Recognition of Urban Transport Infrastructure Objects Via Hyperspectral Images

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Abstract: Actualization of vector maps of the urban transport infrastructure, including street and road network, in conditions of constant changes is a resource-consuming task and it requires the automation of the process. The article considers the solving of problem of transport infrastructure objects recognition in hyperspectral images by deep convolutional neural networks. The hyperspectral images from different sources are considered for solving the problem. We propose a new approach to the formation of receptive fields of convolutional neural networks: the receptive field covers several pixels, but the depth of the colour channels is limited. In the proposed approach the receptive field moves in three dimensions - in two spatial dimensions and in spectral channels dimension. It gives the ability to recognize the transport infrastructure objects by spatial patterns and spectrum.

1 INTRODUCTION

The modern pace of large cities development entails a permanent changing of transport infrastructure. This is especially noticeable at the stage of preparing the city for receiving a major sporting or cultural event. In general, the changes in the transport infrastructure are determined by several factors:

- steady increase in the level of motorization in the cities;
- construction of new residential buildings;
- reconstruction and building of engineering facilities;
- construction of new sociocultural and sports facilities;
- expanding the boundaries of the city;
- growing demand of citizens to transport accessibility.

Changes in transport infrastructure in most cases are systematized, but at the moment there are no clear mechanisms for notification of all involved organizations and services. Particular difficulties are experienced by non-governmental organizations distributing cartographical information or offering services based on it. Actualization of vector maps of the city street and road network in conditions of constant changes becomes a task, which requires involvement of a large number of resources.

The solution of the problem of timely updating the map data is possible by the automation of the process. One of the methods is recognition of satellite images of areas. At the same time, the use of ordinary photos is associated with the problem of incomplete data and as a consequence of the poor quality of recognition. When operating with a city map it is advisable to use hyperspectral images because they contain a larger amount of information at each point in the image, which greatly improves the quality of transport infrastructure recognition.

Hyperspectral measurements for physical-chemical properties assessment help to evaluate road-transport infrastructure objects conditions. This research trend is concerned in papers (Resende et al., 2014; Mei et al., 2014; Cavalli et al., 2008; Wei et al., 2009; Herold et al., 2004a; Gomez, 2002; Miraliakbari and Hahn, 2014).

Hyperspectral images are third dimensional data array which consists of spatial information about object and spectral information for each spatial coordinate. Each pixel of hyperspectral image is attributable to its spectral feature. Information is represented in tens and hundreds of neighboring bands (about 5-10 nm). Frequently hyperspectral

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information is represented like “hypercube” (Figure 1).

For effective solving of problems mentioned above hyperspectral data must have high spatial resolution and must span spectral region from 0.4 to 2.5 μm. The important aspect is development of road pavement spectral library for different classes and different conditions and typical materials for urban territory on the basis of field data acquired by hand spectroradiometer.

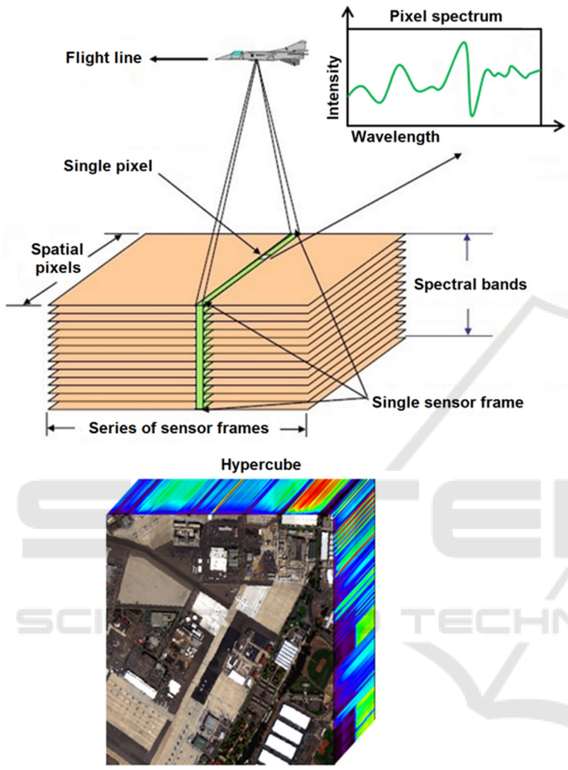

Figure 1: Schema of “hypercube” formation.

