NL-LinkNet: Toward Lighter but More Accurate Road Extraction with Non-Local Operations

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Abstract—Road extraction from very high resolution satellite images is one of the most important tasks in the field of remote sensing. For the road segmentation problem, spatial properties of the data can usually be captured using Convolutional Neural Networks. However, this approach only considers a few local neighborhoods at a time and has difficulty capturing long-range dependencies. In order to overcome the problem, we propose Non-Local LinkNet with non-local blocks that can grasp relations between global features. It enables each spatial feature point to refer to all other contextual information and results in more accurate road segmentation. In detail, our method achieved 65.00% mIOU scores on the DeepGlobe 2018 Road Extraction Challenge dataset. Our best model outperformed D-LinkNet, 1st-ranked solution, by a significant gap of mIOU 0.88% with much less number of parameters. We also present empirical analyses on proper usage of non-local blocks for the baseline model.

Index Terms—Non-Local LinkNet (NL-LinkNet), convolutional neural networks (CNNs), road extraction.

I. INTRODUCTION

Road extraction from very high resolution (VHR) satellite images plays an important role in remote sensing applications. Valuable geographic information that is difficult for people to access can be allowed by extracted road network. For example, it can be used for various tasks such as automated map update, urban planning, road navigation, unmanned vehicles, attention of safety road [1] or support to disaster relief missions.

Many methods on road extraction have been researched for decades. Tupin et al. [2] proposed a method using Markov Random Field (MRF) with extracted linear features from the speckle radar image. Laptev et al. [3] used snakes to detect roads in combination with geometry-constrained edge extraction. Song and Civco [4] proposed a method with support vector machine (SVM) and utilization of index feature on road extraction tasks. In recent years, Convolutional neural networks (CNN) have shown great improvement in detecting roads from VHR satellite images. For instance, FCN [5] based architectures [6], [7], [8], [9], [10], [11] and U-Net [12] based architectures [13], [14] involving D-LinkNet [15], which is the 1st winner of DeepGlobe 2018 Road Extraction Challenge [16], achieved great improvements in road extraction.

Our major concern on using CNN based architectures to extract roads is that CNNs cannot capture long-range dependencies. Since satellite imagery is shot overhead, local features might be covered by other obstacles such as shadow, cloud, tree or building. Therefore, modeling long-range dependencies is important for inferring obscured parts of road. However, single convolution layer generally has small receptive field and considers only few neighborhoods depending on its kernel size. For CNN based architectures, repeating convolution operations propagating signals through feature transformation is the only way to capture long-range dependencies. Thus, lots of additional model parameters and computations are required for CNN based architectures to model long-range dependencies.

In this paper, we propose our novel network named Non-Local LinkNet (NL-LinkNet) with differentiable non-local operations in order to tackle this problem. Our perspective is directly inspired by very recent works on non-local neural network [17] and its image restoration applications [18], [19]. Non-local neural operations compute feature map value as a weighted sum of the features at all positions. Thus, it enables the model to capture distant information and to take account of long-range dependencies. This characteristic of non-local operations perfectly meets our purpose. We also present analyses on proper usage of non-local operations for the baseline model. We provide all crucial implementation details. The code and our trained best model are publicly available [here].

In sum, main contributions of this paper are the threefold.

1) We did the first work to use non-local operations for road extraction on VHR satellite images. Because they can capture long-range dependencies, they can solve geographic limitation that part of roads could be covered by others such as shadow, cloud, building or tree.

2) Our NL-LinkNet outperformed the 1st ranked solution [15] in DeepGlobe Road Extraction Challenge using only 70% model parameters of it. Moreover, our single model showed higher performance than previously published state-of-the-art ensemble model without any sophisticated post-processing like conditional random field (CRF) refinement.

3) We demonstrated effectiveness of non-local operations for road extraction. Non-local neural network achieved promising results for all combinations of pairwise function and location of non-local blocks. Both single and double non-local block model showed superior performance to the baseline.

https://github.com/yswang0522/NLLinkNet
II. NON-LOCAL NETWORK FOR ROAD EXTRACTION

A. Non-local operations for road extraction

Since satellite images are taken overhead at high altitude, they are likely to be blocked by other obstacles. Moreover, roads themselves are bottom of the ground in most cases so they are the most likely to be blocked by other obstacles. On the ground, shadows of tall buildings and trees cover roads. In the Earth’s atmosphere, cloud and shadows of cloud obscure what we would like to see through larger area. To overcome this situation, capturing long-range dependencies is essential.

