DTEM: Dynamic Traffic Environment Mapping for Connected and Automated Traffic Control

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Key Words

Connected and Automated Traffic, Dynamic Traffic Environment Mapping (DTEM), Particle Filtering, High Definition Traffic State Estimation

Introduction

Real-time traffic state estimation and prediction are of importance to the traffic management systems. New opportunities are enabled by the emerging sensing and automation technologies to manage connected and automated traffic in terms of controlling trajectories of automated vehicles. Connected automated vehicles (CAV) are, by nature, moving probe sensors in the traffic systems, because they are in the traffic stream and interact with other non-detectable vehicles constantly. Making use of the rich dataset from these vehicle sensors can enhance our capability in observing the entire traffic stream.

In this paper, we propose a framework, referred to as dynamic traffic environment mapping (DTEM), for the estimation and prediction of detailed states (i.e., speed, location) of vehicles in a traffic stream on a selected roadway segment. Our DTEM framework is based on a particle filtering process, which has provided a considerable amount of solutions in the area of vehicle tracking and location estimation. It is flexible to deal with cases where the dynamic and observation systems are non-linear and/or non-Gaussian. The particle filtering algorithm is an importance sampling technique that estimates the distribution of target by sampling from a series of proposal particles (Arulampalam, et al., 2002), and can by nature consider intrinsic uncertainties (e.g., sensor data errors, process model uncertainties) in the estimation process (Sasiadek, 1999; Li, 2013).

Methodology

The framework of the proposed particle filtering approaches and approximates the system and population through Monte Carlo sampling. One key assumption of the work is that CAV behavior is affected and can partially reflect the existence and behavior of the multiple front non-detectable vehicles and interactions due to the car following process. Except for the CAVs, we define two types of vehicles in the traffic stream. Observed vehicles (OVs) are vehicles in the sensor range of CAVs and their location and speeds can be detected. Inserted vehicles (IVs) are vehicles that cannot be sensed and are completely non-observable. We define a particle as an insertion between two CAVs that includes the OV and the IVs.

The first step of the framework is to insert vehicles and guess the number of insertions through certain rules. Then we will sample the particles with safety constraints. Note that each particle will contain all non-detectable vehicles in the traffic stream between detectable vehicles, such that we are able to account for the interdependency of vehicle positions and speed through the step-by-step process models (i.e., car-following models) of each vehicle. Then we use the IDM to update the states of the particels to next timestamp. Next, we use data of predicted particles and observed OVs to calculate the probability of how close the predicted particle is to the observation. Then we assign the weight of each sampled particle based on the probabilities. To get the particles with higher weights, we use the Resampling Wheel Algorithm to accomplish this task. A new set of particels are selected and we normalize the weights of the new set of particles. Considering that the sum of the weights is 1, the unknown particle state can be estimated as the sum of all samples times their weights respectively. The resampling process is implemented by sampling from the new sets obtained based on the Resampling Wheel Algorithm. Then we repeat the process as shown in **Fig. 1.**

The prediction process is similar to the estimation process except that it uses the predicted states of CAV and OVs to calculate the weights. Historical estimated speeds are used as input data for predictions and time series models are built to predict the future speed of each vehicle in the system. To calculate the best prediction, we adopt a similar process as stated in the estimation.

