Image Segmentation Approaches Applied for the Earth's Surface

Dziana V. Kypriyanava, Dmitry Y. Pertsau, Mikhail M. Tatur

Abstract**—**An analytical review of papers about remote sensing, as well as semantic segmentation and classification methods to process these data, is carried out. Approaches such as template matching-based methods, machine learning and neural networks, as well as the application of knowledge about the analyzed objects are considered. The features of vegetation indices usage for data segmentation by satellite images are considered. Advantages and disadvantages are noted. Recommendations operations for a more accurate classification of the detected areas on the sequence are given.

Keywords**—**Machine learning, remote sensing, semantic segmentation, vegetation indices.

I. Introduction

Remote sensing of the Earth is a process of remote observation of the physical characteristics of areas of interest by measuring the reflected electromagnetic radiation in order to identify them.

Two types of spectrometers are distinguished as the equipment.

The first type is active sensors, where an electromagnetic pulse is created, and then the energy of the signal reflected from the surface is measured. The main advantage of this sensor type is light and clouds do not affect operation. Examples of active systems are SAR (Synthetic Aperture Radar) and LiDAR.

The second type is passive sensors, which measure the natural energy of the Sun reflected from objects and the Earth's surface. The disadvantages include dependence on illumination and weather conditions.

The development of technologies and their rapid implementation into practice has led to an ever-increasing amount of data that needs to be analyzed and processed. So, for example, the Copernicus missions archive size by the end of 2021 is approximately 32.21 PB [1] and continues to grow.

Image processing can be performed for the following purposes:

– image fusion, which combines images taken with different spectrometers (for example, merging multispectral and panchromatic images with different resolutions or merging multispectral and hyperspectral images);

– semantic segmentation, when a semantic meaning is assigned to a selected area of an image;

– search for changes in images of the same area over time;

– Land Use Land Cover, which allows to determine how effectively this territory is used, to identify areas of deforestation, flood zones, control crops, etc.

We analyze ongoing research in LULC field in the paper.

II. Remote sensing data sources

At present, there are a number of national, international organizations and consortiums implementing remote sensing. In the paper, we will focus on two authoritative programs:

– Landsat Data Continuity Mission (Landsat-8 mission);

– Copernicus Program (Sentinel-1 and Sentinel-2 missions).

D. V. Kypriyanava, Belarusian State University of Informatics and Radioelectronics, Minsk, Belarus.
D. Y. Pertsau, Belarusian State University of Informatics and Radioelectronics, Minsk, Belarus.
M. M. Tatur, Belarusian State University of Informatics and Radioelectronics, Minsk, Belarus.

TABLE I
MAIN TECHNICAL CHARACTERISTICS OF SENSORS EQUIPMENT

Mission	Sensors type	Temporal resolution	Spatial resolution	Radiometric resolution
Sentinel-1	radar	6 days	5-40 m. depending on the reception mode	1 dB
Sentinel-2	visible near IR shortwave IR coastal	5 days	10 m. (visible, near IR) 20 m. (shortwave IR) 60 m. (coastal)	12 bits
Landsat 8	panchromatic, visible near IR shortwave IR coastal thermal	16 days	15 m. (panchromatic) 20 m. (visible, near IR, shortwave IR, coastal) 100 m. (thermal)	12 bits

IR = infra-red.

The main technical characteristics of the satellites participating in the programs are summarized in Table 1.

The interest to these missions related to openness and availability of source data, support by cloud computing providers (Google Earth Engine, Amazon AWS).

Satellite imagery has a high spatial resolution (for example, Sentinel-2 image has a resolution of 10,000 x 10,000 pixels, each of which covers an area of 10 x 10 meters on the surface in the visible and near infrared spectra), and the processing is associated with high computational cost.

Therefore, to reduce computational complexity and the number of errors, some researchers recommend cutting out the area of interest and performing all subsequent operations on it (fig. 1).

