Review on Hyper-spectral Imaging System

Sajjad Bagheri Baba Ahmadi, Yaser Ahangari Nanehkaran, Sina Layazali

Abstract— Today many optical analysis techniques have been introduced that can for instance be used to obtain information from cultural heritage objects unavailable with conventional color or multi-spectral photography. One of the those optical techniques is Hyper-spectral imaging that its non-destructive and has ability to distinguish and recognize materials, to enhance the visibility of faint or obscured features, to detect signs of degradation and study the effect of environmental conditions on the object . Hyper-spectral imaging, like other spectral imaging, collects and processes information from across the electromagnetic spectrum. Much as the human eye sees visible light in three bands (red, green, and blue), spectral imaging divides the spectrum into many more bands. This technique of dividing images into bands can be extended beyond the visible; in this article, our goal is describe the basic concept, remote sensing, and applications of Hyper-spectral imaging. Moreover, the paper propose the methods used in remotely sensed data.

Index Terms— Hyper-spectral Images, Multispectral Imaging , Bovine Spongiform Encephalopathy , Near infrared Microscopy , Chemical Warfare Agents, Infrared Microscopy, Energy-Dispersive X-Ray Spectroscopy, Electron Energy loss Spectroscopy, Infrared Spectroscopy, Electron Probe Micro-analyzer, Scanning Transmission Electron Microscope, Toxic Industrial Compounds , Chemical Warfare Agents.

◆

1 INTRODUCTION

Hyperspectral imaging, or imaging spectroscopy, combines the power of digital imaging and spectroscopy. For each pixel in an image, a hyper-spectral camera acquires the light intensity (radiance) for a large number (typically a few tens to several hundred) of contiguous spectral bands. Every pixel in the image thus contains a continuous spectrum (in radiance or reflectance) and can be use to characterize the objects in the scene with great precision and detail.

Hyper-spectral images obviously provide much more detailed information about the scene than a normal color camera, which only acquires three different spectral channels corresponding to the visual primary colors red, green and blue. Hence, hyper-spectral imaging leads to a vastly improved ability to classify the objects in the scene based on their spectral properties. This is illustrated in the figure below, where typical pixel spectra from various materials are shown, along with a typical classification image. Recent advances in sensor design and processing speed has cleared the path for a wide range of applications employing hyper-spectral imaging, ranging from satellite based/airborne remote sensing and military target detection to industrial quality control and lab applications in medicine and biophysics. Due to the rich information content in hyper-spectral images, they are uniquely well suited for automated image processing, whether it is for online industrial monitoring or for remote sensing.

2. Hyper-spectral remote sensing

When light encounters a molecule in its path, the light may scatter and, depending on the properties of the intercepting molecule, the energy of parts of the light spectrum is absorbed or scattered by the atomic bonds, electrons or atoms in the molecule. The wavelength at which this absorption takes place is specific for the atomic bonds, and the molecular architecture of the object, which make identification of individual chemical components possible. By measuring the amount of light that reflects from a surface, it may therefore be possible to identify the composition of that surface.

This principle has been used for a long time to describe the earth surface, starting with aerial photography, and, since roughly 35 years, with satellite-based sensors, which are commonly referred to as Remote Sensing. With the development of better sensors and faster computers, a new field of research is emerging 'Hyper-spectral remote sensing'.
The 'hyper' in hyper-spectral refers to the many light sensors with a very narrow sensitive range. The resulting data often has over 100 contiguous bands, each 10 nm or less wide, and each measurement results in a semi-continuous spectrum over the sensitive range. The high number of bands, and the narrow sensitive range, enables the detection of changes in narrow absorption features that may go undetected when using broadband sensors. This high sensitivity makes it realistic to try to detect changes in chemical composition of vegetation using spectrometry. When the individual sensors are combining into a sensor array, it is possible to measure the reflectance spectra for individual pixels of an image, called imaging spectrometry. By then analyzing the spectral

---

Sajjad Bagheri Baba Ahmadi is currently pursuing masters degree program in Computer Engineering in Cankaya University,Ankara, Turkey, PH-00905436977943.
E-mail: sajad_bagheri67@yahoo.com

Yaser Ahangari Nanehkaran is currently pursuing masters degree program in Information Technology in Cankaya University, Ankara,Turkey, PH-00905545058732.
E-mail: y.ahangari@yahoo.com

Sina Layazali is currently pursuing masters degree program in Computer Engineering in Cankaya University, Student No.201271453, Anakar ,Turkey, PH-00905396159002.
E-mail: sinalayazali@yahoo.com

features of the individual pixels we can spatially map the properties of the earth surface.

