Earth Observation and Remote Sensing Image Mining

Flora Weissgerber, ONERA, DTIS/IVA
flora.weissgerber@onera.fr
ONERA in a nutshell

Research center in

- Aeronautics
- Defence
- Space

Wind tunnel

Electromagnetic signature

Microscope satellite

Map of France with locations marked.
A. Remote sensing
What is remote sensing

Timelapse of Sierra Nevada
Spain

Sentinel-2 Optical sensor RGB images
What is remote sensing

Time Lapse of Hinlopenstretet
Svalbard Norway

Sentinel-1 SAR sensor VV images
What is remote sensing

Observing the Earth (but it can be another planet) from afar, but not too far (generally with a satellite or airborne sensor)

Multiple questions :

- How much are the water reserve in snow ?
- Is the water free for sailing or is the sea ice too thick ?
- What are the damage after an earthquake ?
- Did another country build a nuclear power plant ?
- How do crops grow this year ?
- What was planted ?
- Did someone build a house without permission ?
- …
Outlines

Objectives

1. Knowing what remote sensing is, and what are the different sensors
2. Knowing the specificity of machine-learning/AI for remote sensing

Outlines

- Remote sensing
  - What are the sensors
  - What are the acquisition constraint
- Data :
  - Data platforms
  - Datasets

- AI for remote sensing
  - Semantic segmentation for mapping
  - Tilling
  - Data augmentation
  - Semi-supervised learning
  - Regression
  - Data mining
Sensors
## Sensors

<table>
<thead>
<tr>
<th></th>
<th>Optical wavelength: 400 to 2200 nm</th>
<th>Electromagnetic wavelength: 1cm to 1m</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Passive:</strong></td>
<td>• Optical imaging sensors</td>
<td>• Radiometers</td>
</tr>
<tr>
<td>measure energy that is naturally available</td>
<td><img src="image1.png" alt="Optical Imaging Sensor" /></td>
<td></td>
</tr>
<tr>
<td><strong>Active:</strong></td>
<td>• LIDAR</td>
<td>• SAR imaging sensors</td>
</tr>
<tr>
<td>provide their own energy source for illumination</td>
<td><img src="image2.png" alt="LIDAR Image" /></td>
<td>• Radar altimeters</td>
</tr>
</tbody>
</table>
Optical sensors

Some current sensors:

- ESA: Sentinel-2 [opendata](#)
- NASA: Landsat (Landsat-9, Landsat-8,...) [opendata](#)
- MAXAR (ex-Digital global): Worldview-3, Worldview-2
- AIRBUS/CNES: Pléiades Neo, Pléiades, Spot-7

<table>
<thead>
<tr>
<th></th>
<th>Sentinel-2</th>
<th>Landsat-9</th>
<th>Worldview-3</th>
<th>Pleiade Neo</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Spatial resolution RGB</strong></td>
<td>10m</td>
<td>30m</td>
<td>1.24m</td>
<td>0.3m</td>
</tr>
<tr>
<td><strong>Radimetric resolution/quantization</strong></td>
<td>12 bits</td>
<td>14 bits</td>
<td>11 bits</td>
<td>12 bits</td>
</tr>
<tr>
<td><strong>Number of bands</strong></td>
<td>10</td>
<td>11</td>
<td>29</td>
<td>6</td>
</tr>
<tr>
<td><strong>Swath</strong></td>
<td>290km</td>
<td>185 km</td>
<td>13 km</td>
<td>14 km</td>
</tr>
<tr>
<td><strong>Revisit time</strong></td>
<td>5 days</td>
<td>8 days</td>
<td>14 days / on demand</td>
<td>26 days / on demand</td>
</tr>
</tbody>
</table>
Wavelength and bandwidth

- Each band has a special target:
  - RGB bands
  - Infrared for vegetation or snow
  - Bande 10 for cloud detection
- Trade off between spatial resolution and spectral resolution

<table>
<thead>
<tr>
<th>Pleides</th>
<th>Spectral resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panchromatique (PA)</td>
<td>470 – 830 nm</td>
<td>50cm</td>
</tr>
<tr>
<td>Blue (B0)</td>
<td>430 – 550 nm</td>
<td>2m</td>
</tr>
<tr>
<td>Green (B1)</td>
<td>500 – 620 nm</td>
<td>2m</td>
</tr>
<tr>
<td>Red (B2)</td>
<td>590 – 710 nm</td>
<td>2m</td>
</tr>
<tr>
<td>NIR (B3)</td>
<td>740 – 940 nm</td>
<td>2m</td>
</tr>
</tbody>
</table>

