New building detection with SAR satellite images based on deep learning

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ABSTRACT:

New building detection is useful in city management. The spatial distribution and expansion of new buildings and housings is a key information for urban planning, and can be a source to predict economic and population growth especially in emerging countries. Satellite observations, acquiring images widely with regular intervals, have been an effective means to figure them out. Synthetic Aperture Radar (SAR) images have advantage on change detection because it is an all-weather, an active sensor system. However, the visibility of images is inferior to that of optical sensor images, and it is difficult to identify new buildings from SAR images solely.

In order to overcome the disadvantage, we have developed procedure based on deep learning technique to detect new buildings from a pair of SAR satellite (Sentinel-1) images and examined to what extent our algorithm could extract real new buildings. Target area is selected from suburbs of large cities located on the west coast of the United States, because newly built large structures such as warehouses are large enough for operators to generate supervised data.

The result has achieved accuracy of 0.99 and IoU of 0.35 for application to non-trained image. Detection of buildings and housings is successful whereas we find some mispredictions on agricultural land due to vegetation growth. The result of our study has been accepted by the cloud service of UP42 GmbH (https://up42.com/) and everyone can try our model.

1. Introduction

It is useful in city management to detect new buildings and to find distribution. The spatial distribution and expansion of new buildings and housings is a key information for urban planning, and can be a source to predict economic and population growth especially in emerging countries. Earth observations provide accurate and reliable information on the state of built infrastructure, as well as its change over time. The benefits of satellite EO are already well understood across many areas of government, industry and science as a valuable information source (CEOS, 2018).

Among many satellite observations, Synthetic Aperture Radar (SAR) has advantage on change detection. First, it is an all-weather radar system that can acquire images anytime and anywhere, even in the tropics where target area is often covered by clouds and optical satellites are impossible to observe. Second, it is an active sensor to emit radar toward the ground. We can specify the same conditions for different observation dates, which makes it easier for analytical image comparison. However, the visibility of images is inferior to that of optical sensor images, and it is difficult to identify new buildings from SAR images solely.

Deep learning approach will overcome the disadvantage. If we have sufficient amount of training images with supervised data, it is possible to predict objects on the ground from newly observed satellite image. For optical satellite images there have been many approaches (Hoeser et al, 2020), whereas only a few applications are published for deep-learning based change detection with SAR imageries. Jaturapitpornchai et al., 2019, 2020 made successful results to detect newly built buildings from a pair of ALOS-PALSAR images on big cities of emerging countries: Thailand and Viet Nam.

Following above results, we have developed a procedure to detect new buildings from two SAR images. The main difference is that satellite includes Sentinel-1 because it is currently in operation and can be used for a wide range of applications. We first created supervised data from a pair of old and new SAR images and corresponding optical images (Section 2). The SAR images pairs were augmented and trained with U-net deep learning architecture (Ronneberger et al., 2015), and applied resulting model (Section 3). Finally, we introduce our application on cloud service on UP42 website (Section 4).

2. Collection of supervised data

2.1 Target data

Though our concern is to reveal city growth on emerging countries, for the better condition to make supervised data and image analyses, target area is selected from suburbs of large cities located on the west coast of the United States such as Sacramento and Portland. On the area, new large structures such as shopping malls, warehouses and residential land development are constructed systematically, and they are easier for operators to generate supervised data manually. We also use cloud-free and good-quality optical images on Google Earth for confirmation. Moreover, the area is located on vast flat land and relatively irrelevant to image distortion due to geometric correction of SAR images.

2.2 Satellite image

Sentinel-1 SAR satellite series were adopted for our study because they are now operational observing all over the world and we can expect wide range of applications. We chose IWS (Interferometric Wide Swath) observation mode, ascending orbit and VV polarization for all images. Observation dates are selected to have longest interval within Sentinel-1 operation period and to have corresponding Google Earth images for confirmation (Table 1).

The images were downloaded from Copernicus Open Access Hub website. We used ESA SNAP software for subsequent processing such as calibration, subsetting, geometric correction, and geocoding with SRTM DEM. Spatial resolution for the images is 10m after processing. The size of subsetted images are shown in Table 1.

Table 1: City, area size, and observation date of Sentinel-1 data.