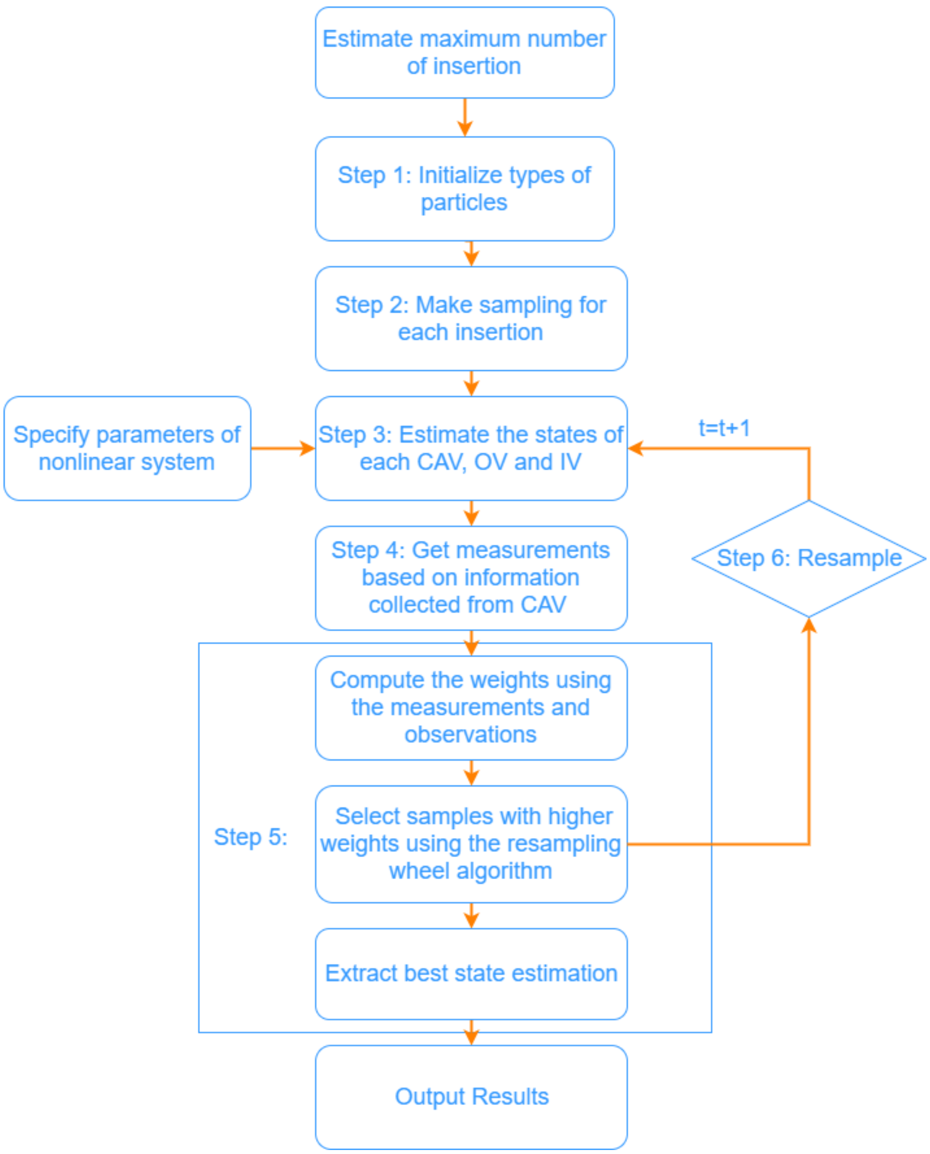

Fig. 1. DTEM estimation flowchart

Results

The freeway and arterial dataset from the Next Generation Simulation (NGSIM) program is applied to test the proposed methodological framework. Seven key factors potentially affecting the performance of the estimation and prediction are included in the sensitivity analysis: CAV penetration rate, traffic congestion, sensor noise level, estimation/prediction time interval, incoming traffic, CAV sensing/data-sharing capability and process model validity (i.e., calibration of IDM).

A comprehensive comparison for all the scenarios in terms of locations and speeds estimation effective penetration rate as well as the estimation of the number of vehicles is listed in **Table 1**. Example results of 5-second prediction are shown in **Table 2**.