Figure 1. MSI spectral bands vs. spatial resolution with corresponding FullWidth at Half Maximum (FWHM). Source: [9]
Pushbroom acquisition

- Line are acquired one at a time
- Use the sensor displacement to create an image
- The line need to be merged LOD0 “as acquired by a CCD matrix”
- There may be vibrations
# Level of processing and impact of the atmosphere

<table>
<thead>
<tr>
<th>Level</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>L0</td>
<td>Original data</td>
</tr>
<tr>
<td>L1C</td>
<td>Orthorectified images, Top of Atmosphere (with clouds mask)</td>
</tr>
<tr>
<td>L2A</td>
<td>Orthorectified images, Ground surface reflectance (with clouds removed)</td>
</tr>
</tbody>
</table>

**Cloud detection:**
- Bande 2: Detect dense clouds (spatial resolution 10m)
- Bande 10: Detect thin cloud (spatial resolution 60m)

**Reflectance:**
- Compensate from the solar illumination
- Compensate from the incidence angle

[Diagram of photon flux at nadir and 30°]

[Map indicating high and medium cloud probability]
Resolution, pixel spacing and pan-sharpening

- **Resolution**: capacity to separate two similar targets depends on the acquisition system.
- **Pixel spacing**: size of a pixel in the image domain.

For real images, when sampled at Shannon, the pixel spacing is half the resolution.

**Pansharpening**

Panchromatic band **finer resolution** than RBG bands.

Pansharpening: Pachro + RGB to have a fine resolution RGB image.
Incidence angle and 3D from stereo acquisition

- **Nadir (0°)**
  - No visible façades
  - Mountains are flattened

- **Off Nadir (here 30°)**
  - Façades are visible
  - Reduce repeat-time
  - 3D is possible using stereo acquisition


https://www.orfeo-toolbox.org/CookBook/recipes/stereo.html
**LIDAR acquisitions**

Some current sensors:

Some current products:
- IGN: [https://geoservices.ign.fr/lidarhd](https://geoservices.ign.fr/lidarhd)

**Waveform**
The energy scattered back from the earth through time

**Point cloud**
Sampled waveform
SAR imaging sensor

Some current sensors:

- Biomass (ESA), P band (to be launched in 2023), wavelength $\lambda=70\text{cm}$
- Alos/Palsar (JAXA), L band, wavelength $\lambda=23.62\text{cm}$
- Sentinel-1 (ESA), C band, wavelength $\lambda=5.5\text{cm}$
- Radarsat-2 (CSA-ASC), C band, wavelength $\lambda=5.5\text{cm}$
- TerraSAR-X (DLR) + TanDEM-X, X band, wavelength $\lambda=3.1\text{ cm}$
How image are measured

1. A electromagnetic pulse is emitted
2. The backscattered pulse is measured
3. **Matched filtering**: the measured signal is compared to the sent signal to determine the time between emission and reception
4. Point Spread Function: cardinal sine
5. The signal is a complex number:
   a. The **amplitude** is linked to the backscattered energy
   b. The **phase** is linked to the distance between the target and the sensor
Synthetic aperture

1. Multiple pulses are emitted along the trajectory
2. The backscattered signal is measured and focus in range
3. The backscattered echoes are **focused in azimut** in a larger converging antenna
   Point Spread Function : cardinal sine

The resolution of the signal is refined and an image is formed
Geometry of SAR sensors

- **Azimuth**: along the trajectory
- **Incidence angle**:
- **Slant range**: perpendicular to the trajectory along the line of sight
- **Ground range**: perpendicular to the trajectory along the ground
Geometric effects in SAR images

1) Layover

2) Shadow

3) Contraction

θ : incidence angle
θ' : incidence angle in the middle of the swath
α : local incidence angle

Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N
Secondary lobes

Antennas secondary lobes: ->
Create replicas visible in the sea
San Francisco, TanDEM image

