Primate Graph Learning for Unified Vector Mapping

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Abstract

Large-scale vector mapping is the foundation for transportation and urban planning. Most existing mapping methods are tailored to one specific type of ground target, due to the different shape topologies and shape regularization of different targets. We propose GraphMapper, a unified framework for end-to-end vector map extraction from satellite images. Our key idea is an unified representation of vector maps of different topologies using a primitive graph, including a set of shape primitives and their pairwise relationship matrix. Based on primitive graph, we design a learning approach to reconstruct primitive graphs in multiple stages. Through incremental primitive learning and pairwise relationship reconstruction, GraphMapper can fully explore primitive-wise and pairwise information for improved primitive graph learning. Additionally, our model achieves powerful context-aware shape regularization by learning directions that are consistent with pairwise relationship estimation. We empirically demonstrate the effectiveness of GraphMapper on two challenging mapping tasks for building footprints and road networks. With the premise of sharing the major design of the architecture, and few task-specific designs, our model outperforms state-of-the-art methods in both tasks on public benchmarks. Our code will be publicly available.

1. Introduction

Up-to-date vector maps are essential for navigation and urban planning. Methods to automatically extract vector maps from aerial or satellite images have greatly advanced in recent years. However, state-of-the-art vector mapping methods are tailored for one specific type of target. Consequently, multiple models must be maintained for comprehensive mapping systems, which increases the burden of model development and limits the system extensibility.

The main challenge of designing an unified method for multiple vector mapping tasks lies in the difficulty to process different geometric primitives and topologies in an unified way. Therefore, specific designs have been required for different types of geometric primitives, such as point and line segment, for best performance [16, 19, 29, 38]. Additionally, accurate location and topology are the two basic requirements for vector mapping. Existing end-to-end methods either only focus on refining location accuracy [23], or try to perform feature learning on both tasks in parallel [34, 38]. We argue that location and topology should be modeled incrementally, based on the intuition that improving location accuracy in advance can disambiguate and simplify topology learning.

The other challenge of high-performance unified mapping is that for certain mapping tasks, such as building mapping, it is critical to achieve aesthetic shape regularization beyond accurate geo-location and topology reconstruction. Shape regularization in vector mapping is essentially reducing the variation of relative relationship between primitives; for example, the angles between line segments of a building polygon usually share a few distinctive values (i.e., 0°, 90°, etc.). By far, most methods regularize shapes through contour optimization or deformation [10, 12, 16, 24, 38]. However, these methods rely on regressed information, which cannot explicitly enforce low variation of primitive relationships. Meanwhile, naively aligning shapes according to relationship types is sensitive to the errors of classified relationships, which further challenges effective learning-based shape regularization.

In this paper, we use primitive graph as a generic representation to build an unified framework, GraphMapper, for multi-type vector mapping. GraphMapper incrementally learns to refine primitives locations and reconstruct their pairwise relationships. Effective topology reconstruction and shape regularization are achieved through the relationship classification of pairwise primitives. With our design, most existing mapping tasks can be converted to image-based primitive graph reconstruction tasks. As shown in Fig. 1, GraphMapper is mainly composed of a convolutional visual feature encoder and two primitive learning structures (PLS) using multi-head attention (MHA) network. We first extract visual features of input image using a convolutional encoder and sample primitives (i.e., points, line segments) from the segmentation maps and keypoints.

