Determining Region of Influence of Ego-Vehicle on Roadways for Vehicle Decision Making

Wushuang Bai[1], Satya Prasad Maddipatla, Evan Pelletier, Liming Gao and Sean Brennan

Department of Mechanical Engineering, The Pennsylvania State University, University Park, Pennsylvania 16802, USA, wxb41@psu.edu

Abstract

Autonomous Vehicles (AVs) are an emerging and highly impactful technology on today's roads. When assessing the performance of AVs, it is useful to study their improvement relative to common metrics such as fuel economy/emissions, safety, and congestion. But metrics of the vehicle's performance alone may not be complete; an AV that is affecting and reacting to a smart traffic light, for example, may improve its own performance, but may cause the same intersection to degrade the performance of other vehicles around the AV. Similar concerns arise in nearly all AV topics: platooning, light pre-emption, lane tracking, etc. Thus, the assessment of the vehicle's impacts on surrounding traffic is important, possibly even more important than the improvements enabled on the AV alone. But what boundary, or factors, define the vehicles, equipment, etc. “surrounding” an AV?

The goal of this work is to characterize the boundary of vehicles “surrounding” an AV, referred to as Region of Influence, or ROI. Specifically, this work focuses on the problem that considering a perturbation is exerted into a traffic system, how far in time and space the perturbation from an AV’s decision can influence the surrounding system’s behavior. To achieve the goal, we utilized AIMSUN, a microscopic traffic simulator, to perform baseline and perturbed simulations. The ROI was evaluated by comparing trajectories of traffic surrounding the ego vehicle using different metrics, including difference in trajectories, Euclidian distance, rate of change of Euclidian distance, total number of lane changes over the whole simulation space versus time and total number of lane changes over the whole simulation time versus distance to ego vehicle. The results show that the ROI can be viewed from different perspectives using these metrics, and it is dependent on speed variance of the traffic.

Keywords: autonomous vehicles; traffic simulation; driving safety; region of influence.

[1] * Corresponding author. Tel.: +1-703-826-4617.
E-mail address: wxb41@psu.edu

1. Introduction

Motivated by the availability of high bandwidth communication between vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), or vehicle-to-cloud (V2C) systems, Autonomous Vehicles (AVs) were proposed as a potential solution to make a better transportation network. Ultimately, this may improve driving safety, reduce air pollution, increase energy efficiency and decrease commuting time [1].

Some standard criteria, such as fuel economy/emissions, driving safety and traffic congestion, are commonly used to evaluate AVs' performance [2]–[4]. However, it might be not sufficient if we only measure the vehicle's performance alone. For example, an AV that affects and reacts to a smart traffic signal may increase its own performance while harming the performance of other vehicles in the same junction. Almost all AV applications raise similar issues: platooning, light pre-emption, lane tracking, and so forth. As a result, assessing the vehicle's influence on surrounding traffic is critical, potentially even more so than the advances enabled by the AV alone, which naturally leads to a question: what boundary or factors determine the vehicles "surrounding" an AV? Or more particularly, how far around an AV's operational area should one simulate to assess impacts on surrounding traffic?

This question turns out to be critical but remains unanswered, which motivates this study. To illustrate the question more clearly and intuitively, the results of two simulations are useful: one is a baseline, and one is a perturbed situation. The simulation is shown for the traffic network in State College, Pennsylvania, where in baseline simulation there is no user control on the vehicle trajectories. However, in the perturbed simulation, one vehicle is selected to be an ego vehicle and is forced to pause in its lane at College Avenue, one of the busiest roads in State College. The vehicle trajectories surrounding the ego vehicle are then compared. At each time point, if the resulting positions are different between baseline and perturbed simulated vehicles, they are considered as influenced by the "parked" ego vehicle; otherwise, the vehicles are considered as not influenced.