Multispectral remote sensors such as the Landsat Thematic Mapper and SPOT XS produce images with a few relatively broad wavelength bands. Hyper-spectral remote sensors, on the other hand, collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands. These measurements make it possible to derive a continuous spectrum for each image cell, as shown in the figure 1. After adjustments for sensor, atmospheric, and terrain effects are applied, these image spectra can be compared with field or laboratory reflectance spectra in order to recognize and map surface materials such as particular types of vegetation or diagnostic minerals associated with ore deposits.

Hyper-spectral images contain a wealth of data, but interpreting them requires an understanding of exactly what properties of ground materials we are trying to measure, and how they relate to the measurements actually made by the hyper-spectral sensor.

3. Remotely sensed data

The use of remotely sensed data for detecting nutrients and trace elements has been developed, tested, and has proven effective for dried, ground samples under controlled conditions (Kokaly and Clark 1999, Rabkin 1987). Although this is cost-effective in projects with many samples to analyze, the potential of remote sensing is not fully exploited.

Ideally, the spatial variation in the chemical composition of the vegetation should be mapped with a minimal amount of sample field. To achieve this, several studies have developed models for predicting nutrients at canopy level in fresh vegetation. Some of these have shown that it is possible to obtain high accuracies; others, however, have achieved only moderately accurate results.

Often these studies have focused on only a few chemicals, such as chlorophyll and other pigments or nitrogen. Pigments such as chlorophyll and carotenes are detectable, with accuracies of over 80 percent reached for sample fields. Nitrogen content, which is related to chlorophyll functioning, can also be predicted quite accurately. The detection of other nutrients and trace elements (phosphorus, potassium, sodium, calcium and magnesium) in fresh vegetation has received less attention, although Mutanga et al. (2003) has carried out some research in this respect.

Many papers on the detection of biochemical focus on their content in grass species.

The cultivated, often larger, species such as maize and sugarcane are important agricultural crops. The health status and yield are influenced by soil nutrient availability, which in turn affects leaf nutrient levels.

Consequently, the potential to detect the nutrient status in agricultural crops is of significant interest. Grasses are also a source of food for grazing herbivores, and the nutrient status of grasses influences the distribution of these herbivores. In the Tarangire ecosystem, the seasonal migration of wildebeest is determined by changes in the phosphorus content of grasses. The detection of nutrients in grasses is therefore