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Methods in both tasks in public benchmarks. In summary, and pairwise relationship matrix of line segments.ing consistency between the network predicted angle matrix
ments; the network learns shape regularization by enforcing
performance results, and predict inlineness between line seg-
find line segment primitives and their topology from seg-
their pairwise connectivity relationship. For building, we
primitives and reconstruct road topology by classifying
road and building mapping. For road, we predict point
classify the relationships of primitive pairs.
shape context modeling. Finally, we use another PLS to
generate geometric directions, which uses a PLS for local and global
2. Related Works
Unified vector mapping. To the best of our knowl-
edge, PolyMapper [22] is currently the only unified learn-
ing method for vector mapping. PolyMapper uses polygons
as the unified representation for buildings and roads. A
CNN-RNN structure is used to recurrently predict point se-
quences. However, representing road as polygons leads to
redundant points, and predicting point sequence can easily
introduce geometric errors. In contrast, GraphMapper sup-
ports learning on different primitives, and holistically re-
constructs the topology of sampled primitives.
Road mapping. Road mapping methods focus on im-
proving topological correctness for navigation purposes. Various techniques are made to improve the connectivity of
road segmentation maps [5, 5, 14, 26, 28, 35]. To reconstruct
road topology from imperfect segmentation results, [25]
uses a binary decision classifier to predict the correctness of
connections of nearby road endpoints from their image fea-
tures, but it does not explore global road structure or shape
prior. Graph-based methods [4, 22, 32] reconstruct road net-
works by iterative searching of the next point in the road
graph, using a CNN or CNN-RNN structure. Shape prior
and global road structure are implicitly modeled in the iter-
ative searching process. Compared to graph-based methods,
our method generates a road graph in one forward run with
all road points available, which allows easier integration of
global and local shape contextual information.

Recently, Sat2Graph [19] achieved the state-of-the-art
performance by connecting segmented key points along
road direction with carefully designed searching rules. Uni-
formly distributed road points and their directions are pre-
dicted using a multi-task CNN. Several steps of post-
processing are performed to reduce artifacts and false con-
nections. Compared to Sat2Graph, our method learns con-
nectivity end-to-end, without complicated post-processing.

Building mapping. Building mapping methods are
now focusing on learning vector results from image in-
puts, where regularized shape representation is often a ma-

or concern. Conventional methods often rely on heuris-
tic rules [1, 30] for shape regularization, which is limited
to simple scenarios and requires extensive tuning. Poly-
gonRNN and its extensions [2, 9, 22] achieved end-to-end
vector mapping from images by recurrently predicting point
sequences. However, RNN-based methods often fail to pro-
duce regularized shapes due to the lack of shape optimiza-
tion design. [12, 16, 24] try to optimize contours using ACM (Active Contour Model) [20] guided by learned semantic informa-
tion. Specifically, DSAC [24] and DARNNet [12] regress the weights of the contour smoothness term based on sem-
antic information for shape generalization, which tend to
generate under-regularized shapes due to inadequate design in simplified representation; [16] further optimizes bound-
ary skeletons to align with learned frame fields, but still
requires complicated post-processing for shape regulariza-
tion. Instead, PolygonCNN [10] and Polygon Transformer
[23] predict point deformation of segmented contours, in
which the results are regularized implicitly by improving the accuracy of building vertices; comparatively, our ap-
proach goes one step further by explicitly modeling shape
regularity. Recently, PolyWorld [38] achieved great perfor-
mance by first deforming keypoints’ coordinates, and then
reconstructing topology through classifying pairwise point
connectivity relationship. Despite that GraphMapper fol-

ows a similar structure, the relationship classification modu-
le in our framework serves multiple purposes: topology
reconstruction for road mapping, and explicit shape regu-
larization for building mapping.

[39] tried to regularize building footprint segmentation
mask using a GAN loss, which can be considered as a par-
allel design to our geometry-based regularization method.

3. GraphMapper
Our main idea is to turn various vector mapping prob-
lems into an unified primitive graph estimation problem.
In the following sections, we will first introduce primitive graph in Section 3.1. Then we explain the design of GraphMapper’s network architecture in Section 3.2, and training targets in Section 3.3. Lastly, we provide details of applying GraphMapper to road and building mapping in Section 3.4.

### 3.1. Primitive Graph

A primitive graph is a homogeneous undirected graph:

\[ G = \{V, E\}, V \in \mathbb{R}^{N \times d}, E \in \mathbb{Z}^{N \times N} \]  \(1\)

where \(V\) represents \(N\) primitives with \(d\)-dimensional coordinates. A point primitive is represented by its image coordinate \((x, y)\); a line segment primitive is represented by the coordinates of its two end points \((x_1, y_1, x_2, y_2)\). \(E\) is the relationship matrix, in which \(E_{ij}\) represents the relationship between \(V_i\) and \(V_j\). Example primitive graph representation for road and building are shown in Fig. 2. Depends on the choice of primitives and pairwise relationships, primitive graph can model various types of targets.

