Semantic Segmentation of Remote Sensing Images With Sparse Annotations

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Abstract—Training convolutional neural networks (CNNs) for very high-resolution images requires a large quantity of high-quality pixel-level annotations, which is extremely labor-intensive and time-consuming to produce. Moreover, professional photograph interpreters might have to be involved in guaranteeing the correctness of annotations. To alleviate such a burden, we propose a framework for semantic segmentation of aerial images based on incomplete annotations, where annotators are asked to label a few pixels with easy-to-draw scribbles. To exploit these sparse scribbled annotations, we propose the Feature and Spatial relational regularization (FESTA) method to complement the supervised task with an unsupervised learning signal that accounts for neighborhood structures both in spatial and feature terms. For the evaluation of our framework, we perform experiments on two remote sensing image segmentation data sets involving aerial and satellite imagery, respectively. Experimental results demonstrate that the exploitation of sparse annotations can significantly reduce labeling costs, while the proposed method can help improve the performance of semantic segmentation when training on such annotations. The sparse labels and codes are publicly available for reproducibility purposes.

Index Terms—Aerial image, convolutional neural networks (CNNs), semantic segmentation, semisupervised learning, sparse scribbled annotation.

I. INTRODUCTION

Semantic segmentation of remote sensing imagery aims at identifying the land-cover or land-use category of each pixel in an image. As one of the fundamental visual tasks, semantic segmentation has been attracting wide attention in the remote sensing community and has proven to be beneficial for various purposes.

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1https://github.com/Hua-YS/Semantic-Segmentation-with-Sparse-Labels

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networks (CNNs) with full supervision for semantic segmentation and have obtained enormous achievements. However, training a fully supervised segmentation CNN requires a huge volume of dense pixel-level ground truths, which are labor-intensive and time-consuming to generate. Moreover, expert annotators might be needed for correctly identifying pixels located at object boundaries and ambiguous regions (e.g., shadows in Fig. 1).

To alleviate the requirement of dense pixelwise annotations, semisupervised learning approaches are proposed to make use of additional information, such as spatial relations (e.g., neighboring pixels are likely to belong to the same class) or feature-level relations (e.g., pixels with similar CNN feature representations are likely to belong to the same class), for semantic segmentation. These methods aim to utilize low-cost annotations, such as points [2], scribbles [3], [4], or image-level labels [5], [6]. As the first attempt, Bearman et al. [2] proposed to learn semantic segmentation models with point-level supervision, where only one point is labeled for each instance. In scribblesupervised algorithms, annotations are provided in the form of hand-drawn scribbles. Wu et al. [3] propose to learn aerial building footprint segmentation models from scribbles. Maggiolo et al. [4] argue that a network directly trained on scribbled ground truths fails to accurately predict object boundaries and propose to employ a fully connected conditional random field (CRF) to refine the shapes of objects. Compared to fully annotated ground truths, scribbled annotations [see Fig. 1(c)] are easier to generate in a user-friendly way. In comparison with point-level annotations [e.g., Fig. 1(b)], scribbles can provide stronger supervisory signals. However, point- and scribble-supervised segmentation methods remain underexplored in the remote sensing community. To this end, we propose a simple yet effective framework for semantic segmentation of remote sensing imagery with low-cost annotations. In this framework, we manually create point- or scribble-level annotations and train networks on them. Besides, we also evaluate polygon-level annotations [see Fig. 1(d)], which can be easily yielded and cover more pixels than the other types of annotations. Since these annotations
are sparsely distributed across the images, we call them sparse annotations in Sections II–IV. In order to better exploit sparse annotations, we propose a semisupervised learning method that encodes and regularizes the feature and spatial relations. To demonstrate the effectiveness of our learning framework, extensive experiments are conducted on two very high resolution (VHR) data sets: the Vaihingen and Zurich Summer.