City name	Size (km)	Observation date
Lathrop	22.35 x 11.96	2015/4/1, 2018/8/31
Bakersfield (1)	10.21 x 5.97	2015/4/1, 2018/8/31
Bakersfield (2)	11.28 x 6.13	2015/4/1, 2018/8/31
Sacramento (1)	20.59 x 7.29	2015/4/1, 2018/8/31
Sacramento (2)	16.24 x 9.57	2015/4/1, 2018/8/31
Portland (1)	10.70 x 5.70	2015/4/1, 2019/5/4
Portland (2)	8.13 x 4.60	2015/4/1, 2019/5/4
Portland (3)	13.78 x 6.31	2015/4/1, 2019/5/4
Portland (4)	16.09 x 4.16	2015/4/1, 2019/5/4

2.3 Supervised data

Supervised data were created manually by operators. In order to emphasize changes, we made superimposing: the old images correspond to RG layer and new images correspond to B layer. Since changed area is highlighted blue on the superimposed image, operators checked a lump of blue pixels, compared with Google Earth image on the same spot, and enclosed the area with polygons with GIS software for true building detections (Figure 1).

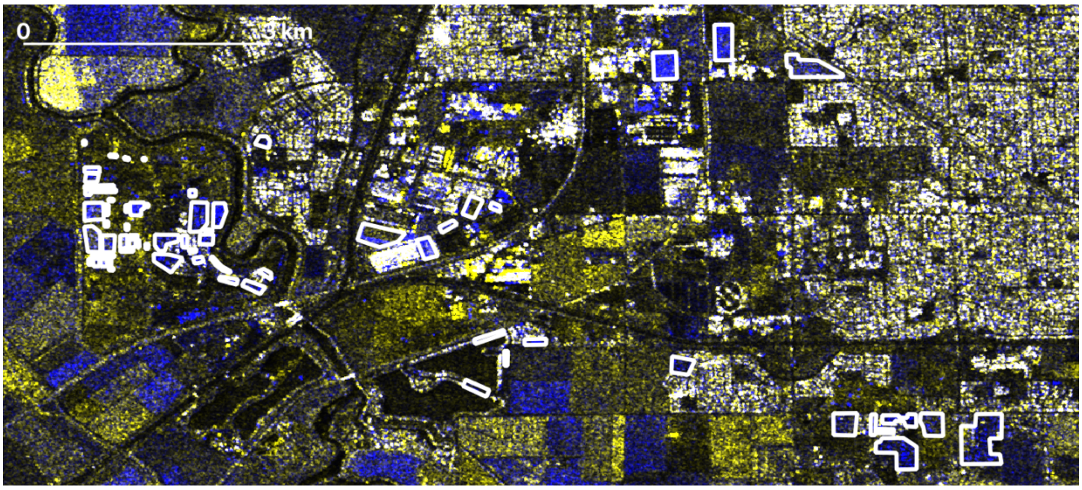

Figure 1: Polygons (bold line) over superimposed data.

3. Training and Prediction

3.1 Training

Before training input, each image and rasterized supervised data was divided into 256 x 256 square sheets and augmented to 1000 sheets. The U-net model (Ronneberger et al., 2015) is used for training. One area (Portland (3) in Table 1) were selected for reference and did not used for training data.

3.2 Results and Discussions for Sentinel-1 images

Our prediction results of our training model are presented below. Figure 2 is the result of Lathrop site which is also used on training. Figure 3 is the result of Portlant(3) which is used as a reference. Table 2 shows accuracy and IoU for both images, achieving IoU=0.351 for reference image.

White pixels on Figure 2 and 3 indicate new buildings according to our trained model, and red polygons show supervised data. Almost all newly built large-scale buildings, with a scale of more than 50 meters (5 pixels) in both Figures 2 and 3, and residential development on the left side of Figure 2 are successfully extracted as “new building”.

We find some mispredictions on both figures. Mispredictions on the left and upper left of Figure 2 are located on agricultural land, thus vegetation growth on some field plots seems to be misjudged as new buildings. Some large polygons on the right side of Figure 3 are not extracted, which is due to flat ceiling with low SAR reflection. As a means of reducing such errors, the use of dual polarization has potential, especially to distinguish building from vegetation. Since Sentinel-1 satellites obtain many images of VV/VH two-polarization observations, we need to expanding our model to at least 2 channel images.

