signal with four bands. These four bands are similar to what the early Landsat satellites measured. It is clear from Figures 1 and 2 that much more information is contained in the hyperspectral data, enabling precise and reliable classification of objects in a scene.

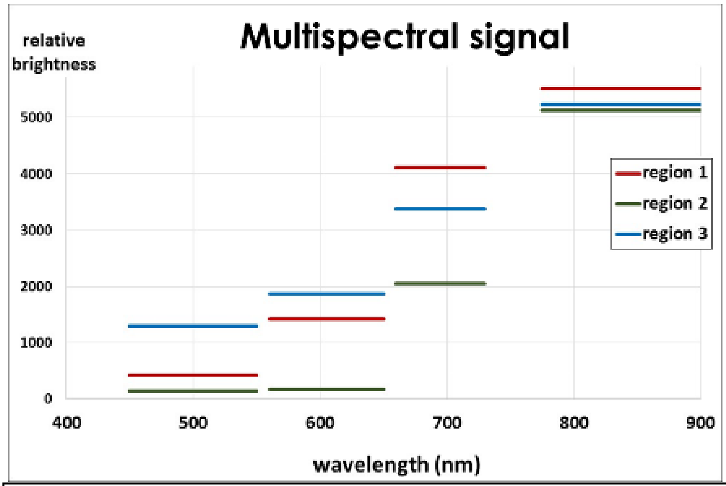

Figure 2. Multispectral data of the same regions from the image in Figure 1. Spectral bands correspond to those used in Landsat satellites.

Hyperspectral imaging is becoming popular at this particular time in human history for two reasons: digital cameras are inexpensive and easily available, and personal computers are big, fast, and cheap. Hyperspectral imaging yields very large datasets – this is definitely a "big data" technology. An average hyperspectral dataset has a million pixels, each with 400 spectral data points, and it is easy to create single images that are a gigabyte and larger. Computers can now handle these large datasets quickly, in real time.

The technology is advancing rapidly, in both research and industrial applications. Its utility is based on the fact that different materials have different reflectance spectra. In agriculture, different plant species have different spectra, as do the same plant species under different health conditions. As canonical examples, consider that hyperspectral data can alert farmers to early signs of crop stress or noxious weed infestations.

Hyperspectral technology in precision agriculture and environmental monitoring will eventually become commercially viable, but currently a few major obstacles must be overcome.[1] Determining accurate relationships between spectral features and plant physiologies is a work in progress and the focus of much research worldwide. This is a necessary step toward precision site-specific applications of herbicides, pesticides, and fertilizers. Furthermore, developing this technology into a working product that is effective under varying environmental conditions is still a few years off into the future. However, such targeted crop management techniques will allow farmers to use fewer chemicals more effectively and produce greater yields, and there is thus strong institutional support for hyperspectral technologies, especially in Asia where food supply and environmental protection are critical issues.

Because indoor factory environments can be controlled somewhat better than in outdoor farmlands and forests, hyperspectral imaging is gaining traction in industrial sorting applications. Standard vision systems often fail to sort items that have similar colors or appearances. Two examples of potentially difficult systems are foods with similar-colored shells or peels, and materials whose composition is unrelated to their visible color, such as recycled plastics. When standard vision systems fail, these sorting tasks fall to humans, which possess arguably the fastest computers and most advanced software available, but are costly, slow, and prone to mistakes.

