

# MachMap: End-to-End Vectorized Solution for Compact HD-Map Construction

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## Abstract

This report introduces the 1<sup>st</sup> place winning solution for the Autonomous Driving Challenge 2023- Online HD-map Construction. By delving into the vectorization pipeline, we elaborate an effective architecture, termed as MachMap, which formulates the task of HD-map construction as the point detection paradigm in the bird-eye-view space with an end-to-end manner. Firstly, we introduce a novel map-compaction scheme into our framework, leading to reducing the number of vectorized points 93% without any expression performance degradation. Build upon the above process, we then follow the general query-based paradigm and propose a strong baseline with integrating a powerful CNN-based backbone like InternImage, a temporal-based instance decoder and a well-designed point-mask coupling head. Additionally, an extra optional ensemble stage is utilized to refine model predictions for better performance. Our MachMap-tiny with IN4K initialization achieves a mAP of 79.1 on the Argoverse2 benchmark and the further improved MachMap-huge reaches the best mAP of 83.5, outperforming all the other online HD-map construction approaches on the final leaderboard with a distinct performance margin (9.8 mAP at least).

## 1. Introduction

As one of the fundamental modules in the autonomous-driving, high-definition map (HD-map) provides centimeter level environment information for ego-vehicle navigation, including detailed geometric-topology relationships and semantic map categories, e.g. ped-crossing, lane-divider and road-boundary. Recently, with the development of deep neural network, online construction of local HD-map from onboard sensors (cameras) has gradually become more advantageous and potential solution.

Figure 1. The illustration of our HD-map processing principles (a) the original ground truth given in challenge (b) reorder polylines to keep the inter-element direction consistency (c) remove redundancy to keep the intra-element sequence compactness

The Online HD-map Construction Track aims to dynamically construct local HD-map from onboard surrounding camera images. In this task, a local HD-map ground truth in Fig. 1 (a) is described by a set of map elements with three semantic categories and each element is designed to a polyline, which consists of a set of ordered points, to deal with complicated and even irregular road structures. Our method mainly focuses on three aspects to handle the competition, (1) map modeling principles. We propose the principles of inter-element direction consistency and intra-element sequence compactness to reduce the intrinsic redundancy of polyline-based map modeling. Concretely, without losing any expression performance, the flow directions of point sequences between different elements should be as consistent as possible, and the point sequences within the same map element should be reserved with as few points as possible. (2) temporal-fusion instance decoder. Based on the multi-cameras features from image backbone, we then employ a temporal-fusion based bird-eye-view (BEV) feature decoder for view-transformation and a bottom-up point-wise instance decoder to extract point descriptor.

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Figure 2. The architecture of our proposed MachMap. Given surrounding images, we generate 2D features from each of views through image backbone and neck. Then the deformable attention are used to aggregate the 3D feature among different views and average it along z-axis. The temporal fusion module fuses the new BEV feature with the one of hidden state of BEV feature, based on which the hidden state is updated. Finally, we conduct instance decoder which utilize instance-level deformable attention to refine content and points features and format the final results. It is worth noting that the results of self-crossing and lane-divider are thinned from the mask.

(3) point-mask coupling head. Considering that different map elements have distinct shape priors, lane-divider is usually polyline and self-crossing is convex polygon, we equip each semantic map category with both segmentation and detection heads under the MaskDINO [6] framework, which greatly improves the flexibility and scalability of our model. Furthermore, the above multi-task training strategy also accelerates the model convergence performance.

Inspired by the above motivations, we propose an end-to-end vectorized HD-map construction architecture, named as MachMap. The entire framework is illustrated in Fig. 2 and all technical details are presented in the next section.

## 2. Method

This section introduces the details of our winning method. We first present the map compaction pipeline, which significantly reduces the difficulty of model training and makes the inference results more compact and efficient. Next the design scheme of each module is presented, and some task-specific improvements are integrated into some off-the-shelf methods. Lastly, we introduce our novel ensemble ideas, which can further enhance our approach.

### 2.1. Map Compaction Pipeline

Different from rasterized scheme, vectorized HD-maps in the given annotations explicitly express the spatial relation between map elements and instance information in their respective categories. Following the newly proposed map modeling principles, we compact the original evenly sampled map representation in two steps, namely orientation rearrangement and redundancy removal.

