Colored visualization of multitemporal SAR data for change detection: issues and methods

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Abstract

This paper proposes a method to generate a colorful product for stacks of SAR images, making it easy to see areas that are subject to change. Two modes of representation are proposed: one intended for Sentinel changes, on a large temporal scale; the other for TerraSAR-X images, allowing you to see point-time events. The importance of fine coregistration and temporal calibration is emphasized. Lastly, filtering methods, in particular by deep learning, based on the temporal redundancy of the data, are proposed.

1 Introduction

Access to remote sensing data and in particular to SAR images is becoming easier. It is thus possible to build large temporal stacks of SAR images, and exploit the temporal dimension for new processing. One of a potential application concerns the improvement of the visual quality of images. Recently, several studies have already shown how efficient is temporal averaging for speckle reduction. Another area of progress is the improvement of estimations. For example, the contribution of temporal rather than spatial estimation to estimate polarimetric parameters used for classification algorithms has already been emphasized in [6].

Finally, change analysis is a major axis of interest, whether for visualizing the human activity, to follow urban sprawl dynamics, for monitoring of forest cover on a global scale, or for agricultural monitoring.

For all these needs, a visualization tool is very useful. Such a product requires as input a temporal stack of images, which must be radiometrically calibrated over time, and finely co-registered. Both of these assumptions are essential and should be thought of as the starting point for the design of a processing over platforms.

Thus, section 2 first discusses the registration and calibration issues. It shows the critical importance of these steps: by comparing products obtained on the Google Earth Engine (GGE) platform, and those obtained on downloaded L1-products, for which our own registration and calibration processes have been applied.

Then, we intend to make visible the information that we want to put forward. In this paper, our approach aims at highlighting human activity, either for one-time event (vehicles, cranes), or longer events such as building constructions. After considering potential existing tools, we propose a new approach to fulfill this need, for two very different resolution ranges: those of TerraSAR-X and Sentinel 1. This approach is proposed in section 3.

Lastly, section 4 presents works about the improvement of the visual quality of input images and then products, Several filtering approaches have been considered, of which the most promising ones are shown: an approach based on BM3D, and a more original filtering approach by deep learning. Different results produced will be presented and discussed before concluding.

2 Image stack preprocessing

2.1 Co-registration

Producing a temporal stack of images begins with the registration of all the images acquired on the same area. This can be done either from the geo-referenced products (GRD), or from the complex images (SLC), in particular for polarimetry and interferometry purpose. A platform such as GGE is interesting for manipulating images quickly, anywhere on the planet. Currently, the Sentinel products available in GGE are however restricted to GRD products.

A fine analysis of the temporal GRD stacks processed or downloaded using GGE, or downloaded with ESA or CNES platforms, shows that the registration is imperfect. Variations of a few pixels may remain. This results in an impression of blur, especially on permanent scatterers, when the signal is temporally averaged. Also, it is very important to fine-coregistrate the images.

We propose to make this fine coregistration using the GeFolki open-source tool, that obtains good results with SAR images, in interferometric or non-interferometric conditions [4]. This tool easily compensates for residual coregistration deformations that remain after georeferencing.

As an example, the image of Fig 1 compares the superimposition of two geo-referenced images from PEPS, before and after co-registration by GeFolki. Deviations of the order of the fraction of pixels are visible if they are not compensated.

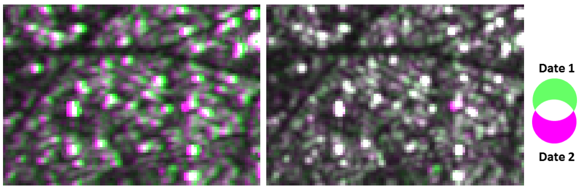

Figure 1: Superposition of two images from PEPS, with and without an additional fine coregistration (Zoom over Paris)

2.2 Quantization and calibration

Like co-registration, the quality of the temporal radiometric calibration has a significant influence on the applied temporal processing. Satellite data are provided calibrated. However, two problems can still be encountered. Firstly, images issued by GGE are provided in logarithmic scale. Values are clamped to the 1st and 99th percentile to preserve the dynamic range against anomalous outliers, and quantized to 16 bits. This operation on the original signal dynamics can have a major impact on the statistical properties and unfortunately is irreversible. Secondly, for the data downloaded without modification of the dynamics, it is possible that the temporal evolutions of the calibration factors are not compensated for each acquisition. In this case, the stack may be imperfectly calibrated temporarily. Temporal calibration methods exist: they are based on the temporal evolution of the statistics of the image [5]. However, it turns out that many scenes contain areas that are not at all constant in time, either at C band or X band: this is the case of crops, mountains covered with a snowpack. Also, we suggest to apply temporal calibration only after selecting the most stable points. This method allowed us to correct calibration biases, especially on very high resolution TSX stack.

