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Automated Vehicle Multi-Object Tracking at Scale with CAN

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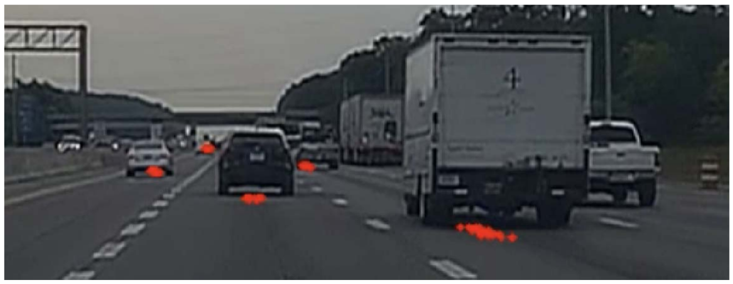

Figure 1. Five vehicles being tracked simultaneously with use of multi-object tracking algorithm associating CAN data.

Abstract

Millions of vehicles are on the road with RADAR sensors in use for adaptive cruise control (ACC), and RADAR sensors are not tracking all of the objects in the field of view. This work shows a work-in-progress tool to improve tracking from RADAR and controller area network (CAN) which should be vitally useful for safety of transportation systems and automated vehicle development. The CAN data provides object detections, but there is a lingering data association problem. The contribution of this work in progress is the solution to the data association problem by posing the data association as a minimum cost network flow problem, and doing it at low cost with an eye toward scalable CPS research.

Keywords: multi-object tracking, network flow, cyber-physical systems, controller area network, automated vehicles

1 Introduction

The contribution of this work-in-progress is effective multi-object tracking (MOT) of vehicles on the highway using sparse radar data from the CAN, the on-board data network, on a stock SAE level 1 vehicle. The CAN data reports detections of an object's position and relative velocity, but does not track objects in the field of view.This significantly degrades the utility of the sensor data for applications which would otherwise benefit from more contextual information about the environment in which the vehicle is operating. Additionally, these vehicles are already deployed in large numbers, so it is worthwhile to improve this data by solving the data association problem. Our preliminary work solves the MOT problem using a minimum cost flow (MCF) algorithm. Using a RAV4 platform, a raspberry pi, and a CAN data logger, we demonstrate a proof of concept in solving the MOT problem while incurring negligible cost; this enables support to scalable CPS research on the stock vehicle platform using data already being transmitted on the vehicle.

2 Related Work

The work [5] showed a way to frame the inter-frame data association problem as an MCF problem. It is a maximum-a-posteriori problem formulation which is solved by casting it onto a network flow and solving the MCF problem. The st-flow is acyclic and composed of arc-disjoint st-paths, i.e. each trajectory is non-overlapping.

Related to this work and [5] are [2–4] which use similar MCF networks to do MOT. In those applications, the detections are created from image object detections provided from a bench-marking source. This work proposes the use of a different and more sparse data source – CAN data.

3 Preliminaries

The MCF problem is defined as follows. Let □ be a weakly connected finite digraph such that |□ (□)| = □, |□(□)| = □. Each arc (□, □)□ (□□) has a flow capacity □□ □≥ 0, and a unit cost of flow □□ □ Each vertex in □ (□) has net zero flow, with the exception of the *supply vertex*, □ and *demand vertex*, □. The net flow □ , moves out from the supply vertex, and to the demand vertex which has net flow −□ [1].

The digraph □ is formed with source □ and sink □ connected to each vertex i.e. radar observation. Flow is initialized at 0; adding flow to an arc corresponds to either starting, associating successive detections, or ending a trajectory. The capacity of arcs are constrained to a maximum flow of 1. This is important because it precludes overlap in st-paths in the flow network, which means st-paths must be arc-disjoint.

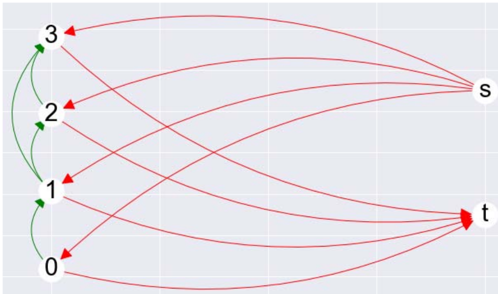

Figure 2. Example of digraph ⍰ constructed from only 4 data points. Each detection from radar is considered discrete, not batched into 'frames'. Costs are only calculated for recent detections, a run-time parameter.

