Remote Sensing and Artificial Intelligence

Jocelyn Chanussot

https://jocelyn-chanussot.net/





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ARTIFICIAL INTELLIGENCE

Programs with the ability to learn and reason like humans

MACHINE LEARNING

Algorithms with the ability to learn without being explicitly programmed

DEEP LEARNING

Subset of machine learning in which artificial neural networks adapt and learn from vast amounts of data

Data, data, data... HPC Algorithms

Remote sensing

- Sensing: Observing, measuring, monitoring
- Remotely: from a distance (close range... or from far away)

Platforms:

♦ satellites♦ airplanes♦ UAV (drones)

Remote sensing

- Sensing: Observing, measuring, monitoring
- Remotely: from a distance (close range... or from far away)

Characteristics:

- Spatial resolution
- Spectral resolution
- Revisit time (temporal resolution)

Advantages:

- Large spatial coverage
- Low cost
- ✤ Agility (UAV)

Remote sensing

- Sensing: Observing, measuring, monitoring
- Remotely: from a distance (close range... or from far away)

Opportunities:

- Monitoring of the environment
- Disaster management
- Urban planning
- Precision farming
- Defense and security

Challenges:

- (Big)Data processing
- High Performance Computing

DeepRed: l'IA au service de l'imagerie infra-rouge













Low spatial resolution



Schönefeld airport Landsat

Very high spatial resolution



Reykjavik Ikonos

Very high spatial resolution



Sunnyvale airport Quickbird Multispectral diversity

Very high spatial resolution



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From low spatial resolution...

• ASTER image 30m



... to high spatial resolution

• WorldView 3 (<1m)



Spatial details in satellite optical images

• WorldView 3 (<1m)



Spatial details in aerial optical images

• True color composite. Transacqua, Italy. Credit: Fondazione Bruno Kessler



Spatial details in images acquired from a drone

• Povo Trento, Italy. Credit: F. Remondino, Fondazione Bruno Kessler



Spatial details in images acquired from a drone

• Tsuruoka, Japan. Credit: K. Uto, JST PRESTO HyperLeaf



Spatial details in images acquired from a drone

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Multi-angular optical remote sensing



Multiangular data open new doors :

- atmospheric correction,
- movement estimation,
- 3D reconstruction...

But require new algorithms

Rio de Janeiro Worldview II Angular diversity

- Works night and day
- See through the clouds
- Interaction with the canopy...



- Active remote sensing faces the same increase of resolution
- ◆ Data are highly corrupted by speckle noise (VHR → Non gaussian distribution, new statistical models are required)



ERS 2 Saragosse





Toulouse Ramses sensor Airborne platform



Eyjafjallajokul TerraSAR-X

Polarimetric information

Tandem-X WorldDEM





Multitemporal data analysis and change detection Same challenges :

- Data with different resolution
- Varying acquisition conditions
- Need for high level representation

Multiscale Unsupervised Change Detection on Optical Images by Markov Random Fields and Wavelets Moser, G. ; Angiati, E. ; Serpico, S. B. IEEE GRSL 2011



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• MODIS 250m t1



• MODIS 250m t2



• MODIS 250m t3







RGB Data

LiDAR Data


Multi-modal remote sensing



Quickbird DigitalGlobe



TerraSAR-X, Infoterra

Multimodal data fusion : -optical + radar data -Data from constellations of satellites -Data with different resolutions, different geometries etc...

 \rightarrow Need for high level (semantic) representation of the information

Extraction and Three-Dimensional Reconstruction of Isolated Buildings in Urban Scenes From High-Resolution Optical and SAR Spaceborne Images Sportouche, H. ; Tupin, F. ; Denise, L IEEE TGRS 2011





- Advanced multi-sensor optical remote sensing for urban land use and land cover classification
- Guest organizer: Saurabh Prasad (Univ. of Houston)





- VHR RGB imagery (5-cm GSD)
- **Multispectral-LiDAR** point clouds, intensity rasters and DSMs (0.5-m GSD)



- Benchmark for urban land use and land cover classification (20 detailed urban classes with materials and vegetal subclasses):
 - Healthy grass
 Stressed grass
 Artificial turf
 Evergreen
 Deciduous trees
 Bare earth
 Water
 Residential buildings
 Commercial buildings
 Roads
- SidewalksCrosswalks
- Major thoroughfares
- Highways
- Railways
- Paved parking lots
- Unpaved parking lots
- Cars
- Trains
- Stadium seats









• Data fusion and per-sensor tracks



Calendar:

•Training set (1.4km² in central Houston) was release on Jan. 15th

•Test set (3.5km²) will be disclosed on March 13th •Submission deadline on DASE is March 25th

Prizes:

- •1st to 4th teams: IEEE Certificates of Recognition + IGARSS invited session
- 1st and 2nd teams: co-author JSTARS submission
 1st team: NVIDIA GPU graphic card