The process of transport infrastructure objects monitoring is associated with a range of features which is defined by a necessity of preliminary processing as well.

Firstly, given that in the three-dimensional land surface structure, road-transport infrastructure objects are the “bottom layer” that can be covered or shadowed by surrounding surfaces such as trees, buildings or vehicles.

Secondly, the problem of hyperspectral data processing would be solved essentially more easily if all image pixels were “pure”, i.e. each pixel contains information only about the single object. However, natural surfaces rarely consist of homogeneous material. Furthermore, the total radiation from all of the objects inside the spatial resolution element is registered by the sensor as single image pixel. Therefore in general the operator-user deals with the so called “mixed pixel”. The mixture dynamics of two or more materials inside the single pixel can be described by linear and non-linear models (Keshava, 2003; Kukharenko, 2013).

Thirdly, remote sensing hyperspectral data contains information not only about the surface but also about the atmosphere conditions. The atmospheric correction procedure intends for rejection of this warping factor and image transformation from spectral brightness units to spectral reflectance index units (Mikheeva and Fedoseev, 2014; Zhuravel and Fedoseev, 2013; Yuanliu et al, 2007; Schowengerdt, 2010, Schott, 2007).

Finally, the spectral profiles of transport infrastructure objects frequently are similar to spectral profiles of typical urban infrastructure artificial objects (roofs of buildings, engineering structures). This fact can influence negatively to results of hyperspectral data processing (Herold et al., 2004a).

To get the satisfactory results during the usage of high resolution hyperspectral images for monitoring and evaluation of road-transport infrastructure objects conditions, several processing stages must be applied (in the case of correct initial data are prepared) (Cavalli et al, 2008; Chang, 2000; Gualtieri and Cromp, 1999; Ratle et al., 2010).

Generally the process of thematic processing can be divided into two main stages (Resende et al., 2014):

- objects of interest detection and extraction;
- classification of road-transport infrastructure objects.

To extract the road pavement the algorithms of controlled classification are used. These algorithms require spectral samples availability (Herold et al., 2004b).

In this case spectral samples are contained in spectral library, which is filled up by the measurements from field and aviation hyperspectrometer. The algorithms of controlled classification offer two approaches: determinate and statistical.

The determinate approach is used in the case when objects classes don’t overlap in the feature space (Schowengerdt, 2010). However, natural and artificial objects are generally nonhomogeneous and spectral characteristics of research objects are similar or particularly overlapped (for example, for different types of soils and road pavements).

Therefore the classification methods which are based on statistical approach for feature variations considering and accept to attribute of pixels to another's classes if the frequency of their appearance is low have been popular (Chandra, 2008).

Despite of extensive researches in the application of hyperspectral images, their usage in solving the problem of recognition of transport infrastructure objects is associated with a number of difficulties described above. One of the methods leveling these difficulties is the application of artificial intelligence techniques to solve the problem (Saprykin and Saprykina, 2015). In recent years the convolutional neural networks have proved themselves in the field of image processing. The researches are actively conducted in the field of recognition of images, consisting of the three color channels (Krizhevsky et al., 2012; Simonyan and Zisserman, 2014). However, the processing of hyperspectral imaging is studied insufficiently, and more research is necessary to find the optimal network architecture and training algorithms. This article considers the problem of recognition of transport infrastructure objects in hyperspectral images by deep convolutional neural networks.