II. METHODOLOGY

A. Supervision With Sparse Annotations

In contrast to conventional dense annotations, sparse annotations have two characteristics: 1) a very small proportion of pixels are assigned semantic classes and 2) objects do not need to be entirely annotated [see Fig. 1(b)–(d)]. This greatly reduces the effort required from the annotators, as complex boundaries and ambiguous pixels can be avoided.

Here, we consider three levels of sparse annotations: point-level, scribble-level, and polygon-level. Specifically, point-level annotations indicate that, for an annotator interaction, only one single pixel is labeled. Scribble-level annotations, also called line-level annotations, are yielded by drawing a scribble line within an object and assigning all pixels along this line the same class label. Similarly, polygon-level annotations can be generated by drawing a polygon within an object and classifying pixels located in the polygon into the same semantic class. Examples of these three levels of annotations are shown in Fig. 1.

B. Feature and Spatial Relational Regularization

When using sparse annotations, the vast majority of pixels in the training images are left unlabeled. In order to exploit both labeled and unlabeled pixels, we develop a semisupervised methodology, named FEature and Spatial relaTional regulArization (FESTA), to enable a semantic segmentation CNN to learn discriminative features while leveraging the unlabeled image pixels. An assumption shared by many unsupervised learning algorithms [7] is that nearby entities often belong to the same semantic class. Examples of these three levels of annotations are shown in Fig. 1.

C. CRF for Boundary Refinement

To further refine the predictions of networks trained on scribbled annotations, we integrate a fully connected CRF [9] into our system, and the energy function of CRF model is

$$
E = \sum_i \theta_u(x_i) + \sum_{ij} \theta_p(x_i, x_j)
$$

where \(\theta_u(x_i)\) is the unary potential and calculated as \(\theta_u(x_i) = -\log P(x_i)\). Here, \(i\) ranges from 0 to the number of pixels in the image, and \(P(x_i)\) is the label probability of pixel \(i\). \(\theta_p(x_i, x_j)\) is utilized to measure pairwise potentials between pixel \(i\) and \(j\). We tested with two Gaussian kernels

$$
k_1 = \exp\left(-\frac{||p_i - p_j||^2}{2\theta_1^2} - \frac{||I_i - I_j||^2}{2\theta_2^2}\right)
$$

$$
k_2 = \exp\left(-\frac{||p_i - p_j||^2}{2\theta_3^2}\right)
$$

where \(p_i\) and \(I_i\) indicate the position and color intensity of pixel \(i\). \(\theta_1\), \(\theta_2\), and \(\theta_3\) are hyperparameters that control the kernel “scale”. In (4), \(k_1\) is known as appearance kernel and tends to classify neighboring pixels with similar appearances [10], i.e., color intensities, into the same classes, while \(k_2\), so-called smoothness kernel, penalizes pixels nearby but assigned diverse labels. This step is expected to make the class map smoother within homogeneous areas.
III. EXPERIMENTAL RESULTS

A. Data Set Description

The Vaihingen data set is a benchmark data set for semantic segmentation provided by the International Society for Photogrammetry and Remote Sensing (ISPRS); 33 aerial images with a spatial resolution of 9 cm were collected over the city of Vaihingen, and each image covers an average area of 1.38 km². For each aerial image, three bands are available, near-infrared (NIR), red (R), and green (G). Besides, coregistered digital surface models (DSMs) are provided for all images; 16 images are fully annotated. In total, six land-cover classes are considered: impervious surface, building, low vegetation, tree, car, and clutter/background. In this letter, we follow the train-test split scheme in most existing works [11], [12] and select five images (image IDs: 11, 15, 28, 30, and 34) as the test set. The remaining ones are utilized to train our models.

The Zurich Summer data set is composed of 20 images that are taken over the city of Zurich in August 2002 by the QuickBird satellite. The spatial resolution is 0.62 m, and the average size of images is $1000 \times 1150$ pixels. The images consist of four channels: NIR, red (R), green (G), and blue (B). Following previous works [14], [15], we only utilize NIR, R, and G in our experiments and train our model on 15 images; the others (image IDs: 16, 17, 18, 19, and 20) are utilized to test. In total, there are eight urban classes, including road, building, tree, grass, bare soil, water, railway, and swimming pool. Uncategorized pixels are labeled as background.