In this study, we targeted the west coast of the United States, but the regional characteristics of urban planning may affect the results. We would like to obtain ground truth on the cities of emerging countries and verify model construction based on locality.

Table 2: Accuracy and IoU for prediction

	Lathrop	Portland (3)
Accuracy	0.995	0.878
IoU	0.989	0.351

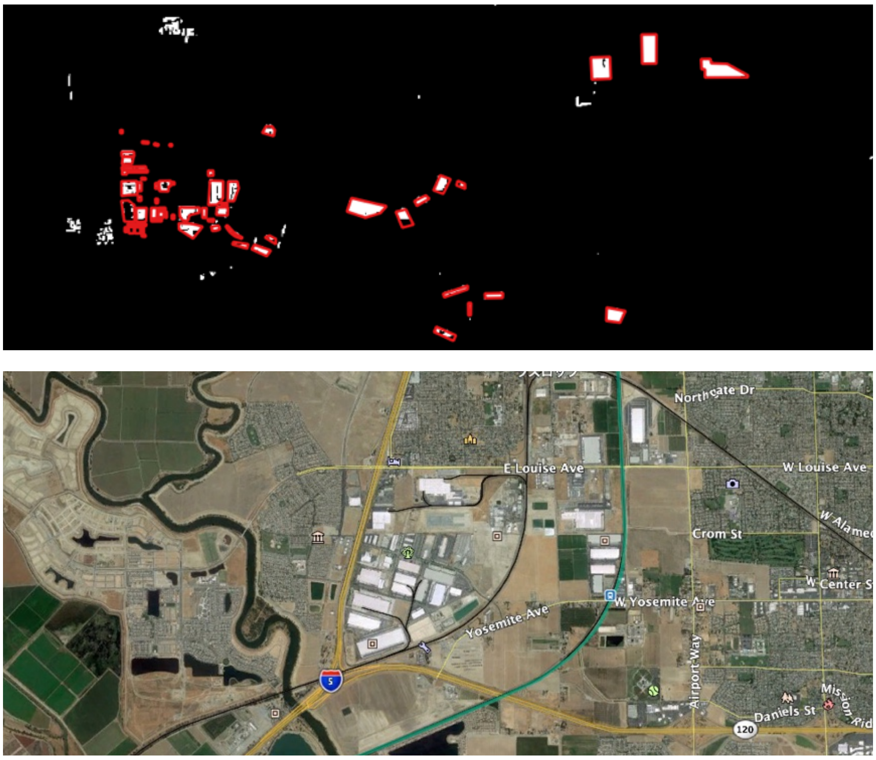

Figure 2: Prediction results and corresponding optical data (Google Earth) on Lathrop