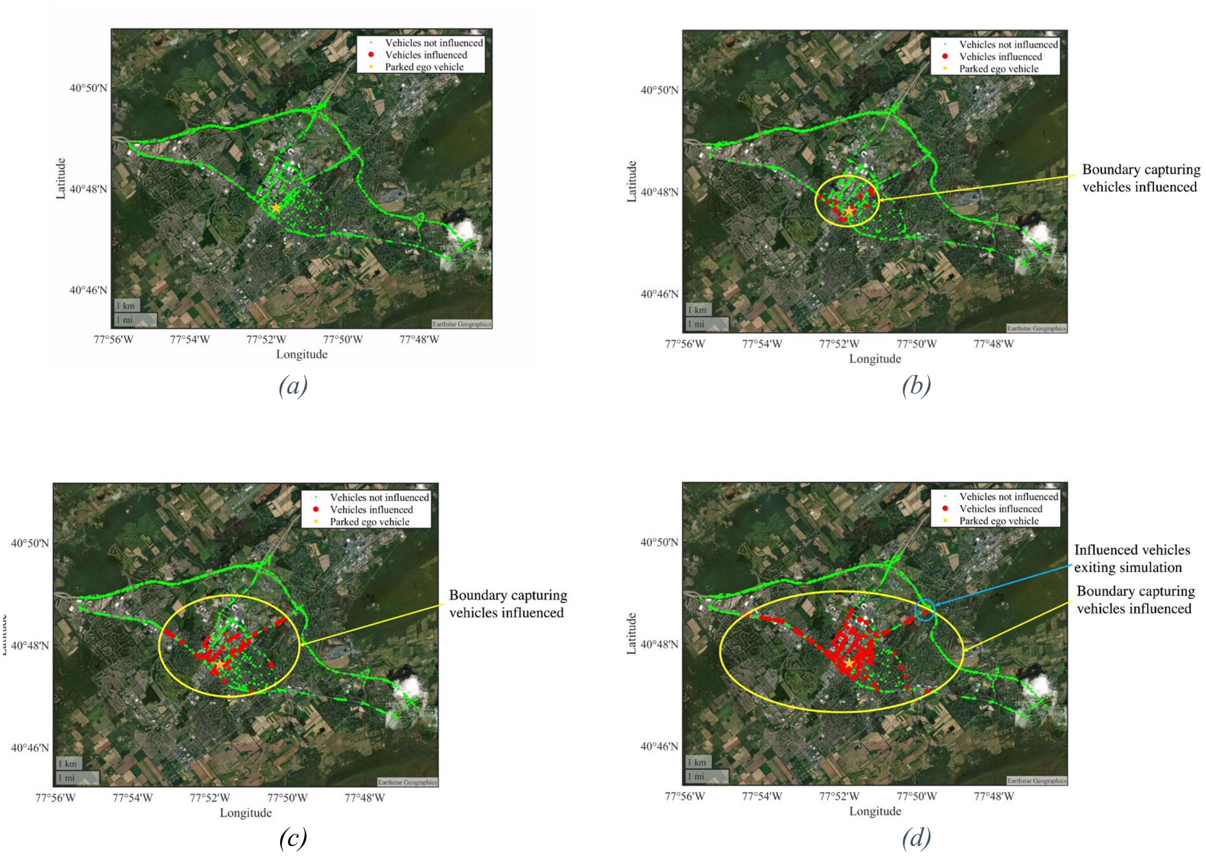


Figure 1 (a): No vehicle is influenced; (b): Boundary for vehicles influenced is small; (c): Boundary for vehicles influenced is big; (d): Critical boundary, beyond which we are losing information of the vehicles influenced.

Figure 1 shows the motivational simulation. Subplot (a) shows the start of simulation where no vehicle is influenced, thus the boundary capturing the influenced vehicles is 0 meters in width. Subplot (b) shows that after a short period of time, a few vehicles are influenced thus forming a small ellipse of boundary. Subplot (c) shows the boundary grows larger as the simulation evolves and subplot (d) shows the critical boundary, beyond which influenced vehicles start to exit the simulation; at this point, the simulation would no longer correctly capture the influence of the parked vehicle and thus assessment of the impact of that vehicle may be thereafter invalid. This simulation provides some intuitive understanding of ROI; however, there remain many theoretical questions such as: what are the factors deciding ROI? What are the metrics to evaluate ROI? Does the ROI affect all vehicle factors (not just position) equally? Etc.

Related work has been conducted by prior researchers to assess vehicle performance or AVs in a local traffic community surrounding an ego vehicle and/or a global traffic network. For example, Assia Belbachir, et al. used simulators to examine the algorithm of control and path planning, which was then connected to other tools for vehicle components and road conditions simulation [5]. Marc Ren´e Zofka, et al. evaluated trajectory planning or vehicle prediction performance, which are high-level automated driving components, via vehicle mechanics and sensor modeling and traffic flow simulation [6]. Linhui, et al. investigated the implementation of vehicle coordination and validated the work by simulation with remarkable improvement of total travel time as well as fuel consumption [1]. In addition, Simone Baldi, et al. proposed an adaptive optimization approach for the traffic network in urban scenario and the overall performance was assessed via AIMSUN simulator [7].

These studies above assess the behaviors in AVs surrounding the ego-vehicle, but the boundary defining “surrounding” an AV or defining “global traffic network” is still unclear within a formal definition. The selection of simulation domain is mostly based on experience and clear expertise. For example, Michal selected a fragment of a road network of Grunwald to compare microscopic traffic flow simulations among TRANSIMS, SUMO and VISSIM [8]. Christoph et al. picked Erlangen to analyze the bidirectional coupling of network simulation and road traffic microsimulation for the purpose of evaluation of Inter-Vehicle Communication protocols [9]. Luise et al. selected the traffic network of Boston, invested scenarios of free flow, traffic jams and network collapse to investigate the vulnerability of the urban traffic system [10].