3 Multitemporal colored products

3.1 Innovative representation proposed

Once realized the steps of registration and time calibration, several methods make it possible to represent the temporal stack of images. [2] propose a RGB colored composition, based on the differences of backscattering coefficients for dry or for wet periods, and on the interferometric coherence. This method has been tested on our data. This product is very interesting for classification purposes; it is less adapted to the change visualization. Moreover, it requires to fulfill interferometric conditions to use the notion of temporal coherence. Finally, backscatter changes are not always seasons-related, especially on the fields.
In the same way, the GGE platform gives as example of a colored composition, a product based on the use of ascending and descending radiometry, as well as on polarization difference. Once again, the visualization is nice to have a quick classification of areas, but is not adapted to changes. Moreover, it does not offer a solution for a pure interferometric stack.
The solution we propose is different. It is achieved in the HSV color space. For hue, a color is associated to the date for which the maximum intensity is reached. Saturation is given by the coefficient of variation σ/μ. This coefficient is indeed theoretically constant for any Rayleigh or Gamma distribution. On the other hand, it is particularly weak for Permanent Scatterers. Finally, if there is a noticeable change, it will be higher. Also, the saturation of the color will be all the stronger as the temporal signal attached to a pixel has a specific temporal evolution. Finally, to code the intensity, to be sure not to miss a point-time event, we take for intensity the maximum intensity of the temporal profile. We call this visualization method REACTIV for ***R**apid and **EA**sy **C**hange detection in radar **TI**me-series by **V**ariation coefficient.*

3.2 Results on Sentinel Images

Even though the resulting quality of GGE visualization is less good, due to dynamic changes and imperfect registration, the visualization process has still been coded on the GGE platform, so the results can be extended to the whole world. On a very large scale, as in the figure 2, colored variations can be seen on the Alps, probably because of the variations of the snow cover.

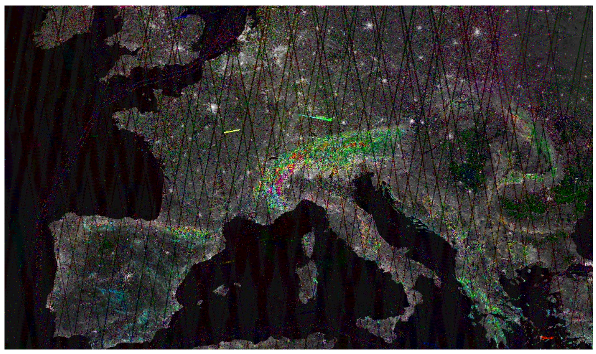

Figure 2: Colored composition over Sentinel 1 images over Europe using GGE.

On a medium scale, we can check that the visualization (see Fig. 3 on the middle) is similar to the one obtained with downloaded images, even though blur and saturation effects can be seen when zooming. The figure shows how it is possible to immediately see the fields, which are the widest areas subjected to change. On other places, it is possible to see in colors very quickly all the parcels cultivated.
Finally, the composition makes also appear locally construction sites in color, as shown on the zoom on the right.

3.3 Results on TSX images

For 98 TerraSAR-X images, the visualization shown in figure 4 makes it possible to visualize as well the numerous building sites in progress, as the presence of barges

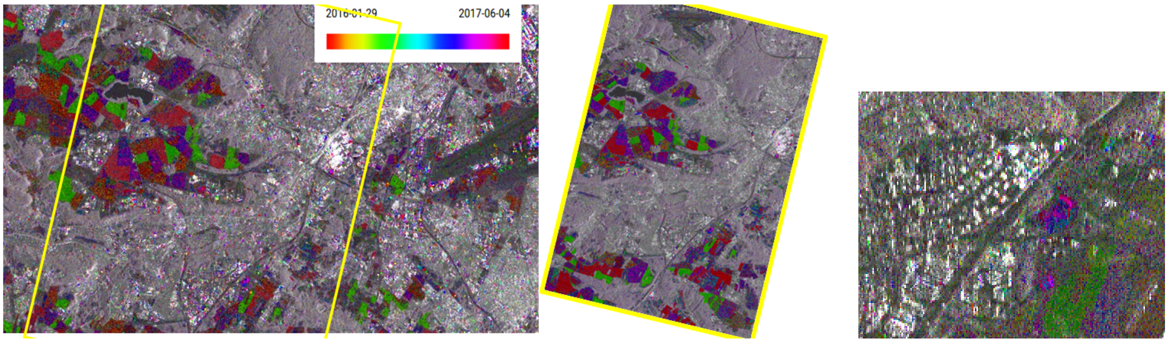

Figure 3: Colored composition over Sentinel 1 images of Saclay after local download on the left, on Google Earth Engine on the middle - Right: zoom over a construction site

to a given date. On construction sites, the associated colors make it possible to go up on key dates.

