Optical Remote Sensing

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2. Spectral Properties of Earth Materials
3. Sensor Technology
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Remote sensing refers to the activities of recording/observing/perceiving (sensing) objects or events at far away (remote) places.

In remote sensing, the sensors are not in direct contact with the objects or events being observed.

The output of a remote sensing system is usually an image representing the scene being observed.

The human visual system is an example of a remote sensing system in this general sense.
What is Remote Sensing?

In a more restricted sense, remote sensing usually refers to the technology of acquiring information about the earth's surface (land and ocean) and atmosphere using sensors onboard **airborne** (aircraft, balloons) or **spaceborne** (satellites, space shuttles) platforms.

These remote sensing satellites are equipped with sensors looking down to the earth. They are the "eyes in the sky" constantly observing the earth as they go round in predictable orbits.

In airborne remote sensing, downward or sideward looking sensors are mounted on an aircraft to obtain images of the earth's surface.
Electromagnetic Waves

The electromagnetic radiation is normally used as an information carrier in remote sensing. An electromagnetic wave is characterized by a frequency and a wavelength.

\[ c = \lambda \nu \]

speed of light = frequency x wavelength
The electromagnetic spectrum can be divided into several wavelength (frequency) regions.
### Electromagnetic spectral regions for remote sensing:

**Visible Light:**
- **Red:** 610 - 700 nm
- **Orange:** 590 - 610 nm
- **Yellow:** 570 - 590 nm
- **Green:** 500 - 570 nm
- **Blue:** 450 - 500 nm
- **Indigo:** 430 - 450 nm
- **Violet:** 400 - 430 nm

**Optical R.S.:**
- **Near Infrared (NIR):** 0.7 to 1.5 μm.
- **Short Wavelength Infrared (SWIR):** 1.5 to 3 μm.
- **Mid Wavelength Infrared (MWIR):** 3 to 8 μm.
- **Long Wavelength Infrared (LWIR):** 8 to 15 μm.
- **Far Infrared (FIR):** longer than 15 μm.

**Microwaves:** 1 mm to 1 m wavelength.
When electromagnetic radiation travels through the atmosphere, it may be absorbed or scattered by the constituent particles of the atmosphere.

Molecular absorption converts the radiation energy into excitation energy of the molecules.

Scattering redistributes the energy of the incident beam to all directions. The overall effect is the removal of energy from the incident radiation.
Earth radiation:
Short wave radiation (0.3~2.5μm) —— reflected radiation
Middle wave radiation (2.5~6μm) —— reflected radiation & thermal radiation
Long wave radiation (≈6μm) —— thermal radiation
Atmospheric windows

(1) 0.30～1.15μm (whole visible region, partial ultraviolet region and partial NIR region): used to detect reflection of solar radiation on earth surface at daytime;

(2) 1.30～2.50μm (NIR region): mainly used in Geologic remote sensing;

(3) 3.50～5.00μm (MIR region): used to detect objects at high temperature, e.g. forest fire, volcano, nuclear blast;

(4) 8～14μm (thermal region): used to detect thermal radiation energy, emissivity under normal temperature;

(5) 1.00mm～1m microwave (millimeter-wave, centimeter-wave, decimeter-wave): can penetrate clouds, vegetation, ice and soil with considerable thickness, can work day and night and under all-weather conditions.
1.2 Interaction of Radiation with Matter

\[ E_1(\lambda) = E_R(\lambda) + E_A(\lambda) + E_T(\lambda) \]

\( E_1 \) incident radiation. \( E_R \) reflected radiation; \( E_A \) absorbed energy; \( E_T \) transmitted energy: vary with the wavelength.
Reflectance:

\[ L_\lambda = \frac{\rho_\lambda E_\lambda}{\pi} \text{ Wm}^{-2} \text{sr}^{-1} \mu m^{-1} \]

\[ \rho_\lambda = \frac{\pi L_\lambda}{E_\lambda} \]

Reflectance curve is a curve which illustrate the variety of object reflectance at different wavelengths. It shows spectral signatures of surface materials.
2 Spectral Properties of Earth Materials

2.1 Spectral Features

2.2 Field Spectrum Measurement
2.1 Spectral Features

Spectral Library

Typical Reflectance Spectrum

- Alunite as seen by three systems
- Chlorite
- Kaolinite
- Cotton fibre
- Atmospheric absorbing spectrum

Wavelength (μm)

Reflectance
2.1 Spectral Features

Processes that cause mineral absorption features

• Electronic

  Interactions between electrons and crystal fields, Electronic transitions(Electronic energy levels)

\[
E_2 - E_1 = \Delta E = \frac{hc}{\lambda} \quad \lambda = \frac{hc}{\Delta E} \, (\mu m)
\]

• Molecular Vibrations
2.1 Spectral Features

Ruby, $\text{Al}_2\text{O}_3 + \text{Cr}^{+++}$
2.1 Spectral Features

Jade, \( \text{Be}_3\text{Al}_2\text{Si}_6\text{O}_{18} + \text{Cr}^{+++} \)
2.1 Spectral Features

Water vapour

Molecular Vibrations
Vegetation is sensitive to optical radiation from the ultraviolet through infrared spectral range and is optimized to absorb solar energy in the visible spectrum to drive the biological process of photosynthesis necessary for plant growth.

Typical spectral curve of vegetation

2.1 Spectral Feature

Transpiration
Photosynthesis
fluorescence

2.7
When plants get ill, Chlorophyll absorption intensity will get weaker and reflectance will get higher especially in red light region. For this reason, ill plants are often in light yellow color.
Spectral characteristics of healthy plants in NIR region:

- High reflectance (45% ~ 50%)
- High transmittance (45% ~ 50%)
- Low absorptance (<5%)

With the increase of Chlorophyll consistency, photosynthesis will be strengthened and more photons in long wavelength will be consumed.
2.1 Spectral Feature

NDVI = \[ \frac{R(860\text{nm}) - R(660\text{nm})}{R(860\text{nm}) + R(660\text{nm})} \] \times 100

Red-edge reflectance:

\[ R_{\text{red}} = \frac{[R(670\text{nm}) + R(780\text{nm})]}{2} \]

Red-edge inflection:

\[ \lambda_{\text{red}} = 700\text{nm} + \frac{R_{\text{red}} - R(700\text{nm})}{[R(740\text{nm}) - R(700\text{nm})]} \times 40\text{nm} \]

Spectral bands selection  \rightarrow  color composition  
\rightarrow  index image
Spectral properties of vegetation:

1. Unlike minerals, all vegetation is composed of a limited set of spectrally active compounds.

2. The relative abundances of these compounds, including water, are indicators of the condition of the vegetation and of the environment in which the vegetation is growing.