### 3.2. Network Architecture

The overall structure of GraphMapper is illustrated in Fig. 1. We reconstruct primitive graphs in three sequential steps. We first extract initial primitives from input images. Then, the location of initial primitives are refined using a primitive learning structure (PLS). The direction or normal direction of each primitive is also estimated at this stage. Lastly, we reconstruct the relationship matrix between pairwise primitives using another PLS.
As both tasks benefit from shape context information, they predict the pairwise relationship of the refined primitives to improve location accuracy and alleviate the difficulty of relationship learning. Then, we extract additional keypoints from semantic segmentation maps.

More specifically, we use a FPN network with resnet backbone to encode input image \( I \in \mathbb{R}^{S \times H \times W} \) into a multi-scale feature \( F \). Then, we predict a semantic segmentation map \( Y_{seg} \in \mathbb{R}^{S \times H \times W} \) and a keypoint heatmap \( Y_{kp} \in \mathbb{R}^{K \times H \times W} \) from \( F \) using two FCN heads.

To sample point primitives, we first extract local maximum points using NMS on all non-background classes of \( Y_{seg} \) and \( Y_{kp} \), resulting \( S + K - 2 \) of candidate points. Then, we combine all candidate points and apply another NMS with category-specific priority scores to remove redundant points to get the sampled points \( V' \in \mathbb{R}^{N \times 2} \), so that points of higher priority categories are kept over lower ones.

We sample line segments by connecting sampled key points. For polygon structures (i.e., building, forest), we trace contours from segmentation maps, which are then simplified using the Douglas–Peucker (DP) algorithm [13]. Points of the simplified contours are combined with sampled key points. We project points to their nearest contours, and connect points according to their projections’ sequence in contour [10]. Note that when the targets are represented by polygons, this method can accurately derive the relative sequence between line segments without learning the connectivity between line segments.

### 3.2.2 Primitive Graph Reconstruction

Given the initialized primitives as input, we first refine the coordinates of primitives to improve location accuracy and alleviate the difficulty of relationship learning. Then, we predict the pairwise relationship of the refined primitives. As both tasks benefit from shape context information, they share a common primitive learning structure. Different from previous methods [38], we reconstruct pairwise relationship based on refined primitives instead of initial primitives. Using refined primitives can reduce the ambiguity for relationship recognition and ground truth relationship generation, which is essential for high quality primitive relationship reconstruction.

**Proposed Learning Structure**. The structure of Primitive Learning Structure (PLS) is illustrated in Fig. 1. Given primitives \( V \) and their visual features as input, visual features at primitives’ locations are pooled using patch pooling. Patch pooling extracts a small crop of image feature centered at each primitive, and compresses the cropped features using a small FCN network. The resulted primitive features \( h_{vis} \) are flattened and individually projected using a MLP \( (f_{proj}) \), the result of which is fed into a multi-layer MHA module \( f_{MHA} \) together with the positional encoding of coordinate primitives [8]. MHA can fuse geometric and visual information and exchange information among primitives to generate local and global contextualized primitive features \( h_{prims} \), which are used by MLP heads to generate output predictions.

**Primitive Refinement**. We use a PLS with two MLP heads to predict the coordinate deformation and directions \( D \in \mathbb{R}^{N \times 2} \) (normal direction for points and line direction for line segments) of input primitives from PLS generated primitive feature \( h_{prims} \). We get refined primitives \( V' \) by adding estimated deformation back to input coordinates. Note that line segments’ direction can also be computed from their coordinates \( V' \). However, we found network predicted \( D \) is more accurate, as it is easier to regress a direction than adjusting both vertices of a line segment to achieve the desired angle while staying close to segmentation boundary.

For direction regression, the discontinuity of rotation angles at 0 and 180° can lead to unstable learning [36] when naively applying \( L2 \) loss on direction angles \( D \). Therefore, we regress the sine and cosine of a surrogate angle which is 2 times the target angle \( A \) as suggested in [36]:

\[
\overrightarrow{D}_i = (\cos(2A_i), \sin(2A_i)).
\]  

Each row in \( D \) is a normalized 2-dimensional vector. During inference, we recover the actual direction \( D' \) from surrogate direction \( D \).

