Feature Pyramid Network for Multi-Class Land Segmentation

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Abstract

Semantic segmentation is in-demand in satellite imagery processing. Because of the complex environment, automatic categorization and segmentation of land cover is a challenging problem. Solving it can help to overcome many obstacles in urban planning, environmental engineering or natural landscape monitoring. In this paper, we propose an approach for automatic multi-class land segmentation based on a fully convolutional neural network of feature pyramid network (FPN) family. This network is consisted of pre-trained on ImageNet Resnet50 encoder and neatly developed decoder. Based on validation results, leaderboard score and our own experience this network shows reliable results for the DEEPGLOBE - CVPR 2018 land cover classification sub-challenge. Moreover, this network moderately uses memory that allows using GTX 1080 or 1080 TI video cards to perform whole training and makes pretty fast predictions.

1. Introduction

The advent of high-resolution optical satellite imagery opens new possibilities to monitor changes on the earth’s surface. The advantages of this data compared to aerial imagery are the almost worldwide availability, and sometimes the imagery data contains additional spectral channels [18, 19]. The geometric resolution with 0.5-1.0 m is worse than for aerial imagery, but for the land cover categorization, it is sufficient [11, 15]. The worldwide availability of the data makes it possible to produce topographic databases for nearly any region of the earth. It, in turn, can help in various industries to enhance their productivity and quality of work whether it is for military purposes of disaster prevention or relief.

In the last years, different methods have been proposed to tackle the problem of creating convolutional neural networks (CNN) that can produce a segmentation map for an entire input image in a single forward pass. One of the most successful state-of-the-art deep learning method is based on the Fully Convolutional Networks (FCN) [17]. The main idea of this approach is to use CNN as a powerful feature extractor by replacing the fully connected layers by convolution one to output spatial feature maps instead of classification scores. Those maps are further upsampled to produce dense pixel-wise output. This method allows training CNN in the end to end manner for segmentation with input images of arbitrary sizes. Moreover, this approach achieved an improvement in segmentation accuracy over common methods on standard datasets like PASCAL VOC [6].

FCN has been further improved and now known as U-Net and Feature Pyramid (FPN) neural networks [19, 14, 13]. We approach the problem of multi-class land segmentation using FPN. FPN uses a pyramidal hierarchy of deep convolutional networks to construct feature pyramids with marginal extra cost. It consisted of bottom-up and top-down pathways. For the bottom-up feature encoder we have chosen to use ResNet50 [8] pre-trained on ImageNet. A top-down pathway with lateral connections is developed for building high-level semantic feature maps at all scales. This architecture shows significant improvement as a generic feature extractor in several applications such as object detection and instance object segmentation [15, 7, 21, 20]. Specific applications of convolutional networks on remote sensing image segmentation have been recently studied [10, 11, 16, 23, 4]. These applications are based mostly on aerial imagery data and contain pretty simple network architectures. In this work, we generalize many ideas and provide a neural network for semantic land segmentation that can work with high-resolution satellite im-
FPN: Feature Pyramid Network

The general scheme for FPN is shown in Fig. 2.

agery and approach problem of multi-class segmentation.

2. Dataset

The training data for land cover challenge contains 803 satellite imagery in RGB format. Each image has a size of 2448x2448 pixels. These images have 50cm pixel resolution, collected by DigitalGlobe’s satellite [2][5]. Moreover, each image in the training dataset contains a paired mask for land cover annotations. The mask is given as a RGB image with 7 classes of labels, using color-coding (R, G, B) as follows: 1) Urban land: (0, 255, 255) - man-made, built up areas with human artifacts (without roads); 2) Agriculture land: (255, 255, 0) - farms, any plantation, cropland, orchards, vineyards, nurseries, and ornamental horticultural areas; confined feeding operations; 3) Rangeland: (255, 0, 255) - any non-forest, non-farm, green land, grass; 4) Forest land: (0, 255, 0) - any land with certain tree crown density plus clear-cuts; 5) Water: (0, 0, 255) - rivers, oceans, lakes, wetland, ponds; 6) Barren land: (255, 255, 255) - mountain, land, rock, desert, beach, no vegetation; 7) Unknown: (0, 0, 0) - clouds and others. A satellite image and corresponding multi-channel mask is shown in Fig.1.

