Use of convolutional neural networks for segmenting images of roads from satellite

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Abstract. The article developed a technique for using convolutional neural networks for automatic segmentation of roads in images obtained from satellites with a synthesized aperture. The analysis of the subject area and the relevance of this study. The development of a neural network based on U-net was carried out in Python 3x using the libraries TensorFlow, TensorBoard, Pandas, Numpy, Scipy, Matplotlib, Sklearn. The neural network was trained on a training sample of 1200 images prepared by hand marking. The accuracy of the developed model when testing on prepared samples was 68%. According to the results of the study, conclusions were drawn and prospects for further functional development of the developed tools were determined.

1. Introduction

The overall growth of cities in the past two decades has led to significant development of transport networks. An actively developing road infrastructure requires frequent updates of road maps. A wide range of applications depend on this information, such as intelligent transportation systems [1], monitoring the spatial development of a city [2], automatic data updates for geolocation systems, or supporting rescue operations in disaster relief. A satellite equipped with synthetic aperture radar (SAR) can scan the terrain. The obtained physical information about the terrain is more resistant than optical images to changes in exposure and color. In addition, SAR sensors can operate regardless of all weather conditions, which is a major advantage when capturing a disaster-stricken region.

Here are a number of recent research papers in this area. For the first time, deep convolutional neural networks (DCNN) demonstrated unrivaled efficiency in image analysis in 2012 [3]. While many DCNN architectures specialize in image classification (predicting one tag from an image: airplane, car, ship, etc.) [4] [5], others have achieved good performance in remote sensing tasks such as semantic tagging of aerial photographs [6] [7]. To maximize the spatial accuracy of the information extraction, we perform pixel segmentation using complete convolutional neural networks (FCNNs).
Introduced in 2015, the convolutional neural network FCN8s [8] trained on the popular POSCAL VOC 2012 reference datasets set a new record for the quality of semantic segmentation [9]. In [10], a technique was proposed for the automatic segmentation of satellite images into several classes, such as buildings, rivers, roads, etc. In [11], a system of road segmentation of various road classes was developed on the basis of a cascade network and a direction module to capture the linear structure of the road.

2. Setting the task
The present study focuses on road extraction from SAR satellite imagery using deep convolutional networks.

3. Method
To solve the problem of road segmentation on satellite SAR images, at the first stage, an algorithm of the system was developed (Fig. 1).

![Figure 1. Algorithm of the road segmentation system](image)

At the second stage, a training sample was formed, consisting of a Training Set, a Test Set, and a Validation Set.

For this, a set of 3600x3600 satellite images was selected and the roads were manually marked. As a result, three types of images were obtained: original images (Fig. 2), an image mask (Fig. 3), and images with a mask overlay (Fig. 4). The total volume of the training sample was 1200 images.
Further, the development of a convolutional neural network was carried out. The neural network was created in Python 3x using the TensorFlow, TensorBoard, Pandas, Numpy, Scipy, Matplotlib, Sklearn libraries. The U-net network was chosen as a neural network model [8]. The neural network consisted of 10 layers (Fig. 5). To train the neural network, a training sample was fed into the input, 75% of which went to training, and 15% to testing. The number of epochs for training was 60. The learning outcomes are presented in fig. 6. The binary cross entropy was used as a loss function; its value at the stage of training completion was 0.1012. The per-step mean Intersection-Over-Union (mIOU) was 0.6884.

The aggregate intersection mean is a common scoring metric for semantic image segmentation that first calculates the IOU for each semantic class and then calculates the average across the classes. IOU
is defined as follows: $\text{IOU} = \frac{\text{true positive}}{\text{true positive} + \text{false positive} + \text{false negative}}$. The predictions are accumulated in a weighted mixed matrix and then $\text{mIOU}$ is calculated from this matrix.

The value of the cost function for the cross validation data was $\text{val_loss} = 0.1321$. And the value of the recognition quality was $\text{val_mean_iou} = 0.6884$. Characteristics at one of the stages of neural network training (epoch 58-60) are shown in Fig. 6.

4. Results

The developed neural network made it possible to perform road segmentation with high recognition quality.

Comparisons of the original satellite image, the image from the training sample and the image obtained as a result of the neural network with road segmentation are presented in Figure 7 respectively.

5. Conclusion

Developed on the basis of a convolutional neural network, a system for segmentation of roads in satellite SAR images has shown its high efficiency. The resulting terrain marking is comparable in quality to manual marking.

The introduction of this system as one of the components of an intelligent transport system [12,13,14] will allow automatic assessment of the beaten track in order to develop and organize new transport networks, and also be used as a marker backbone route network [15, 16] for unmanned aerial monitoring of rural settlements.

Using the developed neural network, it was possible to improve the quality of the analysis of Crimean roads [17, 18].

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