**Primitive Relationship Reconstruction**. We input the refined primitives \( V' \) and visual feature into another PLS to predict relationship matrix \( E \). For a pair of point primitives, we extract additional visual features on the line segment between them using LOI [37] from visual feature, \( Y_{seg} \) and \( Y_{kp} \). These extracted features are concatenated together with their point features in \( h_{prims} \) to form the point pair’s feature. For a pair of line segment primitives, we simply concatenate their features in \( h_{prim} \) as the pair’s fea-

![Diagram of primitive graph representations](image-url)
ture. For $N$ primitives, we get a relationship feature matrix $Q \in \mathbb{R}^{d_r \times N \times N}$. The MLP heads in PLS independently classify each pair’s relationship using their feature in $Q$.

As only spatially neighboring primitives have positive relationship, the ratio of positive and negative relationship in relationship matrix $E$ is often strongly biased. Therefore, only the relationship of primitive pairs within a spatial distance threshold $t$ are used for training to balance positive and negative sample ratio.

Shape regularization. Primitive graph allows explicit representation of shape regularization as the consistency between primitives $V$ and their relationship matrix $E$:

$$L_{\text{reg}} = \sum_{i,j,r} E_{i,j,r} |f_{\text{prop}}(V_i, V_j, r) - f_{\text{prop}}(\nabla_i, \nabla_j, r)|$$

(3)

where $f_{\text{prop}}$ computes the desired property between primitives. The term in $| \cdot |$ represents the difference between computed and desired property between $V_i$ and $V_j$ for relationship category $r$. $\nabla_i$ and $\nabla_j$ are the corresponding ground truth primitives for $V_i$ and $V_j$. This formulation explicitly enforce low variation of primitives’ relative properties. Additionally, by adjusting the strength of regularization according to the probability of its relationship type, the network can learn to balance between shape regularity and location accuracy.

3.3. GraphMapper Learning

GraphMapper is trained with a linear combination of the following losses:

$$(L_{\text{seg}}, L_{kp}, L_{off}, L_{dir}, L_{rel}, L_{reg}, L_{aux})$$

(4)

which we explain below.

Segmentation loss $L_{\text{seg}}$. $L_{\text{seg}}$ is a linear combination of cross-entropy loss and Lovász-softmax loss [6] applied to semantic segmentation map $Y_{\text{seg}}$. Lovász-softmax loss is similar to Dice loss [31] that penalizes the structure of segmentation maps, but achieves more stable training. $L_{kp}$ is a cross-entropy loss applied to key point segmentation map $Y_{kp}$.

Primitive deformation loss $L_{\text{off}}$. $L_{\text{off}}$ is a bi-projection loss [10] that penalizes the deviation of the deformed primitives $V'$ from the ground truth primitives $\nabla$. It first matches the vertices in ground truth to its nearest predictions, then matches the rest of the predicted vertices to its nearest projection in ground truth shape. The mean $L2$ distance between matches is reported.

Primitive direction loss $L_{\text{dir}}$. $L_{\text{dir}}$ is a loss applied to normalized surrogate direction $D$:

$$L_{\text{dir}} = \frac{1}{|D|} \sum (D_i - \overline{D_i})^2$$

(5)

where $\overline{D_i}$ is the unit direction vector of 2 times the ground truth angle for primitive $V'_i$.

Relationship loss $L_{\text{rel}}$. $L_{\text{rel}}$ is a cross-entropy loss applied to elements in $E$:

$$L_{\text{rel}} = -\frac{1}{|U|} \sum_{(i,j) \in U} E_{i,j} \log(E_{i,j})$$

(6)

where $E_{i,j}$ is the ground truth relationship matrix between primitives $V'_i, V'_j$ represented in one-hot format. $U$ is the set of primitive pairs that has distance less than $t$.