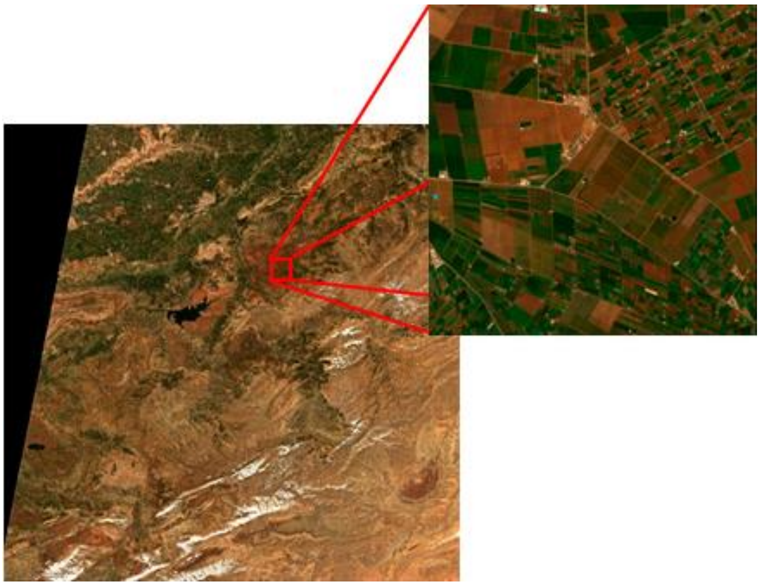

Fig. 1. Example of Sentinel-2 satellite image and research area

III. APPROACHES TO DATA SEGMENTATION AND CLASSIFICATION

Despite the variety of sensors used with different technical characteristics, objects detection in the visible spectrum is reduced to the use of one of the following approaches (fig. 2) [2]:

– template matching-based methods;
– knowledge-based methods;
– OBIA-based methods;
– machine learning-based methods including methods based on deep neural networks.

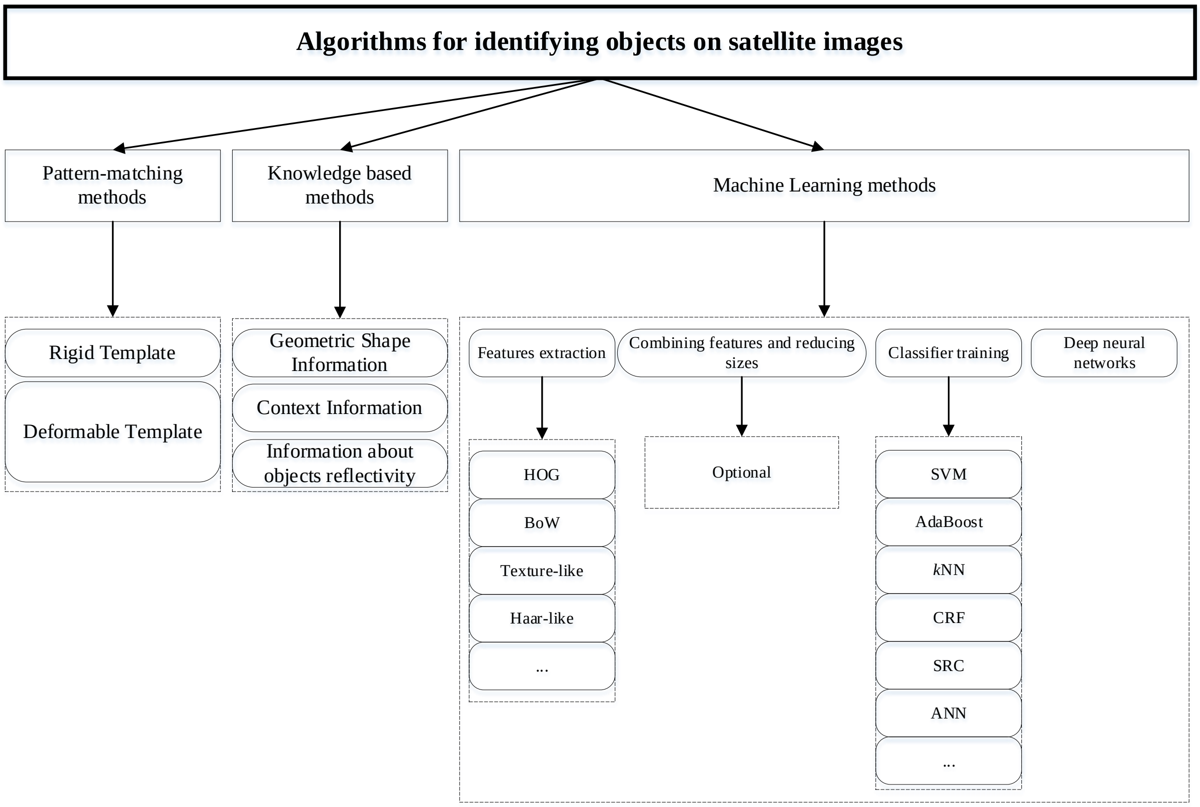

Fig. 2. Classification of algorithms for determining objects on satellite images

2.1. Template matching-based methods

Pattern-matching methods are one of the simplest and oldest methods, involving two steps (fig. 3):

– creating a template for each object that needs to be recognized;

– assessment of the template similarity with the image, taking into account all possible affine transformations. The following metrics are used as similarity metrics: sum of absolute differences, sum of squared differences, normalized cross-correlation, and Euclidean distance.