374 unique registrations (teams)52 countries represented









- **1334** submissions (Total)
 - 538 submissions (Data Fusion)
 - 347 submissions (MS LiDAR)
 - 449 submissions (HSI)
- The contest as an education tool: many student projects in the competition







3rd place: Shuai Fang, Dou Quan, Shuang Wang, Lei Zhang, and Ligang Zhou (*challenger,* Xidian University, China)

OA = 77.39 kappa = 0.73 (1st rank in Hyperspectral Classification Challenge)

A Two-Branch Network with Semi-Supervised Learning for Hyperspectral Classification

3rd place, ex aequo: Sergey Sukhanov, Dmitrii Budylskii, Ivan Tankoyeu, Roel Heremans, and Christian Debes (*AGTDA*, AGT International, Germany) OA = 79.79 kappa = 0.79 (3rd rank in Data Fusion Classification Challenge) OA = 78.05 kappa = 0.77 (2nd rank in Multispectral LiDAR Classification Challenge) Fusion of LiDAR, Hyperspectral and RGB Data for Urban Land Use and Land Cover Classification



Classification map of challenger in Hyperspectral Classification Challenge



Classification map of AGTDA in Data Fusion Classification Challenge



1st place: Yonghao Xu, Bo Du, and Liangpei Zhang

(*Gaussian*, Wuhan University, China) OA = 80.78% kappa = 0.80 (1st rank in Data Fusion Classification Challenge)

OA = 81.07% kappa = 0.80 (1st rank in Multispectral LiDAR Classification Challenge)

Multi-Source Remote Sensing Data Classification via Fully Convolutional Networks and Post-Classification Processing

2nd place: Daniele Cerra, Miguel Figueiredo Vaz Pato, Emiliano Carmona, Jiaojiao Tian, Seyed Majid Azimi, Rupert Müller, Ksenia Bittner, Corentin Henry, Eleonora Vig, Franz Kurz, Reza Bahmanyar, Pablo d'Angelo, Kevin Alonso, Peter Fischer, and Peter Reinartz (*dlrpba*, German Aerospace Center, Germany) OA = 80.74% kappa = 0.80 (2nd rank in Data Fusion Classification Challenge)

Combining Deep and Shallow Neural Networks with Ad Hoc Detectors for The Classification of Complex Multi-Modal Urban Scenes





Classification map of Gaussian in Data Fusion Classification Challenge



Classification map of *dlrpba* in Data Fusion Classification Challenge



Multi-city and crowd-sourced Local Climate Zone classification

We released free open data on 5 cities for training:

- Landsat / Sentinel-2
- OpenStreetMap
- Crowdsourced class labels (from Geo-Wiki)

We ask participants to submit classification maps on 4 other cities (undisclosed so far) **using DASE.**

Guest organizers

Benjamin Bechtel, Uni. Hamburg

Linda See, International Institute for Applied Systems Analysis (resp. Geo-Wiki)





Classes are Local Climate Zones (LCZ, Stewart and Oke, 2012)

Essentially urban structure types

Prediction is requested on a 100m grid









Training cities (Berlin, Rome, Paris, Sao Paulo, and Hong Kong) were disclosed on January 9. The contest is open.

Test (Amsterdam, Madrid, Chicago, Xi'an) cities were released on March 13.

Submission deadline on DASE (automatic accuracy scoring) was April 1.







Paris city (Sentinel-2/Landsat/land use)



Contains modified Copernicus Data 2016





AD

Courtesy of the U.S. Geological Survey

NUDAPT

... and zoom (land use / OSM building footprint / OSM roads)



Data © OpenStreetMap contributors, available under the Open Database Licence





856 submissions of classification maps!

... with an exponential rush as the deadline came closer

Most works combined image and semantic layers

Teams with various backgrounds GIS, satellite imagery, image processing

The contest as an education tool Many student projects in the competition







1st place: Naoto Yokoya, Pedram Ghamisi, Junshi Xia,

University of Tokyo, Japan, and DLR/TU München, Germany (OA = 74.9%, K = 0.71). Multimodal, multitemporal, and multisource global data fusion for local climate zones classification based on ensemble learning

2nd place: Sergey Sukhanov, Roel Heremans, Ivan Tankoyeu, Jérôme Louradour, Darya Trofimova, Christian Debes,

AGT International, Switzerland (OA = 72.6%, Kappa = 0.68) Multilevel ensembling for local climate zones classification

3rd place: Camila Souza dos Anjos Lacerda, Marielcio Gonçalves Lacerda, Leidiane do Livramento Andrade, Roberto Neves Salles

Institute of Advanced Studies – Brazilian Air Force, Brazil (OA = 72.4%, Kappa = 0.68) *Classification of urban environments using feature extraction and random forest*

