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Review of Sentinel-2 applications

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Abstract - Nowadays with satellites monitoring, most easily can be seen daily changes of the land, climate and water. This paper presents a literature review of researches in the field of earth observation, in recent years is done. First an outline of Copernicus and Sentinel-2 data is given. Then, Sentinel-2 applications in remote sensing problems are evaluated. At the end, deep learning and CNN architecture applied on Sentinel-2 images are presented, as well as our next goals.

I. INTRODUCTION

One of the basic fields in earth observation is collecting information about the earth's surface. The obtained data provide a better understanding of our planet and environment we live in, and thus serves as a core for making decision in several different domains. Optical satellites for Earth observation monitor our planet by obtaining images. They obtain images from ground, water, atmosphere and climate changes at different wavelengths of the electromagnetic spectrum [8], [3].

Widely known program for earth observation is Copernicus. Copernicus is European Union's program for earth monitoring. This program offers information based on satellite observations on the earth and non - space data. Copernicus has been especially designed to be suitable for customer necessity. Copernicus' services provide real-time data on a global level, which can be used for local and regional needs.

More recently, this data has become available to the public free. Since the launch of Sentinel-1A in 2014, the European Union has begun the process to set up nearly 20 satellites in orbit before 2030. Sentinel provides images with high temporal and spatial resolution. The Sentinel-2 data is publicly available at https://scihub.copernicus.eu/ as part of the Copernicus program [7].

II. SENTINEL-2

Sentinel-2 is a European mission for continuous, wide-range and high-resolution satellite images. Consist of two identical satellites Sentinel-2A and Sentinel-2B set at 180 degrees. Sentinel-2A launched on 23 June 2015 and Sentinel-2B launched on 7 March 2017. Sentinel-2 satellites covers the following areas:

- all continental land surfaces (including groundwater) between the widths of 84 ° north and 56 ° south,
- all coastal waters to at least 20 km from the coast,
- all islands greater than 100 km2,
- all the islands in the EU,
- the Mediterranean Sea,
- all sealed seas (for example, the Caspian Sea).

Figure 1. Sentinel-2 Coverage

The Sentinel-2 Multispectral instrument (MSI) consist of 13 spectral bands: four at 10 meters, six at 20 meters и three at 60 meters spatial resolution. The revisit time of one satellite is 10 days, or 5 days if they both work together. A swath width of each satellite is 290 km.

The data acquired from Sentinel-2 are used for:

- Land monitoring (spatial planning, agro-environmental monitoring, water monitoring, forest and vegetation monitoring, carbon monitoring, monitoring of natural resources, monitoring of crops)

- Emergency management (natural disasters - floods, fires, landslides, storms, earthquakes, etc., technological accidents, humanitarian crises (for example, after a period of severe drought), civil crises.

- Security (border surveillance, maritime surveillance, support for external action of the EU).

There are many types of Sentinel-2 products. Products consist of fixed-size granules. Granule is the indivisible part of the product. The size of the granules depends on the type of product. Sentinel products include image data in JPEG2000 format, quality indicators, help data and metadata.

The products of Sentinel-2 are given in the Table 1:

TABLE I. SENTINEL-2 PRODUCT TYPES

name	availability	Data volume	Processing levels
Level 0	not available to users	granule ($25x23\ km^2$)	Payload Data Ground Segment (PDGS)
Level 1A	not available to users	granule ($25x23\ km^2$)	Payload Data Ground Segment (PDGS).
Level 1B	available to users	granule – 27MB ($25x23\ km^2$)	Payload Data Ground Segment (PDGS).
Level 1C	available to users	tiles – 500MB ($100x100\ km^2$)	Payload Data Ground Segment (PDGS).
Level 2A	available to users	tiles – 600MB ($100x100\ km^2$)	Sentinel-2 Toolbox

The radiometric resolution is expressed as an important number, usually in the range of 8 to 16 bits. The radiometric resolution of the MSI instrument is 12 bits, allowing image to be obtained in the range of 0 to 4 095 potential light intensity values. Radiometric accuracy is less than 5%. The radiometric resolution also depends on the detector's noise signal (SNR).

TABLE II. SPATIAL RESOLUTION BANDS AND SPECTRUM

Band number	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)	Part of spectrum	Description
1	443	20	60	Visible/VNIR	Coastal aerosol
2	490	65	10	Visible/VNIR	Blue
3	560	35	10	Visible/VNIR	Green
4	665	30	10	Visible/VNIR	Red
5	705	15	20	VNIR	Vegetation (red edge)
6	740	15	20	VNIR	Vegetation (red edge)
7	783	20	20	VNIR	Vegetation (red edge)
8	842	115	10	VNIR	NIR
8b	865	20	20	VNIR	Vegetation (red edge)
9	945	20	60	VNIR/SWIR	Water vapour
10	1375	30	60	SWIR	Cirrus
11	1610	90	20	SWIR	SWIR
12	2190	180	20	SWIR	SWIR

III. SENTINEL-2 APPLICATIONS

There are so many problems in the scope of earth observation, so application on Sentinel-2 can be noted in many fields, like: spatial monitoring of changes in tropical forests [2], methods for mapping vegetation properties [3], identifying glacial features [4], mapping land use and land cover change [5], remote sensing of eelgrass [6].