It is noteworthy that although full pixelwise annotations are provided for all images in the Vaihingen and Zurich Summer data sets, we only use them in the test phase to calculate evaluation metrics. The training of all models is done with scribbled annotations described in the following.

B. Scribbled Annotation Generation

To annotate large-scale images, we employ an online labeling platform, LabelMe, and ask annotators to draw by following these rules: 1) for each class, annotations are supposed to cover diverse appearances (see region (a)–(c) in Fig. 3, where cars of different colors are annotated) and be located in different positions of the image separately and 2) polygon- and line-level annotations are not required to delineate object boundaries precisely [see the annotations of trees in Fig. 1(c) and (d)]. In order to make the time spent on each level of scribbled annotations more equivalent, we ask four annotators (including two nonexperts) to label 7, 5, and 3 objects per class for point-, line- and polygon-level annotations in each aerial image. As a consequence, sparse but accurate annotations can be provided rapidly without effort. Since a point- or line-level annotation is often located in the center area of an object and distant from its boundary, we perform morphological dilation on all point- and line-level annotations with a disk of radius 3. Afterward, pixels involved in dilated annotations are assigned the same class labels as their central points or lines. For polygon-level annotations, pixels within each polygon are assigned the corresponding classes.

Table I shows the average amounts of pixels with sparse and dense annotations in both data sets. It can be seen that sparse annotations are several orders of magnitude fewer than dense annotations. As to the labeling time, it took on average 133, 126, and 161 s per image to produce point-, line- and polygon-level annotations, respectively, for the Vaihingen data set and 177, 162, and 238 s per image for the Zurich Summer data set. In Section III-D, we demonstrate the proposed method allows improving the semantic segmentation results using these sparse annotations. In Section III-D, we discuss the differences observed among the tested annotation types.

C. Training Details

We segment the images with a standard fully convolutional network (FCN) (i.e., FCN-16s [17]) and initialize convolutional layers with Glorot uniform [18] initializers. Specifically, VGG-16 is taken as the backbone, and the outputs of the last two convolutional blocks are upsampled to the original resolution and fused with an elementwise addition. The fused feature maps are finally fed into a convolutional layer, where the number of filters is equivalent to the number of classes. In the training phase, all weights are trainable and updated as FESTA, is implemented on TensorFlow and trained on one NVIDIA Tesla P100 16-GB GPU for 100k iterations.

Table I

| Dataset Name | Point                | Line                | Polygon              | Dense*               |
|--------------|----------------------|---------------------|----------------------|----------------------|
| Vaihingen    |                     |                     |                      |                      |
|              | 18,787               | 480,593             | 4,391,409            | 54,373,518           |
| Zurich Summer| 29,308               | 330,767             | 1,445,270            | 12,266,287           |

*Background/Clutter is not considered.

Fig. 3. Example polygon-level annotations of an image (ID: 13) on the Vaihingen data set. Annotations of cars are zoomed in to illustrate that annotations should include variant visual appearances for one class. Legend—white: impervious surfaces; blue: buildings; cyan: low vegetation; green: trees; and yellow: cars.
parameters of dense CRF $\theta_1$, $\theta_2$, and $\theta_3$ in (4) on validation images and find that satisfactory results can be achieved for both FCN and FCN-FESTA when setting them to 30, 10, and 10, respectively. In the case of large homogeneous areas of an image belonging to the same class, $\alpha$ should be set to a small value, which encourages the network to focus more on geographically nearby samples. Besides, large batch size and sliding window can also help alleviate the influence of such a scenario.