2 CONVOLUTIONAL NEURAL NETWORKS

Recent researches have shown great success of convolutional neural networks in images recognition. The architecture and training algorithms of such neural networks are similar to ordinary feedforward networks, but they are optimized for handling large amounts of input data. The input layer of convolutional neural networks is represented as 3-D data set. When passing through the layers of the neural network the size of the input array is changed, and eventually it is reduced to one-dimensional array, which is easily treated by a conventional feedforward neural network (Figure 2). Such transformation with retention of high learning ability requires a large number of layers, so it is reasonable to use deep convolutional neural network (Simonyan and Zisserman, 2014).

The convolutional neural network consists of the following types of intermediate layers: convolutional layers, max pooling layers and fully connected layers. Convolutional layers serve to identify the characteristics of facilities in accordance with pre-trained patterns. Max pooling layers allow to select the strongest signal from the considered region and reduce the size of data array. At the final stage of data processing the fully connected layer is used, which directly determines what class the facility described by the input data set is (Krizhevsky et al., 2012).

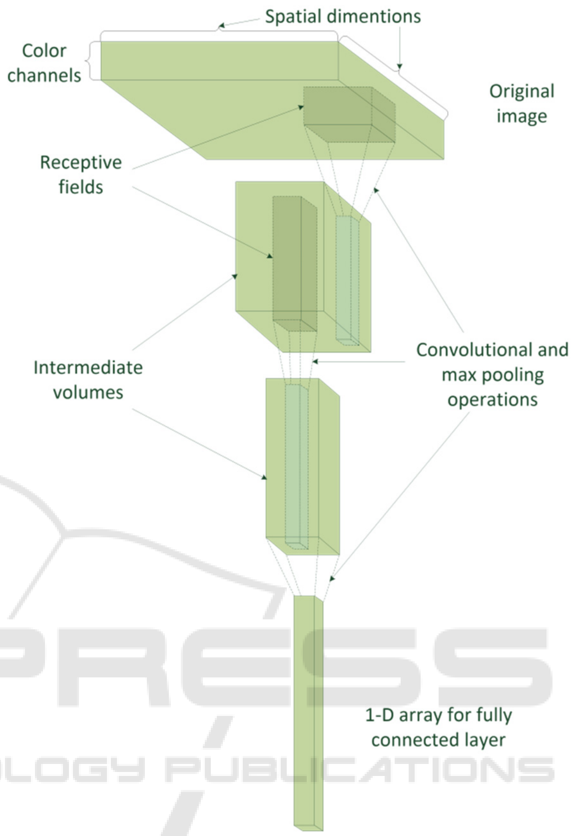

Figure 2: Schema of reducing of the input data set in convolutional neural network.

Convolutional neural network is not fully connected. Each subsequent intermediate network layer is associated with a small number of neurons in the previous layer that unites their presence in a small local area - receptive field. The important point, accelerating the training and working of the neural network, is using the same weights for all receptive fields of the layer (parameters sharing). When designing the convolutional layer such parameters as the depth of the output array, stride, and zero-padding can be varied. By varying the depth of the output array the number of features which are recognizable by the layer can be controlled. Zero-padding is used in the case of the necessity to preserve the original image size.

Due to the small size of the receptive fields the convolutional layer may incorrectly detect a feature, which does not belong to an object. To prevent such mistakes it is necessary to zoom-out the considered area, for this purpose the max pooling layer is used. Neurons in this layer do not use parameters, and therefore the training is not required. Their work comes down to choosing the strongest signal from the treated area. After passing the array through the max pooling layer the most characterized object features are remained.