Most commonly used CNN cannot solve the long-range dependency. Convolution operation refers to only local information through small kernel, making it difficult to refer to distant information. Recurrent operation, which is another local method, is based only on current and previous features. One way to model long-range dependencies using these local methods is to perform these operation repeatedly. However, it implicitly results in many disadvantages such as increased memory, computation and difficulty of optimization.

This is why we borrowed the concept of non-local operation [17] model long-range dependencies. A non-local operation computes a feature map as a weighted sum of all pixels, and it allows the model to capture long-range dependencies and distant information. In Fig. 1, the road in the middle (red box) is covered by trees. Local methods cannot recognize the relationships between relevant roads. Non-local network, however, refers to (orange boxes) nearby roads and extract covered roads correctly. More examples are shown in Fig. 4.

B. Formulation

We used generic non-local operations in non-local networks [17] for road extraction:

\[ y_i = \frac{1}{C} \sum_{j=1}^{N} f(x_i, x_j)g(x_j), \]  

where \( N \) is the input dimension, \( i \in \mathbb{N} \) is the index of an output feature map, and \( j \in \mathbb{N} \) is the index of all possible positions. \( x \in \mathbb{R}^{N \times c_1} \) is the input feature map and \( y \in \mathbb{R}^{N \times c_2} \) is the output feature map where \( c_1, c_2 \) are the number of input channels and output channels. \( x_i, x_j \in \mathbb{R}^{c_1} \) and \( y_i \in \mathbb{R}^{c_2} \) indicate \( i \)-th and \( j \)-th feature of \( x \) and \( i \)-th feature of \( y \), respectively. A pairwise function \( f : \mathbb{R}^{c_1} \times \mathbb{R}^{c_1} \rightarrow \mathbb{R} \) computes a scalar that reflects correlation between \( x_i \) and \( x_j \). The unary function \( g : \mathbb{R}^{c_1} \rightarrow \mathbb{R}^{c_2} \) represents the input signal \( x_j \) as \( c_2 \) channel. Finally, the response is normalized by a factor \( C \in \mathbb{R}^+ \). Compared with traditional convolution or recurrent operations, the non-local operation (1) computes the weighted average of all the features.

C. Instantiation of Non-local Operations and Non-local Block

There are several possible choices for \( f \) and \( g \). We chose a simple form of linear embedding for \( g \):

\[ g(x_j) = W_g x_j, \]

where \( W_g \in \mathbb{R}^{c_2 \times c_1} \) is a parameter matrix to be learned. For the pairwise function \( f \), we considered three pairwise functions. First, we simply used the dot product to evaluate the pairwise relationship:

\[ f(x_i, x_j) = u(x_i)^T v(x_j) = (W_u x_i)^T (W_v x_j), \]  

where \( W_u, W_v \in \mathbb{R}^{c_2 \times c_1} \) are weight matrices; \( u, v : \mathbb{R}^{c_1} \rightarrow \mathbb{R}^{c_2} \). We used \( C = N \) for dot product pairwise function. Next, we considered embedded Gaussian version (3) and Gaussian version (4):

\[ f(x_i, x_j) = e^{u(x_i)^T v(x_j)} = e^{(W_u x_i)^T (W_v x_j)} \]  

and

\[ f(x_i, x_j) = e^{x_i^T x_j} \]  

For both (3) and (4), we chose \( C = \sum_{j=1}^{N} f(x_i, x_j) \) for these pairwise functions. In order to simplify implementation, we used dot-product similarity for the Gaussian version of \( f \).

Lastly, we defined non-local block by connecting result of non-local operation with input feature via residual connection:

\[ z_i = W_z y_i + x_i \]  

where \( y \) is given in (1) and \( W_z \in \mathbb{R}^{c_1 \times c_2} \) are weight matrices. The residual connection in a final step allows us to insert the non-local block into any position of pretrained networks by initializing weight matrix as zero. Fig. 2 illustrates an example of a non-local block with a Gaussian pairwise function. Since satellite images are two dimensional images, we employed...
1 \times 1 \text{ convolutions for all weight matrices } W_u, W_v, W_g, W_z, \text{ instead of } 1 \times 1 \times 1 \text{ convolutions. In addition, half of the channels in } x \text{ was used for internal channel; i.e. } c_2 = c_1/2. \text{ It enabled the model to reduce computation and increase the number of non-local blocks in the whole architecture.}