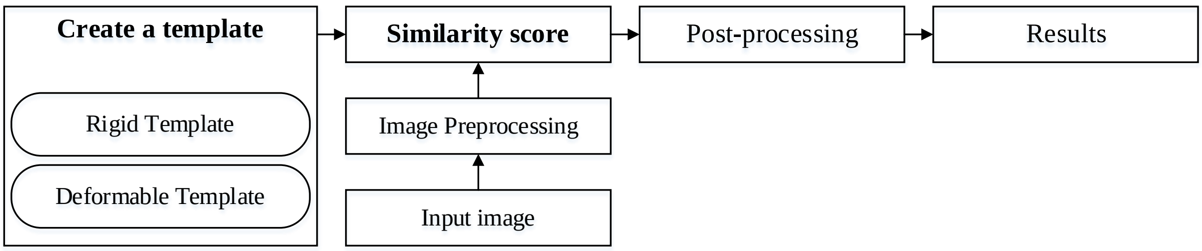

Fig. 3. Sequence of actions in methods based on pattern matching

The main researches are focused on creating a template:

– rigid template matching, which is used to detect specific objects with a simple appearance and small variations (for example, roads and buildings) [3]-[5]. The main disadvantages of the method are dependence on scaling, rotation angle, sensitivity to the point of camera position;

– matching with a deformable template matching, which is used to detect arbitrary objects with a complex appearance (for example, aircraft, ships, etc.) [6]-[9]. The main disadvantages of these approaches are required additional information about the shape of the object, and relatively high computational cost.

2.2. Knowledge-based methods

In knowledge-based methods (fig. 4), the main difficulty is the formation of knowledge and rules, according to which the object in question will be determined in the future. In general, the analysis of the papers shows three main approaches in the area:

– knowledge about the geometric shape and radiometric properties [10];

– knowledge about the context (for example, casting shadows from tall objects) [11], [12];

– knowledge about objects reflectivity.

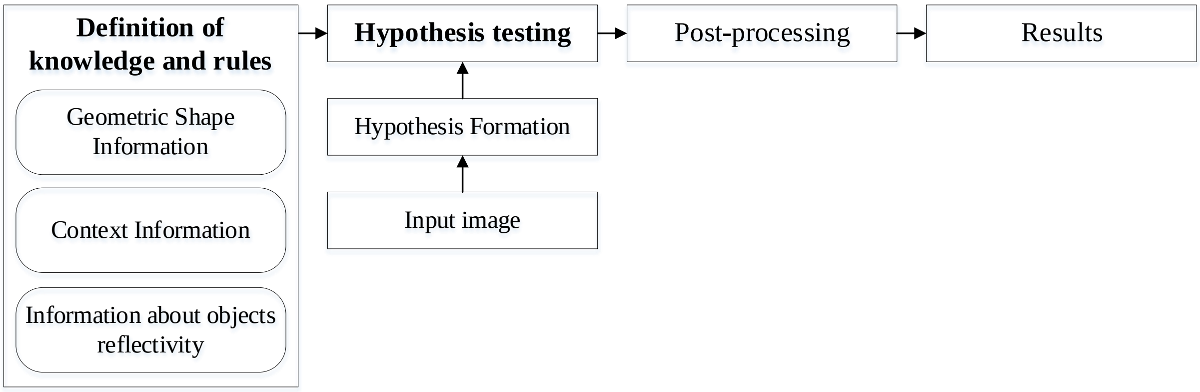

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Fig. 4. The sequence of actions in methods for determining objects based on knowledge

The most promising in the method is the use of information about objects reflectivity and about vegetation indices.

The vegetation index is a metric used to assess various parameters in nature management (including agriculture) based on information from various spectral bands.

With their help, you can:

– assess the dominance of green plants (NDVI [13] or EVI [14] metrics), snow and water cover (NDSI [15] and NDWI [16] metrics, respectively);

– to investigate the effectiveness of fertilizer application (GCI metric [17]) and to detect plant diseases (SIPI metric [18]);

– detect active forest fires (NBR metric [19]);

– compare changes in time in a given area by one or another metric (for example, by tracking the NDVI metric, you can detect differences in plant growth compared to previous years, detect deforestation).

