Sat2Dron 3: Spectral Superresolution
TFG report

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1 Preliminary information

Multispectral (MS) remote sensing sensors are proven to acquire useful information in order to perform object detection, classification and other applications. These sensors acquire information within limited broad spectral bands, usually between 3 and 10 number of bands. This low number of bands become a drawback when performing more detailed analysis of earth's surface. Hyperspectral (HS) sensors are instruments designed to have a considerably greater number of narrow spectral bands compared to MS sensors. Hence, this type of sensor becomes the best option for distinguishing spectral resembling material of the earth's surface. However, availability of immediate HS data is currently lacking.

Most of the work involving superresolution has been in the spatial and temporal modalities in which Deep Learning has achieved state-of-the-art results [1, 2]. Nevertheless, little study has been involved with increasing the spectral information of an image with Deep Learning [3], most of it is using other techniques [4].

2 Objectives

This TFG proposes transforming multispectral data to hyperspectral data using Deep Learning techniques in order to increase the spectral information from the MS data by more than 10 times — from less than 10 number of bands to over a 100 bands —.

2.1 Main objectives

1. Moderate spectral superresolution: increase the number of spectral bands in multispectral data by a factor of 2.
2. Extreme spectral superresolution: increase the number of spectral bands in multispectral data by a factor of 10.

3. Achieve domain adaptation and transfer the learning to other satellites using zero-shot learning techniques.
4. Generate architectures that are innovative and competitive in a research area that does not have a large quantity of literature or resources.
5. Evaluate our model comparing the results obtained with current architectures.

2.2 Side objectives

1. Propose a novel architecture that achieves state-of-the-art performance.
2. Combine all the modalities of superresolution (spatial, temporal and spectral) into one architecture [5].

3 Learning outcomes

1. Master deep learning techniques applied to computer vision.
2. Master the manipulation and processing of satellite remote sensing imagery.
3. Learn the state-of-the-art of superresolution and deep learning in different modalities and be able to use the knowledge to propose novel architectures.
4. Learn by performing a large quantity of computational experiments.
5. Be introduced to the research field.
6. Describe the overall conclusions from all the experiments performed into an article document format.
7. Decompose a big challenge into different tasks and milestones.
8. Be challenged with a project in which there is little literature.

4 Methodology

The management of a project is of a great degree of importance to meet the final objectives and deliver them on time. In order to choose the best alternative available, these next points have been taken into consideration:

- Individual project: the work of the project is realized by a single person. Therefore, there is no need of daily communication and coordination with colleagues, neither of a strict schedule.

- Weekly meetings with supervisor: weekly meetings will be held with my supervisor to show the progress and consult any doubts. This gives me the aim to set weekly minor goals and work from the start of the project.
- Poor literature in the area: the research topic has not been deeply studied by other researchers using the techniques that are being planned to be utilized. Thus, there is a level of uncertainty on the overall project, which makes the timelines not as clear. However, there is some literature on related lines of research, such as performing data fusion of MS and HS [6] or single hyperspectral image super-resolution [7] (which will be analyzed and studied to get a solid understanding of the handling of similar data as ours).
- Novelty: although computer vision and deep learning have already been introduced to me, remote sensing and the satellite scene is a novelty, as well as other tools that will be used. Therefore, the mastering of these tools will be required in order to achieve the goals and it could affect the timelines.

The time management methodology chosen is Kanban[1] due to the fact that it is a methodology characterized for improving the speed and quality of work. It will cause a desire for finishing the current work-in-progress set, as multi-tasking is limited. Moreover, it enables a visible display of the project and work in progress which will be of a great use when communicating with the supervisor. Finally, weekly minor goals will be set in order to increase the motivation and performance.

5 Work plan

1. Documentation (Weeks: 1st-2nd): study the literature, actual and old, of superresolution and deep learning. We will emphasize on the work related to our field and desired satellites, but we will also explore other alternatives. Moreover, the study of the different characteristics of satellites and their instruments will also be realized. This phase is emphasized in the initial part of the project but will remain active throughout the whole project due to its importance and need.
2. Introduction of new tools (Weeks: 2nd-5th): learning to use new tools such as GDAL [9], QGIS [10], Earth Engine [11], among others, and the downloading and processing of satellite imagery. This phase will be the base to get my further work done.
3. Reproduction of state-of-the-art (Weeks: 3rd-7th): in order to achieve a good understanding of the matter and increase the familiarity with the

[1] Trello [8] is the desktop web application chosen for managing the project with Kanban methodology.

new tools and methods, a reproduction of the state-of-the-art scene [3] (no code available) will be produced. This phase overlaps with the previous phase due to the fact that this phase is a way of improving the skills needed and achieve a solid learning on the matter.

4. Proposing a novel architecture (Weeks: 7th-13th): more study and computational experiments will be done in order to achieve a novel architecture that stands out from others. This phase is the most exploratory one, it will be based on research among different areas, learning what can be done in order to improve a solution and thinking outside the box. Getting a very broad knowledge, design architectures based on the characteristics that will get the most out of it and performing trial-and-error will be the objectives of this phase. The timeline for this phase starts from when a good practical understanding is achieved on the problem and it ends soon enough to be able to propose new approaches, such as the zero-shot learning.

5. Zero-shot learning approach (Weeks: 13th-17th): the last main goal of the project is that the learning of the network can be applied to other satellites and instruments different than the one used for training. Using very little or none set of data, we hope to achieve satisfactory results. This phase remains as the last technical phase, the project could diverge to some different specific goal if we find a viable solution to an unsolved problem.

6. Elaborating a final report (Weeks: 18th-22nd): a final article report will be written up explaining our approach and solution to the problem, specifying the processing of data, the design of the architecture, decisions taken, etc.

