Road Network Reconstruction from satellite images with Machine Learning Supported by Topological Methods

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ABSTRACT

Automatic Extraction of road network from satellite images is a goal that can benefit and even enable new technologies. Methods that combine machine learning (ML) and computer vision have been proposed in recent years which make the task semi-automatic by requiring the user to provide curated training samples. The process can be fully automatized if training samples can be produced algorithmically. In this work, we develop such a technique by infusing a persistence-guided discrete Morse based graph reconstruction algorithm into ML framework. We elucidate our contributions in two phases. First, in a semi-automatic framework, we combine a discrete-Morse based graph reconstruction algorithm with an existing CNN framework to segment input satellite images. We show that this leads to reconstructions with better connectivity and less noise. Next, in a fully automatic framework, we leverage the power of the discrete-Morse based graph reconstruction algorithm to train a CNN from a collection of images **without labelled data** and use the same algorithm to produce the final output from the segmented images created by the trained CNN. We apply the discrete-Morse based graph reconstruction algorithm iteratively to improve the accuracy of the CNN. We show experimental results on datasets from SpaceNet Challenge. Full version of the paper appears in [8].

CCS CONCEPTS

- Information systems → Geographic information systems;
- Computing methodologies → Image segmentation.

KEYWORDS

map generation, satellite images, machine learning, topological method, Morse complex

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1 INTRODUCTION

Layout of road networks is essential for diverse applications in geographic information systems. Efficient reconstruction from images and timely updates of road networks are important both for map designs and handling events such as natural disasters. The availability of high-resolution satellite images has enabled such technology in recent years though the process is not fully automatic. Currently the road extraction from satellite images is mainly completed manually [19]. Doing so automatically or even semi-automatically in a reliable manner is challenging as there are a variety of different types of roads whose images are cluttered with noise and occlusions (by cars/trees etc).

Extracting lane-related information from high resolution satellite images has been addressed in recent years [11, 18, 22]. Specifically for road extraction, a range of methods that combine machine learning and computer vision methods have been proposed to reconstruct roads using labelled data. These are semi-automatic in the sense that they use manually curated samples to train the classifier. These methods often consist of two main stages: background segmentation and centerline extraction. The background segmentation is usually done via machine learning methods such as performing feature extraction and pixel-wise label predictions with SVM [4, 16] or CNN [3]. The baseline algorithms for SpaceNet Challenge [19] use the architecture such as U-Net[15] and PSPNet [23]. For the second stage, methods like skeleton or medial axis extraction with pre- and post-processing are often used to obtain the final road networks. However, recovering the correct connections and junctions of roads still remain challenging. This problem is critical since the road network is often used in routing and false breaks in the extraction lead to unacceptable results. This two-stage approach can potentially be fully automatized if training samples can be produced algorithmically.

To achieve the full automatization, one needs to have a direct reconstruction from images that may not be completely faithful but reliable enough to serve as the generator of good training samples. Then, one can iteratively use the technique to improve upon the training samples. This is what we achieve in this work for automatic road reconstruction. It turns out that our direct reconstruction method even improves over the state-of-the-art techniques for semi-automatic reconstructions by providing a more robust algorithm for the second stage. Our direct reconstruction method is a topology-based graph reconstruction algorithm. It uses the recent techniques of topological persistence [9] and discrete Morse theory [10] in topological data analysis. This topology-based approach for recovering hidden structures has been proposed and studied recently [5, 12, 14, 21]. It has been applied to extracting graph-like structures from simulated dark matter density fields [17] and reconstructing road networks from GPS traces [6, 20]. This

discrete-Morse based graph reconstruction framework is clean both conceptually and implementation-wise. Most importantly, as it uses a global topological structure to make decisions (instead of using purely local information to decide whether a point is on or off the road), the algorithm is robust to noise, non-uniform sampling of the data, and reliable at recovering junctions. Very recently, this graph reconstruction algorithm has been further simplified, and theoretical guarantees of this graph reconstruction algorithm for the case when the signal prevails noise have been provided [7].

