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# IMAGE SEGMENTATION OF CLOUDS BASED ON DEEP LEARNING

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The methods for segmentation of images of atomspheric clouds, which are obtained by remote sensing methods using aircraft or satellite onboard systems are developed. The proposed approach is to some extent further improvement of the convolutional neural network of the U-net type. It uses known quality criteria for segmentation, which allows us to compare the proposed approach with already known methods in the field of segmentation of images of atmospheric clouds. A large number of experiments on real images shows the feasibility of using the proposed method of segmentation for automated processing with the requirements for real-time operation. Use of the results is possible in the tasks of monitoring and classification for weather forecasting, agriculture, and other areas related to observations of atmospheric clouds.

**Keywords:** *remote sensing, image segmentation, deep learning, atmospheric clouds.*

# СЕГМЕНТАЦІЯ ЗОБРАЖЕНЬ ХМАР НА ОСНОВІ ГЛИБОКОГО НАВЧАННЯ

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Сучасний розвиток технологій впливає на розробку методів дистанційного зондування атмосфери Землі за допомогою бортових супутникових систем. Дистанційним зондуванням отримують зображення високої роздільної здатності, які придатні для використання різними службами спостереження та прогнозування атмосферних явищ. Кількість даних дистанційного зондування зросла до терабайт, і цей процес постійно триває, що унеможливлює аналіз та оцінку даних оператором-людиною. Це призводить до необхідності автоматизованого моніторингу та обробки зображень. Автоматизована обробка зображень є вирішальною ланкою у прогнозуванні маси хмарності.

Робота присвячена розробці методів сегментації зображень атмосферних хмар. Проаналізовані основні методи сегментації під час застосування до зображень атмосферних хмар, отриманих методами дистанційного зондування. Запропоновано підхід, який є подальшим розвитком моделі глибокого навчання, що базується на нейронній мережі структури U-net класу CNN. Наведено якість сегментації зображень хмарності за допомогою різних методів, де мірою якості є критерії, що базуються на співвідношенні перетину до об'єднання множин (IoU). Оцінено переваги та недоліки запропонованого методу сегментації. Переваги підходу – простота, швидкість та якість сегментації до 5 класів. Встановлено доцільність використання сегментації на основі нейронних мереж з глибоким навчанням, що дало можливість локалізувати хмари на зображенні з високою достовірністю. Результати можна використати в системах моніторингу та класифікації регіонів України за розподілом хмарних мас по сезонах на основі зображень супутникових карт погоди.

**Ключові слова**: *дистанційне зондування, сегментація зображень, глибоке навчання, атмосферна хмарність.*

**Introduction.** The current state of the problem is the development of remote sensing techniques for the Earth's atmosphere using airborne satellite systems. Remote sensing of images is obtained with high resolution, which makes them suitable for use by various services for observing and predicting atmospheric phenomena. This radically changed the remote sensing, and resulted in the creation of a new discipline.

The amount of remote sensing data has grown to terabytes, and this process is constantly ongoing, which makes it impossible to analyze and evaluate data by a human operator. This leads to the need for automated monitoring and processing.

Automated image processing is a crucial element in the process of forecasting masses of cloudiness. Overwhelmingly, remote sensing data is digital images. This includes the image in the visible spectrum as well as multispectral images. The fundamental task of data analysis is to identify useful information. The ultimate goal of automated image processing is their understanding, that is, the ability not only to establish the structure of the image, but also to know what it represents. This involves the use of models that describe the expected structure of the observed objects. In recent decades, the principles of model interpretation of images have been successfully applied to images of artificial objects. However, they turned out to be much more difficult to apply for real images of complex and variable structures. In such cases, it is even problematic to restore the image structure reliably, without a model representation of often noisy and incomplete data presented on the images.

The restoration of cloud characteristics is possible with the help of remote sensing tools and provides for both ground observation and satellite facilities [1]. This complex problem is solved by various means of information processing [2–4]. Good results have been achieved using the classification and segmentation of satellite images [5], as well as using statistical approaches [6].

The segmentation quality greatly affects the quantitative characteristics of cloudiness assessment [7].

**Problem statement.** Segmentation refers to the process of dividing a digital image into several segments (sets of points), and allows to determine how the image pixels belong to different sets. In the case of cloud images, we deal with binary segmentation when examining clouds and background areas.

