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Patternrecognition in oil infrastructure with convolutional neural networks

***R. Okhrimchuk**, **I. Tishaev**, **V. Zatserkovnyi**, **O. Smorkalova** *(Taras Shevchenko National University of Kyiv)*

SUMMARY

In the paper presented an approach for pattern recognition in oil infrastructure with convolutional neural networks. The relative ease and high effectiveness of the approach are shown compared with methods based on spectral signatures

Introduction

The task of identifying changes in the infrastructure of oil producing companies has always been topical from various points of view. However, the main reason for this kind of research is predetermined by competition and market analysis. Timely detection of any activity in the industry and its reliable localization in the terrain is a key to the efficient use of resources of oil producing companies of different scales, as well as investment funds (Lasica, 2015). This is true for many branches of economic activity, for example, it is widely used in agriculture (Lietal., 2017). Figure 1 shows an example of changes in the situation with the equipment for oil production and accumulation.

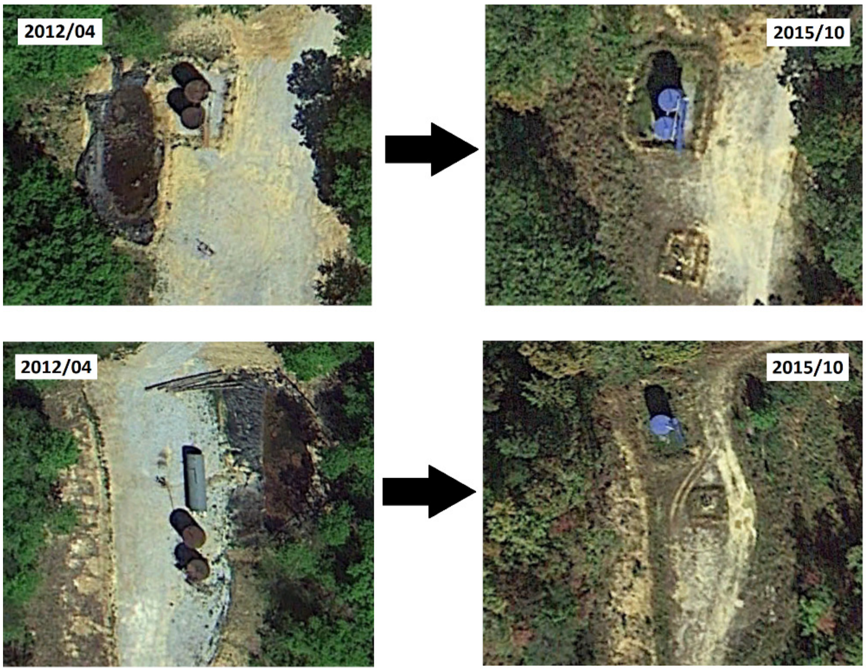

Figure. 1. *Development of production wells in two different locations in 2012 and a state of oil producing and oil storage equipment in 2015.*

Traditionally, this problem is solved on the basis of Change Detection technology by Satellite Image Time Series. Variations of technology suppose the use of not only multi-spectral, but also radar images (Hnatushenko et al., 2019). Difficulties in applying traditional technology are represented by many false positives. Among the mass of changes occurring during the period of time under study there may not be any desired quantities at all. If there are any, then the problem of their classification arises that complicates and increases the cost of technology. The alternative approach that has proven its efficiency in many applications is the use of convolutional neural networks technology. The feature of this approach (with training) consists in using visual images of the desired objects as a training set, but not their spectral signatures (Makantasis et al., 2015; Mozgovoy et al., 2018).

Method

To solve this problem, a pre-trained neural network was chosen. (Szegedyetal., 2016) known as InceptionResNetV2. InceptionResnetV2 It is the convolutional neural network which is trained by more than one million images from the ImageNet database. The network consists of 164 layers. The network has a complex architecture, which is illustrated in Fig. 2. The size of input images is 299 x 299 pixels.