3 CONVOLUTIONAL NEURAL NETWORK FOR HYPERSPECTRAL IMAGES

The initial data for the experiments are hyperspectral images of Samara region which were acquired in 2013-2014 in 36, 48 and 72 spectral bands in the range 0.35–1.05 μm. Field quasi-synchronous measurements via FieldSpec-4 spectroradiometer of Samara transport infrastructure typical objects have been used as patterns (Figure 3). Moreover, to research of hyperspectral data thematic processing methods we use information acquired by AVIRIS and HYDICE sensors parallelly in 224 and 191 spectral bands. The spectral range for AVIRIS data is 0.36–2.5 μm and for HYDICE data is 0.4–2.47 μm. The preliminary processing of initial data is used for vacant channels filtering and atmospheric correction. The module FLAASH, which is the part of program system ENVI, was used for atmospheric correction. We also used another method of atmospheric correction called empirical line method. This method has displayed more accurate results but it can be used only in the case of spectral patterns availability in the processing image. It is desirable to have artificial materials in the image as patterns, or patterns could be artificial materials under condition of once only acquisition with the aerospace data. In the stage of preliminary processing operations of information dimension reduction has been used. The most popular methods of dimension reduction are Principle component analysis (PCA) (Gorban et al., 2008; Rodarmel and Shan, 2002) and Independent component analysis (Robila, 2005). PCA has been used in this research.

Convolutional neural networks are widely used in the classification of images as they provide good recognition quality with relatively small effort. However, when working with hyperspectral images, this advantage can be substantially reduced because of the large dimension of the data, since each point of the image is represented by a vector of hundred or more values. There is an approach that uses a single point of image as the receptive field with a full range of values of spectral vector (Hu et al, 2015). The disadvantage is the insensitivity of the method to the spatial patterns, and as a consequence, the inability to recognize objects by the features.

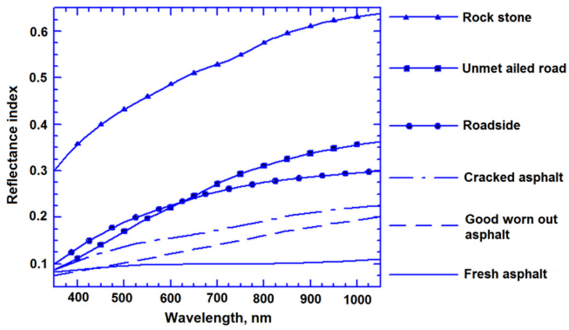

Figure 3: Spectral characteristics of typical transport infrastructure objects in Samara region.

We propose a new approach to the formation of receptive fields, which allows to keep the advantages of the convolutional networks and use the information from all color channels of hyperspectral image. In the proposed approach the receptive field covers several pixels, but the depth of the color channels, that can be used simultaneously, is limited. During operating of the neural network the receptive field moves not only in the horizontal plane, as in the current implementations, but also in the depth of color channels, thus covering the whole available spectrum. The value of the stride for the color channels must be less than the depth of receptive field. This allows to overlap the color channels, to increase the number of processed images in different spectra, and thus improve the quality of recognition.

The described approach of receptive field formation requires changes in the standard structure and training algorithm of the convolutional neural network, since each depth of color channels requires its own set of weighting coefficients (or filters in terms of convolutional neural networks). The requirement is dictated by the fact that the same spatial filters may be responsible for completely different features in different spectral channels. To meet this requirement an extra dimension is introduced to the array of trained filters. Moving in this dimension is performed synchronously with the movement of receptive field to a new depth of spectral channels. With such work organization the weights sharing is carried out only in the horizontal movement of receptive field. During movement deeper into the spectral channels the weights sharing is not used. Thus the structure of neural network differentiates the data streams for different spectral channels.

To implement the described neural network the TensorFlow framework is chosen, because it has a clear API and the flexibility to transform multidimensional data sets (Abadi et al., 2015). TensorFlow has already had an implementation of convolutional neural network. This neural network architecture is highly configurable, that allows to implement the described differentiation of data streams by spectral channels. The framework also allows to use the graphics processor unit (GPU), which significantly reduces the training time of the neural network on hyperspectral images of the city's transport infrastructure.

