

Zero-VIRUS: Zero-shot Vehicle Route Understanding System for Intelligent Transportation

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Introduction

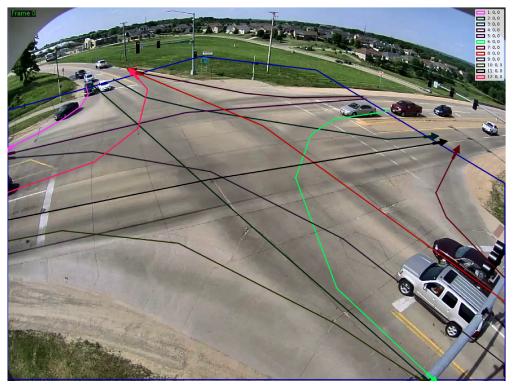
• Al City Challenge 2020 Track 1: Multi-Class Multi-Movement Vehicle Counting

• Input:

- Video from a stable surveillance camera view
- Pre-defined region and movements

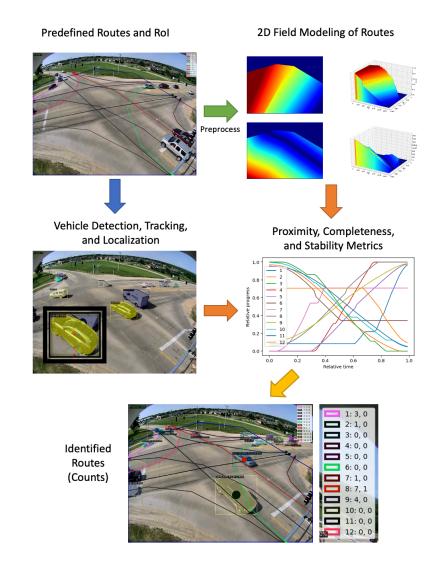
• Goal:

- Report the movement ID of each vehicle at the time of exiting the region
- No ground truth provided



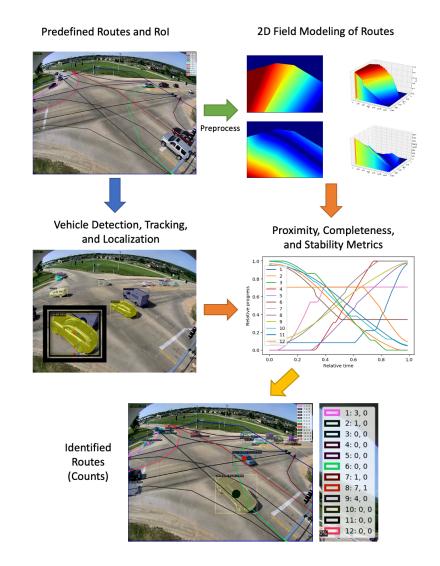
Approach Overview

- Vehicle trajectory
 - Detection, tracking, localization
- Pre-defined route
 - 2D field modeling as feature representation
- Trajectory vs. route
 - similarity metrics: proximity, completeness, stability
- Route classification and vehicle counting



Design Advantage

- No data required
 - No need for ground truth labels
 - No need for statistics
- Online processing
 - Frame by frame for deployment
 - No post-processing, e.g. clustering
- Easy adaption
 - New camera: just define the routes



Vehicle Detection and Tracking

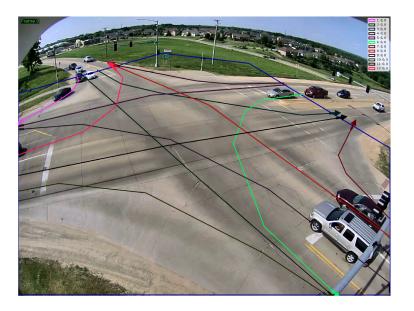
- Detection: Mask R-CNN
 - ResNeXt-101-FPN backbone, trained on COCO
- Tracking: Towards-Realtime-MOT
 - Rol feature from detection model
- Object classes: Car, Truck
 - inconsistent definition with COCO, e.g. pickups
 - Weighted inter-class non-maximum suppression
 - Tracklet label refinement



