Towards the Automatic Detection of Military Activity Using Satellite Radar Time Series

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ABSTRACT

Satellite radar sensors have recently drawn the attention of Defense agencies thanks to their all-weather acquisition capabilities, which make them suitable for regularly and consistently monitoring military targets, as opposed to electro-optical sensors, often affected by weather conditions. However, the use of this technology for military purposes is still in the early stages, especially as far as the automation of the data processing is concerned. In this paper, we present an automatic change detection scheme based on the analysis of radar time series for the large-scale monitoring of areas of interest. The method has been applied to three test cases with the goal of identifying military-related operations. Our preliminary results demonstrate that the proposed method could be used to gather intelligence, paving the way for its operational use in military applications.

1.0 INTRODUCTION

Geospatial intelligence has become an important component of modern warfare. Thanks to satellite images, it is nowadays possible to monitor large areas of interest with a short revisit time, collecting valuable information that would be otherwise difficult to gather.

However, the majority of the images that are currently in use come from electro-optical sensors, which can be severely affected by atmospheric conditions and are therefore limited in terms of usable data they can provide. Moreover, the processing is still largely carried out by visual analysis, although machine learning-based systems are more and more used to reduce the workload.

Recently, Defense agencies have shown a certain interest in satellite radar technology, which has the advantage of offering all-weather and day-and-night acquisition capabilities. Yet, the use of this technology for military purposes is in the early stages. We are still far from its full exploitation, let alone from the automation of the data analysis.

The goal of this paper is therefore to provide some preliminary results on how time series of SAR images could be used in an automatic way for intelligence operations such as monitoring wide areas to identify military activity.

2.0 METHODOLOGY

The proposed methodology is based on the change detection scheme recently published by the authors in [1].

The rationale behind it is to leverage the large amount of satellite data that is nowadays available and create a temporal signature of the area of interest (AOI) to be monitored; this signature is then segmented via the pruned exact linear time (PELT) algorithm [2] to detect change points.

As no a priori information on the possible size and location of the changes is usually available, it is necessary to sweep the entire AOI by dividing it into cells of suitable dimensions, which are separately analyzed to detect and map any relevant changes over time. To this end, the average backscatter (σ_0) from each cell of the AOI grid is extracted from all the available SAR images that contain the cell itself and used to build its temporal signature.

Depending on its geographic location, a target cell might be observed during different passes of the satellite. In order to take into account the multiple backscatter contributions (i.e. from different viewing angles), a separate temporal signature is created for each of the satellite tracks; the obtained time series are then linearly interpolated (1 sample per day) to fill the data gaps and finally averaged to obtain an equivalent σ_0 input feature.

Once the time series are generated, they are analyzed via PELT, which obtains the list of the change points (if any) by solving the following penalized minimization problem:

$$Q_n(s_{1:k}, p) = \min_{n, t_{1:n}} \left\{ \sum_{i=1}^{n+1} [C(s_{(t_{i-1}+1):t_i})] + p \right\}$$

where

- $s = (s_1,...,s_k)$ is the input time series;
- n is the number of change points;
- $t_{1:n} = (t_1,...,t_n)$ their time positions;
- C is a segment-specific cost function (in our analysis, the least squared deviation, suitable for detecting mean shifts);
- and p a penalty term to control overfitting.

An example of a radar time series and the output of the change point detection are shown in Figure 1.

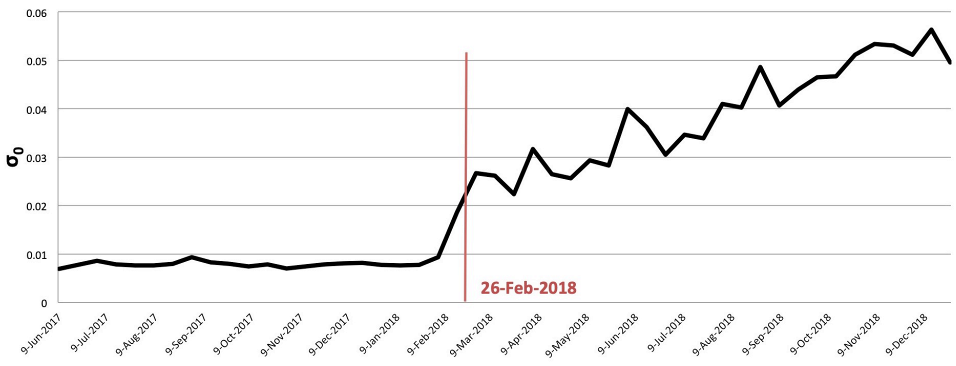


Figure 1:Example of a radar time series and output of the change point detection.

3.0 RESULTS

As a proof of concept, in this section we present three test cases that show the potential of the proposed method to automatically gather intelligence from SAR data.

