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# THE DREAM DATABASE: A MULTIMODE DATABASE INCLUDING OPTICS, RADAR, DSM (SRTM) AND OSM LABELS FOR DEEP MACHINE LEARNING PURPOSES

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## ABSTRACT

This paper describes a multimodal remote sensing database, called DREAM (Data Rang or EArth Monitoring), developed from open-source data. The method of development of the database is described, as well as its specificity. The database includes radar, optical, rasterized Open Street Map datasets, and DEM data for two types of landscapes: France and the United States. Already used in deep learning multimodal data registration and in style transfer simulation, this database can also be used for classification, speckle filtering, and image quality improvement needs.

**Index Terms**— deep learning, database, radar, optical

## 1. INTRODUCTION

Deep learning techniques are booming for many applications in the data processing. Remote sensing is one of the fields where deep learning could be useful, especially since the rise of open access data, for example, distributed by NASA or ESA. However, one of the main difficulties lies in the constitution of data sets, possibly annotated for supervised learning. Besides, access to multi-temporal or even multimodal data is spreading. The processing of this multimodality makes the constitution of databases more tricky: indeed, it is necessary to manage the problems of co-registration of multimodal data, with shared footprints and different tiling.

Within the framework of a project called AI4GEO, France is acquiring an automatic 3D geospatial information production capacity to meet several challenges for many booming sectors of activity, such as economic intelligence or urban planning. The availability of considerable volumes of satellite imagery data, supplemented by airborne or in situ data, now makes it possible to achieve controlled quality levels using new artificial intelligence and Big Data technologies.

In the framework of this project, we have developed a multimodal database. It contains both radar and optical images, OpenStreetMap vectorized data, and DEM data, useful for multiple purposes. The creation of open-access databases is becoming widespread: this approach favors benchmarks and the progression of the field.

It is already in this state of mind that we have proposed the S12Flood [1], MiniFrance [2], and OSCD bases [3]. Among

these databases, only the first one contains both optical and radar images. But these images are devoted to the specific flood detection application.

Recently, the SEN12MS [?] dataset contains patch triplets of corresponding Sentinel-1 dual-pol SAR data, Sentinel-2 multi-spectral images, and MODIS-derived land cover maps. The patches are distributed across the landmasses of the Earth and spread over all four meteorological seasons. This database is useful for data fusion and classification. In our case, the objective was a bit different, as we wanted to address applications-oriented on image quality improvement, for speckle co-registration or filtering, or on detection, rather than on information extraction. For these reasons, we did not keep the image calibration information. On the other hand, other information sources have been added, such as the Digital Surface Model from the Shuttle Radar Topography Mission (SRTM) or the radar images after speckle temporal filtering, which is not the case in the SEN12MS database.

Because of its particularity, we propose our database 'DREAM' in free access: [?].

In the following section, we present the description of the database, its specificity compared to other current databases. Then in Section 3, we will present a certain number of works that have been initiated on this base, in order to inspire future developments allowed by this database. Finally, we propose other application scenarios that could use this database in training.

## 2. DESCRIPTION OF THE DATABASE

### 2.1. Geographical Places

Two main sites have been chosen, with different landscapes: France and the USA. The first database was built in France from Copernicus data mainly, Sentinel 1 and Sentinel 2. The second database in the USA aims at a resolution range twice as high. It contains fully polarimetric L-band UAVSAR data and high-resolution RGB aerial data from the NAIP database. To these data, we have added the Sentinel 1 and Sentinel 2 images also available. We have split all images into different 1024 x 1024 pixel tiles within spread areas. Figure 1 displays the resulting areas in France. The flight paths of the UAVSAR images constrain the different areas for the USA, as shown in