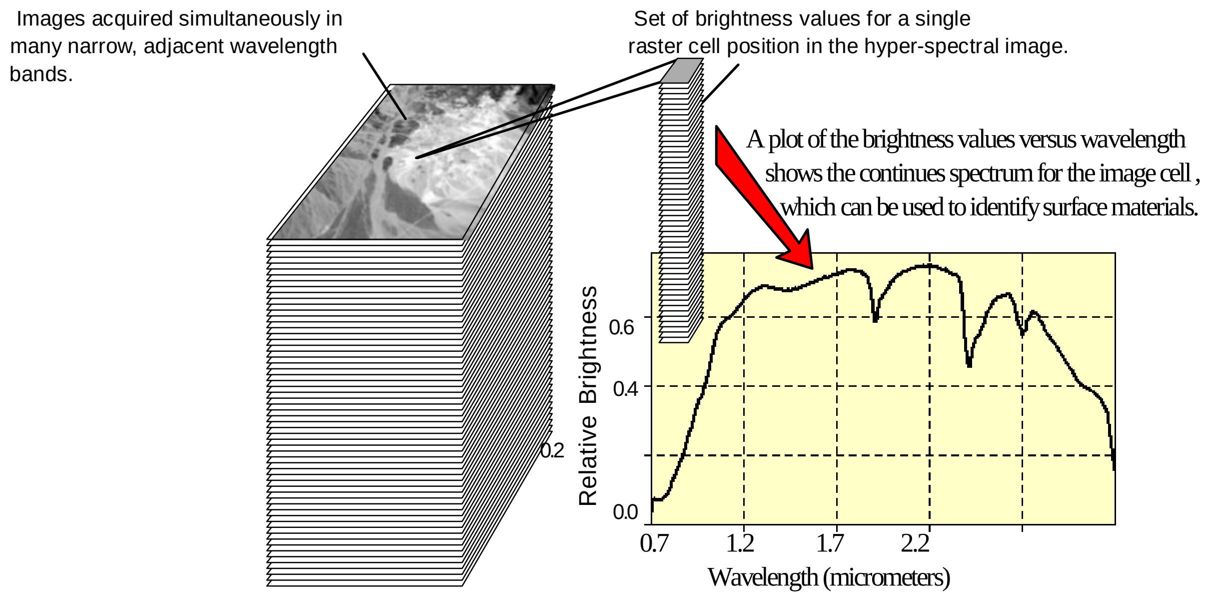

Figure 1. The illustration of hyper-spectral remote sensor measurement

useful, not only for species conservation and for natural resources management, but also for precision agriculture and production forecasts.

3.1 Methods

3.1.1 Study areas

Four plant species from three different climatic regions were selected to maximize the range in internal physiology. The first study area is around Wageningen, the Netherlands, and is located in a temperate climatic region, with a cool and wet climate. The second region is in southern Spain, with a dry Mediterranean climate, and the samples were collected in olive plantations around Alora, just north of Malaga. The last set of samples was collected in the north of Kruger National Park, South Africa, which is located in the dry tropics.

3.1.2 Field sampling

In the Netherlands, samples were collected for heather (Calluna vulgaris L., n=10) and willow (Salix cinera L., n=10). In Spain olive trees (Olea europaea L., n=28) were sampled, and in South Africa mopane trees (Cholophospermum mopane, n=18). In all cases, sampling followed the same experimental set-up. From around the canopy of an individual tree, leaves were collected at a height of approximately 1.5 m and placed in a pile in the sun. Heather was the exception: reflectance was measured before clipping, and samples included young twigs. For each sample, 10 reflectance spectra were recorded using a GER 3700 spectrometer. In order to calculate absolute reflectance, a reference spectrum was measured from a Spectralon reference target between readings. After measuring the reflectance, samples were dried at 70 degrees for 24 hours and stored until analysis.

3.1.3 Chemical analysis

Subsamples were destructed with a mixture of sulphuric acid, selenium and salicylic acid (Novozamsky et al. 1983). The content of the elements nitrogen and phosphorus was measured with a Skalar San Plus auto-analyser. Sodium, potassium and calcium were measured with a flame photometer, and magnesium with an atomic absorption spectrometer.

3.1.4 Spectral processing

To remove random noise from spectra, the ten-reflectance spectra per sample were averaged. From the averaged spectra, derivative spectra were calculated using an adjusted version of the Savitzky-Golay smoothing technique (Savitzky and Golay 1964, Tsai and Philpot 1998). Instead of first smoothing the spectra and then calculating the derivative spectra from the smoothed spectra, the parameters of the fitted third order, seven-band moving polynomial were used to directly calculate the derivative at the centre waveband of the moving spline window. The continuum-removed spectra were calculated as described in Kokaly and Clark (1999), and the band depth was used in this study. Table 1 gives an overview of the absorption features used and the end points between which the continuum line was calculated

3.1.5 Statistics

The datasets were randomly split into two equal-sized subsets, each containing half of the samples for each species. One subset was used for training models (n=33), the other for testing purposes (n=33). To enable comparison between reflectance, derivative data and band depth, the same division of samples into training and test data was used for all three datasets.

Through a stepwise regression routine, the bands with optimal fit to the content were selected for the three training subsets (Reflectance, Derivatives, Band Depth) for each chemical. The number of predictors was limited to four. The parameters of the fitted models were then used to predict the content of the test subset, and the correlation between predicted content and actual content was calculated.

To assess the certainty of the obtained correlation value, a bootstrap was applied. The training and test subsets were combined, and split by species. For each species individually and for all species together, the correlation between

Feature (nm)	*Continuum line start (nm)*	*Continuum line end (nm)*
680	551	716
1194	1132	1280
1460	1338	1646
1730	1652	1778
2100	2030	2218
2300	2238	2366

Table 1. Definition of continuum end points for absorption features observed in the reflectance spectra of fresh leaves

predicted and observed chemical content was bootstrapped with 1000 iterations. The distribution and mean correlation give an indication of the differences in model accuracy between species, and of the robustness of the model.