4 CONCLUSIONS AND FUTURE RESEARCH

In this article, we have reviewed the main problems arising during recognition of hyperspectral images of cities and detection of transport infrastructure objects on them. The new method of the classification of hyperspectral images is proposed. It is based on deep convolutional neural network that differs from the existing ones by movement of the receptive field in three dimensions - in two spatial dimensions and in spectral channels dimension. This approach makes it easier to recognize the transport infrastructure objects in dense urban areas.

Further research is related to carrying out a large number of experiments with hyperspectral images of cities. It is necessary to compare the results of object recognition in images taken from different satellites operating in different spectral ranges and with different number of spectral channels. It is necessary to investigate the usage of artificial neural networks at the stage of clearing and pre-processing of raw hyperspectral images.

Subsequently, it is necessary to carry out a comparative description of object recognition quality of the developed method and the existing methods (for example, Support Vector Machine, Spectral Angle Mapper, Maximum Likelihood Method, Mahalanobis Distance Method, etc.). Comparison of methods should be carried out by several parameters, the most important of which are the accuracy (probability of correct determination of the class), and receiver operating characteristic curve (ratio of the probability of true positive outcome and the probability of false positive outcome). In addition to the qualitative characteristics, the performance, scalability and the ability to process information in concurrent threads should also be compared.

Further work also needs improving the convolutional neural network classifying the transport infrastructure facilities. It is intended the usage of the latest developments in this area: spatial factorization, label smoothing and asynchronous stochastic gradient descent. It is necessary to increase productivity and quality of recognition to allow wide application of the method in transport geographic systems.

Modern intelligent transport systems involve the usage of unmanned aerial vehicles. To date, the payload of such vehicles is presented by a wide range of sensors, including hyperspectral cameras. The data received from the sensors require a semantic interpretation. The proposed in this paper approach to processing of hyperspectral data, focused on effective recognition of the transport infrastructure, may be used as a part of spatial data processing complex in the structure of the modern intelligent transport system.

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REFERENCES

Abadi, M., A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane,´ R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viegas, O. Vinyals, P. War- ´ den, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng (2015). *TensorFlow: Large-scale machine learning on heterogeneous systems*. Software available from tensorflow.org.

Cavalli, R., Fusilli, L., Pascucci, S., Piguatti, S. and Santini, F. (2008). Hyperspectral Sensor Data Capability for Retrieving Complex Urban Land Cover in Comparison with Multispectral Data: Venice City Case Study (Italy), *Sensors*, 8(5), pp. 3299-3320.

Chandra, A.M. (2008). *Remote Sensing and Geografical Information Systems*, Technosphera, Moscow.

Chang, C.I. (2000). An information-Theoretic Approach to Spectral Variability, Similarity, and Discrimination for Hyperspectral Image Analysis. *Information Theory*, *IEEE Transactions on Information Theory*, 46(5), pp. 1927-1932.

Gomez, R.B. (2002). Hyperspectral imaging: a useful technology for transportation analysis. *Optical Engineering*, 41(9), pp. 2137-2143.

Gorban, A., Kegl, B, Wunsch, D. and Zinovyev A. (2008). *Principal Manifolds for Data Visualisation and Dimension Reduction*, Lecture notes in computational science and engineering, Springer, Berlin – Heidelberg – New York.

Gualtieri, J.A. and Cromp, R.F. (1999). *Support vector machines for hyperspectral remote sensing classification*, available at: http://ntrs.nasa.gov/archive /nasa/casi.ntrs.nasa.gov/19990021532.pdf (accessed 5 January 2016).

Herold, M., Roberts, D., Smadi, O and Noronha, V. (2004a). *Road condition mapping with hyperspectral remote sensing*. Available at: http://www.geogr.uni-jena.de/~c5hema/urbanspec/av04_roadmapping_heroldetal.pdf (accessed 5 January 2016).