<- Target secondary lobes:
Cardinal Sine Point Spread Function
Salon de Provence SETHI/ONERA image
Speckle noise

Fully developed speckle (Goodman, 1976): sum of scatterers:

1. Independent and identically distributed
2. Modulus and phase are independent
3. Phase uniformly distributed on a $2\pi$ intervalle

For N channel, the backscattering pixel $p$ follows a complex circular normal distribution:

$$p \sim \mathcal{N}_c(0, \mu) = \frac{1}{\pi \mu} e^{-p^\dagger \mu^{-1} p}$$

- Real part follows a normal distribution of variance $\mu/2$
- Imaginary part follows a normal distribution of variance $\mu/2$
- Phase is uniformly distributed on a $2\pi$ intervalle
- The modulus follows a Rayleigh distribution of parameter $\mu$
Filtering

Maximum likelihood estimator

$$\hat{\mu}_{MV} = \sqrt{\frac{1}{L} \sum_{l=1}^{L} x_l^2}$$

$L = \text{number of image}$

$L = \text{number of neighbouring pixels}$

Without filtering

Temporal filtering

SAR Image

On 36 images

$L = 36$

With a $3 \times 3$ window

$L = 9$

With a $13 \times 13$ window

$L = 169$

With a $3 \times 13$ window

$L = 39$

Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N
Interferometry

Two acquisitions from two slightly different point of view

\[ \phi \equiv 2 \frac{2\pi}{\lambda} (R_1 - R_2) \quad [2\pi] \]

The phase difference is proportional to the height, modulu the ambiguity height

\[ h \equiv \frac{1}{k_z} \phi \quad [h_{amb}] \quad k_z = 2 \frac{2\pi}{\lambda} \frac{B_\perp}{R \sin(\theta)} \]

Applications:
- Create Digital Elevation Model (DEM)
- Measure deformation
  - Earthquake
  - Landslide
  - Sea terminating glacier grounding line
Polarimetry

**Horizontal polarisation**

**Vertical polarisation**

4 polarimetric channels

- **HH**
- **HV**
- **VH**
- **VV**

**Color composition**

- **R:** HH
- **G:** HV
- **V:** VV

Tropical forest, French Guyana, SETHI images (NLSAR denoised)

SOMA district, San Francisco, UAVSAR images (NLSAR denoised)
Radar altimeter

Some current sensors:

- CryoSat-2
- SIRAL/AltiKa


Radiometer

Current instrument:
- SMOS

Passif radar instrument
Measure the faint microwave emissions from Earth's surface

Application: levels of soil moisture, sea surface salinity, sea ice thickness, wind speed over the ocean

Ex: Hurricane surface wind field measurement
## Satellite VS Airborne sensors

<table>
<thead>
<tr>
<th>Airborne sensors</th>
<th>Observation satellite</th>
<th>Weather satellite</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor on plane or drones</td>
<td>Cover large areas</td>
<td>Cover VERY large areas</td>
</tr>
<tr>
<td>Cover a “small” area</td>
<td>Far from the earth (700km)</td>
<td>VERY far from the earth (36000km)</td>
</tr>
<tr>
<td>Close to the earth (10km)</td>
<td>Fixed orbit</td>
<td>Fixed position</td>
</tr>
<tr>
<td>Fixed repeat time</td>
<td>Fixed repeat time (~10 days)</td>
<td>Fixed repeat time (~15 min)</td>
</tr>
<tr>
<td>Temporal stack on a mission timescale (few month or few month per year)</td>
<td>Temporal stack on multiple year</td>
<td></td>
</tr>
<tr>
<td>Sub meter resolution</td>
<td>meter to 10 meters resolution</td>
<td>3km resolution</td>
</tr>
</tbody>
</table>
Sun synchronous orbits

Optical satellites:
Half of the orbit is in the sun and half is in the night
Take images around noon local time

Sentinel-2 orbit (Heavens above)

Radar satellites:
Stay at the sun/night limit
The solar panel are always directed to the sun

TerraSAR-X orbit (Heavens above)
Sentinel-3 and Sentinel-6 non sun synchronous orbit

Altimetry satellite missions:
Near-real-time measurements of sea-surface heights

- Cover most of the oceans
- TOPEX/Poseidon and Jason measures continuity
CryoSat-2 non sun synchronous orbit