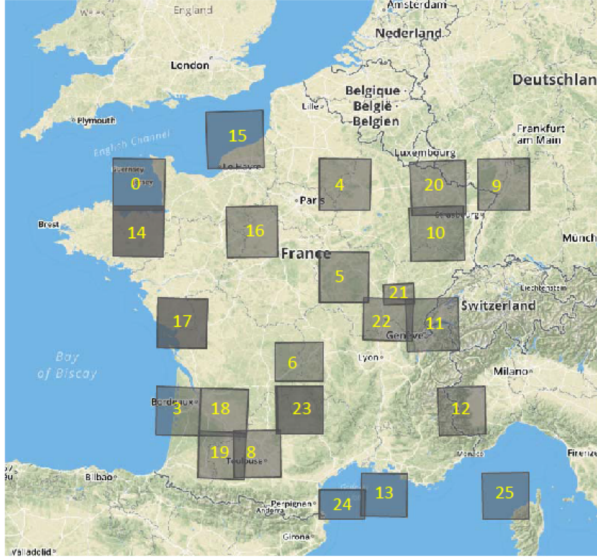


Fig. 1: Caption

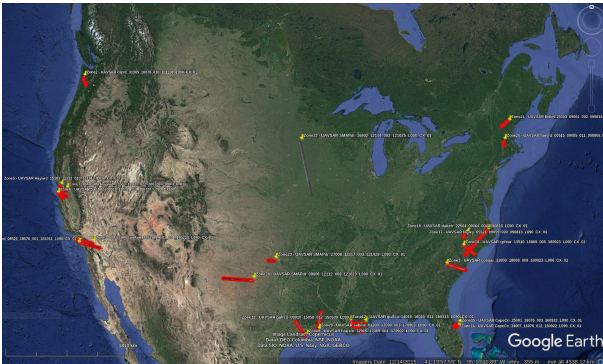


Fig. 2: Caption

Fig. 2.

## 2.2. Preparation of data in France

The tools used are the Google Earth Engine platform and the python GDAL package.

The Google Earth Engine (GEE) platform offers the possibility to download the data Sentinel-1 and 2, stored on Google's servers. The interest of this platform for the rapid development of S1 and S2 data is twofold :

- first of all, the platform allows access to S1 data delivered after the Terrain Correction. This Terrain Correction is essential to have the data in a cartographic repository similar to that of the other data. This Terrain Correction procedure based on DEM SRTM data takes a long time to apply to the data.

- The platform also allows the data to be downloaded on subareas without downloading the whole images.

- Finally, the intuitive functions offered also allow the selection of optics images according to their cloud cover.

To build the database, we launched queries to select Sentinel 1 and 2 data with the best possible overlap across France and no clouds in the case of Sentinel 2 data. The selected data are then downloaded only on the intersecting part.

On the other hand, we have chosen to download the temporally averaged S1 images over one year: this temporal filtering strongly reduces the speckle.

Finally, we have resampled the Sentinel-1 and -2 images at the same 10-meter resolution grid. We have added to the base the corresponding SRTM tiles.

## 2.3. rasterized OSM data

To these images have been added data from the OpenStreetMap data source. The database has been rasterized using the python module pyosm. This library aims to provide a way to extract objects from OpenStreetMap and rasterize those to match a given image as input. OpenStreetMap (OSM) is a collaborative project to create a free editable map of the world. OSM is considered a prominent example of volunteered geographic information.

## 2.4. Preparation of data in USA

The second database constituted is a base sampled at a better resolution (5m). The radar images are images from NASA's UAVSAR (Uninhabited Aerial Vehicle Synthetic Aperture Radar) program, which maps different regions using aircraft-mounted radars. Optical images are from the National Agriculture Imagery Program (NAIP) of the U.S. Department of Agriculture. Radar data are represented in the polarimetric Pauli database, which to some extent makes it easier to interpret the images, with false colors that can be interpreted as in optics: the sea in blue, vegetation in green, cities in red/pink.

For two of these zones, we have intentionally chosen 3 overlapping passes, in order to have different polarimetric realizations of the same zone, the polarimetric effects varying with the orientation of the sensor heading.