For the analysis, we used the freely available images from Sentinel-1, the satellite launched by the European Space Agency (ESA) in 2014 within the framework of the Copernicus programme [3]. It mounts a SAR instrument that operates at a center frequency of 5.405 GHz and supports operation in dual polarization. The typical acquisition mode is the dual-pol Interferometric Wide (IW), which provides a resolution of around 5 × 20 m for Single Look Complex (SLC) products and around 20 × 20 m for Ground Range Detected (GRD) products. Having a repeat cycle of 12 days, and even a shorter revisit period depending on the latitude, this sensor can be successfully exploited to detect large-scale changes over time. Although the Sentinel-1 mission was originally composed of a constellation of 2 satellites (A and B), Sentinel-1B experienced an anomaly in December 2021 and was retired. To ensure that all the temporal signatures had the same time sampling, we therefore decided to use for our analysis only Sentinel-1A images.

The time series have been obtained via Google Earth Engine [4], a cloud platform that provides ready-to-use datasets (amongst them, calibrated and orthorectified Sentinel-1 GRD images) and the computing capacity to run geospatial analysis. The change point detection was performed using the python library *ruptures* [5].

3.1 Dirkou, Niger

As reported by the New York Times [6], since the beginning of 2018 the Dirkou airport has been expanded with the construction of a drone base operated by the U.S. Central Investigation Agency (CIA).

From a radar viewpoint, we should expect an increase of the backscatter from the locations of the newly constructed buildings. Accordingly, one or more change points should be detected in the corresponding time series.

We selected an AOI of about 30 km^2 around the Dirkou airport and then divided it into cells of 500 x 500 m. Considering the possible scale of the changes, this cell dimension seems a reasonable trade-off between sensitivity and computational burden. As can be seen in Figure 2(a), the grid has a total of 132 cells. We processed all the available Sentinel-1 images between June 2017 and December 2018 (47 images) as described in the previous section. As far as the input parameters of the change point detection analysis are concerned, we employed the VV channel and set the penalty term p to 20.

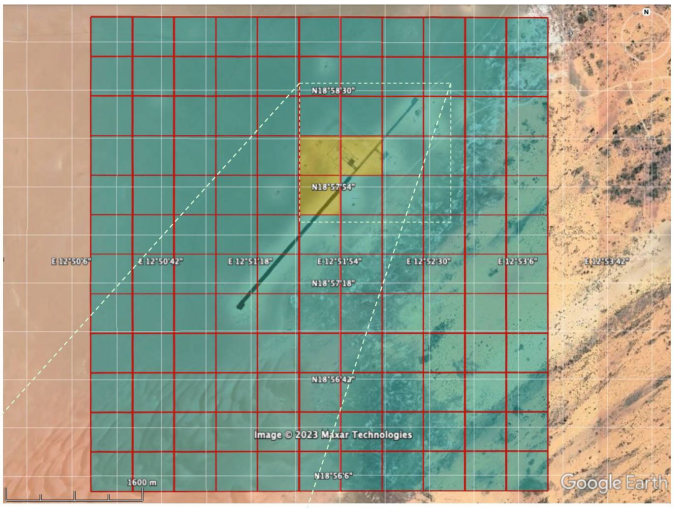
The results are shown in Figure 2(a): the cells coloured in light blue were flagged as not changed, whereas the cells in yellow were flagged as changed. By looking at the images published by the New York Times, shown in Figure 2(b)(c), we could confirm that after January 2018 several buildings and structures were added.

3.2 Soloti, Russia

Since April 2020, the Russian military camp of Soloti (less than 30 km from the Ukrainian border) has been significantly expanded by adding new buildings and converting nearby fields into areas to gather military vehicles. This resulted in a sizeable built-up about which we were not able to find any publicly available information.

For this test case, we have selected an area of about 16 km^2 and divided it into 156 cells of around 300 x 300 m, as depicted in Figure 3(a). For each cell we generated the Sentinel-1 time series by using the available images from June 2019 to December 2020. Since the AOI was covered by three different Sentinel-1 tracks (around 50 acquisitions each), we merged the three time series into a single input feature, as explained in Section 2.0. For the change point analysis, we used the VH channel and set the penalty term to 15.

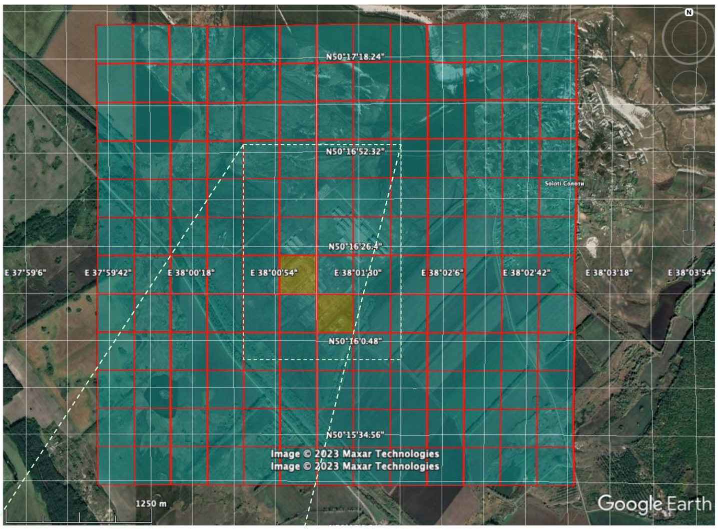
The output is provided in Figure 3(a), where it can be seen that two cells were flagged as changed (in yellow). If we compare the results with the Google Earth ground truth images in Figure 3(b)(c), we can observe that the proposed method was able to pinpoint the locations where, after April 2020, military trucks began to be massed.