3. Vegetation architecture has a very strong influence on the overall characteristics of the reflectance spectrum.

4. The spatial scale of the reflectance measurement is important in determining the observed reflectance.
5. Reflectance in the visible and NIR region (350—800nm) is dominated by absorption from chlorophyll and other accessory pigments.

6. Reflectance in the SWIR (800 to 2500nm) is dominated by absorption from liquid water in the plant’s tissue.

7. Reflectance in the SWIR is modified by minor absorption features associated with some special chemical bonds (C-H, N-H and CH2) bearing compounds such as starches, proteins, oils, sugars, lignin and cellulose.
Spectral feature of soil

primary minerals in soil:
quartz, feldspar, muscovite, a spot of hornblende, pyroxene, apatite, hematite, pyrite

secondary minerals in soil:
① simple saline compound: carbonate, sulfate, chloride and ....
② hydrous oxide: ferric oxide, aluminum oxide, silicon oxide...
③ layer aluminum silicate minerals: kaolinite, surface and hydrous micas...
2.1 Spectral Feature

Water is a very important component in soil. With increase of water in soil, reflectance of soil will gets lower. Especially in water absorption bands (1.4, 1.9 and 2.7 μm), reflectance gets lower very obviously. (water content: A: 0.32; B: 0.25; C: 0.14; D: 0.07)

Spectral curve of soil with a low water content (g/cm³)
Generally, factors influencing on soil reflected spectra:

minerals, moisture content, organic matter, ferric oxide and soil texture…
2.1 Spectral Feature

**Spectral feature of water**

Clean natural water has great absorption of radiation in region of 0.4-2.5 µm. Absorptance is obviously greater than other materials on earth surface.

In visible region, interaction of energy and materials is much more complex. Spectral reflected characteristics are mainly derived from these three aspects as follows:

1. Reflection on water surface
2. Reflection of substance in water bottom
3. Reflection of suspended substance in water

In NIR and MIR region, water almost absorbs all radiant energy. That is to say, clean natural water is similar to a blackbody in these regions. Between 1.1 and 2.5 µm in wavelength, clean natural water reflectance is near to be zero.
2.2 Field Spectrum Measurement

Spectrometer/ Spectroradiometers:

Spectrometer can obtain continuous spectral radiation curve of ground objects in the region from UV to NIR of solar reflected radiation (300-2500nm)

How to obtain Reflectance:

- Use spectrometer (ground/field) to measure radiant energy of object and standard white board respectively. Their ratio is the spectral reflectance of ground object.

- The reflectance of standard white board in wavelength from 400-2500 nm is 100%.
2.2 Field Spectrum Measurement

indoor artificial illumination:

advantages: Many times spectral measurements of in limited time. Easy to control light source, view field and geometrical shape of object measured.

disadvantages:

(1) Visible light is much weaker than solar light and generates more infrared radiation.
(2) Because of parching effect, vegetation samples will lead to water loss.
(3) For irregular objects, it should be paid special attention that how to set the distance from itself to light source.
2.2 Field Spectrum Measurement

Solar illumination:

Advantages: solar light source is just the light source of surroundings detected and is very steady

disadvantages:

(1) because of atmospheric absorption, there is no signals in some region

(2) steady weather conditions are requisite

(3) Measurement time should be around noon. Especially in winter, the time is very short
2.2 Field Spectrum Measurement

**Two-channel field Spectroradiometer:**

Obtain spectra of objects and standard white board simultaneously
2.2 Field Spectrum Measurement

**Function of Field Spectroradiometer in hyperspectral remote sensing:**

1. Radiometric calibration of sensors in HRS experiments
2. Field spectral data is requisite for some models of image reflectance conversion
3. Standard spectral data and Field spectral libraries
4. Deliberation of performance index of HRS sensors
5. Geological minerals mapping
6. Directional reflected characteristics of objects
7. Quantitative relation between field spectral data and object characteristics (biophysical and biochemical parameters)
3 Sensor Technology

3.1 Basic Concepts
3.2 Imaging Characteristics of HRS
3.3 Expression of Hyperspectral Image data
3.4 Key imaging Technologies of HRS
3.5 Spatial Imaging Models of Imaging Spectrometry
3.6 Spectral Imaging Models of Imaging Spectrometry
3.7 An Introduction of Imaging Spectrometry
3.1 Basic Concepts

**Imaging technology** of remote sensing always go head in the two aspects as follows:

1. to improve image Spatial Resolution by narrowing the Instantaneous Field Of View (IFOV) of sensors
2. to improve image Spectral Resolution from increasing bands and narrowing bandwidth

**Spectroscopy**

**Imaging spectrometry**

**Imaging technology**
3.1 Basic Concepts

(1) Spectral Response:

\[ Lr = \int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} Le(\lambda) f(\lambda) d\lambda \]

\( f(\lambda) \): Spectral Response Function
(2) Spectral Resolution:

Bandwidth of 50% of spectral response
3.1 Basic Concepts

(3) Dwell Time

The time which IFOV of a sensor scans a ground cell

(4) Spectral Sampling Interval

The interval of peak value of two adjacent spectral channels

(5) Contrast Ratio (CR)

$$CR = \frac{B_{\text{max}}}{B_{\text{min}}}, \text{ brightness scale: 0 ~ 10}$$
3.1 Basic Concepts

(6) Spatial Resolution:

Angular Resolving Power is determined by Instantaneous Field of View, IFOV (unit is mrad). Ground area of IFOV is called Ground Resolution Cell.