It is worth to mention that the values of the mask image may not be pure 0 and 255. As a result, the recommended threshold for binarization is 128 for each label. Moreover, the labels are not perfect due to the high cost of annotating small objects. For this problem, we use feature pyramid network (FPN) to implement land segmentation. The general scheme for FPN is shown in Fig. [2].

3. Model

Objects segmentation in different scales is challenging in particular for small objects. For this problem, we use feature pyramid network (FPN) to implement land segmentation. The general scheme for FPN is shown in Fig. [2].

4. Training

As the first step in training, we prepared masks as seven channel images using one hot encoding. Then, as the evaluation metric, we use Jaccard index (Intersection Over Union or IoU). It can be interpreted as a similarity measure between a finite number of sets. For two sets A and B, it can be defined as following:

$$ J(A, B) = \frac{\left| A \cap B \right|}{\left| A \cup B \right|} = \frac{\left| A \cap B \right|}{\left| A \right| + \left| B \right| - \left| A \cap B \right|} $$

Since an image consists of pixels, the last expression can be adapted for discrete objects in the following way:

$$ J = \frac{1}{n} \sum_{c=1}^{7} \sum_{i=1}^{n} \left( \frac{y_i^c \hat{y}_i^c}{y_i^c + \hat{y}_i^c - y_i^c \hat{y}_i^c} \right) $$

where $y_i^c$ and $\hat{y}_i^c$ are a binary values (label) and corresponding predicted probability for the pixel $i$ of the class $c$. In
Figure 2. Feature pyramid network with Resnet50 encoder pre-trained on ImageNet. As an input, we have an RGB image. The number of channels increases stage by stage on the left part of the scheme while the size of the feature maps decreases stage by stage. The arrows on top show transformations implemented between the layers. In the final step, feature maps upsample to the same size and concatenated. Then, the number of channels decreases to the number of classes, and the resulting image is upsampled to the original image size.

In addition, we introduce the class weights $w_c$ that could help us to prevent difficulties with classes imbalance. For simplicity, in this problem we set $w_c = 1$ for $c \in [1, \ldots, 7]$.

Since image segmentation task can also be considered as a pixel classification problem, we additionally use common classification loss functions, denoted as $H$ that for a multi-class segmentation problem is a categorical cross entropy.

The final expression for the generalized loss function is obtained by combining Eq. (2) and $H$ as following:

$$L = \alpha H + \beta (1 - J)$$

By minimizing this loss function, we simultaneously maximize probabilities for right pixels to be predicted and maximize the intersection $J$ between masks and corresponding predictions. For the land classification problem, using validation technique, we found $\alpha = 1$ and $\beta = 0.5$ that provided the best performance.

For training our network, we split our dataset using 1/4 hold out values for validation. Then, on the fly, we make several augmentations to increase the diversity of our data artificially. For spatial augmentation, we use scale transformations $0.6 - 1.4$ of the original image and mask. Then, we randomly rotate the image and mask by 30 degrees. From the resulting image and mask, we take random crops with size 448x448 pixels. These images are subject to color transformation such as random contrast/brightness/HSV.

One video card GTX1080Ti with 11 Gb of memory allows using the batch size of 8 images.

We train our network using Adam optimizer with learning rate $1e^{-4}$ and decay $1e^{-4}$ [12]. The training is done for 20k iterations (batches) saving weights from several best iterations. Since the dataset is fairly limited in its size and labels of train images are not robust the predicted value for IoU is varied significantly between iterations as well as between classes. To reduce the effect of over-fitting, we use spatial dropout operation on the output of our network with $p = 0.5$ [22]. After that, the training and validation IoU became close to each other at value 0.55 with a standard deviation around 0.13 between classes and standard deviation 0.03 between iterations.