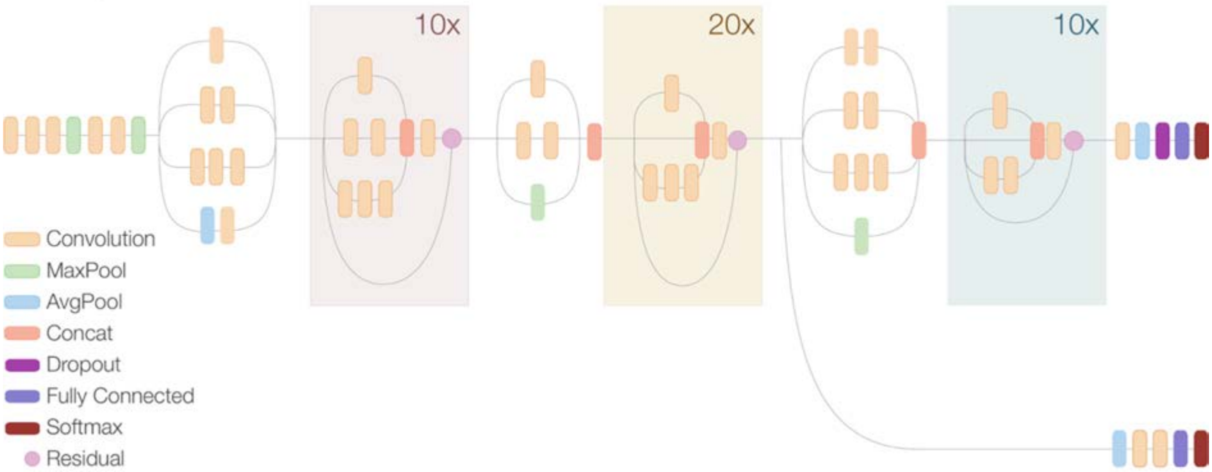

Figure 2 *A compressed view of InceptionResnetV2 blocks https://ai.googleblog.com/2016/08/improving-inception-and-image.html*

The process of neural network training consists in adjustment of weight coefficients of convolutional layers with the use of a pre-created training set. Training sample consists of a set of images significant in volume containing (or not containing) the target object. The example of such a training sample is illustrated in Figure 3. Oil storage tanks are represented as an object of search.

Similar validation and/or test samples have been created in parallel with the training sample. These samples are fully analogous to the training one (each image in such samples is classified as "contains the target" or "doesn't contain the target"), but they consist of unique (not used in the training sample) images. Technically, network training is carried out by means of a long process of continuous correction of network weights in the course of unordered (random) sorting of input images from the training sample with periodic quality control of training on test and validation samples.

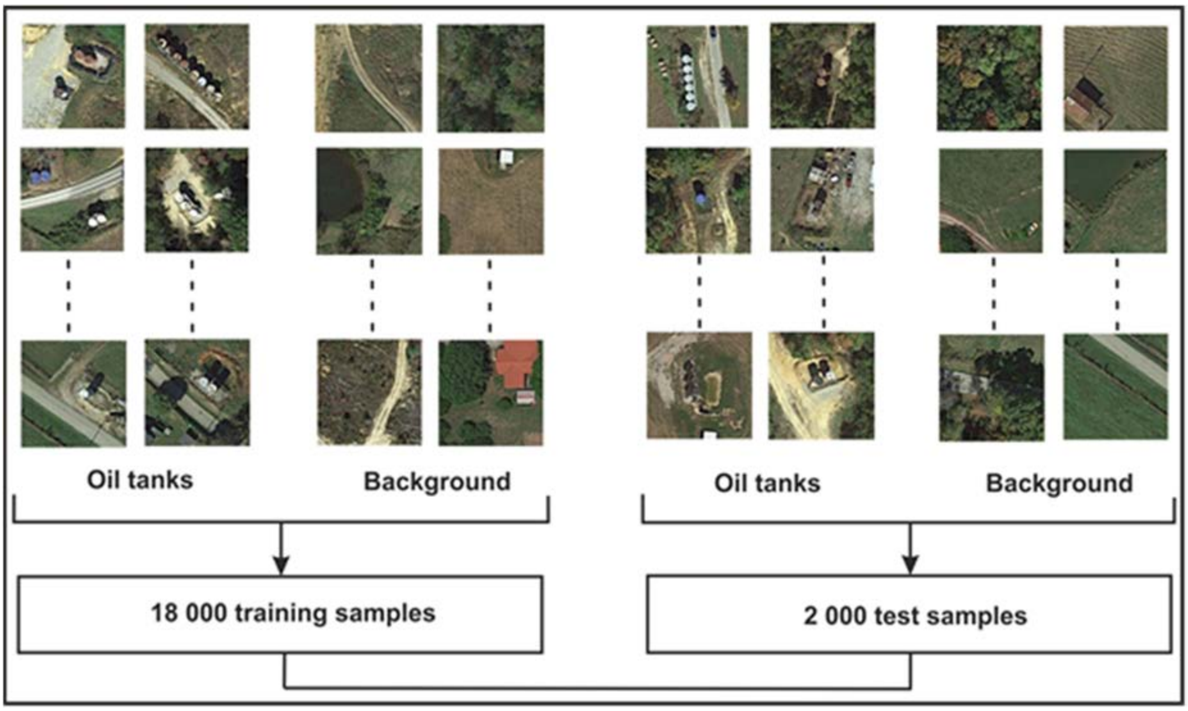

Figure 3. *The example of training and test samples for training in detection of oil storage tanks.*

In the operating mode, the neural network configured to detect target objects receives images with the same characteristics as the images of the training sample (a physical size in pixels, quantity of channels, data type), but with completely arbitrary semantic content. At the output, the network generates an n-

component vector whose components are the probabilities of assigning the input image to each of n-classes.
Technically, the process of recognizing large-sized scenes (significantly larger than the size of images delivered to the network input) is implemented by passing through the scene a scanning window of required size with the given step and overlap area (Figure 4).