Table 1 Location/speed estimation effective penetration rates and accuracy for No. vehicles (one OV observed)

Scenario			**CAV Rate**		
			12.5%	25%	50%
With incoming traffic	**Congested Traffic** (Location|Speed|No. vehicles)				
	Sensor noise (m)	0.5	54% | 75% | 88%	70% |85% | 90%	87% |95% | 93%
		1	50% | 69% | 87%	66% |78% | 89%	85% |90% | 93%
		2	47% | 64% | 81%	61% |74% | 86%	78% |86% | 90%
	Uncongested Traffic (Location|Speed|No. vehicles)				
	Sensor noise (m)	0.5	64% | 83% | 90%	77% | 89% | 91%	85% | 96% | 95%
		1	57% | 76% | 87%	70% | 85% | 91%	80% | 92% | 91%
		2	55% | 69% | 83%	61% | 79% | 88%	73% | 86% | 90%
Without incoming traffic	**Congested Traffic** (Location|Speed|No. vehicles)				
	Sensor noise (m)	0.5	66% | 83% | 93%	80% | 90% | 97%	88% | 96% | 100%
		1	62% | 80% | 91%	75% | 87% | 95%	85% | 96% | 100%
		2	51% | 70% | 88%	65% | 86% | 91%	80% | 90% | 99%
	Uncongested Traffic (Location|Speed|No. vehicles)				
	Sensor noise (m)	0.5	75% | 86% | 96%	86% | 95% | 99%	95% | 100%| 100%
		1	67% | 82% | 93%	78% | 89% | 97%	92% | 98% | 100%
		2	66% | 81% | 90%	77% | 85% | 96%	90% | 94% | 99%

Table 2 5-second location prediction effective penetration rates (One OV observed)

Scenario			**CAV Rate**		
			12.5%	25%	50%
With incoming traffic	**Congested Traffic**				
	Sensor noise (m)	0.5	47%	61%	76%
		1	41%	56%	74%
		2	38%	52%	69%
	Uncongested Traffic				
	Sensor noise (m)	0.5	51%	62%	78%
		1	47%	59%	72%
		2	40%	54%	67%
Without incoming traffic	**Congested Traffic**				
	Sensor noise (m)	0.5	62%	71%	82%
		1	57%	68%	80%
		2	52%	62%	75%
	Uncongested Traffic				

	Sensor noise (m)	0.5	73%	80%	90%
		1	69%	76%	87%
		2	60%	67%	83%

When the CAV penetration rate is as high as 50%, our framework shows the performance of effective penetration rates between 82% and 100%. When the CAV penetration rate is 25%, the accuracy of location estimation is between 65% and 77% when only 1 OV observed. The accuracy of 5-second location prediction is between 60% and 80% for traffic with a fixed number of vehicles. There is a significant improvement in the performance of about 10% on average when the CAV rate increases from 25% to 50%. Our sensitivity analysis also shows that lower sensor noise will make the estimation and prediction more accurate, and incoming traffic will lead to fluctuation as new vehicles joining the traffic. The results also suggest that the performance gradually improves after 10 – 15 steps (5-8 sec), and the performance becomes stable after about 20 steps (10 sec). We tested the algorithm with arterial traffic and the effective penetration rate is between 80% and 90%. We also provide queue length estimation with an averaged absolute error rate of less than 10% when the CAV penetration rate is low, such as 12.5% and 25%, indicating accurate queue length estimation in most cases.

Conclusion

We develop a DTEM framework that can efficiently and accurately estimate and predict the real-time state of a partially observed traffic system. The developed approach is general and applicable to both freeway and arterial traffic with different congestion conditions. The framework explicitly accounts for the uncertainties that intrinsically exist in the dynamic traffic system. The DTEM framework serves as a foundational input for future cooperative automation programs by providing as inputs the dynamic traffic environment conditions for control of CAV trajectories and infrastructure.

Our testing results show that DTEM can accurately estimate and predict vehicle location and speed even at low market penetrations. Generally, our framework provides a method to efficiently and accurately estimate the real-time HD traffic state and make a short-term prediction of a partially observed traffic system.

References

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