Contributions: Our contribution is twofold. (1) First, in a semi-automatic framework, we apply the discrete-Morse based graph reconstruction algorithm on the segmented satellite images obtained by a CNN. This, of course, requires user provided training samples to train the CNN. We show that this leads to reconstructions with better network connectivity and less noise compared to some existing state-of-the-art technique. (2) More importantly, next, in a fully automatic framework, we develop a novel method to leverage the power of the discrete-Morse based graph reconstruction algorithm to train a CNN from a collection of images **without labelled data** so that it can produce segmentation for new images. To elaborate, we start with running the graph reconstruction algorithm on the raw satellite images to obtain some initial reconstructions. We then put the pixels from reliable branches of the output graph as positive and others as negative to create the labels for the training, and produce an intermediate CNN classifier. We predict the segmented images for the training set using this intermediate CNN and then repeat the same process on the output to gradually improve the CNN. Our experiment shows that after several iterations of training, the labels computed from the graph reconstruction algorithm become less noisy and the performance of the classifier improves significantly. If we relax the condition slightly and assume that we know the labels for only 10% of the train set, we can incorporate this partially labelled data into our framework, and the performance of the classifier becomes even better. We experiment on datasets from SpaceNet Challenge [19] and compare our results with the results of the winner’s algorithm, using the APLS score ([19]) as well as another metric which we call average Hausdorff distance. Our reconstructions tend to have better connectivity and are less noisy and we show promising experimental results of this new framework on datasets from SpaceNet Challenge.

Organization: Section 2 introduces our semi-automatic framework and fully automatic framework. Section 3 provides experiment results for both frameworks. A full version of this abstract is in [8].

2 APPROACHES

On the high level, the road network reconstruction from satellite images framework has two stages: We apply the simplified version of the discrete-Morse based graph reconstruction algorithm `MorseGraphRecon()` [7] to extract road networks from the segmented images (sometimes called “road masking” in the literature). Our approach mostly uses this reconstruction algorithm as a black box, interested readers should see [7] for more details.

2.1 Semi-automatic framework

The semi-automatic framework follows the high-level two-stage approach: In the first stage, we train a CNN using training images

Figure 1: Pipeline for Stage 1 (CNN training) for our fully automatic framework. Note that no input satellite image has labels for roads!

consisting of ground-truth roads labeled. We feed raw satellite images to this trained CNN to obtain segmented images. In the second stage, we apply the discrete-Morse based graph reconstruction algorithm to extract the road-network from the segmented image. For the second stage to work more accurately, we need to detect road ends called “tips” in the segmented images obtained in the first stage. We take advantage of the CNN to add a simple “tip-detection” stage that enhances the segmented images. For details of reconstructing tips, see the full version [8].

CNN architecture. We use the architecture from the winner’s approach of the Spacenet Challenge [2]. It uses resnet34 [13] as encoder and unet-like [15] decoder.

2.2 Fully Automatic Framework

The ground truth labeling used in the semi-automatic framework is itself a graph like structure. So we propose to create the labels using the discrete-Morse based graph reconstruction algorithm without the knowledge of the ground truth. These labels are used to train a CNN for the image segmentation. The segmented images are again labeled by the output of the graph reconstruction algorithm and fed to the CNN for training purpose. A few iterations of training and labeling improves the quality of the image segmentation significantly as our experiments show. This framework is particularly useful when there is no or very few labelled data to begin with.

Our framework can deal with the following two scenarios. We perform **label-free learning** when we do not have ground truth roads for any input satellite images to begin with. We perform **partially-labeled learning** when we have a small fraction of images (say 10% of training set) with road labels.

Label-free case. We describe the framework for the label-free case, and the partially-labeled case can be handled by a slight modification of it. The high-level pipeline of Stage 1 (training a CNN for segmenting an input image) is in Figure 1. Given an input set of raw satellite images (with no labels), we split it into the training and testing sets, denoted by I_0^{tr} and I_0^{test} , respectively. We run algorithm `MorseGraphRecon()` on each image from I_0^{tr} , and let $\hat{G}$ be its corresponding output. We use a large threshold for simplification in algorithm `MorseGraphRecon()` so as to generate a reconstruction of the more reliable part of the input. Then we label pixels on $\hat{G}$ as positive and pixels on the complement of $\hat{G}$ as negative. Next we train the CNN classifier with those labeled pixels, and this is our first classifier $C_0 = \text{MorseLabelTrain}(I_0^{tr})$ (shown in Algorithm 1).