(1) inter-element direction consistency. The directions of elements in original map annotations are in a state of chaos, such as lane-dividers of moving forward from front-to-back or back-to-front as shown in Fig. 1 (a). We noticed that the inconsistency of directions can negatively affect the training

of the model. To reduce the discreteness of map organization, we follow a certain strategy to make the orientation of map elements as orderly as possible, and guarantee that this process does not lose any details of the map. Specifically, under the principle of conforming to the observation order of human eyes, a simple and intuitive strategy is to reorganize all polylines according to the rules of from-front-to-back and from-left-to-right in bird-eye-view space.

(2) intra-element sequence compactness. Vectorized maps with evenly-distributed points have redundant semantic information, while compacted-points representation is sparse, which is more suitable for expression and storage of maps. To this end, we extract keypoints for all elements to supervise model training. Concretely, we adopt Douglas-Peucker algorithm [11] and Visvalingam algorithm [12] to condense a polyline composed of line segments to a similar polyline with fewer points. For these methods, points are removed in order of least to most importance, with importance related to the distance and triangular area respectively.

### 2.2. MachMap Architecture

We follow the general query-based design paradigm [5, 10], as illustrated in Fig. 2, where the overall structure can be roughly divided into three parts: BEV feature extractor, temporal-fusion instance decoder and point-mask coupling head. Afterwards, we introduce each module sequentially according to the flow of information.

Backbone. Giving a list of 2D images  $I \in \mathbb{R}^{N \times 3 \times H \times W}$ , extracting unified textures representation within images is a top-priority task. With regards to this, we utilize a shared InternImage [13] as strong backbone to extract image features, which employs deformable convolutions [1] as its core operator and has been meticulously designed. During the downsampling process, a series of feature maps in varying scales are generated and then aggregated by the Bi-directional Feature Pyramid Network (BiFPN) [16].

Multi-view Encoder. Since the map vectors we ultimately need to predict lay in 3D space, it is necessary to elevate surrounding features from camera-view to ego-view space. Rather than direct transformation from camera-view to ego-view, we predefine a set of reference points and arrange them in a BEV raster.

After that, we employ the camera intrinsics and extrinsics to project them onto several images and then aggregate the surrounding features. By averaging on the  $x$ -axis, we obtain the final bird-eye-view features  $B \in \mathbb{R}^{H_B \times W_B \times C}$ .

Temporal Fusion Module. The provided dataset is collected and organized chronologically, with precise poses for each sample. This makes it possible to align current features with previous ones by poses, resulting in a larger real-world perception range beyond the current position. We follow the long-term fusion strategy proposed in VideoBEV [3], which affines the previous hidden state  $H_{t-1}$  of BEV feature into the current one  $B_{t-1}$  using vehicle ego pose. The latter is concatenated with the current BEV feature  $B_t$  in the channel dimension and fused by a 1D convolutional layer as,

$$B_{t-1} = \text{Affine}_{\text{pose}}(H_{t-1}) \quad (1)$$

$$H_t = \text{Conv}_{1D}(B_{t-1} \parallel B_t) \quad (2)$$

where  $\parallel$  denotes the concatenation operator. The fused features are cached as the next hidden state and used as input for subsequent instance decoder. In practice, since the timestamp offset between adjacent frame is too small, we group the timestamps at specific intervals to expand the performance gain brought by this temporal-fusion module.

Instance Decoder. To benefit from multi-task loss, we opt for the MaskDINO [6] framework, which conducts object detection and segmentation tasks simultaneously. Each query consists of content and position vectors, with the former is utilized to generate instance masks, while the latter undergoes iterative updates to yield normalized coordinates directly. Yet, due to the hierarchical relationship between map elements and their corresponding points sets, we adopt the query design paradigm in MapTR [7] for better adaptation to map element modeling. This implies that the query is point-wise, and a set of which can be aggregated to form a single instance and obtain its corresponding instance mask.