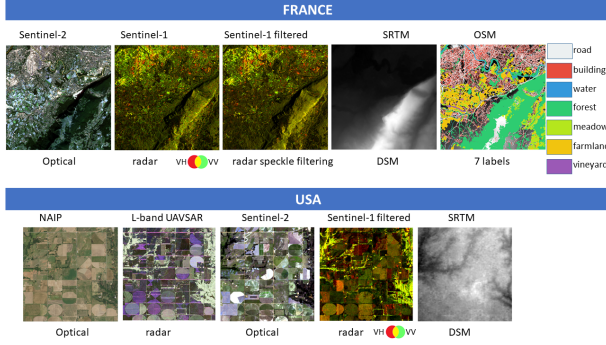
The figure 3 give examples of the different patches for a given tile.

## 3. EXAMPLES OF USE CASES

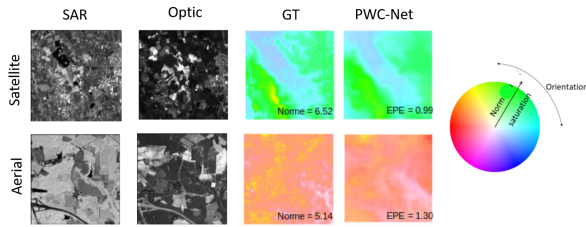
We have initially developed this database to serve deep learning optical and SAR image co-registration algorithms. Then we used it to perform learning transfer between optical and radar images. We illustrate the first results of these applications in this section.

### 3.1. Coregistration

To use remote sensing data as geospatial data, it is necessary to georeference it. To do this, terrain correction for satellite



**Fig. 3: Caption**



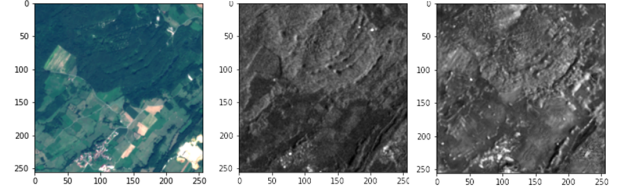
**Fig. 4: Estimated optical flows using a PWC-multimodal model trained on the Satellite database. Upper row: results on a Satellite example, bottom row: results on a Aerial example. On the right, hue/saturation color encoding of the optical flow. GT denotes the Ground Truth**

images, and corrections related to trajectory uncertainties for airborne sensors, must be applied. In practice, the georeferencing of the data achieve mostly sufficient registration accuracy between Sentinel 1 and Sentinel 2 data. However, as soon as finer resolutions are addressed, the registration errors sometimes become significant, of the order of several pixels. To counter this problem, we have developed a multimodal re-setting algorithm using optical flow.

The underlying idea is to take our Sentinel 1 and Sentinel 2 database, which we assume to be well coregistered, and to apply a synthetic deformation function generated by us to them. This deformation function is the target on which we are trying to teach a deep neuronal architecture.

This idea has led to the development of a registration algorithm called PWCnet-multimodal, which already gives promising results in terms of generalization to high-resolution data, and better than a previous dense coregistration algorithm, GeFolki, in terms of accuracy.

The figure 4 shows examples of optical flows trained on the French database (on the 10mx10m grid), and tested on other images of this same database, or an image of the USA database, with a 5mx5m grid. The diversity of the database's resolutions thus makes it possible to test the generalization capabilities of training models.



**Fig. 5: First results obtained by using the pix2pix architecture for generating a SAR-image from an optical one. Left: the optical image. Second : the SAR real one. Right: the generated one**

### 3.2. Transfer from optics to radar

Large amounts of multi-modal data can be used to learn a style transfer between an image from one modality to an image from another modality: this is the case for GAN-type architectures [4].

Initial results based on images in France have made it possible to simulate realistic SAR images from optical images.

Work is in progress: it is inspired by a pix2pix [5] architecture: indeed, this "supervised" model fits for cases where two images of the same area are available. An example of first result is given on Fig. 5.

## 4. DISCUSSION

The proposed "DREAM" base is unique in terms of number of available modalities: optical, speckle filtered or unfiltered radar, OSM, and SRTM. Although several works have started concerning the exploitation of this base, we believe that many other applications are possible, in particular semantic segmentation based on the exploitation of OSM data, but also image quality improvement, via speckle filtering or the improvement of resolutions. We plan to further enrich the current database with maps of activity or change rates, and better-resolved optical aerial data over France.

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