Trajectory Enhancement

- Localization with segmentation
 - Point C: bottom center of segmentation mask
 - Scale factor: diagonal of bounding box
- Interpolation and smoothing
 - Linear interpolation to fill in gaps
 - 1D-gaussian smoothing
- Movement and region filter
 - Filter out stopped period based on local average speed, e.g. traffic lights or jams
 - Within a pre-defined region of interest





Route Modeling

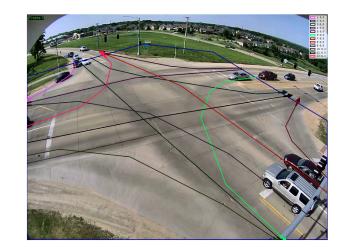
- Route: A polyline $\mathbf{R}_i = \begin{bmatrix} P_1^i & P_2^i & \dots & P_n^i \end{bmatrix}_i^T$
- Proximity field: distance to a route

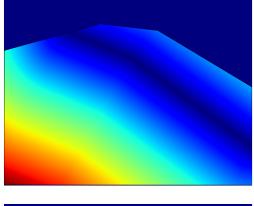
 $\mathbf{F}_{p,\mathbf{R}_i}(X) = \min_j d(X, \overline{P_j^i P_{j+1}^i})$

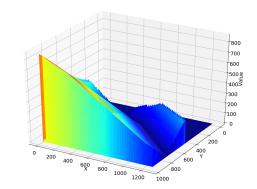
• point-segment distance

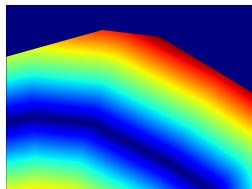
$$d(X, \overline{P_j^i P_{j+1}^i}) = \begin{cases} \|\overrightarrow{XP_j^i}\| & \alpha_j \le 0\\ \|\overrightarrow{XX_j^i}\| & 0 < \alpha_j < 1\\ \|\overrightarrow{XP_{j+1}^i}\| & \alpha_j \ge 1 \end{cases}$$

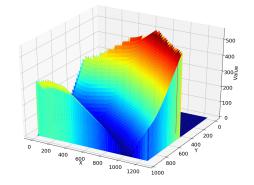
$$X_{j}^{i} = P_{j}^{i} + \alpha_{j}^{i}(X) \overrightarrow{P_{j}^{i}P_{j+1}^{i}}$$
$$\alpha_{j}^{i}(X) = \frac{\overrightarrow{P_{j}^{i}X} \cdot \overrightarrow{P_{j}^{i}P_{j+1}^{i}}}{\|\overrightarrow{P_{j}^{i}P_{j+1}^{i}}\|^{2}}$$











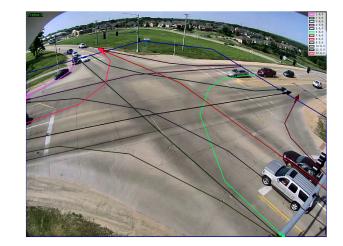
Route Modeling

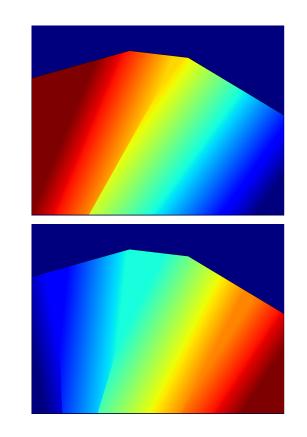
• Completeness field: relative location within a route