4. Applications

Spectral imaging refers to the acquisition of a series of digital images at a number of different, well- defined optical wavelengths. Traditionally, if the number of wavelength bands is smaller than ten, the term Multispectral Imaging (MSI) is used. MSI is used extensively in many application areas, including the field of restoration and conservation of artworks, where MSI can be regarded as common technology. If the number of wavelength bands is much larger than ten, usually the term Hyper-spectral Imaging (HSI) is used. HSI has already proven its worth in various fields such as agricultural research; environmental studies and defense .HSI instruments used for these applications typically are mounted on an aircraft or satellite to record the surface of the Earth. Hyper-spectral imaging spectrometers produce data with high spectral resolution domains (in the to detect subtle spectral features and defined chemical and physical properties of the sensed objects. This powerful capability has been successfully used in many applications, such as geological mapping, agricultural monitoring and optimization, environmental damage assessment, forestry surveys, vegetation monitoring, water-quality assessment, detection of man-made materials and more. This technology is continually becoming more available to the public. Organizations such as NASA and the USGS have catalogues of various minerals and their spectral signatures, and have posted them online to make them readily available for researchers.

4.1 Agriculture

Although the cost of acquiring hyper-spectral images is typically high, for specific crops and in specific climates, hyper-spectral remote sensing use is increasing for monitoring the development and health of crops. In Australia, work is under way to use imaging spectrometers to detect grape variety and develop an early warning system for disease outbreaks. Furthermore, work is underway to use hyper-spectral data to detect the chemical composition of plants, which can be used to detect the nutrient and water status of wheat in irrigated systems. Another application in agriculture is the detection of animal proteins in compound feeds to avoid bovine spongiform encephalopathy (BSE), also known as mad-cow disease. Different studies have been done

to propose alternative tools to the reference method of detection, (classical microscopy).

One of the first alternatives is near infrared microscopy (NIR), which combines the advantages of microscopy and NIR. In 2004, the first study relating this problem with hyper-spectral imaging was published. Hyper-spectral libraries that are representative of the diversity of ingredients usually present in the preparation of compound feeds were constructed. These libraries can be used together with chemo metric tools to investigate the limit of detection, specificity and reproducibility of the NIR hyper-spectral imaging method for the detection and quantification of animal ingredients in feed.

4.2 Mineralogy

Geological samples, such as drill cores, can be rapidly mapped for nearly all minerals of commercial interest with hyper-spectral imaging. Fusion of SWIR and LWIR spectral imaging is standard for the detection of minerals in the feldspar, silica, calcite, garnet, and olivine groups, as these minerals have their most distinctive and strongest spectral signature in the LWIR regions.

Hyper-spectral remote sensing of minerals is well developed. Many minerals can be identified from airborne images, and their relation to the presence of valuable minerals, such as gold and diamonds, is well understood. Currently, progress is towards understanding the relationship between oil and gas leakages from pipelines and natural wells, and their effects on the vegetation and the spectral signatures. Recent work includes the PhD dissertations of Werff and Noomen.

4.3 Surveillance

Hyper-spectral thermal infrared emission measurement, an outdoor scan in winter conditions, ambient temperature -15°C—relative radiance spectra from various targets in the image are shown with arrows. The infrared spectra of the different objects such as the watch glass have clearly distinctive characteristics. The contrast level indicates the temperature of the object. This image was produced with a Specim LWIR hyper-spectral imager.

Hyper-spectral surveillance is the implementation of hyper-spectral scanning technology for surveillance purposes. Hyper-spectral imaging is particularly useful in military surveillance because of countermeasures that military entities now take to avoid airborne surveillance. Aerial surveillance was used by French soldiers using tethered balloons to spy on troop movements during the French Revolutionary Wars, and since that time, soldiers have learned not only to hide from the naked eye, but also to mask their heat signatures to blend in to the surroundings and avoid infrared scanning. The idea that drives hyper-spectral surveillance is that hyper-spectral scanning draws information from such a large portion of the light spectrum that any given object should have a unique

Spectral signature in at least a few of the many bands that are scanned. The SEALs from DEVGRU who killed Osama bin Laden in May 2011 used this technology while conducting the raid (Operation Neptune's Spear) on Osama bin Laden's compound in Abbottabad, Pakistan.