Based the IFOV and flight altitude, we can calculate the image spatial resolution:

\[ \text{GR} = 2 \times \tan(\text{IFOV}/2) \times \text{altitude} \]

\[ \alpha = \frac{L}{r} \text{ rad} \]
(6) Spatial Resolution:

\[
IFOV = \frac{1}{1000} \text{ rad} = 1 \text{ mrad}
\]

Angular resolving power = 1 mrad

Flight height 1 m,
5 line-pairs/cm

\[
r = 1000 \text{ mm}, \quad L = 1 \text{ mm}
\]
Angular Field of View (FOV): 

\[
\text{FOV} + H \quad \gggg \quad \text{Ground Swath (GS)}
\]

\[
\text{GS} = \tan\left(\frac{\text{FOV}}{2}\right) \times \text{altitude} \times 2
\]
(8) Line scanning velocity $v$ (line/s):

Ground speed of aircraft must satisfy:

$$V \leq \text{pixel resolution} \times \text{Line scanning velocity}$$
3.1 Basic Concepts

(9) SNR:

SNR is the ratio of the signal detected by a sensor to noise. Generally, SNR, image spatial resolution and spectral resolution contradict each other and cannot be improved simultaneously.

\[
\frac{V_s}{V_N} = \frac{D_0^2 \omega \tau_a \tau_0 D_\lambda^*}{4 \sqrt{A_D \Delta f}} X_T \Delta T
\]

- **\(D_0\)** Effective aperture of optical system
- **\(\omega\)** Instantaneous Angular Field of View
- **\(\tau_a\)** Atmospheric average transmittance
- **\(\tau_0\)** Average transmittance of optical system
- **\(D_\lambda^*\)** Detectivity of the detector
- **\(A_D\)** Photosensitive area of the detector
- **\(\Delta f\)** System electronical noise bandwidth
- **\(X_T\)** Spectral integral
- **\(\Delta T\)** Time integral

**Noise sources:**

- **Photon noise**
- **Detector noise**
- **Postdetector electronic noise**
3.1 Basic Concepts

Figure 21. Laboratory kaolinite spectrum convolved to various signal-to-noises.

Laboratory kaolinite spectrum converted to various SNR
3.2 Imaging Characteristics of HRS

**Imaging spectrometer:**

Compared to field spectrometer, imaging spectrometer gather spectra not only for point targets but for continuous areas; namely it is imaging.

Compared to conventional multispectral RS, its spectral channels are not discrete but continuous. So we can obtain a smooth integrated spectral curve.

**Characteristics of HRS:**

1. high spectral resolution
3.2 Imaging Characteristics of HRS

Characteristics of HRS:

(2) a combination of image and spectra information

![Diagram](attachment:diagram.png)
3.2 Imaging Characteristics of HRS

Characteristics of HRS:
(3) many spectral channels, continuous imaging in some region over wavelengths
3.3 Expression of Hyperspectral Image data

(1) The Image Cube

Spatial plane: O-XY
Line spectral plane: O-XZ, O-YZ
3.3 Expression of Hyperspectral Image data

(2) two-dimensional spectral curve

(3) three-dimensional spectral curved surface
3.4 Key imaging Technologies of HRS

（1）Technologies of Detector Focal Plane

**CCD**: detector arrays
visible and NIR: Si
NIR: InGaAs
SWIR: InSb, PbS
MIR: InSb
Thermal infrared: HgCdTe
3.4 Key imaging Technologies of HRS

（1）Technologies of Detector Focal Plane

Hybrid-focal-plane bonding techniques
Factors influencing spectral response of a sensor:

（1）Energy Flux, namely energy detected by the sensor

（2）Flight Height: for a given ground cell, energy detected has a negative correlation with flight height.

（3）Spectral resolution: the wider spectral channels (namely spectral resolution is lower), the stronger signal is

（4）IFOV: determined by the size of detector elements and focal distance of scanning optical system

（5）Dwell Time: a positive relation with spectral response
3.4 Key imaging Technologies of HRS

(2) Spectrophotometry Technology
   Dipersive imaging spectrometer;
   Interferential imaging spectrometer
   Light-filter imaging spectrometer

(3) Technologies of High-speed Data Collection, Transmission, Record and Real-time Lossless Compression

(4) Technologies of Spectral and Radiometric Calibration

(5) Technologies of Imaging Spectral Information Processing
3.5 Spatial Imaging Models of Imaging Spectrometer

(1) Whiskbroom Imaging Spectrometer
Advantages (Whiskbroom):
(1) wide FOV;
(2) good registration of pixels;
(3) easy to calibrate detector;
(4) wide Spectral region

Disadvantages:
Dwell time is too short, difficult to improve spectral and spatial resolution and SNR
3.5 Spatial Imaging Models of Imaging Spectrometer

(2) Pushbroom Imaging Spectrometer side
Advantages (Pushbroom):
(1) Dwell Time is much longer, hence spectral and spatial resolution can be improved
(2) without optical mechanical scanning component, the bulk of instrument is small
Disadvantages:
(1) difficult to augment FOV;
(2) difficult to calibrate CCD arrays;
(3) Difficult to develop Short wave and IR detector arrays
3.6 Spectral Imaging Models of Imaging Spectrometer

(1) Spectrophotometric imager

glass prism spectrometer
3.6 Spectral Imaging Models of Imaging Spectrometer

(2) Fourier Imaging Interferometer

**Advantages:** high light flux, high spectral resolution, small bulk.

**Disadvantages:** high-precision optical design and calibration, data processing and application.

Light intensity of coherent radiation detected $I(\delta)$:

$$I(\delta) = \frac{1}{2} I(0) + \int_0^\infty B(\delta) \cos 2\pi \sigma \delta d\sigma$$

Fourier cosine transfer of incoming radiation on $B(\sigma)$ and interferogram $E(\delta)$:

$$\int_0^\infty [I(\delta) - \frac{1}{2} I(0)] \cos(2\pi \sigma \delta) d\sigma$$

Optical path difference $\delta_{\text{max}}$ determines spectral resolution:

$$\Delta \sigma = \frac{1}{\delta_{\text{max}}}$$
3.6 Spectral Imaging Models of Imaging Spectrometer

1) **Time Modulated Imaging Interferometer** (moving mirror Imaging Interferometer):

A whole period is needed to finish sampling to take a interferogram

Unsuitable for the detection of object at a high speed

2) **Spatial Modulation Imaging Interferometer**

No need to move components
Static spectral imaging
3.6 Spectral Imaging Models of Imaging Spectrometer

Conversion of Diffraction Grating and Interferential Spectral Resolution

Grating: wavelength $\lambda$
Interferometer: wave number $V$
$V = \frac{1}{\lambda}$