D. Non-local Network Architectures

The entire architecture of our NL-LinkNet is illustrated in Fig. 3. For the decoder part, we used the decoder block (green arrow) inspired by [13]. Local block can be any backbone network using the traditional local method, and we employed ResNet34 [20]. Although D-LinkNet won the first place in the recent challenge [16], we did not use the dilation block, which was the main contribution of D-LinkNet. This is because we wanted to show the effectiveness of non-local block on road extraction. From the baseline, we designed our NL-LinkNet described in Fig. 3. When designing the architecture, we considered the following two factors:

a) Location of non-local blocks: Non-local block can be added to any layers in any architecture. To maximize efficiency of non-local block, we considered two constraints to choose location of non-local blocks into our network. First, We put non-local blocks as close to the last layer as possible to increase the efficiency of non-local operations. Since the information in the latter feature map have more condensed information, non-local operation can capture long-range dependencies with less computations. Second, we maximize the utility of non-local operations. In order to experiment in various settings, it is important to use memory efficiently. On the consideration of adding non-local block into the front layers, it takes too much memory for large feature map size. Therefore, non-local blocks after 3rd and 4th layer were considered in our experiment settings.

b) Choice of local blocks: We used ResNet34 layers as our local block for the rest of experiments. The recent state-of-the-art models [13, 15] have shown that small backbone networks such as ResNet18 and ResNet34 are effective for road extraction. In addition, since the relatively small ResNet34 has room for memory, we could experiment on non-local blocks with various settings (number of blocks, location of blocks).

III. EXPERIMENTS

A. Dataset and Evaluation Metric

In order to check effectiveness for road extraction, we used DeepGlobe 2018 Road Extraction Challenge dataset [16] for experiments. The size of all the images in this dataset is 1024 × 1024 pixel². Each image is RGB image with 0.5 GSD, collected by DigitalGlobe’s satellite. The mask is gray scaled binary image of the same height and width as the input image. In mask image, white stands for road and black stands for the backgrounds. The dataset consists of images 8,579 in total, including 6,226 images for training, 1,243 for validation, and 1,110 images for testing.

We used mean intersection-over-union (mIOU) for evaluation metric. mIOU is the same evaluation metric used in DeepGlobe 2018 Road Extraction Challenge. To evaluate the models accurately, road and non-road pixels are set to 255 and 0, respectively. For more details on dataset and evaluation metric, refer the original dataset paper [16].

B. Implementation details

a) Fine-tuning: We used fine-tuned model weights from ImageNet-pretrained ResNet34 network to adapt them for road extraction. According to the same settings with [13, [15], the 1000-way classifier in the last layer, was replaced by the decoder. Sigmoid function was added to the last output of the network to use the binary cross entropy loss function.

b) Training Phase: We used binary cross entropy as the loss function and optimized the model with Adam optimizer [21]. We trained the model with a batch size of 8 on 4 Titan 1080 GPUs with 12GB on-board memory. and crop size was 1024 × 1024. The learning rate was initially set to 0.0003. We did a grid search of learning rate in the range between 1.00e-4 and 1.00e-3 with the interval of 1.00e-5. During training, the learning rate fell off step by step by a factor of 0.2 when loss did not fall several times. The network converged in 180 epochs and convergence took about 47 hours. Some data augmentation techniques were done including image shifting, multi-scaling, vertical flip and horizontal flip for each input. The proposed model was implemented using PyTorch [22].

c) Test Phase: Test time augmentation was also done including image horizontal flip, vertical flip, diagonal flip. For some experiments, we did multi-scale testing (MS) with scales of [0.75, 1.0, 1.25]. Overall, we have 8 (without MS) or 24 (with MS) images and we normalized the final masks divided by our the threshold of 4 (witout MS) or 12 (with MS) to generate binary outputs. Note that we did not use more sophisticated post-processing methods like CRF. Without using CRF, our models outperformed all the other published methods.