An important disadvantage of segmentation is that there is no accurate reference sample to evaluate the quality of a particular segmentation method. Based on this, the only subjective assessment can be the expert experience and Intersection over Union (IoU) criteria. All traditional segmentation approaches involve an expert operator who, if necessary, adjusts the system parameters in order to achieve a better work result [8–10]. The only completely automated segmentation exception can be systems based on machine learning methods [11].

To effectively solve various problems of image segmentation, their mathematical formulation is necessary, first of all it includes a mathematical description, that is, a model of image presentation as an object of study. It is very desirable that mathematical models allow solving the problems of analysis and synthesis [12, 13]. That is, according to the known parameters of the model, it should be possible to select the parameters that describe images with the specified properties. This is necessary for the visual evaluation of the obtained images and for testing the processing algorithms. Modern methods used in solving problems associated with preprocessing, in particular segmentation in most cases, operate on statistical data models [14, 15].

From the point of view of computing resources, it is very effective to use cluster analysis methods for segmentation. The essence of clustering is that all source objects (in this case, pixels) are divided into several groups that do not overlap, so that objects that fall into one group have similar characteristics, while in objects from different groups these characteristics should be significantly different. The resulting groups are called clusters. The initial values in the simplest way for clustering are pixel coordinates $(x, y)$, in more complex cases, for example for half-tone images, a three-dimensional vector $(x, y, I(x, y))$ is used, where $I(x, y)$ – grayscale. Images of cloudiness are low contrast; in such conditions good results can be achieved using clustering algorithms that are sensitive for a narrow range of magnitudes. The basic idea is to define a $k$-center, one for each cluster. The image is projected into *n*-dimensional space. For initial initialization, the maximum distance criterion is used to set apart the kernel as the farthest. In the next step, each of the space vectors must be mapped to the nearest core. After that, the kernels are updated according to algorithm.

To improve the performance of the segmentation method of low contrast images, the criterion of the initial initialization of the kernels in space is modified, which can significantly increase the sensitivity in problem areas of the image.

All kernels gradually change their location until the condition for the completion of the iterative process occurs. The algorithm minimizes the objective function by the method of least squares.

The least studied, but the most promising are approaches based on deep learning. Generation and discriminatory models show the best generalizing properties among image segmentation methods. Separately, we can distinguish convolutional neural networks (CNN), which provide better segmentation of cloud images.

The CNN structure gives the best segmentation results of the cloud images among all the investigated algorithms. The advantage is also a fully automatic mode without operator intervention. The disadvantages include a long learning process and the need for a large training set. It is expensive to create an expert training sample, where each image is analyzed by an expert.

A training set may consist of different image classes, but a better result can be expected when using samples from the same class of images [16]. In our case reinforcement learning does not appear to fully meet expectations.

Images of clouds are obtained by means of remote sensing, such as aerial photography or satellites. To compare the work of segmentation methods, composite-structured images are used with which you can assess the shortcomings of each of the proposed methods. The original image of cloudiness is obtained using remote sensing tools.

**Model description.** The proposed model (Fig. 1), similar to U-Net [17], receives three-channel (RGB) images of arbitrary size and returns segmented image of atomspheric clouds, in our case there are 15 classes of segmentation. Within the framework of the experiment, the model was trained on the basis of the created database of 1300 images. The training sample plays a critical role in the training of the proposed model.

To increase the amount of training sample extra augmentation is proposed. The experiments used augmentation of several directions:

- image distortion due to angle change;
- distortion of images through blurring;
- image distortion by additive noise;
- image replication by zooming.

The functional part of the proposed model can be divided into two main parts from the sides of separating bottleneck. The modified clustering cloud image segmentation algorithm shows good results with low contrast. The advantages include high speed and minimal participation of the operator-expert.

The first 3 convolution layers is of 64 elements with convolution mask within 3×3. Batch normalization is added to accelerate the training process; it avoids losses when using gradient methods such as a back propagation method. The next two layers consist of 128 and 3×3 convolution layers. And two layers consist of 256 elements with 3×3 and 1×1 masks respectively.