Shape regularization loss $L_{\text{reg}}$. We enable shape regularization by training with $L_{\text{reg}}$. We set $f_{\text{prob}}$ in Eq. 3 to

$$f_{\text{prop}}(D_i, D_j, r) = \begin{cases} \cos(2|D_i - D_j + 2\pi|/\pi) & , r = 1 \\ 0 & , r = 0 \end{cases}$$

(7)

which computes the cosine between two line directions. Here $r = 1$ means two primitives have certain relationship with fixed angles, such as parallel or perpendicular. $r = 0$ means no relationship, therefore no regularization. Practically, we compute an angle matrix for all line segment pairs as shown in Fig. 1. $L_{\text{reg}}$ is evaluated using the angle matrix and relationship matrix.

Auxiliary loss $L_{\text{aux}}$. To facilitate the learning of geometric shape features in MHA, we would like primitives’ visual feature $h_{uis}$ to be more related with geometric properties. Therefore, we add an auxiliary predictor on features pooled by patch pooling in primitive refinement PLS to predict coordinate offsets and primitive directions. Hence, $L_{\text{aux}}$ is a linear combination of a deformation loss and a direction loss applied to the auxiliary predictions.

3.4. Implementation Details

We only provide essential details here due to the limitation of space. Please refer to Supplementary for more implementation details.

Training and testing. To provide reasonable shapes for primitive graph reconstruction modules, we pre-train primitive detection before training all modules end-to-end. We use Adam optimizer [21] with batch size 12 and initial learning rate 2e-4. The max number of primitives per image is set to 150 for training and 300 for inference. Extra sampled primitives are discarded.

Road Network Mapping. We predict point primitives and pairwise connectivity for road mapping. We segment the buffered region of 5 pixels wide around road centerlines. Following [19], we predict four classes of key points in $Y_{kp}$: junctions, overlays (crossing point of overlapping road), end points (end points of road line segments that are not junctions or overlays), and interpolated points (points of fixed intervals interpolated on road line segments). Here, we don’t use $L_{\text{reg}}$ as primitive refinement can already achieve required shape regularization on road.
Figure 3. Qualitative result of road mapping. Column 1-2 are from City-Scale dataset; column 3-4 are from SpaceNet Road dataset.

To reconstruct road network, we connect point $V'_i$ to a maximum of $t_i$ points that have connectivity probability in $E$ larger than threshold $t_r$. We set $t_i = 3$ for junctions, and 2 for other points. We apply L2 normalization to the primitive features before the last MLP layer of the second PLS to improve feature embedding quality, as inspired by contrastive learning studies [3, 11, 17].

**Building Mapping.** We predict line segment primitives and pairwise inlineness for building mapping. We trace contours from $Y_{seg}$, and reconstruct primitive graph for each group of line segments that belongs to the same contour, so that network can learn the context information within a building instance without the interference of other building geometries. At inference time, inline line segments are merged to simplify output polygons. Please see more details in Supplementary.

4. Experiments

4.1. Datasets And Metrics

**Road Network.** (1) SpaceNet road dataset [15]: it contains 2549 satellite images of size $1300 \times 1300$ pixels with resolution around 0.3m. This dataset is challenging due to the diverse scenarios from 5 cities around the globe. Following the setting of [19], images are resized to 1 meter resolution, and the same train-test-valid splits are used. (2) City-Scale Dataset [19]: it contains 180 tiles of size 2000 $\times$ 2000 with 1 meter spatial resolution. Ground truth vector annotations were collected from OpenStreetMap [18]. This dataset covers 20 U.S. cities, but with less diversity compared to the SpaceNet road dataset.

Road network topology is evaluated using TOPO [7] and Average Path Length Similarity (APLS) [15]. TOPO measures the similarity of sub-graphs near seed points sampled from the inferred graph and ground truth graph. The similarity of two matched graphs are evaluated as precision, recall and F1 score. The similarity of all sub-graphs are averaged and reported. APLS measures the similarity of graphs using the shortest path between sampled point pairs on each graph, which is more sensitive to topology structure compared to TOPO.

**Building.** CrowdAI Mapping Challenge Dataset [27] (CrowdAI dataset): It contains 280741 annotated aerial images for training and 60317 for testing. Each image has size $300 \times 300$ pixels.