IV. RESULTS AND DISCUSSIONS

In this section, we demonstrate effectiveness of our proposed non-local neural network for road extraction. First, we compare performance of NL-LinkNet with the other state-of-the-art methods. Then, we describe effective usage of non-local operations with different locations and pairwise functions in our NL-LinkNet. Our baseline is the architecture in Fig. 3. without any NLB, which is described in section II-D.
A. Performance Evaluation

1) Quantitative Comparison: Table I shows the results of different single model methods on DeepGlobe 2018 Road Extraction Challenge validation dataset. For a detailed description of NL-LinkNet in Table I please refer section IV-B1.

Our NL34-LinkNet achieved the best performance (65.00%) among all published methods without any sophisticated post processing such as CRF and MS. Only with MS, our NL4-LinkNet with a single non-local block surpassed the first-ranked solution [15] by a significant margin (0.88% mIOUs). Further, our single model outperformed even the ensemble model of D-LinkNet [15], U-Net [12], an LinkNet [13], which recorded 64.66% and won the first place in DeepGlobe 2018 Road Extraction Challenge [13]. We note that Table I only includes results of published single models for fair comparison.

2) Visual Comparison: Fig. 4 shows visual performance of different methods on road extraction. For all cases in Fig. 4, the non-local operation gave more excellent results on extracting roads than local methods. In details, our best NL-LinkNet model showed great performance on cases of noisy background, narrow roads and disconnected roads. Especially, in the third row, our NL-LinkNet also successfully extracted roads, which was a similar example of Fig. 1. It implies that relevant information can be only captured in non-local operations with maximized size of receptive field. Meanwhile, other previous local methods could not detect them because they use only local information using kernels with small receptive fields. Even D-LinkNet use dilation convolution to increase receptive fields, it cannot capture long-range dependencies properly. Detailed comparison is described in section IV-B3.

B. Analyses of different settings

1) On location of non-local blocks: Table II illustrates performance of NL-LinkNet with non-local blocks at different locations. NLB is a non-local block and DB is a dilation block. NL3-LinkNet and NL4-LinkNet use the non-local block in 4rd stage and 5th stage, respectively and NL34-LinkNet is the combination of both. We use ResNet34 layers as our local blocks and the embedded Gaussian version of $f$.

Comparing performances of NL3-LinkNet and NL4-LinkNet in Table II, higher performance could be achieved by attaching non-local block to the latter layer. Why does NLB in the back layer show better efficiency? As we go deeper into the network, the feature map size gets smaller through several strides. We conjecture this causes the more condensed information is located in the latter stages. Hence, at the same
amount of computation, NLB in the back stage can refer to more condensed information and achieves better performance. In addition, in the table II adding non-local blocks achieves at least 1.08% improvement. It proves non-local operation is crucial for road extraction regardless of the location. It also implies the maximized receptive field of non-local block can link all the condensed information for better understanding of contextual information. Just adding one non-local block (NL4-LinkNet) lead to 1.33% improvement over the baseline.

2) On different pairwise functions: Table III compares performances depending on different types of pairwise function. Except the baseline, NL4-LinkNet was used in the experiment. Embedded Gaussian and Gaussian version $f$ showed noteworthy improvements on mIOU. On the contrary, dot-product version of $f$ achieved relatively slight improvement on performance. With embedded Gaussian pairwise function, just adding two non-local blocks led to 1.52% improvement over the baseline.

3) $D$-LinkNet vs. NL-LinkNet: Even though both operations have the same purpose of increasing the receptive field, all of our models with NLB prominently outperformed the model with DB used in D-LinkNet. Furthermore, in Table II NL-LinkNet is a lighter model because it has only 70% model parameters compared to D-LinkNet. It implies better efficiency of non-local blocks for road extraction. Dilated blocks with a sequence of different dilation might capture long-range dependencies better than convolutional method. However, it faces the problem of limited accessible number of pixels. On the other hand, non-local method can access all the distant and relevant information in the satellite image. Hence, non-local block can capture better long-range dependencies.

V. CONCLUSIONS

In this paper, we proposed the Non-Local LinkNet for road extraction from VHR satellite images. In order to detect roads, long-range dependencies is essential because obstacles such as trees, buildings, shadows block roads. While traditional convolutional methods only refer neighborhoods or previous features, non-local operation can capture distant information referencing all the features in satellite images. Our NL-LinkNet achieved 65.00% mIOU scores, which is higher than any of the other publications so far on the DeepGlobe 2018 Road Extraction Challenge dataset. It also outperformed 1st ranked solution in the challenge with less number of model parameters. Additionally, we explored effectiveness and efficiency of non-local blocks by varying locations and pairwise functions.