We made predictions on the whole image with 2448x2448 pixels padding it by 8 pixels so that the side is divisible by $32 = 2^5$. It helped to prevent artifacts related to the bottom-up pathway of the network. To improve the robustness of our predictions, we also implemented test time augmentation (TTA) that composed of averaging of 4 predictions that correspond to 90 degrees rotation each.
5. Conclusions

We developed multi-class land segmentation algorithms using feature pyramid network with ResNet50 network pre-trained on Imagenet in the bottom-up pathway and a neatly designed loss function. The main difficulty in this multi-class problem come from inaccurate labeling of classes in the training dataset. To prevent over-fitting, we used pretty strong spatial dropout on the last layer of the network as well as test time augmentation technique. The best public score of our model on the public leaderboard is 0.493.

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References

[1] https://spacenetchallenge.github.io/
[2] http://deepglobe.org/
[3] http://ods.ai/
[4] K. Chen, K. Fu, M. Yan, X. Gao, X. Sun, and X. Wei. Semantic segmentation of aerial images with shuffling convolutional neural networks. IEEE Geoscience and Remote Sensing Letters, 15(2):173–177, 2018.
[5] I. Demiri, K. Koperski, D. Lindenbaum, G. Pang, J. Huang, S. Basu, F. Hughes, D. Tuia, and R. Raskar. Deepglobe 2018: A challenge to parse the earth through satellite images. arXiv preprint arXiv:1805.06561, 2018.
[6] M. Everingham, S. A. Eslami, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman. The pascal visual object classes challenge: A retrospective. International journal of computer vision, 111(1):98–136, 2015.
[7] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In Computer Vision (ICCV), 2017 IEEE International Conference on, pages 2980–2988. IEEE, 2017.
[8] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.
[9] V. Iglovikov, S. Mushinskiy, and V. Osin. Satellite imagery feature detection using deep convolutional neural network: A kaggle competition. arXiv preprint arXiv:1706.06169, 2017.
[10] V. Iglovikov and A. Shvets. Ternausnet: U-net with vgg11 encoder pre-trained on imagenet for image segmentation. arXiv preprint arXiv:1801.05746, 2018.
[11] V. I. Iglovikov, S. Seferbekov, A. V. Buslaev, and A. Shvets. Ternausnetv2: Fully convolutional network for instance segmentation. arXiv preprint arXiv:1806.00844, 2018.
[12] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.
[13] A. Kirillov, K. He, R. Girshick, and P. Dollár. A unified architecture for instance and semantic segmentation. http://presentations.cocodataset.org/COCO17-Stuff-FAIR.pdf
[14] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie. Feature pyramid networks for object detection. In CVPR, volume 1, page 4, 2017.
[15] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár. Focal loss for dense object detection. arXiv preprint arXiv:1708.02002, 2017.
[16] Y. Liu, D. Minh Nguyen, N. Deligiannis, W. Ding, and A. Munteanu. Hourglass-shapenetwork based semantic segmentation for high resolution aerial imagery. Remote Sensing, 9(6):522, 2017.
[17] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015.
[18] M. Pesaresi and J. A. Benediktsson. A new approach for the morphological segmentation of high-resolution satellite imagery. IEEE transactions on Geoscience and Remote Sensing, 39(2):309–320, 2001.
[19] O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. In International conference on Medical image computing and computer-assisted intervention, pages 234–241, 2015.
[20] A. Shvets, V. Iglovikov, A. Rakhlin, and A. A. Kalinin. Angiodysplasia detection and localization using deep convolutional neural networks. arXiv preprint arXiv:1804.08024, 2018.
[21] A. Shvets, A. Rakhlin, A. A. Kalinin, and V. Iglovikov. Automatic instrument segmentation in robot-assisted surgery using deep learning. arXiv preprint arXiv:1803.01207, 2018.
[22] J. Tompson, R. Goroshin, A. Jain, Y. LeCun, and C. Bregler. Efficient object localization using convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 648–656, 2015.
[23] M. Volpi and D. Tuia. Dense semantic labeling of sub-decimeter resolution images with convolutional neural networks. IEEE Transactions on Geoscience and Remote Sensing, 55(2):881–893, 2017.