The main advantage of their use is the absence of the need for markup and data preparation.

The disadvantages of the approach include:

– existing assessment methods are not very accurate [20]-[22]: for example, it's difficult to distinguish densely planted crops from forests;

– in some metrics, it is necessary to adjust the threshold values depending on the climate, natural and landscape features.

Thus, vegetation indices usage without additional analysis in semantic segmentation is difficult and strongly depends on the studied object classes and the area where the survey is performed.

2.3. Methods based on machine learning and deep neural networks

The development of machine learning-based methods, the development of classifiers and methods to represent features has led to significant progress in object detection on satellite images. A generalized scheme of the method operation is shown in fig. 5 [23]-[26].

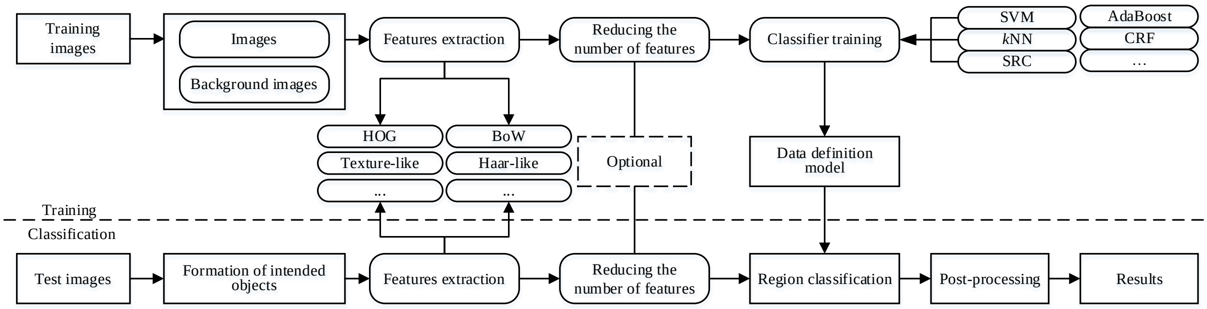

Fig. 5. Generalized scheme of work of methods based on machine learning algorithms

An analysis of the main neural networks architectures used for semantic segmentation in remote sensing allows us to distinguish the following architectures:

– based on convolutional neural networks for object recognition (fully connected neural networks [27], [28], DeconvNet [29], DeepUNet [30], DeepResUnet [31], etc.);

– based on generative adversarial network for removing artifacts (for example, clouds) from images and reconstructing images (pix2pix [32]-[34]);

– based on Transformer (HRNet [35], SE-HRNet [36], OCRNet [37], [38]).

The advantage of neural networks usage is the most reliable and detailed results (with high-quality model training).

The disadvantages of the approach include:

– a high-quality test set with already labeled data is needed;

– high computational costs.

The solution to the first problem could be the use of existing resources for the Sentinel-2 satellite. For example, the CORINE Land Cover project [39] provides access to labeled and validated data for 39 countries of the European Union. The markup is made in accordance with 44 classes [40] covering various fields of application and correspond to similar ones defined in the CORINE program [41].

A limitation that requires careful data selection for training is the need to select labeled data in accordance with the area where it is planned to apply the resulting model. For example, for the vegetation cover in the Republic of Belarus, it does not make practical sense to train the model on data that is characterized by desert and bare rocks.

2.4. Classification of data on the earth's surface images

The classification of data on the earth's surface images (for example, the identification of crops such as radish, tomatoes, wheat, etc.) is a more complex task. There are two key challenges in solving it:

– low spatial resolution of publicly available data (spatial resolution of 10 x 10 m per pixel may not be sufficient for unambiguous identification);

– the lack of ready-made test sets for training neural network. However, their self-preparation is possible. For this, CropScape [42] can be used as initial data; no freely available information suitable for data labeling applicable to the Republic of Belarus without additional processing has been identified.

IV. Conclusion

Thus, the general technique for semantic segmentation of remote sensing images can be represented as follows:

– apply one or more vegetation indices (EVI, NDWI, NDSI metrics) to identify areas with studied classes, thereby reducing the likelihood of false positives;

– apply a convolutional neural network or machine learning algorithm to match each pixel with a specific class;

– to refine and correct the boundaries taking into account the geometric features of the class (for example, the absence of gaps on the roads, agricultural fields, as a rule, have the correct shape, etc.), generalize the information received and form polygons.

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