Wave number resolution $\Delta V$: cm$^{-1}$

$$\Delta \lambda = \frac{1}{\frac{1}{\lambda} - \Delta V} - \lambda$$

$\Delta \lambda = \Delta V \times \lambda^2$

While $\Delta V = 100$,

$\Delta \lambda_{400\text{nm}} = 1/(1/400 - 100 \times 10^{-7}) - 400 \approx 1.6\text{nm}$

$\Delta \lambda_{800\text{nm}} = 1/(1/800 - 100 \times 10^{-7}) - 800 \approx 6.5\text{nm}$

$\Delta \lambda_{2000\text{nm}} = 1/(1/2000 - 100 \times 10^{-7}) - 2000 \approx 41\text{nm}$

<table>
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<tr>
<th>$\mu m (\lambda)$</th>
<th>cm$^{-1}$ (V)</th>
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<tbody>
<tr>
<td>0.5</td>
<td>20000</td>
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<tr>
<td>1.0</td>
<td>10000</td>
</tr>
<tr>
<td>10.0</td>
<td>1000</td>
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</table>
3.7 An Introduction of Imaging Spectrometers

Astronautics Imaging Spectrometer System-------USA

**HIRIS** (24km swath, 30m pixel, 192 bands, 11 nm channels, 0.4-2.5 µm), 1988-1992 end

**TRW**, Lewis, 382 bands, 1987 failure;

**Warfighter-1**, **OrbView-4**, (5 km swath, 8-20 m pixel, 200 bands, 10 nm channels, 0.4-2.5 µm), 2001 failure

**FTHSI**, **MightSat-II**, (150 bands, 450-1050 nm, 30 m), 2000 success.

**Hyperion**, **EO-1**, (7.5 km swath, 30 m pixel, 220 bands, 10 nm channels, 0.4-2.5 µm), 2001 success.
Astronautics Imaging Spectrometer System-------USA

Warfighter-1/Orbview-4: Launch failed in Sep 2001

HRS imager system parameters:
Ground Swath : 5km, Spectral Coverage : 200 (450-2500nm)
Spectral Resolution: 10nm(12bits) SNR: >200
Spatial Resolution: 8m (4m multi/1m pan), 20m

Hyperion/EO-1: Launch succeeded in Jan 2001
Ground Swath : 7.5km, Spatial Resolution : 30m,
Spectral Coverage :0.4—2.5μm
Spectral Bands:220
Visible—NIR(400-1000nm): 60bands,
SWIR(900-2500nm): 160bands.
3.7 An Introduction of Imaging Spectrometers

Astronautics Imaging Spectrometer System------Europe

PROBA/CHRIS:  Launch succeeded in Oct 2001

Five selective modes

Spectral Coverage:  0.4—1.05μm
Spectral Resolution:  6—33nm
Ground Swath:  13km
Spatial Resolution:  17m/34m

MODE 1:  411nm-997nm,  34m,  62bands
MODE 2:  411nm-1019nm,  17m,  18bands,  water quality RS
MODE 3:  442nm-1019nm,  17m,  18bands,  land RS
MODE 4:  489nm-792nm,  17m,  18bands,  vegetation RS
MODE 5:  442nm-1019nm,  17m,  37bands,  land RS
### 3.7 An Introduction of Imaging Spectrometers

#### Astronautics Imaging Spectrometer System------China

**HJ-1A**

<table>
<thead>
<tr>
<th>Environment hyperspectral remote sensing imaging spectrometer</th>
<th>amount(num)</th>
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<tbody>
<tr>
<td>bands</td>
<td>128(bands selective loading)</td>
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<tr>
<td>spectral coverage/μm</td>
<td>0.45~0.95</td>
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<tr>
<td>spectral resolution/nm</td>
<td>5</td>
<td></td>
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<tr>
<td>spatial resolution/m</td>
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<tr>
<td>ground swath/km</td>
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<td>AFOV</td>
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<td>Digitization /bit</td>
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<tr>
<td>SNR/dB</td>
<td>50<del>100(450</del>950nm 5% reflectance)</td>
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<tr>
<td>radiometric calibration precision</td>
<td>Absolute calibration precision 10%, relative calibration precision 5%</td>
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</tr>
<tr>
<td>dwell time/ms</td>
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</tr>
<tr>
<td>original data rate/(Mbit/s)</td>
<td>60 (all over the spectrum)</td>
<td></td>
</tr>
</tbody>
</table>
3.7 An Introduction of Imaging Spectrometers

(1) MAIS

**Modular Airborne Imaging Spectrometer**
71 spectral bands
VIS—NIR: 32 bands (0.44~1.08μm)
   Spectral resolution: 20nm
SWIR: 32 bands (1.5~2.45μm)
   Spectral resolution: 25nm
TIR: 7 bands (8.0~11.6)
   Spectral resolution: 0.45μm
IFOV: 3.0mrad
FOV: 90 degree
Scan rate: 10-20 (lines/sec.)
Digitization: 12bit
3.7 An Introduction of Imaging Spectrometers

MAIS Data in Tarim Basin of China (32 bands/30,000km²)
OMIS

**Operational Module Imaging Spectrometer**

- 128 spectral bands
- VIS—NIR: 64 bands (0.4~1.1um)
  - Spectral resolution: 10nm
- NIR: 16 bands (1.1~2.0um)
  - Spectral resolution: 30nm
- SWIR: 32 bands (2.0~2.5um)
  - Spectral resolution: 15nm
- MIR: 8 bands (3.0~5.0um)
  - Spectral resolution: 250nm
- TIR: 8 bands (8.0~12.5um)
  - Spectral resolution: 500nm
- IFOV: 3.0mrad, FOV: >70°
- Scan rate: 5-20 (lines/sec.)
- Digitization: 12bit
3.7 An Introduction of Imaging Spectrometers

OMIS-1 Optical System Sketch
3.7 An Introduction of Imaging Spectrometers

OMIS Data in Beijing

OMIS Data in Shaanxi Prov.
(3) PHI

**Pushbroom Hyperspectral Imagers**

Spectral coverage:
VIS to NIR (450-850nm)
Spectral bands: 244
Spectral resolution: <5nm
Spectral sampling interval: 1.9nm
FOV: 21° (0.36rad)
IFOV: 1.5 mrad
Pixels per line: 376
Digitization: 12 bits
Sensor weight: 9kg
3.7 An Introduction of Imaging Spectrometers