Traditionally, commercially available thermal infrared hyper-spectral imaging systems have needed liquid nitrogen or helium cooling, which has made them impractical for most surveillance applications. In 2010, Specim introduced a thermal infrared hyper-spectral camera that can be used for outdoor surveillance and UAV applications without an external light source such as the sun or the moon.

4.4 Physics

Physicists use an electron microscopy technique that involves microanalysis using either energy-dispersive X-ray spectroscopy (EDS), electron energy loss spectroscopy (EELS), infrared spectroscopy(IR), Raman spectroscopy, or cathodoluminescence (CL) spectroscopy, in which the entire spectrum measured at each point is recorded. EELS hyper-spectral imaging is performed in a scanning transmission electron microscope (STEM); EDS and CL mapping can be performed in STEM as well, or in a scanning electron microscope or electron microprobe (also called an electron probe micro analyzer or EPMA). Often, multiple techniques (EDS, EELS, CL) are used simultaneously.

In a "normal" mapping experiment, an image of the sample is simply the intensity of a particular emission mapped in an XY raster. For example, an EDS map could be made of a steel sample, in which iron X-ray intensity is used for the intensity grayscale of the image. Dark areas in the image would indicate non-iron-bearing impurities. This could potentially give misleading results; if the steel contained tungsten inclusions, for example, the high atomic number of tungsten could result in bremsstrahlung radiation that would make the iron-free areas appear to be rich in iron.

By hyper-spectral mapping, instead, the entire spectrum at each mapping point is acquired, and a quantitative analysis can be performed by computer postprocessing of the data, and a quantitative map of iron content produced. This would show which areas contained no iron, despite the anomalous X-ray counts caused by bremsstrahlung. Because EELS core-loss edges are small signals on top of a large background, hyper-spectral imaging allows large improvements to the quality of EELS chemical maps.

Similarly, in CL mapping, small shifts in the peak emission energy could be mapped, which would give information regarding slight chemical composition changes or changes in the stress state of a sample.

4.5 Astronomy

In astronomy, hyper-spectral imaging is used to determine a spatially resolved spectral image. Since a spectrum is an important diagnostic, having a spectrum for each pixel allows more science cases to be addressed. In astronomy, this technique is commonly referred to as integral field spectroscopy, and examples of this technique include FLAMES and SINFONI on the Very Large Telescope, but also the Advanced CCD Imaging Spectrometer on Chandra X-ray Observatory uses this technique.

4.6 Chemical Imaging

At war, Chemical Warfare Agents (CWAs) and Toxic Industrial Compounds (TICs) attacks are some of the most malicious threats for any field troops. In fact, soldiers can be exposed to a wide variety of chemical hazards both on and off the battlefield. These threats are mostly invisible and very hard to detect. However, the hyper-spectral imaging technology offers a unique standoff detection, identification and imaging capability for such chemical warfare agents. The Telops Hyper-Cam, introduced in 2005, has demonstrated this capability in multiple field CWA-TIC measurement campaigns. With its standoff capability, the Hyper-Cam enables on-the-field detection and identification of multiple CWAs and TICs in various environments, at distances up to 5 km and with concentrations as low as a few ppm.

4.7 Environment

Most countries require continuous monitoring of emissions produced by coal and oil-fired power plants, municipal and hazardous waste incinerators, cement plants, as well as many other types of industrial sources. This monitoring is usually performed using extractive sampling systems coupled with infrared spectroscopy techniques. Some recent standoff measurements performed allowed the evaluation of the air quality but not many remote independent methods allow for low uncertainty measurements. The Telops Hyper-Cam, an infrared hyper-spectral imager, now offers the possibility of obtaining a complete image of emissions resulting from industrial smokestacks from a remote location, without any need for extractive sampling systems. Emission quantification measurements have been achieved with the Hyper-Cam which can now be used to independently, safely and rapidly identify and quantify polluting emissions from a remote location.

5. Conclusion and suggestion

We report on the basic concept, remote sensing, remotely sensed data, and applications of Hyper-spectral, also we survey various aspects of this method. In this article, we finally, concentrated on the use of hyper-spectral imaging in various application. However, HSI technology is steadily becoming a valued research tool, especially in biomedical research and in our opinion; we can make further progress in this area.

Acknowledgements

We are obliged to Asst. Prof. Dr. Reza ZARE HASSANPOUR, for the valuable information provided by him in his respective fields. We are grateful for his cooperation.