Eliakim Hamunyela in his doctoral thesis "Spatial monitoring of changes in tropical forests using observations from multiple satellites" talks about how to improve satellite monitoring of forest changes by addressing key challenges that hinder correct and timely spotting of disturbances in forests from satellite data. More specifically, the thesis assesses whether the problem is with the season, a small-scale omission and low-scale and low-noise forest disorders, the innate noise in the time series of satellite images and inter-sensory differences in the multi-sensory time series. Researches were accomplished in wet tropical forests in Brazil and dry tropical forests with a strong season in Bolivia. In addition, a distinction between the spatial context model and the seasonal model is done. [2]

In paper [3], Juan Pablo collects the latest methods for optimized and automatic assessment of vegetation properties. His main goal was "To analyze, optimize and automate the most up-to-date methods for mapping vegetation properties in the preparation”. A GUI software package called ARTMO (Automatic Radiative Transfer Modeler Operator) was developed. The tool was applied to the assessment of the LAI and the LCC in the agricultural place Barrack, Spain.

Ruben Egbers performs data processing and identifies the glacial features in Sentinel-2 images. The pretension of his research was to examine how Sentinel-2 images are processed and whether these images are useful for the study of glacial features such as snowy peaks. The operations of Sentinel-2 data were made in the Sentinel-2 Toolbox. He investigated mountain range named Karakoram, which includes several long glaciers, such as the Baltor glacier or the glacier Hisspar. Karakoram glaciers are not retreating, but receive a mass (Hewitt, 2005), which makes this area interesting for studying. [4]

The focus of this research was to map and analyze the land use and land cover (LULC) between 1999 and 2017 in Kalmar municipality, with a method for detecting changes in the object. The study of LULC changes is of great significance because there is a decline in agricultural land, a growing population, and a rise in urban areas. The outcome of LULC modification have bigger impact than climate change in the future. Object-based detection of changes between remote scanned images is conducive to the analysis of LULC changes. The research methods consisted of an object-based post-classification method, for detection of LULC changes. In order to achieve higher accuracy of classification, the method was combined with visual inspection and by manual re-classification of the wrongly classified objects. Four LULC classes were mapped and analyzed. Maps showed that between 1999 and 2017, urban land use increased by 7 km2 and 20% and the agricultural lands decreased by 24 km2 and -10%. The main drivers for the loss of agricultural land were the expansion of urban areas and the growth of vegetation. The results of this study have shown that the detection of object-based changes helps to gain insight into LULC changes over time. [5]

In paper [6] was investigate Eelgrass (a seafood with long strips of leaves that grow in coastal waters and salty pads) as an ecologically important and fragile kind of grass as a plant that lives in or near the sea that is common in Denmark and the Northern Hemisphere. The depth of the boundaries of the eelgrass population is used to assess the ecological status of coastal waters, and coverage is used to assess the health of ecosystems. This thesis was used Sentinel-2 images with object-based analysis and diverse machine-learning algorithms for classification of submerged water vegetation in the Roskilde Fjord. The results established that the Random Forest is the most suitable machine learning algorithm for classification of water vegetation, and a parameter on a scale of 10 produces images that receive the highest accuracy of the classification. [6]

In the papers above, Sentinel-2 satellite images were used in remote sensing problems. Despite that, we are more interested about deep learning and CNN as deep learning architecture applied on Sentinel-2 images.

Deep learning is a new machine learning technique that learns features and tasks directly from data. Deep learning can be defined as AI method or techniques for learning in neural networks (ANNs) that contain more than one hidden layer. It is almost everywhere: Object recognition, Object classification, Object detection, segmentation, pose estimation, Image captioning, question answering, Machine translation, Speech recognition, Robotics [19], [20]. Many different architectures for deep learning exist such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural network. CNN is a combination of biology, math and computer science. CNN is comprised of several layers divided into two parts: feature learning (Conv, Relu,and Pool) and classification (FC and softmax). Every layer transforms an input 3D volume to an output 3D volume with some differentiable function that may or may not have parameters (e.g. Conv/FC do, ReLU /Pool do not). Each Layer may or may not have additional hyperparameters (e.g. Conv/FC/Pool do, ReLU doesn’t). A classic CNN looks like

Input->Conv->ReLU->Conv->ReLU->Pool->ReLU->Conv->ReLU->Pool->FullyConnected

First layer in CNN is always a convolution layer where we use filter to get activation map (feature map) from an input image. There are also two main parameters that we can change to modify the behavior of each layer. They are stride and padding.