Now feeding each original training image from I_0^{tr} to C_0 returns a collection of segmented images I_1^{tr} , where in each image, every

Algorithm 1: MorseLabelTrain(I)**Data:** Images I **Result:** Classifier C

```

1 begin
2   Compute the triangulation  $K$  of  $I$  and take pixel values as
   road-likelihood map  $\rho$ 
3    $\widehat{G} = \text{MorseGraphRecon}(K, \rho, \delta)$ 
4   Label pixels on  $\widehat{G}$  as positive, pixels on the complement of
    $\widehat{G}$  as negative
5   Train a CNN classifier  $C$  by above features
6   return  $C$ 

```

pixel has a value reflecting the likelihood of it being positive (on the road). We repeat the steps with images in I_1^{tr} and obtain a new CNN classifier $C_1 = \text{MorseLabelTrain}(I_1^{tr})$. In a generic i -th iteration of this process, feeding the training images I_i^{tr} to C_i returns segmented images I_{i+1}^{tr} , which we use to train a new CNN classifier $C_{i+1} = \text{MorseLabelTrain}(I_{i+1}^{tr})$. The process terminates when the segmented images I_i^{tr} undergo little changes over iterations.

Partially-labelled case. For this scenario, we start training the CNN classifier using only the labelled training images to obtain C_0 . In each of the subsequent iteration $i > 0$, we use both the labels computed from the segmented images I_i^{tr} at this iteration, as well as the original labels from the ground truth.

3 EXPERIMENTS

Datasets. We consider data from the SpaceNet Challenge 3 [19]. It includes four cities: Las Vegas, Paris, Shanghai and Khartoum. We only use the RGB 16-bit geotiff in our experiments. Each image from the dataset covers 400m by 400m with a size of 1300px by 1300px. The ground truth for each image is a graph representing the centerline of the roads. The width of the roads in the masks is 4 meters. To evaluate the results, we need to compare the proposed graphs with the ground truth. So we only take the train set from this challenge (since ground truth is only known for this set).

Metrics. We use the Average Path Length Similarity (APLS) [19] and average Hausdorff distance to evaluate the results. APLS is the metric used for evaluation in SpaceNet Challenge 3, it may not be accurate when the size of the graph is small. To obtain a more comprehensive picture, we also use another metric.

DEFINITION 3.1. Let $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ be two input graphs. For $a, b \in V_1$ where $\text{path}(a, b)$ exists in G_1 , let a' (resp. b') denote the closet node to a (resp. to b) in G_2 . $L(\cdot, \cdot)$ denote the length of the shortest path. First we define the cost of $\text{path}(a, b)$:

$$c(a, b) = \begin{cases} \min \left\{ 1, \frac{|L(a, b) - L(a', b')|}{L(a, b)} \right\}, & \text{if } \text{path}(a', b') \text{ exists} \\ 1, & \text{otherwise} \end{cases}$$

We next define $C(G_1, G_2) = 1 - \frac{1}{N} \sum c(a, b)$ Where $N = \#$ unique paths in G_1 , and we take the sum over all unique paths. Finally, the APLS score of G_1 and G_2 is defined to be the harmonic mean of $C(G_1, G_2)$ and $C(G_2, G_1)$: $\text{APLS}(G_1, G_2) = \frac{2}{\frac{1}{C(G_1, G_2)} + \frac{1}{C(G_2, G_1)}}$.

DEFINITION 3.2. Let G_1 and G_2 be two graphs; P_1 the point set sampled from G_1 ; P_2 the point set sampled from G_2 ; and d denotes the Euclidean distance. The one-directional Hausdorff distance is:

$$S_{HA}(G_1, G_2) := \begin{cases} \frac{1}{|P_1|} \sum_{p \in P_1} d(p, P_2), & G_1 \neq \emptyset \text{ and } G_2 \neq \emptyset \\ \text{MAX}, & \text{Only one graph is empty} \end{cases}$$

$S_{HA}(G_1, G_2)$ is set to 0 if both G_1 and G_2 are empty. MAX is a specific maximum value. We set $S_H(G_1, G_2) = S_{HA}(G_1, G_2) + S_{HA}(G_2, G_1)$ as the final average Hausdorff distance between G_1 and G_2 .

Parameters. In the entire pipeline, the persistence threshold δ (for the discrete-Morse based reconstruction algorithm) and the arc-intensity threshold τ (used to further remove noisy arcs during the post-processing) affect the results most. See the full version [8] for the parameter tuning.