(a)

(b) (c)

Figure 2: Airport of Dirkou, Niger. (a) the AOI has been divided into 132 cells. For 3 of them (in yellow) at least one change point has been detected in 2018; (b) Maxar ground truth image (January 2018); (c) Planet Labs ground truth image (September 2018).



(a)

(b)

(c)

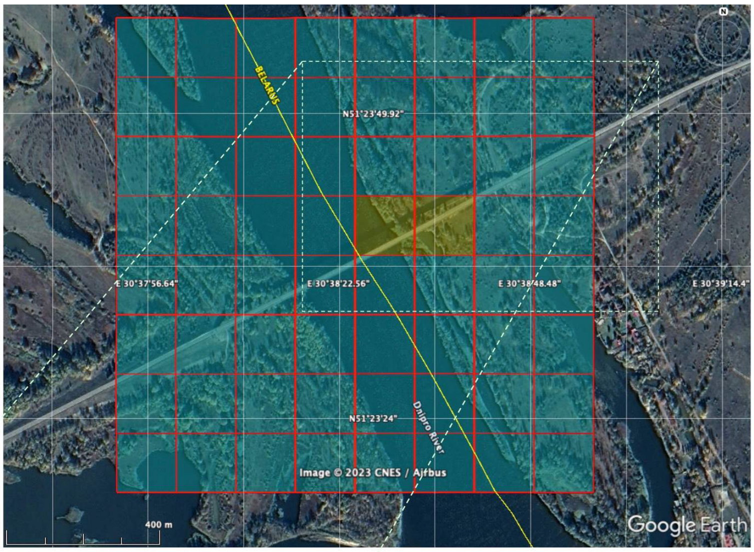
Figure 3: Military base of Soloti, Russia. (a) the AOI has been divided into 156 cells. For 2 of them (in yellow) at least one change point has been detected in 2020; (b) Maxar ground truth image (April 2020); (c) Maxar ground truth image (March 2021).

3.3 Pustynky, Ukraine

At the end of February 2022, during the very first days of the Russo-Ukrainian war, a bridge over the Dnipro river at the Kamaryn-Slavutych border crossing between Ukraine and Belarus was partially destroyed. We here expect a change in the radar backscatter due to the presence of debris from the bridge.

In order to be sensitive to changes at this scale, for this AOI we had to use a finer grid. We defined a smaller area of about 1.5 km^2 and divided it into squares of 150 x 150 m, for a total of 64 cells. The area can be observed during both the ascending and descending pass of Sentinel-1, therefore we were able to use 33 x 2 images (the analysis was limited to the dates between April 2021 and April 2022) to create the input time series. By using the VH channel alone and setting the penalty term to 5, we were able to identify two cells for which changes between January and March 2022 had occurred.

As can be seen in Figure 4(a), they correspond to the location of the bridge section within the Ukrainian territory. To qualitatively assess the results, we can look at Figure 4(b)(c), which show two SkySat images, taken on February 22 and February 26, respectively. From the second image, it can be clearly seen that, on the right bank of the river, the bridge has indeed collapsed.



(a)

(b) (c)

Figure 4: Bridge near Pustynky, Ukraine. (a) the AOI has been divided into 64 cells. For 2 of them (in yellow) at least one change point has been detected between January and March 2022; (b) Planet Labs ground truth image (22 February 2022); (c) Planet Labs ground truth image (26 February 2022).

4.0 CONCLUSIONS

In this paper, we presented a methodology for the automatic detection of military activity by means of SAR data. The area to be monitored is divided into cells of suitable dimensions for which we create separate temporal signatures by computing their average backscatter over time. These time series are then individually analyzed via the PELT change point detection method to detect if and when there have been changes.

We have tested the approach on three test cases of military-related operations, i.e. the construction of a drone base in Niger, the expansion of a Russian military base at the Ukrainian border, and the partial destruction of a bridge between Ukraine and Belarus.

The preliminary qualitative results, based on the analysis of Sentinel-1 data, confirm that, even at medium resolution, satellite radar data can be successfully used to gather intelligence, and show that the proposed method is effective in pinpointing the locations where major changes have occurred, paving the way for its operational use in military applications.

5.0 REFERENCES

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