Go to higher latitudes than sun synchronous sensors

Geostationary orbits for weather forecast

The orbit is at 36 700km
Fixed point above the earth

Earth 12,742 km

observation satellite: 800 km

Geostationary 36,700 km
Coregistration

Having multiple images/signals on the same grid

Two main options:

1. Having all the images on a geographical grid
   - EO browser / google earth engine idea
     - Correcting all the acquisitions specificities

2. Choosing the geometry of one image and transforming the other images
   - Using image properties (Gefolki)
   - Using geographical information

EO Browser S1/S2 over Italy
GeFolki  https://github.com/aplyer/gefolki

Optical flow method used in:

- Computer vision
- Particule image velocity
- Mono and multi modal remote sensing
  - Coregistration
  - Flow estimation

Geographical link

Input: NDSI + geographical coordinate

DEM to get a geographical coordinate per SAR pixel

SAR grid

Interpolation

Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N
Data platforms and datasets
Data platform: EO-Browser

https://apps.sentinel-hub.com/eo-browser/
Data platform: Google Earth Engine

code.earthengine.google.com
Datasets:

A list of dataset for remote sensing:

https://github.com/chrieke/awesome-satellite-imagery-datasets
Datasets: ISPRS Vaihingen and Potsdam

Very nice dataset to start:

- All the patches come from the same image
- three RGB bands: infrared, red and green + DSM
- 5 labels: building, impervious surfaces, tree, low vegetation/grass, car
Databases: Inria

Task: Semantic segmentation - Roof detection

Images: 30 cm resolution

Different cities: San Francisco, Lienz (Austria), Kitsap County, WA Transfer/Generalization
Databases : AIRS

Task: Building detection
City: Christchurch
Images: Very High Optical data
Databases: Semcity

Task: instance building segmentation
City: Toulouse
Image: very high resolution multi-spectral images

HAL Id: hal-02948177, version 1 DOI: 10.5194/isprs-annals-V-5-2020-109-2020
Datasets: Spacenet 5

Task: Road network extraction
Cities: Moscow, Mumbai, San Juan
Image: very high resolution optical images
Datasets: Spacenet 7

Task: building detection and tracking through time
Cities: ~100 unique geographies
Images: Very high optical images
Datasets: Spacenet 6

Task: Building detection
City: Roterdam
Images: very high SAR and optical data
Datasets: Mini France

Task: Semantic segmentation

Cities:
Labeled training data: Nice, Nantes/Saint Nazaire.
Unlabeled training data: Le Mans, Brest, Lorient, Caen, Calais/Dunkerque and Saint-Brieuc.
Test data: Marseille/Martigues, Rennes, Angers, Quimper, Vannes, Clermont-Ferrand, Cherbourg, Lille

Images: RGB IGN aerial images

Labels: 15 classes
Datasets: DLR-SkyScapes: Aerial Semantic Segmentation Dataset for HD-mapping

- 31 classes
- Road marking
- Airborne optical acquisition

Datasets: Resisc45

Task: image classification

Number of classes:
Dataset: HRSCD

Task: semantic change detection

Images: RGB aerial images from IGN BD ORTHO database

Labels: 5 labels from Urban Atlas
Datasets: Xview 2

Task: Assessing building damage after a disaster is a critical first step in disaster response.

Images: Before/After optical images

Location:

The XBD Dataset
1 dataset 6 different types of disasters 15 countries 850,736 annotated buildings 45,362 km² of “before” and “after” images

Hurricane Harvey
- Pre-disaster
- Post-disaster
- Labeled imagery (ground truth)
- Damage assessment from xView 2 model

Santa Rosa Wildfire
- Pre-disaster
- Post-disaster
- Labeled imagery (ground truth)
- Damage assessment from xView 2 model
Datasets: Xview 3

Task: Detect “dark” vessels (the one without AIS)

Detect vessel and classify them “fishing” vs. “not fishing”

Images: SAR Sentinel-1 images
B. AI for remote sensing
The AI tasks

- Image classification
  - A label per image

- Detection
  - A bounding box around an object

- **Mapping**
  - Semantic segmentation: a label per pixel
  - Vectorisation
  - End to end instance segmentation