References

[1] Ana Brook and Eyal Ben-Dor " Advantages of the Boresight Effect in Hyperspectral " Remote Sens. 2011,3,484-502;doi:10.3390/rs3003484 .

[2] L.L Randeberg,I.Baarstad, T.Loke,P.Kaspersen and L.O. Svaasand"Hyperspectral imaging of bruised Skin," in : Proceedings of SPIE BIOS 2006, in press.

[3] . ^ a b c Schurmer, J.H., (Dec 2003), Air Force Research Laboratories Technology Horizons

[4] ^ a b Ellis, J., (Jan 2001) Searching for oil seeps and oil-impacted soil with hyperspectral imagery, Earth Observation Magazine.

[5] ^ Smith, R.B. (July 14, 2006), Introduction to hyperspectral imaging with TMIPS, MicroImages Tutorial Web site

[6] ^ Lacar, F.M., et al., Use of hyperspectral imagery for mapping grape varieties in the Barossa Valley, South Australia , Geoscience and remote sensing symposium (IGARSS'01) - IEEE 2001 International, vol.6 2875-2877p. doi:10.1109/IGARSS.2001.978191

[7] ^ Ferwerda, J.G. (2005), Charting the quality of forage: measuring and mapping the variation of chemical components in foliage with hyperspectral remote sensing, Wageningen University, ITC Dissertation 126, 166p. ISBN 90-8504-209-7

[8] ^ Tilling, A.K., et al., (2006) Remote sensing to detect nitrogen and water stress in wheat, The Australian Society of Agronomy

[9] ^ Fernández Pierna, J.A., et al., 'Combination of Support Vector Machines (SVM) and Near Infrared (NIR) imaging spectroscopy for the detection of meat and bone meat (MBM) in compound feeds' Journal of Chemometrics 18 (2004) 341-349.

[10] ^ a b c Holma, H., (May 2011), Thermische Hyperspektralbildgebung im langwelligen Infrarot, Photonik.

[11] ^ Werff H. (2006), Knowledge based remote sensing of complex objects: recognition of spectral and spatial patterns resulting from natural hydrocarbon seepages, Utrecht University, ITC Dissertation 131, 138p. ISBN 90-6164-238-8.

[12] ^ "Fleurus (Municipality, Province of Hainaut, Belgium)". CRW Flags Inc.. Retrieved 2010-04-21

[13] ^ Marc Ambinder (May 3, 2011). "The secret team that killed bin Laden". National Journal. Retrieved September 12, 2012.

[14] ^ Frost&Sullivan, Technical Insights, Aerospace&Defence (Feb 2011): World First Thermal Hyperspectral Camera for Unmanned Aerial Vehicles

[15] ^ Specim's Owl sees an invisible object and identifies its materials even in a pitch-dark night.

[16] ^ "FLAMES - Fibre Large Array Multi Element Spectrograph". ESO. Retrieved 30 November 2012.

[17] ^ "SINFONI - Spectrograph for INtegral Field Observations in the Near Infrared". ESO. Retrieved 30 November 2012.

[18] ^ Farley, V., Chamberland, M., Lagueux, P., et al., "Chemical agent detection and identification with a hyperspectral imaging infrared sensor," Proceedings of SPIE Vol. 6661, 66610L (2007).

[19] ^ Tremblay, P., Savary, S., Rolland, M., et al., "Standoff gas identification and quantification from turbulent stack plumes with an imaging Fourier-transform spectrometer," Proceedings of SPIE Vol. 7673, 76730H (2010).

[20] ^ A. Picon, O. Ghita, P.F. Whelan, P. Iriondo (2009), Spectral and Spatial Feature Integration for Classification of Non-ferrous Materials in Hyper-spectral Data,IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, VOL. 5, NO. 4, NOVEMBER 2009.

[21] Marvin E. Klein 1,*, Bernard J. Aalderink 1, Roberto Padoan 2, Gerrit de Bruin 2 and Ted A.G.Steemers2 “Quantitative Hyperspectral Reflectance Imaging” Sensors 2008, 8, 5576-5618; DOI: 10.3390/s8095576 .

.

[22] Randall B. Smith, Ph.D., 5 January 2012 “Quantitative Hyperspectral Reflectance Imaging”© MicroImages, Inc., 1999-2012.