SUREDOS24

Super-Resolution and Downscaling
for EO and Earth Science

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Session 1: Advanced Artificial Intelligence and Deep Learning for Super-Resolution Applied to Sentinel-2

Freddie Kalaitzis (Univ. Oxford) - Mikolaj Czerkawski (ESA ϕ-lab)

Main outcome / summary

- Status update about S-2 & related missions
  - Overview of intermediate processing levels (L1B, L1C, L2A, L3), pilot products (L2H, L2F), CHIME (hyper), LSTM (thermal)
- Generative & non-generative methods
  - Generative more prone to hallucinations
- Generative models, like diffusion, for S-2 SR
  - Inference speedup with latent diffusion
  - Large data requirements, filled by carefully engineered synthetic data
- Benchmarking, finding the right data & the right data for the task of SR
- S-2 SR has been tested in a variety of contexts, from modest upscaling factors of 2x or 4x, up to the more controversial territory of 10x.
  - Small risk of hallucinations in 4x. Significant risk in 10x & above.

Main outcome / summary

- Task-driven SR demonstrated as a way of accommodating downstream task context for the solving this inverse task.
- A variety of approaches ranging from completely data-centric to more informed designed pipelines that take advantage of unique features of S-2 modality
- SR mostly demonstrated in the spatial context, but also one work has demonstrated an approach to super-resolve in the spectral dimension
- Harmonisation & work on aligning multi-modal data is an important element for building the next generation of datasets
- Open access SEN2NAIP dataset has been presented
- The limited geographical extent of certain VHR sources of data remains a challenge

Recommendations

- Benchmarking is still challenging. We need better metrics & test data.
- We need large-scale global datasets for SR.
- We must identify metrics that the community agrees with. Currently the approaches of measuring performance varies a lot.

SUREDOS24

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Session 2: Super-Resolution Applied to a Wide Variety of Earth Observation Data

Enrico Magli (Polito) and Nicolas Longépé (ESA ϕ-lab)

Main outcome / summary

- 10 presentations covering a wide range of sensors, SAR, Night Time Light imagery (NTL), Thermal Infra Red (TIR), Video...
- There's a lot of available high-res images from 3rd parties (WorldView-3, Pleiades NEO, GeoSat-2), and licensing allows redistribution of derivative products.
- Commercial providers such as Maxar and Airbus stay on the safe side in terms of scaling factor (x2) for their SR products, to render the image more appealing
- Deep learning based SR methods generally outperform model-based ones, also for video SR. They may run faster if accelerated via GPU
- For VideoSR, understanding the interframe motion is key to getting good super resolution performances and recover lost details.
- GANs may provide large SR factors, but it is not obvious how to assess quality.
- For image SR it is important to avoid generating artifacts and quantifying uncertainty. Calibration of uncertainty is also an open question.

Main outcome / summary

- Assessing effective resolution is deemed of importance; methodology such as ELF (automatic image Edge detection and measurement of edge spread function) - however sharpness is one of the many metric to be considered.
- Sometimes there's no ground truth data; this calls for unsupervised quality assessment
- It is difficult to obtain paired high-res and low-res images for supervised learning; domain-adapted SR handles unpaired datasets
- Add of ancillary data could be potentially useful, even if coming from another domain (see presentation of problem of accessibility of TIR or NTL data, and integration of S-1 and/or S-2)

Main outcome / summary

- Deep learning predictors can be used to design "virtual" instruments, beyond Super Resolution (extending to spectral dimension, polarimetry from single-pol to quad-pol SAR...)
- Unsupervised SR may be performed using internal learning, e.g. using kernel estimation or neural implicit representations. Most DL uses the quantity of many examples as this source of information (prior). But possible to learn a lot from the sample itself, for example, by analysing textures. Benefits from multiscale pattern that repeat across scale