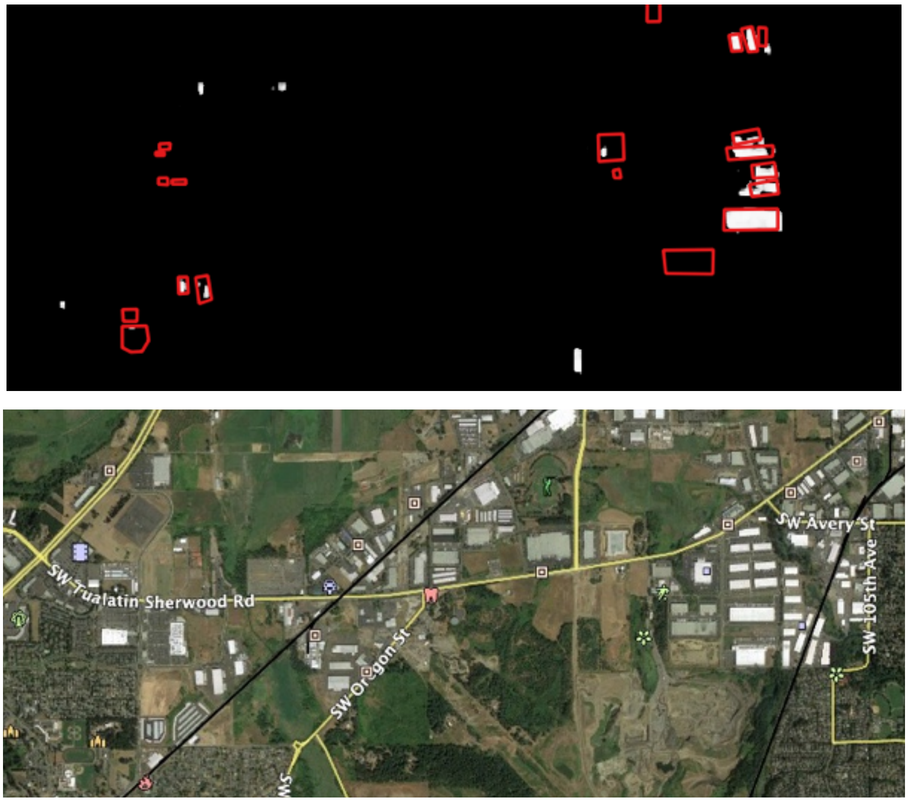

Figure 3: Prediction results and corresponding optical data (Google Earth) on Portland(3)

4. Application on cloud service

As a means of applying these results to various fields, we have implemented our prediction program in the cloud serve operated by German company, UP42 GmbH (a subsidiary of AIRBUS) that enables satellite imagery search and following data analyses on the website. Everyone can use our algorithm on the website of UP42, and we will obtain new building detection as GeoTiff file.

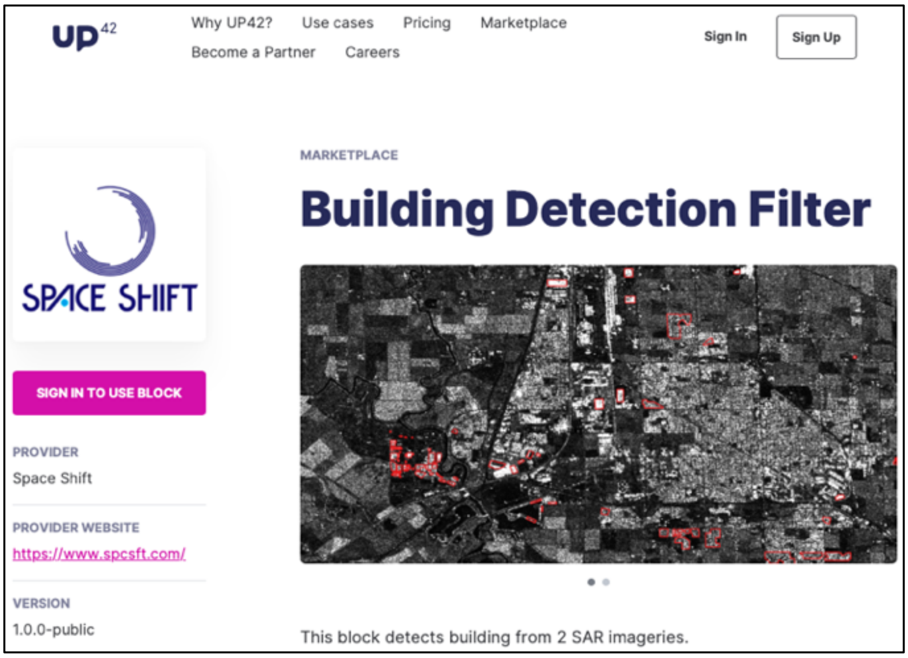

Figure 4: Processing block on UP42
https://marketplace.up42.com/block/06a81a0f-f5cd-4374-98fb-cf456feea295

References

CEOS, 2018. Sattelite Earth Observations in Supprot of the Sustainable Development Goals (The CEOS Earth Observation Handbook Special 2018 Edition)

Hoeser, T.; Bachofer, F.; Kuenzer, C. 2020. Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review—Part II: Applications. Remote Sensing, 12, pp. 3053-3095.

Jaturapitpornchai, R.; Matsuoka, M.; Kanemoto, N.; Kuzuoka, S.; Ito, R.; Nakamura, R., 2019. Newly Built Construction Detection in SAR Images Using Deep Learning, Remote Sensing, 11, pp. 1444-1468.

Jaturapitpornchai, R.; Rattanasuwan, P.; Matsuoka, M.; Nakamura, R., 2020. CORN: An Alternative Way to Utilize Time-Series Data of SAR Images in Newly Built Construction Detection, Remote Sensing, 12, pp. 990-1014.

Ronneberger, O.; Fischer, P.; Brox, T. 2015. U-net: Convolutional networks for biomedical image segmentation. In Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Inter-Vention, Munich, Germany, pp. 234–241.