- Regression
  - A value per pixel

- Data mining
Semantic Segmentation Metrics

Aij: the number of pixels of the true class i, predicted as class j

\[
OA = \frac{\sum_{i=0}^{N-1} A_{i,i}}{\sum_{j=0}^{N-1} \sum_{i=0}^{N-1} A_{i,j}}
\]

\[
mF1 = \frac{1}{N} \sum_{k=0}^{N-1} F1_k
\]

\[
mIoU = \frac{1}{N} \sum_{k=0}^{N-1} IoU_k
\]

\[
F1_k = \frac{2 \sum_{j=0}^{N-1} A_{k,j}}{A_{k,k} + \sum_{i=0}^{N-1} A_{i,k}}
\]

\[
IoU_k = \frac{A_{k,k}}{A_{k,k} + \sum_{j=0, j \neq k}^{N-1} A_{k,j} + \sum_{i=0, i \neq k}^{N-1} A_{i,k}}
\]
Random forest VS Deep Neural Network

Random forest:
- Collection of Decision Tree
- Decision per pixel
- Algorithm example: IOTA 2
  [https://framagit.org/iota2-project/iota2/](https://framagit.org/iota2-project/iota2/)

Advantages:
- A sparse ground truth can be used
- Small dataset can be used

Deep Convolutional Neural Network

Advantages:
- A notion of connexity

Disadvantages
- Large/dense dataset needed

Widely used in literature, win challenges!
Spacenet-1 Building detection challenge (2017) won with a Random forest
All the following Spacenet Challenges were won by CNNs.
Unet kingdom

Unet: Deep Convolutional Neural Network

Encoder-Decoder architecture.
Lot of encoder choice (Resnet, Efficient-net,...)

Type of loss:

- Cross Entropy: 1 label per pixel
- Binary cross entropy: 1 class or multilabel problem
Tiling: 1 remote sensing image VS patches

Remote sensing image are very large

Tilling is important to create Train/Val/Test patches

To predict on a large image:

1. Tilling and prediction with overlap
2. Test time augmentation: Augmentation to have multiple predictions
Class imbalance HRSCD example

The most represented class is often the best predicted

Small classes may never be predicted

Options:
- Non uniform sampling
- Loss weighing: \( w = 1/\text{class}_\text{frequency} \)

Cannot compensate very big imbalance

Imbalance even larger for changes
No change: 99.232%

<table>
<thead>
<tr>
<th>Label</th>
<th>Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Background</td>
<td>0.176959</td>
</tr>
<tr>
<td>1 Artificial surfaces</td>
<td>0.11508</td>
</tr>
<tr>
<td>2 Field</td>
<td>0.618345</td>
</tr>
<tr>
<td>3 Forest</td>
<td>0.0836437</td>
</tr>
<tr>
<td>4 Wetland</td>
<td>0.000195238</td>
</tr>
<tr>
<td>5 Water</td>
<td>0.00577677</td>
</tr>
</tbody>
</table>
Ground truth precision

- They maybe error in the ground truth
- They are variation between annotators
- It is difficult to have very precise borders

BUT border account for a large proportion of the pixel in a dataset

Illumination and seasonal change

Differences in season mean differences in shadows, vegetation state.
Data augmentation can help
Geometrical data augmentation

Original image + label

D4 group: 7 data augmentation

Question in remote sensing:

- Help generalisation for another city but not always generalisation within the same image
- Image acquisition parameters:
  - Optics: The shadows cannot face south
  - SAR: layover is linked to the trajectory (often North/South in satellite RS)
Raster and vectorisation

**Vector**: a polygon with few geographic coordinate surrounding an area (very light)

**Raster**: an image with a class per label

Framefiel learning: from the image to the vector
Two steps:
1. Detection of edge, interior and framefield
2. Active contour model to detect corner and create a polygon

Semi-supervised learning

Labelling is very expensive

A lot of unlabelled data exists:
- Sentinels mission do on going acquisition
- Mission archive are often open after some time
- Labelling is done only on a small part of the image

Use unlabelled data!

Mean Teacher: the model has to predict the same labels after two different augmentations

Pseudo labelling: Retrain successively the model pseudo label predicted by the model at the previous step
Regression

Regression is hard

To regress height from SAR data

To regress BIOMASS estimated using LIDAR from SAR data