In our research we apply activation function which is a combination of a piecewise linear function and a sigmoid function. It is shown that this form of activation function is the most optimal in terms of our task and will have the benefits of further optimization of the model.

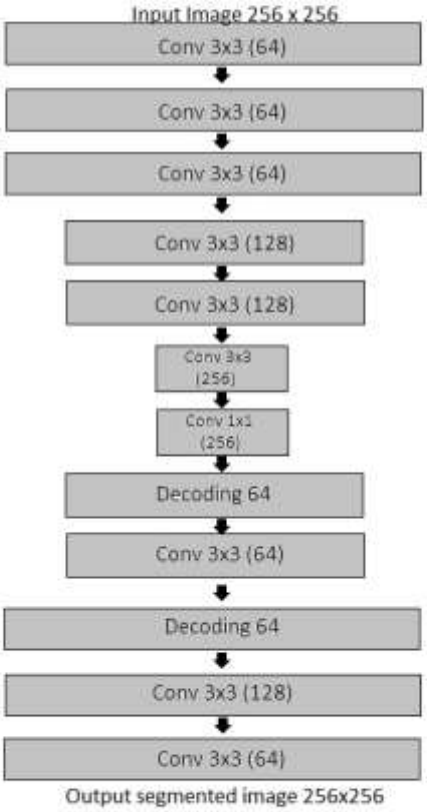


Fig. 1. Proposed architecture of the deep model for segmentation.

Fig. 2. shows the form of the activation function.

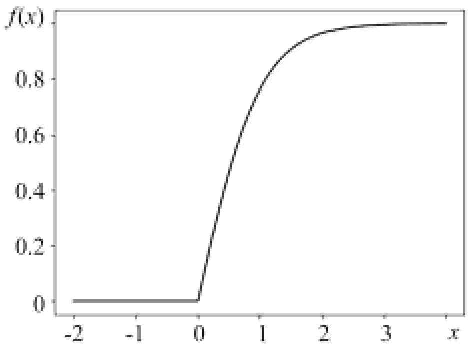


Fig. 2. The form of the activation function.

Analytical representation of the activation function:

$$f(x) = \begin{cases} 0 : x < 0\,, \\ x : x \le 0.5\,, \\ \dfrac{1}{1+e^{-x}} : x > 0.5\,. \end{cases} \qquad (1)$$

The model is trained using gradient methods. In this case, the derivative of the proposed function will look like:

$$f'(x) = \begin{cases} 0 : x < 0 \, , \\ 1 : x \le 0.5 \, , \\ f(x)(1 - f(x)) : x > 0.5 \, . \end{cases} \tag{2}$$

It is found that the training sample may consist of images of different classes, but the best result can be expected when using images of the same type.

Experimental studies of the accuracy of the segmentation algorithm, depending on the size of the training sample, have been carried out. As the criterion for evaluating the IoU criterion chosen, it has the most integrative features in the case of segmentation.

The proposed structure of CNN gives the best qualitative results of segmentation of images with clouds in comparison with other algorithms. The advantage is also a fully automatic mode of operation without operator participation. The disadvantage is a long process preparation and dependence on a large sample for training.

Cloud segmentation can be done by dividing the image into one cloud class (Fig. 3). However, in this case only generalizing information can be obtained, while multi-segmentation allows us to calibrate clouds by intensity level.

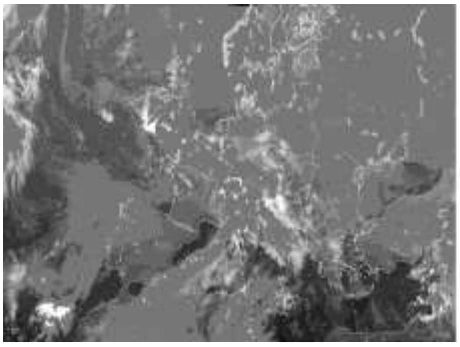

Fig. 3. Segmentation of the image of clouds into one class and background.

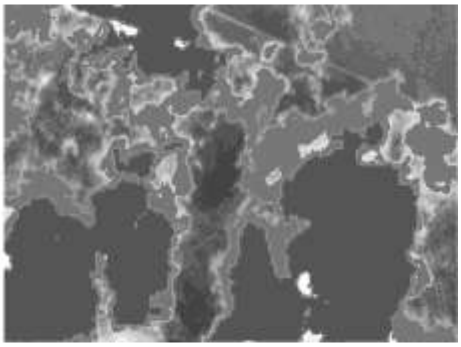

Fig. 4. Segmentation of the image of clouds into several classes.