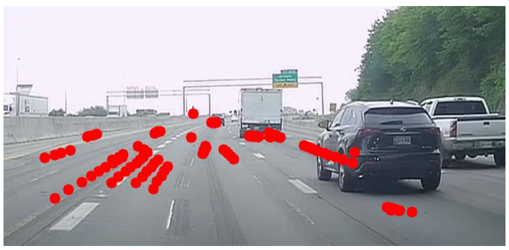

Figure 3. Radar data points (red) taken directly from the CAN bus and plotted in corresponding dashcam image.

Data Range	1s	5s	30s	60s	300s
Run Time	0.23s	1.48s	10.39s	43.69 s	184.33s

Table 1. Run time to find vehicle trajectories with MOT algorithm with parameters from Figure 1. Includes graph creation from input data and running SSP.

4 Data Association

Costs are defined as: 0 for arcs leaving from the source ⍰ or entering the sink ⍰, ⍰ ⍰⍰⍰⍰ for detections themselves (where ⍰ is the rate of false positives for the sensor), and the distance between detections as a function of sensor measured xy-distance and velocity difference, ⍰⍰ ⍰ See Figure 2 for an example of ⍰. Note that arcs with the cost of detections are hidden inside the numbered detection vertices.

Therefore, by solving for the MCF using successive shortest paths (SSP), the optimal data association is found given the costs. Each minimum cost path augmenting the st-flow corresponds to an individual vehicle's trajectory.

5 Results and Future Work

Data used to test the MCF MOT were CAN data collected from a drive on the freeway from a stock SAE level 1 vehicle as shown in Figure1. Preliminary manual analysis from a 30 second segment of dashcam video shows that there are 16 vehicles identified in video, and 16 vehicle *tracklets*, a subset of a vehicle trajectory, created from the MOT algorithm. However, four of the CAN-derived tracklets are redundantly tracking a vehicle already tracked. When plotting the tracklets in image space we see that no vehicles are tracked two lanes to the left/right; this is due to limitations with the field of view of the RADAR sensor. When considering only vehicles in the lanes to the right, left, and straight ahead there are 12 tracklets (excluding 4 redundant) and 11 vehicles visible from dashcam footage. This discrepancy is explained by the total occlusion of a vehicle within the initial 5 seconds and its reappearance within the last 5 seconds, making it challenging to stitch these tracklets together.

In future work we will consider occlusion, and cases such as distinguishing between 18-wheelers and two independent vehicles. Ground truth data is hard to find for this work because of the novelty of the data source. NuScenes provides some radar data but it is not from CAN. Note that we have no control or provided explanation of how data from the vehicle sensors may have been pre-processed before our access on the CAN bus. We plan to create a form of ground truth by taking established and characterized 3D object detection and tracking methods from concurrent dashcam footage to allow for evaluation of key metrics such as average multi-object tracking accuracy. We also plan to implement this tracker in ROS for real-time use, using an approach akin to [4]. Tracking of local object locations at scale has plenty of feature potential: ego vehicle lane tracking, characterization of local trafic flow (aggressiveness, density), training data for automated vehicle controllers on this platform.

6 Acknowledgements

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References

[1] JA Bondy and USR Murty. 2008. Graph theory. 2008. *Grad. Texts in Math* (2008).

[2] Laura Leal-Taixé, Gerard Pons-Moll, and Bodo Rosenhahn. 2011. Everybody needs somebody: Modeling social and grouping behavior on a linear programming multiple people tracker. In *2011 IEEE international conference on computer vision workshops (ICCV workshops)*. IEEE, 120–127.

[3] Hamed Pirsiavash, Deva Ramanan, and Charless C Fowlkes. 2011. Globally-optimal greedy algorithms for tracking a variable number of objects. In *CVPR 2011*. IEEE, 1201–1208.

[4] Congchao Wang, Yizhi Wang, Yinxue Wang, Chiung-Ting Wu, and Guoqiang Yu. 2019. muSSP: Eficient min-cost flow algorithm for multi-object tracking. *Advances in Neural Information Processing Systems* 32 (2019), 425–434.

[5] Li Zhang, Yuan Li, and Ramakant Nevatia. 2008. Global data association for multi-object tracking using network flows. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*. IEEE, 1–8.