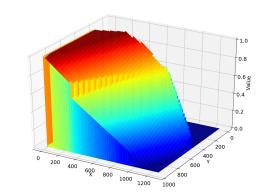
$$\mathbf{F}_{c,\mathbf{R}_{i}}(X) = \frac{\alpha_{j^{*}}^{i}(X) \| \overrightarrow{P_{j^{*}}^{i} P_{j^{*}+1}^{i}} \| + \sum_{j=1}^{j^{*}-1} \| \overrightarrow{P_{j}^{i} P_{j+1}^{i}} \|}{\sum_{j=1}^{n-1} \| \overrightarrow{P_{j}^{i} P_{j+1}^{i}} \|}$$

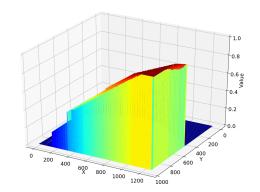
$$j^* = \operatorname*{arg\,min}_{j=1,2,\ldots,n-1} d(X, \overline{P^i_j P^i_{j+1}})$$

$$\alpha_j^i(X) = \frac{\overrightarrow{P_j^i X} \cdot \overrightarrow{P_j^i P_{j+1}^i}}{\|\overrightarrow{P_j^i P_{j+1}^i}\|^2}$$







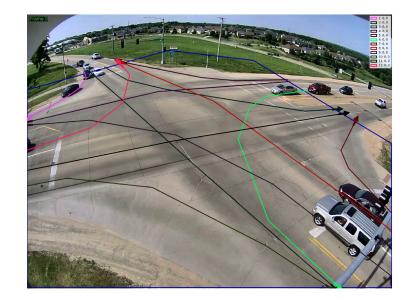


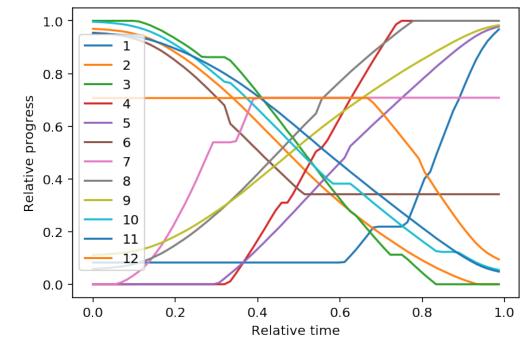
Route Identification

• Proximity metric: scale-normalized average distance

$$d(\mathbf{T}_{x,j}, \mathbf{R}_i) = \frac{\mathbf{F}_{p,\mathbf{R}_i}(\mathbf{P}_{x,j})}{\mathbf{S}_{x,j}}$$
$$M_p(\mathbf{T}_x, \mathbf{R}_i) = \sigma(a - b\frac{1}{n}\sum_{j=1}^n d(\mathbf{T}_{x,j}, \mathbf{R}_i))$$

- Completeness metric: how a vehicle goes along a route
 - Linear model to approximate change of completeness. A perfect slope should be 1 $M_{c}(\mathbf{T}_{x}, \mathbf{R}_{i}) = \min(c_{x,i}, \frac{1}{c_{x,i}})$





Route Identification

- Stability Metric: does vehicle go along the route at constant distance
 - Linear model to approximate the change of scale-normalized distance. A perfect slope should be 0. $d(\mathbf{T} + \mathbf{R}) = e^{-j} \frac{j}{2} + f^{-j}$

$$d(\mathbf{T}_{x,j},\mathbf{R}_i)=e_{x,i}rac{J}{n}+f_{x,i}$$
 $M_s(\mathbf{T}_x,\mathbf{R}_i)=\exp(-rac{1}{2}e_{x,i}^2)$