We use IoU (Intersection Over Union) and AP/AR (Average Precision/Average Recall) to evaluate the overall correctness of generated polygons. Since IoU and AP/AR cannot describe the cleanness of predictions at boundaries, we adopt Mean Max Tangent Angle Error (MTE) [16] and C-IoU [38] as additional evaluation metrics to IoU and AP/AR. MTE computes the max angle error of all line segments for each building and report the average value over the entire dataset [16]. C-IoU is IoU weighted by polygon simplicity, where more points in predicted polygon means lower polygon simplicity and lower C-IoU. Here, polygon simplicity is evaluated using $N$ ratio, which is the ratio of the number of vertices between predictions and ground truth [38].

4.2. Benchmark results

**Road network extraction.** We compare GraphMapper with Sat2Graph [19] in Fig. 3, which is considered the state-of-the-art method in road network mapping. GraphMap-
Figure 4. Qualitative evaluation of building footprint mapping results. From top row to bottom row are results from Frame Field Learning [16], Polyworld [38] and GraphMapper. Yellow boxes highlight the differences of different methods.

| Method                           | AP  | AP50 | AP75 | APs | AP25 | AR  | AR50 | AR75 | ARs | AR25 | ARL |
|----------------------------------|-----|------|------|-----|------|-----|------|------|-----|------|-----|
| FFL (with field), mask           | 57.7| 83.8 | 66.3 | 33.8| 73.8 | 68.1| 91.0 | 77.7 | 47.5| 80.0 | 86.7|
| FFL (with field), simple poly    | 61.7| 87.6 | 71.4 | 35.7| 74.9 | 65.4| 89.8 | 74.6 | 42.5| 78.6 | 85.8|
| FFL (with field), ACM poly       | 61.3| 87.4 | 70.6 | 33.9| 75.1 | 64.9| 89.4 | 73.9 | 41.2| 78.7 | 85.9|
| PolyWorld (offset off)           | 58.7| 86.9 | 64.5 | 31.8| 80.1 | 71.7| 92.6 | 79.9 | 47.4| 85.7 | 94.0|
| PolyWorld (offset on)            | 63.3| 88.6 | 70.5 | 37.2| 83.6 | 75.4| 93.5 | 83.1 | 52.5| 88.7 | 95.2|
| GraphMapper, mask                | 63.6| 88.3 | 69.6 | 35.6| 85.8 | 75.9| 93.1 | 82.8 | 50.7| 90.2 | 98.1|
| GraphMapper, final               | **72.8**| **89.1**| **79.7**| **46.6**| **90.6**| **91.3**| **83.1**| **93.3**| **88.1**| **61.5**| **95.2**| **97.2**|

Table 1. COCO evaluation results for building on CrowdAI Dataset.

| Method                          | IoU | C-IoU | MTA  | N ratio |
|---------------------------------|-----|------|------|---------|
| FFL (no field), simple poly     | 83.9| 23.6 | 51.8° | 5.96    |
| FFL (with field), simple poly   | 84.0| 30.1 | 48.2° | 2.31    |
| FFL (with field), ACM poly      | 84.1| 73.7 | 33.5° | 1.13    |
| PolyWorld (offset off)          | 89.9| 86.9 | 35.0° | 0.93    |
| PolyWorld (offset on)           | 91.3| 88.2 | 32.9° | 0.93    |
| GraphMapper                     | **93.9**| **88.8**| **30.4°**| 1.01    |

Table 2. IoU, MTA, C-IoU and N ratio evaluation results on CrowdAI Dataset.

Quantitatively, GraphMapper consistently shows improvement for APLS and TOPO on both road datasets (Tab. 3) compared to Sat2Graph [19], where TOPO F1 is improved by 6.2 ~ 9.3, and APLS is improved by 4.4 ~ 4.9.

Building footprint extraction. Qualitative evaluation results are reported in Fig. 4. We compare GraphMapper with two recent methods, Frame Field Learning (FFL) [16] and PolyWorld [38], that represent the state-of-the-art in building polygon mapping. All methods can accurately capture small and simple building polygons. GraphMapper shows the best shape regularization, polygon simplicity and accuracy.