Nagano
Image Cube of 80-bands PHI HRS Image

Minamimaki
(4) **AVIRIS**

Spectral coverage:
VIS to NIR (400-2500nm)

Spectral bands: 224

Spectral resolution: <10nm

FOV: 30°

IFOV: 1.0 mrad

Digitization: 12 bits
3.7 An Introduction of Imaging Spectrometers

AVIRIS Signal-Noise Ratio

SNR

Wavelength, nm

2004
2001
1994
1987
(5) HYMAP

Spectral coverage:
VIS: 400-800nm, 15nm bands;
NIR: 881-1335nm, 14nm bands;
SWIR1: 1400-1813nm, 12nm bands;
SWIR2: 1950-2543nm, 16nm bands;

Spectral bands: 126

FOV: 60°

IFOV: 2.5 mrad (along_track)
2.0 mrad (across_track)

Pixels per line: 512
4 Image Processing and Applications

4.1 Spectral Feature Selection and Extraction
4.2 Remote Sensing Image Classification
4.3 Examples of Remote Sensing Application
4.1 Spectral feature selection and extraction

1) Large spectral data quantity and calculation quantity

Suppose that Original spectral band number is N, number after selection is M, N>M, so the number of spectral features combination is:

\[ C = \frac{N!}{(N-M)! M!} \]

If N=100, M=3:

\[ C = \frac{100!}{(100-3)! 3!} = 161,700 \]

2) Statistic parameters’ estimate errors will be larger

With the increase of bands, the statistic parameters of samples will be more and more. In order to get more accurate estimation of parameters, the number of training samples must be 10 times of bands. When the number of samples is invariable, there will be Hughes effects on the accuracy of classes with the changes of band numbers.
4.1 Spectral feature selection and extraction

Average Error Ratio

\[ P(e|m,n) \]

Hughes effect
4.1 Spectral feature selection and extraction

Spectral Feature Selection is that a subclass is selected in the spectral feature space aiming at the special object. This subclass is a shrunken spectral feature space, but it includes the main feature spectra of this object, and the subclass can distinguish other ground samples with maximized limit in many object combinations.

Spectral feature Selection:  
Search for spectral feature position  
Spectral correlation analysis  
Statistics of spectral distance
4.1 Spectral feature selection and extraction

Location search of spectral features ---- Continuum removal

![Graphs showing spectral feature selection and extraction with continuum removal.](image-url)
4.1 Spectral feature selection and extraction

Continuum removal

Absorption spectral curves of dolomite and kaolinite

Projections of dolomite and kaolinite in the selected feature space
4.1 Spectral feature selection and extraction

Image color composition based on the spectral feature selection — quick search of interested objects in image

RGB bands and their corresponding complementary colors
4.1 Spectral feature selection and extraction

Spectral feature correlation analysis

\[ r = \frac{S_{xy}}{\sqrt{S_{xx} S_{yy}}} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}} \]
4.1 Spectral feature selection and extraction

spectral distance

mean of spectral curve

Spectral average $\mu$  $Mean$
Standard deviation $\sigma$  ± $Stdev$
Extremum $\Delta$  $Max / Min$
Measurement of spectral bands distance

(1) Euclidean distance

\[ d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ki} - x_{kj})^2} \]

(2) Normalized mean distance

\[ d_{\text{norm}} = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2} \]

(3) J-M distance

\[ J_{ij} = [2(1 - e^\alpha)]^{1/2} \]

In it,

\[ \alpha = \frac{1}{8} (\mu_i - \mu_j)^T \left( \frac{\sigma_i + \sigma_j}{2} \right)^{-1} (\mu_i - \mu_j) + \frac{1}{2} \log_e \left[ \frac{(\sigma_i + \sigma_j)/2}{|\sigma_i| \cdot |\sigma_j|^{1/2}} \right] \]

(4) Comparability measurement

\[ \cos \theta_{ij} = \frac{\sum_{k=1}^{p} x_{ki} x_{kj}}{\sqrt{\sum_{k=1}^{p} x_{ki}^2 \sum_{k=1}^{p} x_{kj}^2}} \]
4.1 Spectral feature selection and extraction

Feature Extraction

\[
\begin{align*}
&\text{Hyper-spectral image} \\
&X_1 \quad X_2 \quad X_3 \quad X_4 \quad X_5 \\
\end{align*}
\]

\[
F(x_1, \ldots, x_5) \\
\]

\[
\begin{align*}
&\text{Optimized feature space} \\
&Y_1 \quad Y_2 \\
\end{align*}
\]

(1) Feature Extraction based on the K-L transform (Principal Components Transform)

Statistic curve of covariance matrix eigenvalue of AVIRIS hyperspectral image of 50 channels ---- Ordering the deviation from small to large
(2) Minimum Noise Fraction transform

MNF transform orders the transformed components by the value of signal-to-noise ratio but not deviation. Every observed pixel $z$ is made up of a signal vector $s$ with none noise in ideal condition and a noise vector $n$. $z$ can be shown as:

$$z = s + n$$

In MNF algorithm, we first use low-pass filter to extract noise image $N$ from original image $Z$, then calculate covariance matrix $\Sigma_z$ and $\Sigma_n$ of $Z$ and $N$.

Calculate $\Sigma_n^{-1}\Sigma_z$ the eigenvalue $\lambda_i$ and eigenvector $u_i$, suppose these eigenvalue are satisfied with the relations:

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$$

Let:

$$U = (u_1, \cdots, u_L)$$

Then MNF transform can be expressed as:

$$Y = U^T Z$$
4.1 Spectral feature selection and extraction

Feature Extraction — — wavelength Information

(1) absolute position information of band shape features (wavelength)
   reflectance feature span: wavelength interval?