D. Comparing With Existing Methods

We compare an FCN [17] learned using the proposed FESTA (FCN-FESTA) against an FCN learned with weighted loss function (FCN-WL) [16] on sparse annotations. We also report segmentation results of the baseline FCN trained on dense labels. In addition, we study the influence of the fully connected CRF by comparing FCN-FESTA+dCRF and FCN+dCRF [4]. Each model is trained and validated on sparse annotations independently. Per-class $F_1$ scores, mean $F_1$ scores, and overall accuracy (OA) are calculated on test images with dense annotations. Considering that each model is learned on labels from four annotators, respectively, we average metrics obtained by each annotator and report them in the form of mean ± standard deviation.

Table II exhibits numerical results on the Vaihingen data set. FCN-FESTA+dCRF achieves the highest mean $F_1$ scores in training with all kinds of scribbled annotations, which demonstrates its effectiveness. To be more specific, with the point- and polygon-level supervision, FCN-FESTA improves the mean $F_1$ score by 3.95% and 3.33% compared to FCN-WL, respectively. By refining predictions with dense CRF, FCN-FESTA+dCRF achieves improvements of 2.38% and 4.03% in comparison with FCN+dCRF. It is interesting to observe that line-level scribbles improve the segmentation performance the most, and FCN-FAST+dCRF learned with such annotations obtains the highest mean $F_1$ score, 70.58%. Moreover, we note that FESTA can enhance the network capability of recognizing small objects, i.e., car, in high-resolution aerial images. Example segmentation results of networks trained on annotations are visualized in Fig. 4.

Numerical results on the Zurich Summer data set are shown in Table III. As can be seen, FESTA contributes to increments of 3.92%, 1.37%, and 1.31% in the mean $F_1$ score when training with point-, line-, and polygon-level annotations. By utilizing line annotations and dense CRF, FCN-FESTA+dCRF obtains the highest mean $F_1$ score, 69.43%. Besides, we note that the exploitation of dense CRF plays a significant role in improving the results of networks trained on point-level scribbles. Example visual results of networks trained on annotations are shown in Fig. 5. In our experiments, we also train networks with multiclass dice loss and find that results are comparative to those learned with cross-entropy loss.

E. Discussion on Annotation Type

To further study the influence of annotations, we also train baseline FCNs on dense annotations and report numerical results in Tables II and III. As shown in Tables II and III, line-level annotations lead to the best performance on both data sets, even though the number of labeled pixels is an order of magnitude smaller than polygon annotations (see Table I). Although it was expected that line annotations would outperform point annotations, due to their ability to capture within-object variations, we were surprised to see that they also outperformed polygon annotations. We suspect that this
is linked to the fact that the number of pixels per object grows quadratically for polygons and linearly for lines. This would lead to a more balanced weighing of differently sized objects in the case of line annotations and an underweighting of smaller objects in the case of polygon annotations, which could harm the model’s performance. Another reason could be that, since drawing a line is faster than drawing a polygon, annotators for the line features provided more scribbles in the same time budget.

In spite of the mean $F_1$ performance boost provided by FESTA, there is still a large gap with respect to the FCN model trained with dense ground truths of 13% in Vaihingen and 8% in Zurich. This gap is, however, not evenly distributed across the classes. The gap is smaller or nonexistent in classes, such as water, tree, grass, or soil, which are often homogeneous in terms of materials. On the contrary, it is larger for classes with more diverse materials (and therefore, observed spectral values), such as building and car (in the Vaihingen data set). It is noteworthy to mention that the class railway, in the Zurich data set, is systematically missed in all cases, including the densely supervised FCN.

### IV. Conclusion

In this letter, we propose a simple yet efficient framework for semantic aerial image segmentation using sparse annotations and a semisupervised learning objective. In order to validate the effectiveness of our approach, we conduct experiments on the Vaihingen and Zurich Summer data sets. Numerical and visual results suggest that the proposed method contributes to the improvement of semantic segmentation results using several kinds of sparse annotations. Although models learned on sparse annotations achieve relatively lower accuracies than those using dense annotations, we show that using a semisupervised deep learning approach can help to close this performance gap while leveraging sparse annotations that can significantly reduce the costs of label generation. As future work, the proposed framework can be further improved by introducing graph-based models and prior knowledge learned from label semantics.

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