Quantitative evaluation results are reported in Tab. 1. GraphMapper significantly outperforms Polyworld [38] by...
9.5/7.7 in COCO AP/AR. The improvements are largely contributed by primitive refinement and relationship reconstruction, which improved AP/AR by 9.2/7.2 to segmentation mask (GraphMapper, mask). We report IoU, C-IoU and MTA evaluation results in Tab. 2. GraphMapper outperform all competing methods in all metrics. The improved C-IoU and MTA numerically demonstrated that GraphMapper can generate more regularized vector shapes compared to previous methods, which is consistent with our visual comparison. Our N ratio is also closer to 1 compared to other methods, which suggests our method generate polygons with more similar complexity to ground truth.

Table 4. Building ablation study on CrowdAI Dataset.

| Method         | IoU   | C-IoU  | MTA   | N ratio |
|----------------|-------|--------|-------|---------|
| simple poly    | 92.3  | 81.6   | 38.5° | 1.26    |
| w/o incremental| 93.8  | 78.3   | 34.6° | 1.11    |
| w/o reg        | 94.4  | 82.7   | 31.5° | 1.28    |
| GraphMapper    | 94.3  | 89.5   | 30.4° | 1.01    |

Table 5. Road Ablation study on City-Scale dataset.

| Method   | Prec. | Rec. | F1   | APLS  |
|----------|-------|------|------|-------|
| w/o sort | 87.2  | 80.1 | 82.5 | 66.2  |
| w/o incremental | 89.6 | 81.2 | 84.8 | 67.6  |
| GraphMapper | 89.9 | 82.9 | 85.9 | 68.9  |

4.3. Ablation Study and Discussion

We report ablation study results in Tab. 4 for building and Tab. 5 for road. In these two tables, GraphMapper is our proposed model; simple poly uses DP algorithm [13] over traced polygons without primitive refinement or relationship reconstruction; w/o incremental refines primitives and predicts relationships in parallel with shared MHA encoder; w/o reg removes regularization loss $L_{reg}$ during training; w/o sort classifies relationship by thresholding relationship probability in $E$.

Incremental Reconstruction. For building mapping, incremental modeling (GraphMapper) shows to significantly improve C-IoU by 11.2% and MTA by 4.2% compared to parallel modeling (w/o incremental). Similarly for road mapping, TOPO and ALPS are improved with incremental reconstruction. We believe that improved performance of incremental modeling is caused by the improved accuracy of ground truth matching for relationship learning when using refined primitives instead of initial primitives.

Shape regularization. Relationship reconstruction for shape regularization shows to improve C-IoU by 6.8 and MTA by 1.1° compared to without shape regularization loss (w/o reg) for building mapping, which suggests that relationship learning with consistency between primitives’ properties and their relationships can effectively regularize shapes for vector mapping.

Sorting in embedding space. We compare out point connections strategy with naive connectivity relationship classification (w/o sort) in road mapping. Our method is shown to improve TOPO F1 by 3.4 and ALPS by 2.7 compared to standard relationship classification (w/o sort). We found the improvement is mainly due to reduced redundant connections between points, and reduced sensitivity to the threshold (See supplementary materials) of connectivity probability.

5. Conclusions

We propose GraphMapper, an end-to-end model for unified vector mapping from satellite images. By converting vector mapping tasks into primitive graph estimation tasks, GraphMapper can explicitly model topology reconstruction and shape regularization without tedious post-processing. We applied GraphMapper to building and road mapping with few task-specific designs and achieved favorable performance to existing methods. The simplicity and strong performance of GraphMapper effectively reduced the complexity for comprehensive mapping tasks.

There are several directions for future work. One direction is to further improve the compatibility between shape learning features and image recognition features for better co-learning of vector shapes and image features. Another direction is that GraphMapper relies on primitive sampling to capture geometric critical locations, which can be challenging for complicated scenarios, such as junctions and neighboring parallel roads. Predict point sequences along road can reduce the need for point sampling, but unable to use global map geometry context for optimal decision making. How to combine the benefits of these two methods can be an interesting future research direction.
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