Recommendations

- Need additional effort from agencies (ESA) to support access to massive HR datasets. ESA TPM Scheme should support the creation of specific training and validation HR/VHR datasets.
- Consider releasing low-level products (e.g., raw data), and involve users in the definition of the process
- Supervised training of SR methods may incur domain gap issues as training data are scarce
- It is not obvious how to properly assess the resolution enhancement and performance. Usual metrics may not be very informative, and in some cases may not properly discriminate between different methods
- Physics may be added to AI models to help with explainability -> change of paradigm: explainable, physic-aware and trustworthy SR

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Super-Resolution and Downscaling for EO and Earth Science

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Session 3: Downscaling Techniques in the Context of Earth Science and Earth Observation Applications

Luca Brocca (IRPI CNR) and Anna Jungbluth (ESA)

Main outcome / summary

- 5 Presentations covering super-resolution/down-scaling for diverse EO data and applications:
  - Precipitation, air temperature, nitrogen dioxide, land surface temperature, soil moisture
- Input Data:
  - Satellite data: Sentinel 5P/TROPOMI, MetOp/GOME-2, PRISMA etc.
    - Higher level data products: Sentinel 3/LST, ESA CCI Biomass, MODIS/LST, MODIS NVDI etc.
  - Modelled data: AROME
- Models:
  - Neural Networks, Unets, Residual Dense Networks, Random forests, LightGBM
- Desired scale:
  - 250 m to 1 km

- Some presentations compared multiple ML models, others found simple approaches to work best
- Pixel-level random forests worked well in some cases
- Model performance improved through inclusion of additional data, e.g. location information, DEM features
- The same super-resolution approach (and data alignment routine) worked for Level-1 and Level-3 data products (Davide de Santis)
- Combination of ML and geostatistical methods facilitated super-resolution from 25 km to 1 km (Odunayo David Adeniyi)

Recommendations

- Huge need of reference data for validation at high resolution. Hard to perform "robust" spatial validations of model predictions when ground truth data is sparse or missing. How do we address this?
- How to further improve the spatial resolution, e.g. better than 1 km for precipitation and 300 m for LST?
- Are even higher resolutions needed? For which application(s) (e.g. urban heat islands, convective systems)? Who are the downstream users? What is the HR data used for?
- Sharing of tools & resources. Each project starts with spatial and temporal alignment. Can we create sharable software tools to avoid re-inventing the wheel?

SUREDOS24

Super-Resolution and Downscaling for EO and Earth Science

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Session 4: Super-Resolution Product Quality, Adoption and Downstream Services

Luis Gómez Chova (Univ. Valencia) and Zoltan Bartalis (ESA)

Main outcome / summary

- 7(-1) presentations covering the assessment of SR products and its application to different downstream tasks:
  - Waste Detection
  - Water bodies monitoring
  - Urban Planning & Building delineation
  - Landcover mapping & Forest monitoring
  - Precision farming, Water quality & Air pollution
- Most SR methods applied to Sentinel-2 but also to Hyperspectral Images and time series
  - Lack of reference datasets beyond RGB-NIR force us to use approximations such as Wald protocol
- Super-resolution, fusion and pansharpening are intimately related
  - There is not a single metric determining the best model
  - SR quality assessment can take advantage of current Cal/Val activities
- Application-independent (metric-based) and task-based validations are complementary and valuable. For most real-life users though, there should be significant improvements in the EO application performance if we want a broad adoption of SR-enhanced datasets.

Recommendations

- Different quality metrics are used to assess the performance for SR methods
  - A common protocol should be proposed to validate RS SR
- Each SR work uses its own dataset (cross-sensor, simulated, harmonized, biased, multispectral, hyperspectral, multiscale, ...)
  - Common datasets should be proposed (at least to benchmark SR models)
- SR validation can be based on downstream tasks (mandatory with no HR reference)
  - Most suitable tasks should be selected
  - Downstream tasks performance improvement due to SR should be quantify
  - Downstream & end-to-end approaches should be compared
- Joint effort to generate full multi/hyperspectral reference datasets
  - Access to HR images beyond RGBNIR is required: ESA TPM :)
- To mainstream the adoption of SR, it would be key to engage user communities who already use EO data, in order to pragmatically evaluate real-life improvements thanks to SR enhancement.