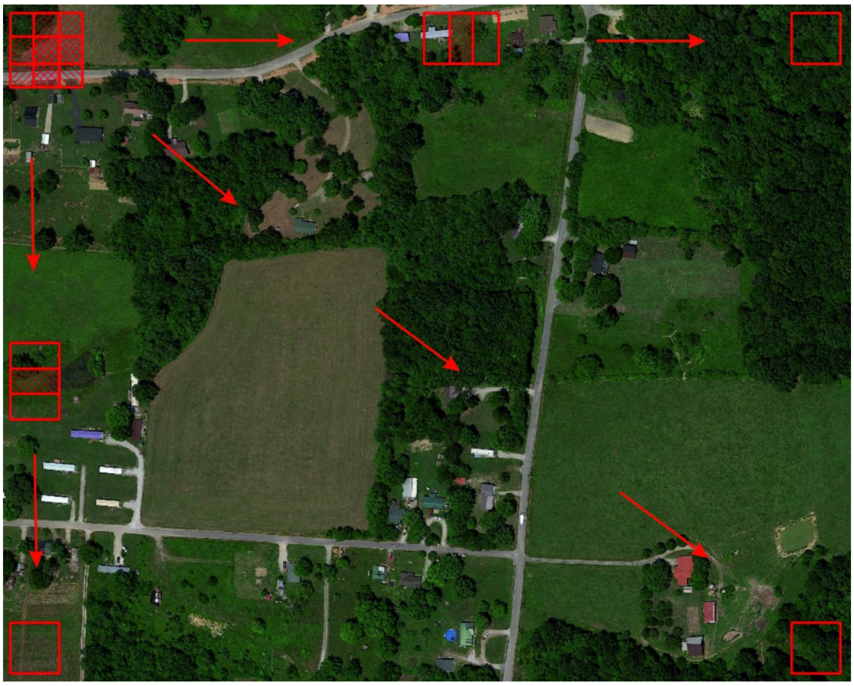

Figure 4. *The scheme of recognizing the scenes significant in size*

At each position of the scanning window the image of required sizes is cut out of the original scene and delivered to the input of trained network. The resulting image is formed as a superposition of classification results of all images obtained at all positions of the scanning window. The resulting image has probabilistic meaning: areas of its increased values indicate the places where location of targets is more likely. Further on, by applying threshold processing (if required) you can create an appropriate vector thematic layer. The examples of the trained network are shown in Fig. 5. Python 3, Keras, QGIS were used as main working tools.

Figure 5. *Examples of source images (left) and recognition results combined with them (right).*

Conclusions

Recognition of artificial small-size objects is possible to efficiently implement on the synthesized RGB images of high spatial resolution by using the deep-learning method of convolutional neural networks. In this way it is possible to eliminate the need to use the results of remote sensing in other than optical ranges that significantly reduces the cost of recognition technology. The described approach is of practical interest and is in demand in the field of identification of objects in oil and gas industry of small-scale enterprises.

References

Hnatushenko, V., Mozgovoy, D., Hnatushenko, V., Spirintsev, V. and Udovyk, I. [2019] All-weather monitoring of oil and gas production areas using satellite data. *NaukovyiVisnykNatsionalnohoHirnychohoUniversytetu № 6*

Lasica, R. [2015] A new age for oil and gas exploration remote sensing data and analytics are changing the industry. *Earth Imaging Journal*

Li, W., Fu, H., Yu, L. and Cracknell, A. [2017] Deep Learning Based Oil Palm Tree Detection and Counting for High-Resolution Remote Sensing Images. *Remote sensing*, 9, 22

Makantasis, K., Karantzalos, K., Doulamis, A. and Doulamis N. [2015] Deep supervised learning for hyperspectral data classification through convolutional neural networks. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* 4959-4962

Mozgovoy, D., Hnatushenkoa and V., Vasyliev V. [2018] Accuracy evaluation of automated object recognition using multispectral aerial images and neural network. *Tenth International Conference on Digital Image Processing*

Szegedy, C., Ioffe, S. and Vanhoucke, V. [2016] Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. *Thirty-First AAAI Conference on Artificial Intelligence*