(2) relative position information of band shape features (band ordering)
   Wavelength span: descent order? Ascent order?
4.1 Spectral feature selection and extraction

Spectral morphological analysis --- spectral feature parametrization

(1) Spectral slope and exposure
(2) Spectral binary coding
(3) Spectral derivative
(4) Spectral integral
(5) Spectral absorption index (absorption position, absorption depth, absorption width, absorption symmetry)
(6) Functional simulation of spectral curve
4.1 Spectral feature selection and extraction

(1) spectral slope and exposure

In spectral span \([\lambda_1, \lambda_2]\), simulated a line below:
\[ R = aX + b, \quad X \in [\lambda_1, \lambda_2] \]
Then:

\[ a < 0, \text{ negative slope, SSI } = -1 \]
\[ a > 0, \text{ positive slope, SSI } = 1 \]
\[ a = 0, \text{ flat slope, SSI } = 0 \]
(2) spectral binary coding

- Binary coding
  
  \[ h(n) = \begin{cases} 
  0 & \text{if } x(n) \leq T \\
  1 & \text{if } x(n) > T 
  \end{cases} \]
  
  \[ n = 1, 2, \ldots N \]

- Coding only at special wavelength range

- Subsection coding

- Multi-threshold coding
  
  \[ h(n) = \begin{cases} 
  00 & \text{if } x(n) \leq T_a \\
  01 & \text{if } T_a < x(n) \leq T_b \\
  11 & \text{if } x(n) > T_a 
  \end{cases} \]
  
  \[ n = 1, 2, \ldots N \]
(3) **Spectral Derivative**

\[ R'(\lambda_i) = \frac{R(\lambda_{i+1}) - R(\lambda_{i-1})}{\lambda_{i+1} - \lambda_{i-1}} = \frac{dR(\lambda)}{d\lambda} \]

(4) **Spectral integral**

\[ \varphi = \int_{\lambda_1}^{\lambda_2} f(\lambda) d\lambda \]
4.1 Spectral feature selection and extraction

(5) spectral absorption index

- **Absorption Position, AP:**
  The wavelength whose reflectance is the lowest in the spectral absorption vale, that is $AP = \lambda$, when $\rho\lambda = \text{Min}(\rho)$

- **Absorption Depth, AD:**
  At the range of band absorption, the distance from the lowest point of reflectance to normalized continuum, $AD = 1 - \rho_0$, $\rho_0$ is the reflectance of absorption vale.

- **Absorption Width, AW:**
  Spectral width at half the maximum absorption depth (FWHM)

- **Absorption Asymmetry, AA:**

![Diagram showing absorption indices](attachment:image.png)
(5) Spectral absorption index

\[ SAI = \frac{\rho}{\rho_m} = \frac{d\rho_1 + (1-d)\rho_2}{\rho_m} \]

\[ d = \frac{(\lambda_m - \lambda_2)}{\lambda_1 - \lambda_2} \]
(6) Functional simulation of spectral curve

Vegetation visible spectral reflectance (VVS R) model

\[ R(\lambda) = R_0 + (R_g - R_0) \exp \left\{ -C \left[ \ln \left( 1 + \left( \frac{\lambda - \lambda_g}{F_C} \right) \right] \right\} \]

\[ R(\lambda) \in [500nm, 680nm] \]

Use Inverted-Gaussian model to express red edge reflectance band shape of vegetation (670-800nm) with definite quantity.

\[ R(\lambda) = R_s - (R_s - R_o) \exp \left( - \frac{(\lambda_o - \lambda)^2}{2\sigma^2} \right) \]

In it: \( R_s \) stands for maximum spectral reflection value

\( R_o \) stands for minimum spectral reflection value

\( \lambda_o \) is maximum absorption wavelength

\( R(\lambda) \) is the reflectance at wavelength \( \lambda \)

\( \sigma \) is the standard deviation of Gauss equation
Data simulation of Inverted-Gaussian (IG) model

A. Best iterative fit

Set the original value of model parameters, the range of each parameters and the criterion of minimum square deviation. And then set the iterative step to the parameters (0.1nm, 0.03nm, 0.1% respectively in general). At last, iterate according to the step length. Don't stop iterating until catching the minimum allowed error. It can be shown from the iterative result that IG model parameters are awfully not sensitive to original value of $\sigma$ at the range of 15nm to 45nm.
When the number of pixels are larger, each pixel eigenvector of similar ground objects show multidimensional normal distribution approximately.
The essential of classification divide multidimensional feature space into some regions (subspace). Each region is equivalent to a class, it is also that pixels in the region in the same class.

The standard of classification or dividing area can summarize two methods:

First, from statistic characteristics of each class (or group), study the region which the class should belong to. For instance, the mean of each class are centers, then subsume the points which is in the range of standard deviation to a class.

The second method is from dividing boundaries in classes, then builds boundary function or discriminant function, usually called discriminant analysis.

4.2 remote sensing image classification
4.2 remote sensing image classification

The general process of remote sensing image supervised classification:

```
Make sure of classification type → Feature selection → Training data extraction → Measuring total statistics → Classification → Results test
```

The general process of remote sensing image unsupervised classification:

```
Feature selection → Make sure of classification number and transcendent knowledge → Measuring total statistics → Classification → Make sure of classification type → Results test
```
From the angle of spectral image, the effect of remote sensing image classification depends on the following factors:

1. **Divisibility of classes**: under unartificial influence the original bands of ground objects are divisible, which is the premise of remote sensing image classification;

2. **Dimensions of image bands space**: in general, the SNR of image bands reaches some degree, the more the spectral bands are, the better classification is.

3. **The quantity of training samples**: more larger the number of training samples are, more complete and representative the training characteristics of ground objects are, so it is good for classification.

4. **The type of classifier and the project of classification**
4.2 remote sensing image classification

Classifier design

Input model A, B, C

classifier

Output model

A

B

C

Classification feature

Classification criterion

Classification rule

Classification algorithm

classifier
4.2 Remote sensing image classification

Classifier is composed of 4 parts: feature, criterion, rule and algorithm.