Using the proposed neural network approach, based on deep learning, it is possible to segment image into several cloud classes (Fig. 4).

In Fig. 5. the result of a single-class neural network image segmentation with clouds over Ukraine is shown.

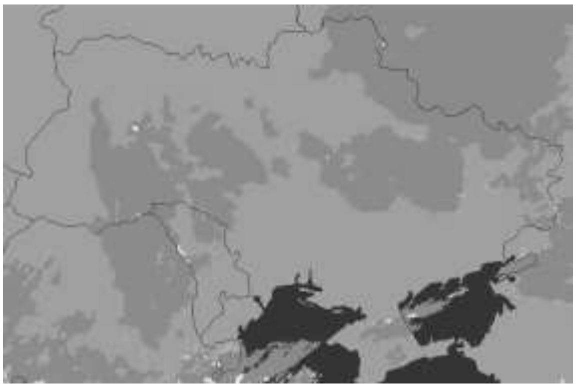

Fig. 5. The image segmentation of clouds over Ukraine.

The speed of the image processing algorithm is the important parameter that is paid attention to when developing the system of image segmentation. The speed of the algorithm depends on the use of computing power when solving a specific problem.

In the case of the neural network approach, there are two important stages in which computational complexity plays an important role. The most computationally complex is network training, since it is processing a large amount of data in iterative process to establish the weights of the network. The stage of direct work of a trained network is usually at lower computational cost, but the requirements for operational efficiency are much higher. Such processing systems must operate within real time.

**Table 1. Comparison of various segmentation methods with direct application for atmospheric images (256×256)**

| Model | IoU (1-class) | IoU (5-classes) | IoU (8-classes) | Opereation Time(s) CPU(i5-2700) |
|---|---|---|---|---|
| Thresholding | 0.68 | 0.42 | 0.34 | 0.1 |
| Clasterization | 0.73 | 0.54 | 0.42 | 0.7 |
| U-Net | 0.93 | 0.76 | 0.66 | 1.2 |
| Mask R-CNN | 0.81 | 0.74 | 0.71 | 2.2 |
| Proposed approach | 0.91 | 0.73 | 0.63 | 0.7 |

As a result of comparing the work of various segmentation methods with direct application for atmospheric images of cloudiness obtained by remote sensing techniques, Table 1. was formed.

It can be seen from the table above that the proposed approach to cloud segmentation has its advantages. With a small number of segmentation classes by criterion IoU it shows comparative results with U-Net with better operation time results. Drawbacks begin to appear when the number of segmentation classes is more than 5, but in the case of cloud segmentation this is not critical.

**CONCLUSION**

As a result of the study, a comparison was made of the main technologies that can be used in segmentation of atmospheric images obtained by remote sensing methods. The proposed approach is a further development of the deep learning model based on CNN class U-net. It is shown that the proposed approach demonstrates good properties in mono segmentation and in multi segmentation cases. Intersection over Union criterion is used to assess the quality of segmentation. It was also experimentally established that with increasing classes to 5 or more, the proposed approach is somewhat inferior to Mask R-CNN with the same size of the training sample. This can be attributed to the large discrimination potential of Mask R-CNN. The advantages of the proposed approach include simplicity, speed and quality of segmentation with up to 5 classes. The proposed approach can be used in the systems of monitoring and classification of the regions of Ukraine on the distribution of cloud masses in the seasons based on images of satellite weather maps.