Herold, M., Gardner, M, Noronha, V. and Roberts, V. (2004b). *Spectrometry and hyperspectral remote sensing of urban road infrastructure*. Available at: http://www.eo.uni-jena.de/~c5hema/pub/rse04_heroldetal.pdf (accessed 5 January 2016).

Hu, W., Huang, Y., Wei, L., Zhang, F., and Li, H. (2015). Deep Convolutional Neural Networks for Hyperspectral Image Classification. *Journal of Sensors*, vol. 2015, Article ID 258619, 12 pages.

Keshava, N. (2003). Survey of Spectral Unmixing Algorithms. *Lincoln Laboratory Journal*, 14(1), pp. 55-78.

Krizhevsky, A., Sutskever, I. and Geoffrey E.H. (2012). ImageNet Classification with Deep Convolutional Neural Networks. *Advances in Neural Information Processing Systems 25*. Curran Associates, Inc. Pp. 1097-1105. Available at: http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf.

Kukharenko, B.G. (2013). Algorithms of analysis of hyperspectral images components, *Supplement of Journal "Information technologies"*, No. 6, - 32 p.

Mei, A., Salvatori, R., Fiore, N., Allegrini, A. and D'Andrea (2014). A Integration of field and laboratory spectral data with multi-resolution remote sensed imagery for asphalt surface differentiation. *Remote sensing*, Vol. 6, pp. 2765–2781.

Mikheeva, T.I. and Fedoseev, A.A. (2014). Clusterization of Hyperspectral Data of Transport Infrastructure Objects Monitoring. *Reporter of Samara Scientific Center of Russian Academy of Sciences*, Vol. 16 No. 4 (2), pp. 435-442.

Miraliakbari, A. and Hahn, M (2014). Development of multi-sensor system for road condition mapping. *The International archives of the photogrammetry, remote sensing and spatial information*, Vol. XL-1, pp. 265–272.

Resende, M., Bernucci, L. and Quintanilha, J. (2014). Monitoring the condition of roads pavement surfaces: proposal of methodology using hyperspectral images, *Journal of Transport Literature*, 8(2), pp. 201–220.

Ratle, F., Camps-Valls, G. and Weston, J. (2010). Semisupervised neural networks for efficient hyperspectral image classification, *IEEE Transactions on Geoscience and Remote Sensing*, 48(5), pp. 2271–2282.

Robila, S. (2005). *Investigation of Spectral Screening Techniques for Independent Component Analysis Based Hyperspectral Image Processing*. Available at: http ://www.cs.uno.edu/~stefan/ (accessed 5 January 2016).

Rodarmel, C. and Shan, J. (2002). Principal component analysis for hyperspectral image classification. *Surveying and Land Information Science*, 62(2), pp. 115-122.

Saprykin, O. and Saprykina, O. (2015). Multilevel Modelling of Urban Transport Infrastructure. *In Proceedings of the 1st International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS-2015)*, Portugal, Lisbon: SCITEPRESS, pp. 78-82.

Schott, J. (2007). *Remote sensing: the image chain approach*, 2nd ed., Oxford University Press, USA.

Schowengerdt, R.A. (2010). *Remote Sensing: Methods and Models for Image Processing*. Technosphera, Moscow.

Simonyan, K. and Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *CoRR*. abs/1409.1556.

Yuanliu, X., Runsheng, W. and Shengwen, L. (2007). Atmospheric correction of hyperspectral data using MODTRAN model. *Proceedings of 16th National Symposium on Remote Sensing of China*, 7 pages.

Zhuravel, J.N. and Fedoseev, A.A. (2013). Specificity of Hyperspectral Remote Sensing Data Processing for the Tasks of Environment Monitoring, *Computer Optics*, Vol. 37 No. 4. - pp. 471-476.

Wei, J., Zhou, G., Zheng, Z. (2009). *Survey and analysis of land satellite remote sensing applied in highway transportations infrastructure engineering*. Available at: http://www.asprs.org/a/publications/proceedings/baltimore09/0102.pdf (accessed 5 January 2016).