4th place: Yong Xu, Fan Ma, Deyu Meng, Chao Ren, Yee Leung,

Chinese University of Hong Kong and Xi'an Jiaotong University, China (OA = 69.9%, Kappa = 0.65). *A co-training approach to the classification of local climate zones with multi-source data*



VHR & video data

VHR data: Deimos-2 satellite, 2 dates

- 4 bands, 4m resolution
- 1 pan, 1m resolution

Video from ISS (Iris camera,

- 60s length, 1m resolution) Area: Vancouver, Canada

Guest organizers

Roberto Fabrizi, DeimosImaging/Urthecast









1st place

Lichao Mou and Xiaoxiang Zhu "Spatiotemporal scene interpretation of space videos via deep neural network and tracklet analysis"



Fig. 4. Our final results. From left to right: spatial scene labeling, temporal activity analysis, and traffic density estimation.

2nd place

Maria Vakalopoulou, Christos Platias, Maria Papadomanolaki, Nikos Paragios and Konstantinos Karantzalos "Simultaneous registration, segmentation and change detection from multisensor, multitemporal satellite image pairs"





Fig. 4: Charge Detection from multitemperal, multi-sensor between: (a) a Deimos Mauch'15 and a De left), (b) an kris video sequence (free frame) and a Deimos May'15 (¥-DZ, right).

3rd place

Dave Kelbe, Devin White, Andrew Hardin, Jessica Moehl and Melanie Phillips. "Sensor-agnostic photogrammetric image registration with applications to population modeling"

4th place

Zuming Huang, Guangliang Cheng, Hongzhen Wang, Haichang Li, Limin Shi and Chunhong Pan. "Building extraction from multi-source remote sensing images via deep deconvolution neural networks"





IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 47, NO. 11, NOVEMBER 2009

Decision Fusion for the Classification of Hyperspectral Data: Outcome of the 2008 GRS-S Data Fusion Contest

Giorgio Licciardi, Fabio Pacifici, Student Member, IEEE, Devis Tuia, Student Member, IEEE, Saurabh Prasad, Member, IEEE, Terrance West, Student Member, IEEE, Ferdinando Giacco, Christian Thiel, Jordi Inglada, Emmanuel Christophe, Jocelyn Chanussot, Senior Member, IEEE, and Paolo Gamba, Senior Member, IEEE 3857







1 band

Panchromatic . one grey level value per pixel

2-10 bands

Multispectral . 2-10 bands . limited spectral info



tens or hundreds of narrow bands
detailed spectral info



Improved spectral diversity : hyperspectral imagery











Spectral Mine Imaging



Oil spill detection - MV "Full City" Grounding

(~1000 tons of heavy bunker oil (IF 180) & ~120 tons of marine diesel oil on board)





PCA visualization of oil spill (Pink = oil on seawater, Yellow = sand on sea floor, Green = Seawater).







Submarine « Vegetation Index »

Description of minerals Sand / rocks

Description of vegetals and corals Seaweeds / Algaes / corals

Recycling - Sorting

NIR spectral imaging Plastics sorting PS, PET, LDPE, PVC...



Mapping food composition

- VNIR and SWIR range
- Based on C-H, O-H and N-H bonds
- Fat, protein, carbohydrate and water content



Frying - Fat and Water content in a donut

Reference: CCFRA, Campden, UK


Hyperspectral imaging: applications



Hyperspectral imaging: noise



Hyperspectral imaging: noise



Hyperspectral imaging: noise



Hyperspectral imaging: opportunities



Hyperspectral imaging: challenges



Data Science Experts (DSE)

- Top 50 in Europe in the industrial space landscape (European Space Agency start-up competition, 2020)
- Copernicus Masters France Award (ESA, CNES, 2020)
- i-Nov award (BPI, 2021)
- Creative Destruction Lab (Canada) and Copernicus Accelarator (Europe)











Data Science Experts

Energy

• Forecast of the production of photovoltaic energy





Daytime / Nighttime remote sensing

Data

ar- 6



20.00

Drone-based acquisitions

• Detection of archeological remains in Atacama desert (Chile)







Damage assessment: wildfire





Damage assessment: wildfire





Damage assessment: flood



- Severity of the flood
- Crop bending









dec. 2, 2020



dec. 8, 2020



dec. 14, 2020



dec. 20, 2020

https://aiperion.earth/





QlevEr Sat

• A cube-sat with embedded AI Deforestation in tropical forests









OrbitalALChallenge Bal-time insights, real-world impact

The winners of the OrbitalAI Challenge have been announced





Remote sensing



- + physical modeling
- + interaction with end-users

Future challenges







Constellation of small platforms

Artificial Intelligence, distributed computing, HPC, frugal and embedded AI Incorporating physics into deep learning, incorporating deep learning in physics Explainable AI

Multiscale, multimodal and multitemporal remote sensing