Output Head. Using only coordinates from point regression has some drawbacks. Firstly, there is a keypoint mismatching issue, where a well predicted instance may occur a mismatched point which belongs to other instance, as a result, a single bad apple spoils the whole bunch. Secondly, for ped-crossing, there exists a strong geometric prior, which is difficult to depict through vectors. However, masks not only can effectively constrain the geometry shape of instances, but it also impose a significant penalty on mismatched points during training. Empirically, we obtained ped-crossing and lane-divider through post-processing of instance masks, while point regression is employed only for road-boundary. As the common practice, we adopt cross-

entropy and dice loss [9] for masks and loss for point regression. In addition, we also add semantic loss to the BEV features as auxiliary supervision, and our final loss as,

$$L = \lambda_{\text{cls}} L_{\text{cls}} + \lambda_{\text{pts}} L_{\text{pts}} + \lambda_{\text{mask}} L_{\text{mask}} + \lambda_{\text{sem}} L_{\text{sem}} \quad (3)$$

where  $\lambda$  is the balance weight for different losses.

### 2.3. Ensemble Strategy

The predicted map vectors of our model are represented in normalized coordinates, which are then rescaled to the actual range 60-30m in the ego coordinate system during the post-processing stage. Yet the actual visible content from images greatly exceeds this range, which often leads to ambiguities in the existence of certain elements at the border position of exact map region that may be ignored by a single model. Accordingly, the use of ensemble techniques can mitigate prediction variability and curb overfitting by summarizing multiple models together.

By utilizing chamfer distance as a metric for measuring the similarity between instances, we present the ensemble algorithm in the Algorithm 1. Given a base set and a list of proposals, which are derived from multiple other predictions and sorted by confidence in descending order, we can compare each proposal with the base set one by one. If their similarity is low, we can consider them as missed true positives and add them to the base set. In addition to multi-model ensemble, we also conduct multi-frame ensemble. Despite the utilization of temporal fusion module, some instances are still absent, which were accurately recalled in previous frames. This inspires us to compensate some erratic predictions by ensemble with predictions from previous frames. It's worth noting that the integration of multi-frame and multi-model can share the same algorithm, with only modifying the source of candidate proposal list.

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#### Algorithm 1 MachMap Ensemble Algorithm

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Input: Base-list  $B$ , Proposal-list  $P$  and score-list  $S$ , CD-threshold  $T$

Output: Added proposal list and score-list  $AS$

1:  $P; S \leftarrow \text{SortProposalByScore}(P; S)$

2:  $A \leftarrow []; AS \leftarrow []$

3: while  $P.\text{length} \neq 0$  do

4:   Flag  $\leftarrow$  False

5:   Head  $\leftarrow P.\text{pop}()$ ; HeadScore  $\leftarrow S.\text{pop}()$

6:   for Base in  $B$  do

7:     Sim  $\leftarrow \text{ChamferDistance}(\text{Head}; \text{Base})$

8:     if Sim <  $T$  then

9:       Flag  $\leftarrow$  True

10:      break

11:    end if

12:   end for

13:   if Flag then

14:      $B.\text{append}(\text{Head})$

15:      $A.\text{append}(\text{Head})$

16:      $AS.\text{append}(\text{HeadScore} \cdot \alpha)$     $\alpha$  is a score decay factor

17:   end if

18: end while

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Category	# images	# instances	# points (raw)	# points (compacted)	AP <sub>0.2m</sub>	AP <sub>0.3m</sub>	AP <sub>0.4m</sub>	AP <sub>0.5m</sub>
ped-crossing	19523	55686	3593548	252219 (93.0%)	98.33	99.46	99.92	100.00
lane-divider	26222	133186	7426425	335534 (95.5%)	99.91	99.98	99.99	100.00
road-boundary	27283	84384	7018193	469533 (93.3%)	97.38	99.70	99.92	100.00

Table 1. The effectiveness and correctness verification of map compaction principles. All statistical numbers are collected on both training and validation sets. Note that # means 'the number of' and the blue color means the proportion of point reduction. APes that the average precision between before and after the compaction, where a prediction as true-positive only if the distance is less than