(1) Classification feature
- feature selection, feature extraction

(2) Classification criterion
Usually, classification criterion should reflect the distribution of patterns:
  - mean linear divisibility - Euclidean distance
  - normal distribution - Mahalanobis distance
  - linear indivisibility - likelihood

Criterion selection should consult classification feature:
- Spectrum wave shape - spectral semblance or spectral included angle.
- Reflectivity feature of independent bands - criterion of distance
4.2 remote sensing image classification

(2) classification criterion

- correlation coefficient
  \[ r_{ij} = \frac{\sum_{k=1}^{p} (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)}{\sqrt{\sum_{k=1}^{p} (x_{ki} - \bar{x}_i)^2 \sum_{k=1}^{p} (x_{kj} - \bar{x}_j)^2}} \]

- coefficient of similarity
  \[ \cos \theta_{ij} = \frac{\sum_{k=1}^{p} x_{ki} x_{kj}}{\sqrt{\sum_{k=1}^{p} x_{ki}^2 \sum_{k=1}^{p} x_{kj}^2}} \]

- Eculidean distance
  \[ d_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ki} - x_{kj})^2} \]
4.2 remote sensing image classification

(2) Classification criterion

**absolute distance**

\[ d_{ij} = \sum_{k=1}^{p} |x_{ki} - x_{kj}| \]

**Mahalanobis distance**

\[ d_{ij}^2 = (x_i - x_j)^T \sum_{ij}^{-1} (x_i - x_j) \]

**mixed distance**

\[ d_{ig} = \sum_{k=1}^{p} |x_{ki} - M_{kg}| \]
(2) Classification criterion

- **dispersion**
  \[
  D_{ij} = \frac{1}{2} tr \left( \sum_i - \sum_j \right) \left( \sum_i^{-1} - \sum_j^{-1} \right) + \frac{1}{2} \left( \mathbf{m}_i - \mathbf{m}_j \right)^T \left( \sum_i^{-1} + \sum_j^{-1} \right) \left( \mathbf{m}_i - \mathbf{m}_j \right)
  \]

- **standard distance**
  \[
  D_{gh} = \sqrt{\sum_{i=1}^{p} \frac{(M_{ig} - M_{ih})^2}{S_{ig} S_{ih}}} \\
  S_{ig} = \sqrt{\frac{1}{n_g - 1} \sum_{k \in g} (x_{ik} - M_{ig})^2}
  \]

- **J-M distance**
  \[
  J_{gh} = \left\{ \int x \left[ \sqrt{p(x \mid g)} - \sqrt{p(x \mid h)} \right]^2 \, dx \right\}^{1/2}
  \]

- **Minkowski distance**
  \[
  d_{ij} = \left[ \sum_{k=1}^{p} \left| x_{ik} - x_{jk} \right|^q \right]^{1/q}
  \]
4.2 remote sensing image classification

(2) Classification criterion

- **Chebyishev distance**

\[
d_{ij} = \max_{1 \leq k \leq p} |x_{ik} - x_{jk}|
\]

- **maximum absolute distance**

\[
d_{ij} = \max(|x_{i1} - x_{j1}|, |x_{i2} - x_{j2}|, \ldots, |x_{ip} - x_{jp}|)
\]

- **range standard distance**

\[
d_{ij} = \frac{1}{P} \sum_{k=1}^{P} \frac{|x_{ik} - x_{jk}|}{R_k}
\]

\[R_k = x_{\max.k} - x_{\min.k}\]
(3) Classification rule

- rule of least error: error probability of classification is least
- rule of least risk: loss of conditional expectation is least
- rule of Neyman-Pearson: conditional probability
- rule of Fischer: distance between groups is most, in a group is least.
- least squares criterion: square error is least
- rule of divisibility based on entropy function: posterior probability distribution
4.2 remote sensing image classification

(4) Classification algorithm – algorithms of unsupervised classification

- parallelepiped algorithm (nonagency parallelepiped classification)
- clustering algorithm
- dividing algorithm (ISOMIX)
- dynamic clustering algorithm
- K – mean algorithm
- ISODATA algorithm
4.2 remote sensing image classification

(4) algorithm of classification –
algorithm of supervised classification

◆ parallelepiped algorithm (parallelepiped classification by input parameters)

◆ minimum distance classification

◆ Fisher linear criterion classification

◆ Bayes criterion classification (maximum likelihood criterion classification – MLC)

◆ fuzzy classification

◆ neural network classification

◆ decision tree

◆ expert system classification
4.2 remote sensing image classification

**Algorithm selection:**

1. If the pattern is linear and divisible, please select the simpler algorithm, such as minimum distance classification.

2. If the pattern is non-linear and divisible, please select the non-linear classification algorithm, such as lamination algorithm or neural network algorithm.

3. If the pattern is non-linear and indivisible, we should do mathematical transformation of feature to get new classification feature, then according to the situation after feature transformation to select algorithm.

4. If the pattern effect of one division is not satisfactory, we can select the algorithm which divide patterns several times.

5. The effect of algorithm selection should be verified by test classification precision. On the contrary, the classification effect can be base of algorithm selection.
Features of hyperspectral image classification

**Advantages:**
① With high spectral resolution, it can get elaborate characteristic spectrum.
② In the the same spatial resolution, remote sensor can cover more wider wavelength range.
③ With many bands, it is convenient for correcting each other.
④ Quantitative continuous spectrum curve afford conditions for bringing image classification to spectrum mechanism model of ground objects.

**Disadvantages:**
① If data redundancy is processed improperly, it could do bad for classification precision.
② It requires much for quantitative manage, and complex data pre-processing.
③ There is high correlativity among bands, and lots of bands. It requires much for the quantity of training samples.
④ It requires much to use statistic classification model for selection of spectral characteristics.
4.2 remote sensing image classification

Algorithm of classification in face of hyperspectral image feature:

The first is the classification method based on data statistic characteristics;
The second is the classification method based on ground objects properties, which is primarily identified by spectral characteristics of ground objects with physical optics properties.

Classification strategy in general:

1. Spectral characteristic matching (feature selection, feature extraction)
2. Spectral waveform matching (distance, angle)
4. Image classification with correlative spectral in pixel space
4.2 Remote sensing image classification

① Binary code matching

For the feature with much difference, code redundancy could be much larger.

② Spectral waveform matching

A. Characteristic function matching

B. Compute the linear semblance between spectrum vector of samples and spectrum vector of each pixel.

\[ R'_n(\lambda) = R_n(\lambda) - R(\lambda) \]

\[ F = \frac{n \sum o_c L_c - \sum o_c \sum L_c}{\sqrt{n \sum o_c^2 - (\sum o_c)^2} \cdot n \sum L_c^2 - (\sum L_c)^2} \]
4.2 remote sensing image classification

③ Spectral Angle Mapping (SAM)

Generalized included angle cosine of two vectors: 
\[ \theta = \cos^{-1} \frac{T \cdot R}{|T||R|} \]
\[ \theta = \cos^{-1} \frac{\sum_{i=1}^{n} t_i \cdot r_i}{\sqrt{\sum_{i=1}^{n} t_i^2} \sqrt{\sum_{i=1}^{n} r_i^2}} \quad \theta \in \left[ 0, \frac{\pi}{2} \right] \]

④ Image classification based on envelope curve elimination

- Band feature extraction with envelope curve elimination for classification
- Spectral band with envelope curve elimination for classification.
4.2 remote sensing image classification

Envelope curve elimination with spectral band for classification:

- Highlighting the spectral feature information of ground objects, it is convenient for comparing and matching of image spectrum.
- For the ground objects whose spectrum curves are similar and gently, spectrum curves after envelope curve elimination are also similar, and brightness difference of primary image are ignored when classifying, so it could bring on precision drop.