REFERENCES

[1] S. Gupta, D. Srivatsav, A. V. Subramanyam, and P. Kumaragurur, “Attentional road safety networks,” arXiv preprint arXiv:1812.04860, Dec. 2018.
[2] F. Tupin, H. Maître, J.-F. Margin, J.-M. Nicolas, and E. Pechersky, “Detection of linear features in sar images: Application to road network extraction,” IEEE Trans. Geosci. Remote Sense., vol. 36, no. 2, pp. 434–453, Mar. 1998.
[3] I. Laptev, H. Mayer, T. Lindeberg, and W. Eckstein, “Automatic extraction of roads from aerial images based on scale space and snakes,” Machine Vis. and App., vol. 12, no. 1, pp. 23–31, Jan. 2000.
[4] F. Hu, G.-S. Xia, J. Hu, and L. Zhang, “Road extraction using svm and image segmentation,” Photogramm. Eng. Remote Sens., vol. 70, no. 12, pp. 1365–1371, 2004.
[5] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in Proc. CVPR, 2015, pp. 3431–3440.
[6] X. Wang, R. Girshick, A. Gupta, and K. He, “Convolutional neural networks for large-scale remote sensing image classification,” IEEE Trans. Geosci. Remote Sens., vol. 55, no. 2, pp. 645–657, Feb. 2017.
[7] Y. Wei, Z. Wang, and M. Xu, “Road structure refined cnn for road extraction in aerial image,” IEEE Geosci. Remote Sens. Letters, vol. 14, no. 5, pp. 709–713, May 2017.
[8] F. Hu, G.-S. Xia, J. Hu, and L. Zhang, “Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery,” Remote Sensing, vol. 7, pp. 14680–14707, 2015.
[9] C. Henry, S. M. Azimi, and N. Mørk, “Road segmentation in sar satellite images with deep fully-convolutional neural networks,” IEEE Geosci. Remote Sens. Letters, 2018.
[10] Z. Zhong, J. Li, W. Cui, and H. Jiang, “Fully convolutional networks for building and road extraction: Preliminary results,” in Proc. IEEE IGARSS, Nov 2016.
[11] O. K. Vaine, “Using deep convolutional networks to detect roads in aerial images,” Northwegen Univ. of Sci. and Tech., 2016.
[12] Z. Zhang, Q. Liu, and Y. Wang, “Road extraction by deep residual u-net,” IEEE Geosci. Remote Sens. Letters, May. 2015.
[13] L. Zhou, C. Zhang, and M. Wu, “Linknet: Exploiting encoder representations for efficient semantic segmentation,” in Proc. Int. Conf. Vis. Comp. Img. Proc., 2017.
[14] Z. Zhang, Q. Liu, and Y. Wang, “Road extraction by deep residual u-net,” IEEE Geosci. Remote Sens. Letters, Nov. 2017.
[15] L. Zhou, C. Zhang, and M. Wu, “D-linknet: Linknet with pretrained encoder and dilated convolution for high resolution satellite imagery road extraction,” in Proc. CVPR Workshops, 2018.
[16] I. Demir, 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,” in Proc. CVPR Workshops, 2018.
[17] X. Wang, R. Girshick, A. Gupta, and K. He, “Non-local neural networks,” in Proc. CVPR, 2018.
[18] J. Liu, B. Wen, Y. Fan, C. C. Loy, and T. S. Huang, “Non-local recurrent network for image restoration,” in Proc. NeurIPS, 2018.
[19] Y. Zhang, K. Li, K. Li, Z. Bineng, and Y. Fu, “Residual non-local attention networks for image restoration,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2019.
[20] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. CVPR, 2016, pp. 770–778.
[21] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in Proc. Int. Conf. Learn. Represent. (ICLR), 2015.
[22] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, “Automatic differentiation in pytorch,” in Proc. NIPS Workshop, 2017.
[23] O. Filin, A. Zapara, and S. Panchenko, “Road detection with eosresunet and post vectorizing algorithm,” in Proc. CVPR Workshops, 2018.
[24] T. Sun, Y. Wexiang, and Y. Wang, “Stacked u-nets with multi-output for road extraction,” in Proc. CVPR Workshops, 2018.
[25] J. Doshi, “Residual inception skip network for binary segmentation,” in Proc. CVPR Workshops, 2018.