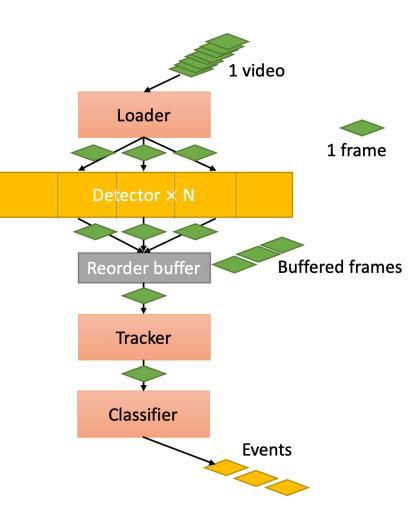
• Aggregation and classification

$$egin{aligned} S(\mathbf{T}_x, \mathbf{R}_i) &= \min(1, \max(0, w_p M_p(\mathbf{T}_x, \mathbf{R}_i))) \ &+ \min(1, \max(0, w_c M_c(\mathbf{T}_x, \mathbf{R}_i))) \ &+ \min(1, \max(0, w_s M_s(\mathbf{T}_x, \mathbf{R}_i))) \end{aligned}$$

$$C(\mathbf{T}_x, \mathbf{R}) = rg\max_i S(\mathbf{T}_x, \mathbf{R}_i)$$

System Implementation

- Mask R-CNN from Detectron2 in PyTorch
- Toward-Realtime-MOT from its author
- Pipelined system
 - Frame-level parallelism
 - Out-of-order execution for bottleneck
 - 9 fps on single 2080Ti GPU
 - Support up to 8 GPUs



Dataset and Metrics

- 2020 AI City Challenge Track 1 dataset split A
 - 5 hours video
 - 20 unique cameras in different light and weather conditions
 - Diagrams of routes with text descriptions of each camera
- Our annotation: route polylines of each camera
- Official metric:
 - Efficiency: running time and a base factor of hardware
 - Effectiveness:

$$wRMSE = \sqrt{\sum_{i=1}^{k} \frac{i}{\sum_{j=1}^{k} j} (\hat{x}_i - x_i)^2}$$

Results

- No ground truth provided
- Only leaderboard results
- Full test set

| Rank | Team ID | Team name (and paper) | Score |
|---------------|---------|-----------------------|--------|
| 1 | 99 | Baidu [20] | 0.9389 |
| 2 | 110 | ENGIE [27] | 0.9346 |
| 3 | 92 | CMU [46] | 0.9292 |
| 6 | 74 | BUT [37] | 0.8829 |
| 7 | 6 | KISTI [5] | 0.8540 |
| 9 | 80 | HCMUS [43] | 0.8064 |
| 13 | 75 | UAlbany [6] | 0.3116 |
| N/A (General) | 60 | DiDi [2] | 0.9260 |
| N/A (General) | 108 | VT [1] | 0.8138 |

Table 1. Summary of the Track 1 leader board.

- 50% test set
 - Maybe overfitted, maybe imbalanced subset

| Rank | TeamID | Score |
|------|--------|--------|
| 1 | Ours | 0.9444 |
| 2 | 99 | 0.9415 |
| 3 | 110 | 0.9381 |

Ablations

- Effectiveness of three metrics on a 60-second clip
 - Proximity metric, completeness metric, stability metric

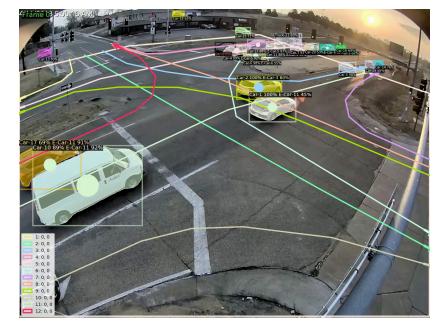
| Metrics | Effectiveness Score |
|-----------------|---------------------|
| M_p | 0.8903 |
| M_p, M_c | 0.9455 |
| M_p, M_c, M_s | 0.9554 |

Qualitative Results





https://drive.google.com/drive/folders/1s3TPykPa3JTaPOHUVO QF8S4iUi3SduAN?usp=sharing





Conclusion

- Zero-shot vehicle route identification
 - Minimal manual effort: define routes
 - Effective and efficient
- Future improvement
 - Detector: finetune between Car and Truck ----Biggest problem now
 - Trajectory: use ground trajectory if cameras are calibrated
- Zero-VIRUS, no coronavirus!