Using Reinforcement Learning to Iteratively Construct Road Networks from Satellite Images and GPS Data

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Abstract

Constructing road networks manually is a time consuming and labor-intensive process. This paper proposes a new method to iteratively construct road networks using reinforcement learning from a combined tensor-based representation of satellite image and GPS trajectory data.

Introduction

Accurate and up to date road maps are important to industry and governmental applications. Creating and maintaining these maps manually is a time consuming, labor-intensive, and costly process. If this process could be automated effectively, it would greatly benefit the applications that rely on these maps. This paper proposes a new research topic to address this issue.

The method proposed involves the creation of a new combined tensor-based representation of satellite imagery and GPS trajectory data. Reinforcement learning techniques will then be applied to construct the road network graph by iteratively adding new vertices and edges, connecting existing edges, or marking vertices as finished.

If successful, this method could provide a new high performing method for the automatic construction of road networks. This would benefit various applications with cost effective, accurate, and up to date road maps.

Background

This paper builds off of and is inspired by two main papers, Sat2Graph (He et al. 2020) and RoadRunner (He et al. 2018).

Sat2Graph introduces a novel graph encoding scheme which they call Graph-Tensor Encoding (GTE). GTE provides a tensor-based representation of the graph allowing for neural network models to work directly with the graph representation.

The RoadRunner paper proposes a method of iteratively constructing road networks from GPS trajectory data. One of their big contributions is to consider the trajectories as a whole instead of aggregated individual points. This allowed them to have high precision in complicated areas where separate roads come close together or overlap.

This paper builds off of the GTE scheme proposed in the Sat2Graph paper to represent satellite image data and seeks to develop a new similar tensor-based encoding scheme to represent GPS trajectories. Using a combined tensor of both the satellite and GPS data, a reinforcement learning agent will be trained to iteratively construct the road network graph, replacing the complex hand designed algorithms proposed in other papers.

Approach

The proposed approach breaks down into two parts, creating the combined tensor-based representation of the satellite image and GPS trajectory data and then the iterative graph construction using reinforcement learning.

First the area to be mapped is broken up into a m x n grid where m and n are the length and width of the area in meters. This provides a resolution of 1 meter by 1 meter, which is a similar resolution to what other papers have used.

For the satellite image representation, the encoding scheme proposed in the Sat2Graph paper, GTE, will be used. This encoding scheme represents the graph as a $M \times N \times (1 + 3\cdot D)$ tensor. The vector at each position (M_i, N_j) is $(1 + 3\cdot D)$ vector. The first position encodes the probability of a vertex at that location. The area around the position is then split up into D radial sectors. The remaining positions are split up into D 3-element sections. Where first element in each section encodes the probability of an outgoing edge in the sector. The remaining two elements encode the relative position of the edge within that sector. A CNN is then trained to map directly from the satellite image to this representation.

For the GPS trajectory representation, we will propose a new tensor-based encoding scheme. Based on the findings in the RoadRunner paper, it is important to preserve the trajectory information of the GPS data as opposed to simply aggregating all the position data into a heatmap like representation. This allows for higher precision in areas where separate roads overlap or come near to each other. The proposed encoding scheme for the GPS trajectory data is as a M x N x H x W tensor. At each point (M_i, N_j), a heat map of the H x W area around the point is created to represent the positions reached by trajectories after they have passed through the point. This will allow for the data to be aggregated while still preserving the information of the trajectories necessary for high precision in complicated areas.

These two representations will be put together to provide a combined representation of both the satellite image and GPS trajectory data. This should allow the RL agent to benefit from the information in both types of data.

Once the combined tensor representation has been created, an RL agent will be trained to iteratively expand the graph. To begin, seed points will be selected to act as an initial graph to expand upon. At each step in the expansion the RL agent will be provided with a vertex in the graph to expand from, the graph constructed so far represented in the GTE scheme, and the combined representation of the satellite and GPS data in an X x Y area around the vertex. The RL agent will then take one of three actions: add a new vertex and connecting edge, connect to an existing vertex, or mark the vertex as finished.

Vertices will be split into two groups, finished and unfinished. The RL agent will be continually provided with vertices from the unfinished group to expand from. If it marks a vertex as finished it will move it to the finished group. Whenever the RL adds to the graph, any vertices marked finished in the surrounding area will be moved to the unfinished group to be re-evaluated. The RL agent will continue to draw vertices from the un-finished group until all have been marked finished, at which point the graph will be completed.

Evaluation

To evaluate our method, we will use two common metrics TOPO and APLS.

TOPO compares the topological similarity of sub-graphs of the constructed and ground truth road networks around randomly sampled points. The more similar the sub-graph, the better the method performs.

APLS works by comparing the lengths of the shortest path in the constructed and ground truth road networks between randomly sampled points. The closer the lengths the better the method performs

These two metrics would be used to compare the performance of the proposed method to the performance of existing methods for road network construction.

Discussion

We expect to find two benefits from the proposed method. First, using both satellite images and GPS data should provide more information allowing for better road network construction. Second, using an RL agent to iteratively construct the graph should outperform the complex hand designed algorithms used by current iterative graph-based approaches.

The expected improvements in road network construction would benefit applications that rely on accurate and up to date road maps by outperforming existing automated solutions.

Conclusion

Many industry and governmental applications rely on accurate road maps. These are time consuming and expensive to produce manually. An automated solution to mapping road networks would benefit the many applications that rely on them.

This paper builds off prior work in the field to propose a new method to tackle this problem. A novel representation of combined satellite image and GPS data was shown that can benefit from the combined information of both types of data and a reinforcement learning based approached was proposed to replace the complex hand designed algorithms of similar graph-based approaches.

If shown to be successful, this new method would benefit the many applications that rely on accurate and up to date road networks maps.

References

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