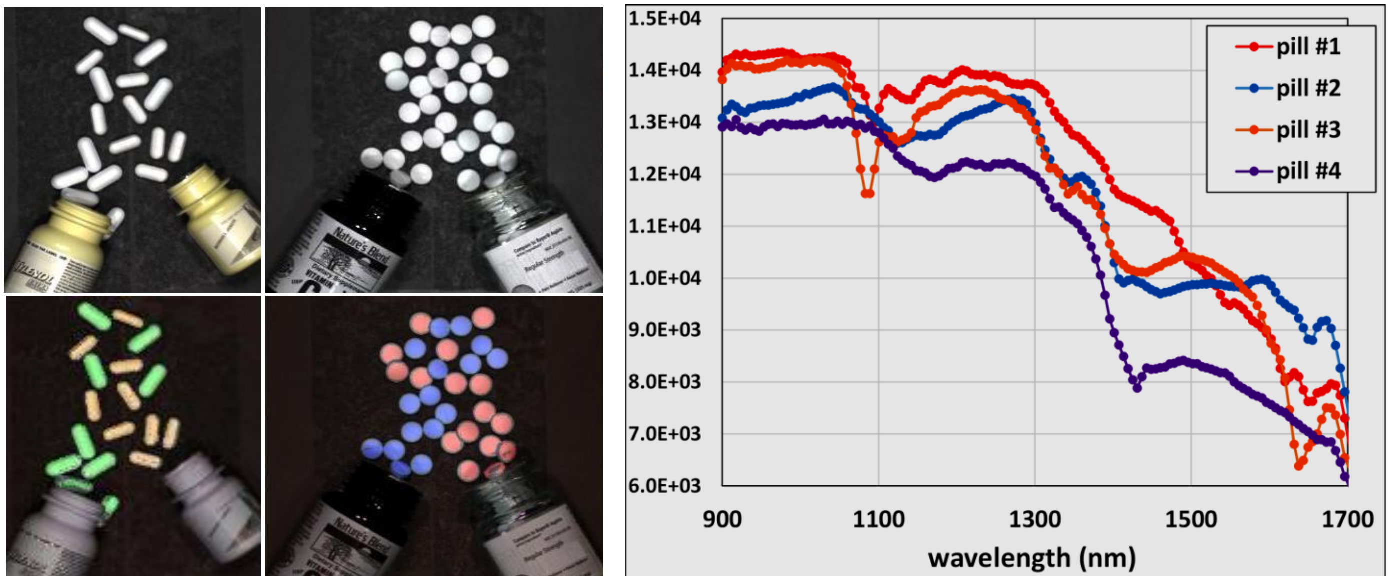

Figure 3. RGB image of white pills (top images), and false-color classification of hyperspectral data (bottom images). Reflectance spectra of the four pills are shown in the graph at right. Hyperspectral data allows the different pills to be easily identified.

Hyperspectral data, on the other hand, can easily distinguish differences between similarly colored materials, and furthermore can access information outside the visible range, in both the infrared and ultraviolet. Advanced automated sorting systems that are successful with difficult systems involve integrating hyperspectral sensors with real-time analysis software and robotic actuators.

While designing and manufacturing hyperspectral cameras is a technically challenging activity, producing reliable hyperspectral analysis software for industrial sorting is both a barrier and an opportunity. Because there are widely used simple algorithms existing alongside a wealth of knowledge about deep machine learning, hyperspectral machine vision software development is one of the most exciting fields in the topic.

Traditional methods of analyzing spectral imaging data use the concept of "vegetation indices"[2] or more generally just "indices," colloquially called "band math." These indices are scalar quantities associated with each pixel, calculated via simple algebraic combinations of measured intensities of a few specific spectral bands. For example, a historically venerable vegetation index is the Normalized Difference Vegetation Index (*NDVI*), which dates from the early days of multispectral remote sensing. Given a full reflectance spectra at each pixel, the value of *NDVI* can be calculated at each pixel as

$$NDVI = \frac{IR - Red}{IR + Red}$$

where "*NIR*" is the reflectance at an infrared band (around 750 nm), "*Red*" is the reflectance of a red band (around 650 nm), and *NDVI* is a number between -1.0 and 1.0. The magnitude of *NDVI* is a rough indicator of plant health. *NDVI* was well suited to early multispectral cameras that recorded four broad-band datapoints at each pixel (usually blue, green, red, and near-infrared). This is what was measured in the early Landsat satellites.