3.1 Semi-automatic reconstruction results

	APLS		S_H	
	Buslaev[1]	ours	Buslaev[1]	ours
AOI_2	0.8211	0.8278	18.3539	17.7841
AOI_3	0.5848	0.6324	291.0188	289.9532
AOI_4	0.6630	0.6632	69.5775	68.9596
AOI_5	0.6069	0.6477	44.4201	41.6037

Table 1: APLS score and average Hausdorff distance for the test set. The MAX value used for average Hausdorff distance is 500 pixels, the size of each image is 1300px by 1300px.

We compare our framework with the method of the winner of SpaceNet Challenge 3 [1]. Buslaev's algorithm tends to have more extra branches, and worse connectivity. Tables 1 shows the scores under the two metrics. Each score is an average of scores for all test images. Table 2 shows the running time. Our framework gives better score under both two metrics and all four datasets. See the full version [8] for more details.

	Train	Test	Road extraction
AOI_2	$2 \times 242m$	$8m \times 2$	$22m \times 9$
AOI_3	$77m \times 2$	$2m \times 2$	$6m \times 9$
AOI_4	$293m \times 2$	$10m \times 2$	$27m \times 9$
AOI_5	$71m \times 2$	$2m \times 2$	$6m \times 9$

Table 2: The running time: m stands for minutes; $2\times$ means it will be run twice (for both road and tip detections). $9\times$ comes from the tuning of the parameters.

3.2 Fully automatic reconstruction results

In the following experiments, we randomly select 200 images as the training set I_0^{tr} , and 50 images as the test set I_0^{test} for each dataset. We evaluate the method by computing the APLS scores on the original test set after each iteration. We initialize our fully automatic approach by converting each RGB image to grayscale and then applying a Gaussian filter. One could potentially use other image processing methods to further pre-process it. When applying the graph reconstruction algorithm, we use the same parameters used in Section 3.1.

Alternative method for centerline detection. To show that the discrete-Morse based graph reconstruction algorithm is important for our fully-automatic training framework, we develop the following alternative scheme `SkeletonLabelTrain()` as a baseline to compare: the graph reconstruction algorithm is replaced with the Buslaev's [1] skeleton extraction algorithm (as described in Section 3.1). Note that this skeleton extraction used in [1] is not designed to work directly on the raw satellite images. Hence to improve the performance of this the baseline method `SkeletonLabelTrain()`, we will still first use the discrete-Morse graph reconstruction algorithm (or if there are partially-labelled data, using those first) at the beginning of the training process, and switch to the skeleton extraction algorithm only after a few iterations.

Results for label-free case. We show results here for dataset AOI_2, which is a cleaner dataset from SpaceNet Challenge. Our new fully-automatic framework is less effective on AOI_5, which is much more noisy; however, we will show later that, with 10% labelled images, it can obtain reasonable results on the challenging AOI_5 dataset as well. In Figure 2, we show the APLS-score for test images using the CNN C_i learned at the i -th iterations, as i increases (the average Hausdorff distance shows a similar trend). In particular, I_i^{test} ($i > 0$) represents the output reconstructed from the segmented images of the set I_0^{test} using the trained CNN C_{i-1} . In Figure 3, we show an example of the reconstructed graph using the CNN from different iterations of our fully automatic training process: observe that at the beginning, only part of signals are captured. Subsequently, the classifier becomes better and more and more signals are captured.

Figure 2: APLS-score for testing images, based on our label-free framework (`MorseLabelTrain()`), compared to the alternative method `SkeletonLabelTrain()`. The first two iterations for `SkeletonLabelTrain()` is done by `MorseLabelTrain()` and thus are not shown. After 6 iterations, the score does not improve for `SkeletonLabelTrain()` any more.

With 10% ground truth. Now we use a small set of labelled data: Specifically, we assume that only 10% images (i.e, 20 images) have labels (i.e, ground-truth roads given). For `MorseLabelTrain()`, all scores improve. It is important to note that with only 10% labeled-images, we can now also handle the challenging AOI_5 dataset, and achieve an APLS-score of 0.607. (For the case of AOI_2, compared to the label-free case, the score of our new `MorseLabelTrain()` improves to 0.721 from 0.592). This iterative procedure does not seem to help `SkeletonLabelTrain()` much, with scores even getting worse for the noisy dataset AOI_5. See the full version [8] for details.

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Figure 3: Left: raw satellite image (ground truth in yellow, even though it is not used!). Middle / right: the reconstructed graph using CNN after the first and the 11-th iterations.

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