1. Long, C.N.; Sabburg, J.M.; Calbo, J.; Pages, D. Retieving cloud characteristics from ground-based daytime color all-sky images. *Journal of atmospheric and oceanic technology*, 2006, 23, 633–652. https://doi.org/10.1175/JTECH1875.1
2. Rusyn, B.; Lutsyk, O.; Kosarevych, R.; Korniy, V. Segmentation of atmospheric clouds images obtained by remote sensing. *14th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET)*, **2018**, 213–216. https://doi.org/10.1109/TCSET.2018.8336189
3. Cui, Z.; Yang, J.; Qiao, Y. Brain mri segmentation with patch-based cnn approach. *Chinese Control Conference (CCC)*, *IEEE*, **2016**, 7026–7031. https://doi.org/10.1109/ChiCC.2016.7554465

4. Bengio, Y.; Courville, A.; Vincent, P. Representation learning: A review and new perspectives. *Pattern Analysis and Machine Intelligence, IEEE*, **2013**, 35(8), 1798–1828. https://doi.org/10.1109/TPAMI.2013.50
5. Christodoulou, C.I.; Michaelides, S.; Pattichi, C. Multifeature texture analysis for the classification of clouds in satellite imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **2003**, 41(11), 2662–2668. https://doi.org/10.1109/TGRS.2003.815404
6. Ricciardelli, F.; Romano, F.; Cuomo, V. Physical and statistical approaches for cloud identification using Meteosat Second Generation-Spinning Enhanced Visible and Infrared Imager Data. *Remote Sensing of Environment*, **2008**, 112 (6), 2741–2760. https://doi.org/10.1016/j.rse.2008.01.015
7. Rusyn, B.P.; Tayanov, V.A.; Lutsyk, O.A. Upper-bound estimates for classifiers based on a dissimilarity function. *Cybernetics and Systems Analysis*, **2012**, 48(4), 592–600. https://doi.org/10.1007/s10559-012-9439-2
8. Yuan, Y.; Hu, X. Bag-of-words and object-based classification for cloud extraction from satellite imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **2015**, 8 (8), 4197–4205. https://doi.org/10.1109/JSTARS.2015.2431676
9. Benediktsson, J.; Palmason, J.; Sveinsson, J. Classification of hyperspectral data from urban areas based on extended morphological profiles. *IEEE Transactions on Geoscience and Remote Sensing*, **2005**, 43, 480–491. https://doi.org/10.1109/TGRS.2004.842478
10. Flouzat, G.; Amram, O.; Cherchali, S. Spatial and spectral segmentation of satellite remote sensing imagery using processing graphs by mathematical morphology. *Proceedings of the IEEE Geoscience and Remote Sensing Symposium, IGARSS 98*, **1998**, 4, 1769–1771. https://doi.org/10.1109/IGARSS.1998.703646
11. He, K.; Gkioxari, G.; Dollar, P.; Girshick. R. Mask R-CNN. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **2017**, 43(2), 386–397. https://doi.org/10.1109/TPAMI.2018.2844175
12. Savoy, F. M.; Lemaitre, J.; Dev, S.; Lee, Y. H.; Winkler, S.; Cloudbase height estimation using high-resolution whole sky imagers. *Proc. IEEE International Geoscience and Remote Sensing Symposium*, **2015**, 1622–1625. https://doi.org/10.1109/IGARSS.2015.7326095
13. Liu, S.; Zhang, L.; Zhang, Z.; Wang, C.; Xiao, B. Automatic cloud detection for all-sky images using superpixel segmentation. *IEEE Geoscience and Remote Sensing Letters*, **2015**, 12(2), 354–358. https://doi.org/10.1109/LGRS.2014.2341291
14. Rusyn, B.; Lutsyk, O.; Lysak, Y.; Korniy, V. Quantitative analysis of metallographic images. *Modern Problems of Radio Engineering, Telecommunications and Computer Science Proceedings of International Conference (TCSET)*, **2006**, 553–557.
15. Nazarkevych, M. Research of Ateb-Gabor Filter in Biometric Protection Systems. *IEEE 13th International Scientific and Technical Conference on Computer Sciences and Information Technologies (CSIT)*, **2018**, 1, 310–313. https://doi.org/10.1109/STC-CSIT.2018.8526607
16. Long, J.; Shelhamer, E.; Darrell, T. Fully convolutional networks for semantic segmentation. *IEEE Conference on Computer Vision and Pattern Recognition*, **2015**, 3431–3440. https://doi.org/10.1109/CVPR.2015.7298965
17. Falk, T.; Mai, D.; Bensch, R.; Brox, T.; Ronneberger, O. U-Net: deep learning for cell counting, detection, and morphometry. *Nature Methods*, **2019**, 16, 67–70. https://doi.org/10.1038/s41592-018-0261-2


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