NDVI can give at best a rough estimate of plant health. Since the advent of airborne spectrometers and hyperspectral sensors many newer and more precise indices have been invented, with new indices invented continuously. An example of a common vegetative index that measures chlorophyll, the "Modified Chlorophyll Absorption Reflectance Index" (MCARI), takes the form

$$MCARI = \rho_{700} - \rho_{670} - 0.2(\rho_{700} - \rho_{550})\left(\frac{\rho_{700}}{\rho_{670}}\right)$$

while an index that measures anthocyanins in plants, the "Anthocyanin Reflectance Index #2" (ARI2) takes the form:

$$ARI2 = \rho_{900}\left(\frac{1}{\rho_{550}} - \frac{1}{\rho_{700}}\right)$$

In these equations, ρ_x is the measured reflectance at wavelength x.

Figure 4 shows a map of MCARI for the farmland in Figure 1. Bright locations in the map indicate high values of MCARI, while dark regions indicate low values of MCARI. The interpretation of MCARI is that higher values imply higher chlorophyll activity.

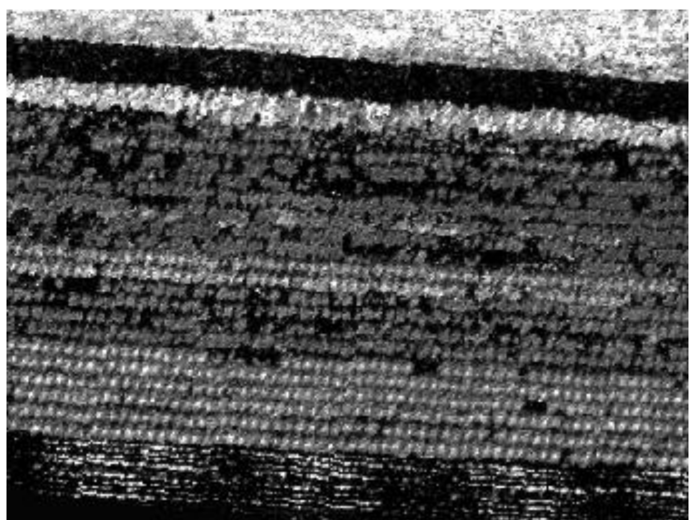

Figure 4. Map of the Modified Chlorophyll Absorption Reflectance Index, of the field shown in Figure 1.

Originally developed for agriculture and environmental monitoring, indices have now expanded to other fields, such as water quality, biology, and geology. In medicine indices related to water and oxygen are used to determine properties of human muscle tissue during surgery.

Although indices are useful tools, they only incorporate a very small portion of the information available in broad continuous spectra. Hyperspectral data carries much more information than a few selected spectral bands, and of course can yield all indices upon request. However, employing the entire spectra along with statistical methods yields much more reliable classifications, and this is exactly what is used in advanced machine vision applications.

Machine learning algorithms which utilize the entire spectra along with rigorous statistics can successfully classify the difficult systems discussed above. Techniques such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) have proven successful in hyperspectral sorting applications. When combined with spatial recognition algorithms, hyperspectral machine vision can make for very smart computers with very sensitive eyes. This allows assembly-line machines to identify a large range of materials, patterns, coatings, defects, and contaminants.

Despite the clear advantages showing potential benefits, hyperspectral imaging is still in its infancy, and significant developments are required before it becomes mainstream technology. High-intensity illumination with tunable spectral output is very important to achieve reasonable SNR, although this is helped by the recent and massive availability of LED's. Speed limitations in the form of data acquisition, processing speed, and computational complexity must be managed to meet many real-world applications. And developing analytical techniques that work reliably in real-world situations will be a constant challenge. Nonetheless, these issues will be solved, probably soon, and hyperspectral machine vision shows promise of solving previously intractable problems. The future of this exciting technology, for both research and industry, appears bright.

[1] For a good review of hyperspectral remote sensing, see: G. A. Shaw and H. K. Burke, *Spectral Imaging for Remote Sensing*, Lincoln Laboratory Journal, **14**, 3 (2003).

[2] For a good discussion of vegetation indices, see **Hyperspectral Remote Sensing of Vegetation**, edited by P. S. Thankabail, J. G. Lyon, and A. Huete, CRC Press (2012).

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