6 Work progress

6.1 Update I

6.1.1 Summary

The work done till the date of this first update report of this project has been in accordance with the work plan established in a previous report. The deadlines and outcomes of the established plan has been achieved with great results and will be presented in the next sections.

6.1.2 Activities and progress

The major work defined by the plan was to develop a reproduction of the state-of-the-art of the specific problem of increasing the spectral bands of a multi-spectral image (6 bands) to a quasi-hyperspectral image (170 bands). In order to develop this, the implementation is divided in 3 parts: obtaining the satellite imagery of the area of interest where the experiments will be executed, the preprocessing of this imagery and building the deep learning model designed to increase the spectral bands.

6.1.2.1 Obtaining satellite scenes

The desired scenes have been located and downloaded through a software that I am currently developing which gives easy access to different servers through APIs and provides methods for obtaining and processing scenes from the main earth observing satellites. The area of interest selected has been the Karnataka state of India according to the paper [3]. The satellite for the MS data is the Landsat 7 ETM+ [12] and the EO-1 Hyperion [13] for the HS data. The obtained scenes consist of an image over the area of interest for each desired satellite in the same date.

6.1.2.2 Preprocessing of images

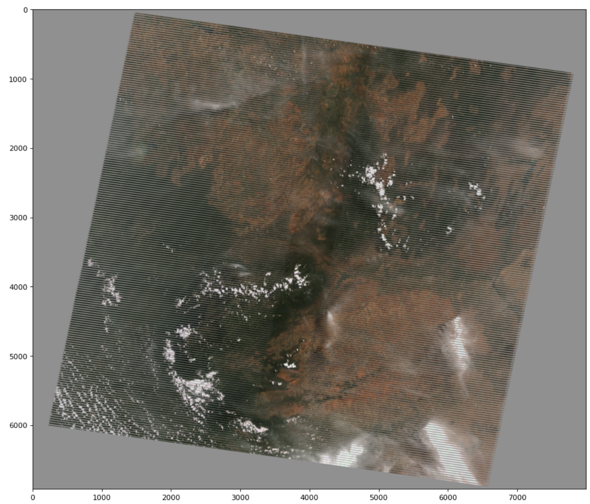
Preprocessing of the scenes is needed so that they meet the requirements for being well introduced to the deep learning model built later. Each satellite image has different preprocessing needs:

- Landsat 7 preprocessing: the first technique applied consists of a 3x3 mean filter gap filling of the scene due to an error in the sensor of the satellite [14] that corrupts the image and does not provide pixel information in continual thin diagonal lines. Then, I clip the raster to fit the rectangular shape of the Hyperion scene, this makes both scene to be co-registered and they now have the same size and cover the same area. Next, I extract 5x5 window size patches for every common pixel with the Hyperion data. Finally, the data gets normalized in values in the range of [0-1] and divided randomly in 2 different subsamples: 50% of pixels for the training set and 50% for the test set. Results of the clipping and gap filling are shown in Figure 1.

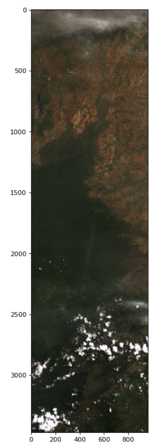
- Hyperion preprocessing: Hyperion data will be normalized and split randomly in half for generating the training and test set (maintaining correspondence with Landsat 7 pixels).

6.1.2.3 Deep learning model

The architecture of the deep learning model has also been designed according to the state-of-the-art and it consists of 3 convolutional layers with 3x3 kernel size followed by ReLU activation functions. In the proposed model, the Hyperion spectral bands are the target variables and the six bands of Landsat 7 are the predictor variables. The model is using Adam as the optimizer and Mean Squared Error as the loss function. As the batch size and learning rate are not specified in the paper, I have executed a grid search in order to find the best combination with a considerable execution time. A batch size of 512 and a learning rate of 0.0002 will be set for the model.



(a) Before preprocessing

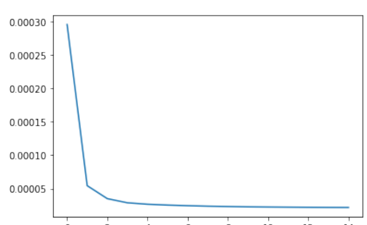


(b) After preprocessing

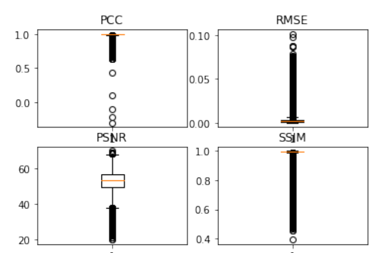
Figure 1: Preprocessing on Landsat 7 ETM+

6.1.3 Outputs and evaluation

The training set of the data has been processed by the network and the loss, computed with the MSE metric, has been measured along the whole training, which is shown in Figure 2a. In order to evaluate the quality of the output data, four statistical metrics are going to be measured comparing the generated test data with the ground-truth Hyperion test data. The metrics selected are: Pearson's correlation coefficient, root-mean-square error, peak signal-to-noise ratio and structural similarity index. The results measured are shown in different boxplots in Figure 2b.



(a) Training loss curve.



(b) Statistical metrics.

Figure 2: Testing of the network

6.1.4 Risks, issues and next challenges

Despite the great results shown in the report, more study will be done in the methods of the original paper and our reproduction to build it as close as possible so that a more representative understanding of the processes can be extracted from these experiments.
Next steps on this project involve study and experimentation. A study of cutting-edge architectures will be conducted focused on the objective of coming up with a different approach to the same problem that could be focused on the effect of time and zone variation in the spectral response.

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