ID	Data	Backbone	PreTrain	# Epochs	w/o Opt.	AP <sub>crossing</sub>	AP <sub>divider</sub>	AP <sub>boundary</sub>	mAP
1	train	tiny	ADE20K	6	7	61.01	65.87	65.70	64.19
2	train	tiny	ADE20K	72	7	76.75	73.51	74.68	74.98
	train+val	tiny	ADE20K	72	7	78.34	74.74	76.02	76.37
3	train+val	tiny	from -	6	3	84.82	79.66	80.63	81.70
~	train+val	huge	ADE20K	36	7	81.45	75.34	77.14	77.98
4	train+val	huge	from - ~	12	3	86.66	81.54	82.29	83.50
4	train+val	tiny	IN-1K	72	7	76.46	72.32	75.91	74.90
5	train+val	tiny	from - 4	6	3	82.01	76.23	79.10	79.11

Table 2. The performance of different MachMap milestone models under thresholds [0.5; 1.0; 1.5]m. we employ InternImage [13] as backbone and tiny/huge means its scale. The from - / ~ / 4 ' means loading corresponding checkpoint and more epochs netuning. Note the weights of ADE20K/IN-1K are public. The term Opt. means our improving techniques including ema, ida, temporal and ensemble

## 3. Experiments

### 3.1. Existing Benchmarks

The Argovers2 [14] contains 700, 150 and 150 video clips in the training, validation, and testing sets respectively. Each sequence has a DOF map-aligned pose and seven ring views with the image resolution of 7048 1550 or 1550 2048 pixels. The given data from challenge is a subset of Argovers2. We utilize all frames from the challenge training set to verify the effect of different ablations but - nally all frames from training and validation sets are used to reach better performance. We focus on three categories, lane-divider, ped-crossing and road-boundary.

### 3.2. Implementation Details

**Training Setup.** We adopt common data augmentation including random scaling, cropping, and flipping. At the same time, an IDA [4] matrix is updated to record view transformation to maintain spatial consistency. Then the final input shape is fixed at 896 768, as this aspect ratio is close to the front view, i.e. 2048 1550, which contains the most abundant visual map information. For BEV features, the default spatial shape of BEV queries is 64 32, which corresponds to the perception ranges in lidar coordinate system [a0, 30]m for the Y-axis and [-15, 15]m for the X-axis. Note all map masks are interpolated to 200 to ensure that distinct elements can be easily distinguished without occupying too much memory. As for the hyperparameters of loss function, we set cls, pts, mask, sem to 2, 20, 1, and 3 respectively.

**Training Strategy.** We train our model with a total batch of 8 on 8 GPUs. The AdamW [8] optimizer is employed with

Rank	Team	AP <sub>crossing</sub>	AP <sub>divider</sub>	AP <sub>boundary</sub>	mAP
1	Mach (ours)	86.66	81.54	82.29	83.50
2	MapNeXt	68.94	76.66	75.34	73.65
3	SCR	70.37	75.08	74.73	73.39
4	LTS	72.67	73.20	71.80	72.56
5	USTC-VGG	69.05	73.24	70.76	71.02

Table 3. Top 5 entries on the test leaderboard of challenge.

a weight decay of  $10^{-2}$  and a learning rate of  $10^{-4}$ . Our training process consists of two stages: base training and ne-tuning. Firstly, we initialize the InternImage [13] with public pretrained weights [2, 15] and then train our model for 60 epochs without any tricks except a multi-step schedule with milestones [0.7; 0.9] and  $\gamma = \frac{1}{5}$ . Afterward, we apply all proposed improving techniques to ne-tune the model for extra epochs with a learning rate of  $10^{-4}$ .

### 3.3. Experimental Results

Table 1. Our statistical results show the compacted map can reduce more than 93% points without expression performance losing under the threshold 0.5m, even it can still maintain more than 97% performance under stricter 0.2m.

Table 2. Comparing the results in row-1&2, training more epochs brings a performance gain of more than 10 points, which shows that accelerating the convergence speed is still a vital future work. Compared with row-3&4; 5&6; 7&8, using the proposed improving techniques can always bring more than 5 points of increase. Moreover, even starting with IN-1K as pretrained weights, our model still achieves 79.1.

Table 3. We succeed the championship with a performance advantage of 0.85 mAP over the second place, demonstrating the effectiveness of our proposed MachMap method.

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