⑤ Neural network classification based on target analysis

target analysis:
- spectral histogram analysis
- characteristic band space projection analysis

target combination:
- logical operation
Classification with pixel space associating spectral image

ECHO (Extraction and Classification of Homogeneous Objects) (Kettig and Landgrebe, 1976) is a kind of image data processing method which first process clustering in spatial neighborhood automatically, then reclassify every clustering center. This method may get better effect in the way of spatial continuity.
4.2 remote sensing image classification

Classification with an emphasis on band statistics, involving decision tree

Mixing decision tree structure
Statistic method has some common defects when facing hyperspectral data with magnanimous bands, especially the quantitative data with specific spectral physical meanings.

1. It will bring some difficulties to classification, due to Hughes phenomena exists, and the large quantity of training samples, increase of hyperspectral remote sensing bands.

2. Specific spectral physical meanings of hyperspectral data are ignored usually, band selection and clustering from the angle of pure mathematics entirely, thus it should waste enormous connotation of hyperspectral data.

3. Distribution of ground objects in nature has been regular specifically. If using algorithm of classification based on mathematical models entirely, the result would be some illogical in general.

4. In the classification of decision tree or layer, the sequence has much effect to the results. And the results always are irreversible and random.

4.2 remote sensing image classification
4.2 Remote Sensing Image Classification

Expert decision-making classification with feature optimization

two principles:

(1) The principle based on spectrum feature optimization and parametrization

It’s prior to spectrum feature extraction and optimization, and constructing spectrum feature parameter with exclusive property.

(2) The principle of obscure definition and expert decision-making in class determination

Because of complexity in nature (one side there are solar radiation change, effect of atmosphere and environment, the other side there are various difference among ground objects themselves), and a drop of SNR led by band narrowing and quantity increasing, we should avoid using 0/1 criterion for each pixel adscription. Thus, each classified chart-spot all has double properties of “expandability” and “shrinkage”. Expert knowledge make effects on decisions finally, that could avoid many wrong judgments.
Expert decision-making classification with feature optimization

Make sure of classification type type: (A, B, C, D, E)

Spectral feature extraction and parametrization

\( \varphi (A) = f_A(X_1, \ldots, X_n) \)
\( \varphi (B) = f_B(X_1, \ldots, X_n) \)

Other types (C, D, E)

Spectral feature selection (C, D, E)

\( f_C(X_1, \ldots, X_n) \rightarrow f_C(X_i, \ldots, X_j) \)
\( f_D(X_1, \ldots, X_n) \rightarrow f_D(X_k, \ldots, X_l) \)
\( f_E(X_1, \ldots, X_n) \rightarrow f_E(X_m, \ldots, X_n) \)

Spectral space projection

Independent spectral space (C)
Expert criterion \( \varphi (C) \leq [\alpha_3, \beta_3] \)

Dependent spectral space (D, E)

Similarity \( D: \delta_D (X_k, \ldots, X_l) \)

Similarity \( E: \delta_E (X_m, \ldots, X_n) \)

Expert criterion \( \varphi (D) \leq [\alpha_4, \beta_4] \)

Expert criterion \( \varphi (E) \leq [\alpha_5, \beta_5] \)

Expert criterion \( \varphi (C) \leq [\alpha_1, \beta_1] \)

Expert criterion \( \varphi (B) \leq [\alpha_2, \beta_2] \)

Spectrum analysis for classification type

Image calibration: Bands \( (X_1, \ldots, X_n) \)
4.2 Hyperspectral image classification

1) **Spectrum features parametrization and target extraction**

- Spectrum integral parameter
- Spectral absorption depth parameter with envelope curve elimination
- Reflection ground and red side spectrum parameter

![classified result - woodland](image1)
![classified result - mulching plastic](image2)
![classified result - Kidney bean](image3)
2. Obscure definition and expert decision-making in classes determination

Minimum distance classification extracting Japanese cabbage distribution

Similarity mapping of Japanese cabbage

Classified results of expert-decision of Japanese cabbage
4.2 Hyperspectral image classification

End-to-End Hyperspectral Processing (Dr. F.A. Kruse)

- Apparent Reflectance
- MNF
- PPI
- n-D
- ID
- Map Distribution And Abundance
- Spatial/Spectral Browsing
- Spectral Data Reduction
- Spatial Data Reduction
- Visualization
- Identification
4.2 Hyperspectral image classification

Spectral Similarity Mapping (with Japanese Cabbage)
Spectral Similarity Mapping (with Chinese Cabbage)
Tree Identification

Jam Identification
Vegetation environment assessment effected by mining

groundwater pollution, soil contamination (acidification by mineral deposit)

normal soil

Vegetation healthy

bad

good

Vegetation healthy

bad

good

4.3 Hypersepectral Remote Sensing—Environment Investigation
4.3 Hypersepectral Remote Sensing—Environment Investigation

Spectral comparison truly extracted from HyMap
4.3 Hypersepectral Remote Sensing—Environment Investigation

- No vegetation cover
- Acidification area
- Normal vegetation area

Vegetation acidification:
- LOW
- HIGH
Vegetation acidification

LOW → HIGH

Acidification area

Normal vegetation area
4.3 Hypersepectral Remote Sensing—Environment Investigation

Vegetation-cover area with strong environment-stressed
Vegetation Acid Index (VAI) image

(Calcite-CaCO$_3$)  (Dolomite-MgCO$_3$)

Rock and Mineral mapping results:
- Epidote
- Chlorite
- Mica
- Calcite
- Montmorillonite
- Salt-alkali
Hematite outcrop

Fe$_2$O$_3$
Hematite outcrop finding
Hematite outcrop finding

- natural grass
- plastic grass

Roofing sheet metal
Difference and identification