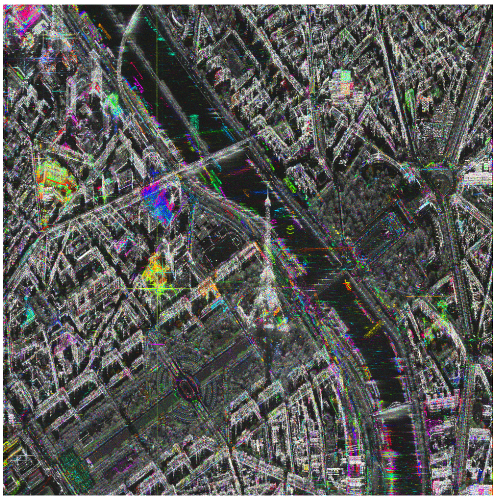

Figure 4: Colored composition over TSX images of Paris.

At higher resolution, a stack was created using 18 images in staring spotlight mode. A zoom of the resulting colored representation is shown on the figure 5: it is centered on some buildings of the Front de Seine in Paris. The central building, the *Grenelle Tower*, appears in orange colors. Its two colors corresponds to dates to which the facades were renovated: June and July 2015 for the lower and upper parts respectively of the building.

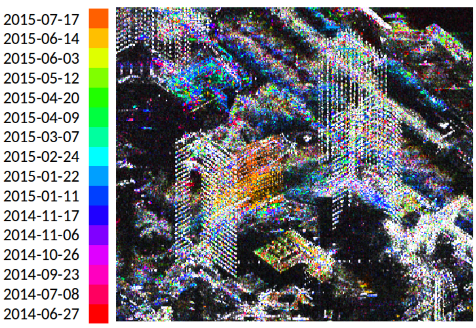

Figure 5: Our colored product over staring TSX images of Paris.

4 Filtering methods

One way to further improve visualization methods is to take advantage of the temporal redundancy of images to develop filtering techniques. In this study, we have focused on the one hand on video methods by applying them to the radar, and on the other hand by developing an innovative method by deep learning.

4.1 By BM3D

Several traditional filtering methods have been tested from image and video denoising. Here we show the result of one of them, Block-matching and 3D filtering (BM3D) algorithm [3], combined with a temporal median filter on three successive images. We have replaced the intensity channel of the HSV composition with the filtered intensities, to result in the figure 6.

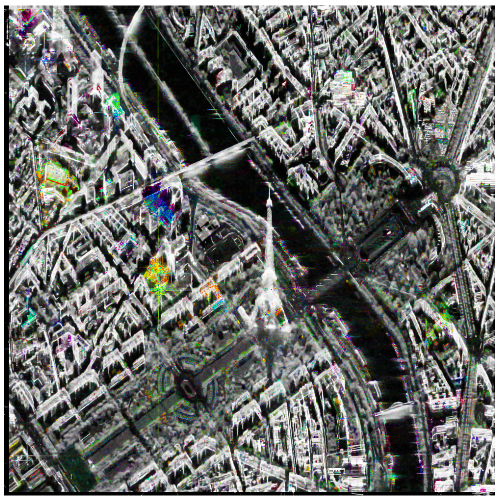

Figure 6: RGB composition over TSX images of Paris using filtering intensity by BM3D.

4.2 By deep learning

An innovative method is to train a network from a couple of images taken randomly in the stack of images. The approach is then to try to predict the image 2 from the image 1. To this aim, a U-net network [1] is used.

Between the two images, under no-change assumption, only the speckle noise fluctuates. Gradually, the neural network learns to keep only the important elements, and to attenuate the noise. In this work, the network has only been trained on the Saclay site. The filtering operation thus applied to all the images of the stack gives the result shown in the figure 7.

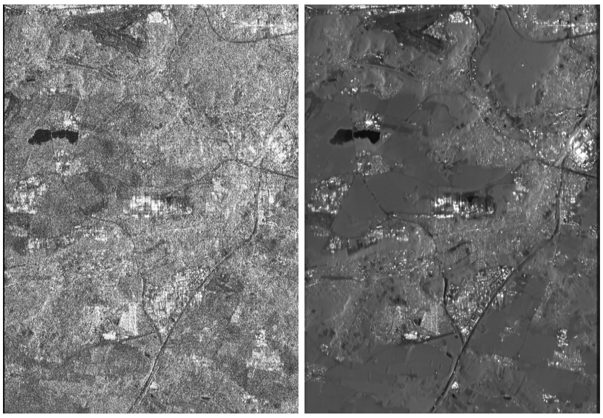

Figure 7: Results of deep learning filtering methods over Saclay, after learning on this test site. Left: original Image. Right: filtered stack.

figure In order to check if the learning step makes it possible to extend the function to other sites, we then applied the network trained on Saclay to a Sentinel image taken on Paris. Resulting image is shown in figure 8. Although the result is not perfect, it is very encouraging: the method will be improved by automatically learning on a multitude of data on the planet, without requiring a labeling of the data, only by exploiting the temporal redundancy.

Figure 8: Filtering results over Paris using a deep learning approach trained over Saclay.

5 Conclusion

This paper has proposed a visualization product for a SAR image stack, that highlights areas of change or activity. The importance of calibration and coregistration has been demonstrated. Promising filtering methods based on temporal redundancy have also been proposed. These analyzes are useful for the development of future detection of anthropogenic activity and change detection tools.

References

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