The value of stride is mostly set on 1 or 2, and the value of padding on 0. The output from the convolution layer is calculated with equation output=(W-F+2P)/S+1. For example, if we have an input size [32x32x3], filter 5x5x3, stride 1 and pading 0, we will get the output= (32-5+2*0)/1+1=28. ReLU is rectified linear units' layer that applies the function f(x)=max (0, x) to all input values. This layer changes all the negative activations to zero. This layer does not change the size of the volume. Pooling layer or downsampling layer is layer for resizing images that gives on output the maximum numbers from each subregion. The Max pooling function is the most used type of pooling. Neurons in a fully connected layer have full connections to all activations in the previous layer. The last one uses a softmax activation function for classifying to compute the class scores. CNN are mostly applied to images, video and natural language processing [21], [22], [23]. CNN for image classification start with low-level features like curves and edges and then building up more specific concept to recognize the classes. The network is usually trained by using backpropagation [14], [1]. The goal of back-propagation is to optimize the weights in order neural network to learn how to correctly map inputs to outputs. Back-propagation consist of three parts: forward pass, calculating the total error and backwards pass. The most common Convolutional Networks architectures are: LeNet (developed in 1998), AlexNet (2012), ZefNet (2014), VGGNet (2014), GoodLeNet (2015), ResNet (2016), Xception (2017), Convolutional Block Attention Module (2018), Channel Boosted CNN (2018) … Deep learning and convolution neural networks, applied to satellite image recognition problems are presented in the following papers [8] - [13].

Since it is important to have information about the earth, LULC maps were created. LULC maps still took in manual work and data availability after long period (even a few years). Automatic methods for LULC classification exist, but there was a problem when they have a large-scale LULC classification. CNN cannot be directly applied to LULC. There were a small number of bases used to adapt the CNN to LULC classification. After acceptance of CNN architecture, they both were used for classification of Sentinel-2 images. Training data was taken from Sentinel-2. Researcher used annotation from OpenStreetMap database. TensorFlow framework and Inception-v3 CNN architecture were used. The result showed that CNNs were good for LULC classification. [8]

Several methodologies have been proposed for classification of satellite images, but CNN has proved to be one of the better ones and is therefore used in this paper [9]. In particular, a method for classifying a satellite image using CNN architecture was proposed. Six-layer CNN architecture consisting of an input layer, three convolution layers, two sub-sampling layers and at the end a fully connected layer is used. Satellite images were collected to apply the proposed CNN architecture. The database contained 6 classes of different areas (airport, bridge, forest, harbor, land and urban area) each of 200 images or total 1200 images. From each class 50 images were used for training, and the rest 150 for testing. According to the experiments carried out and the obtained results, it was shown that the proposed method for classification could be an encouraging alternative to existing schemes based on extraction for feature.

With the development of INSPIRE, a few Spatial Data Infrastructures (SDI) became publicly available. At the same time, Copernicus satellites (Sentinel) produce huge amounts of image data. For image processing U-net Convolution Neural Network (CNN) architecture was developed. The research was based in Netherlands. They classified six classes: build-up area, water, cropland, forest, grassland and undefined area. A comparison of the Convolution Neural Network (CNN) with the Random Forest model was also performed [10].

A challenge in satellite images is automatic target detection. Khan and al. [11] proposed a system for classifying target and non-target objects. They detected aircrafts. The system they proposed was based on EdgeBoxes and Convolutional Neural Network (CNN). The architecture of CNN contains five layers: two convolutional, two pooling and one fully connected layer. A military dataset consists of 500 aircraft images, 5000 non-aircraft and 26 test images. The test images were taken from Google Earth. The results shown that the proposed system was good for detecting aircrafts in satellite images.

Authors in paper [12] and [13] deal with HSR (high-resolution satellite) images. For image scene classification, [12] proposed an agile CNN architecture known as SatCNN. They have used convolutional layers with many small kernels and obtained average precision of around 99.65% for 40 minutes training. SAT data sets (SAT-4 and SAT-6) were used for training. SAT-4 consist of 500 000 and SAT-6 of 405 000 images covering four/six classes. The use of NVIDIA, CUDA and CuDNN library made convolutions to move more quickly. In the second paper [13] was proposed a new model (multi-scale CNN) for geospatial object detection in HRS images. For training were used NWPU VHR-10 datasets (positive dataset contains 650 images and the negative dataset contain 150 images) and the average precision of 89.6% was obtained.

IV. CONCLUSION

Sentinel-2 is one of the most essential data acquired for earth monitoring. In this article, we make a literature review (an overview) at recent studies in which researchers used image obtained from Sentinel-2 satellites in order to see the changes in the life environment. In addition, we are interested in research that make image classification using CNN and deep learning. Our aim is using CNN to make classification on Sentinel-2 and INSPIRE images to search for uncultivated workable land in Balkan Peninsula.

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