Some preliminary consideration was given to the questions such as “how big domain is needed to simulate”. Qiong et al. selected a district in Budapest Hungary to conduct traffic simulations evaluating the impact of autonomous vehicles on urban traffic network. In the work of Qiong, special attention was paid to the domain of simulation. Instead of selecting the exact domain, a wider test area was selected to avoid the neglect of traffic dynamics in the perimeter of the interested district. But even that, a formal definition of the “wider test area” was not given in a manner that can be clearly reused in other simulations [11].

A concern in studying AVs is that a small perturbation in driving behavior, particularly when repeated over many nearly identical vehicle implementations, may cause a large change in the traffic system [12]. The key contribution of this paper is a new concept, Region of Influence, or ROI, indicating the region over which a perturbation into the traffic as an input can influence the whole traffic system in time and space.

The remainder of this paper is organized as follows. Section 2 details the methodology to perform traffic simulations and proposes several metrics to evaluate ROI. Section 3 describes the ROI evaluation results. Finally, conclusions are discussed in Section 4.

2. Methodology

2.1 Traffic simulation settings

Advanced Interactive Microscopic Simulator for Urban and non-urban Networks (AIMSUN) is a widely used commercial traffic modeling and traffic network simulation tool which can simulate the behavior of an individual vehicle in a traffic network as well as the response of the network accordingly [13]. AIMSUN was chosen because it is highly customizable and extensible with various available Application Programming Interface (API) and development kits. Based on its unique characteristics and flexibility, many applications have been developed, for example, Baldi, et al. employed AIMSUN to evaluate their traffic-responsive strategy in urban scenarios [7]. Due to these advantages mentioned, this work leverages AIMSUN for traffic simulations.

A key output of this work is to verify the analysis flow and the metrics for ROI evaluation, thus relatively short roadways and relatively large perturbations are chosen, and traffic variations are kept simple. Taking this into consideration, the simulations settings are shown in Table 1: the simulation road is a 10-km virtual double lane straight road. The mean velocity is 60 mph. The baseline is a traffic simulation where there is no artificial control of the ego vehicle trajectory, while the perturbed is a traffic simulation where a perturbation of speed change is added to the ego vehicle for the first 1 km of simulation and the other settings are identical to the baseline, as shown in Figure 2. A high flow rate of 1800 veh/hr is selected to make the perturbation more impactful on surrounding traffic. In addition, since accident rates increase as speed deviates from the traffic average speed [14], we investigate two traffic “temperature” modes in the preliminary analysis: "frozen" and "warm" modes. Other traffic parameter variations, such as vehicle mix, micro-mobility, flow rate variation by time period and weather condition variation are overlooked in this study for the purpose of simplification.

Table 1 Traffic simulation settings.

Road type	Double lane, straight
Road length	10 km
Perturbation	A speed change of -20 mph on the ego vehicle for 1 km
Mean velocity	60 mph
Traffic temperature mode	“Frozen”: speed std = 0 mph; “warm”: speed std = 5 mph
Flow rate	1800 veh/hr

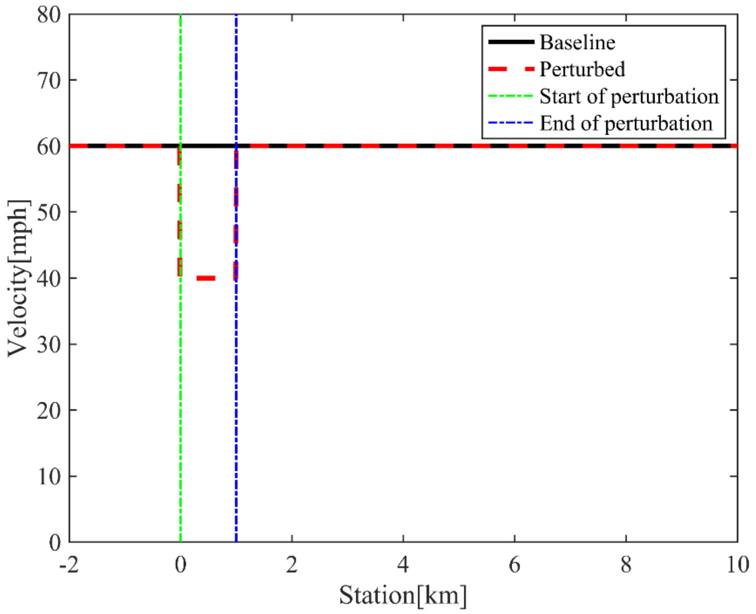


Figure 2 Velocity settings of ego vehicle in baseline and perturbed simulations.

2.2 Perturbation analysis process

The analysis flow is shown in Figure 3. Firstly, the authors ran the baseline and perturbed simulations separately, then compared the trajectories of traffic surrounding the ego vehicle. The differences of the trajectories were evaluated using several metrics.

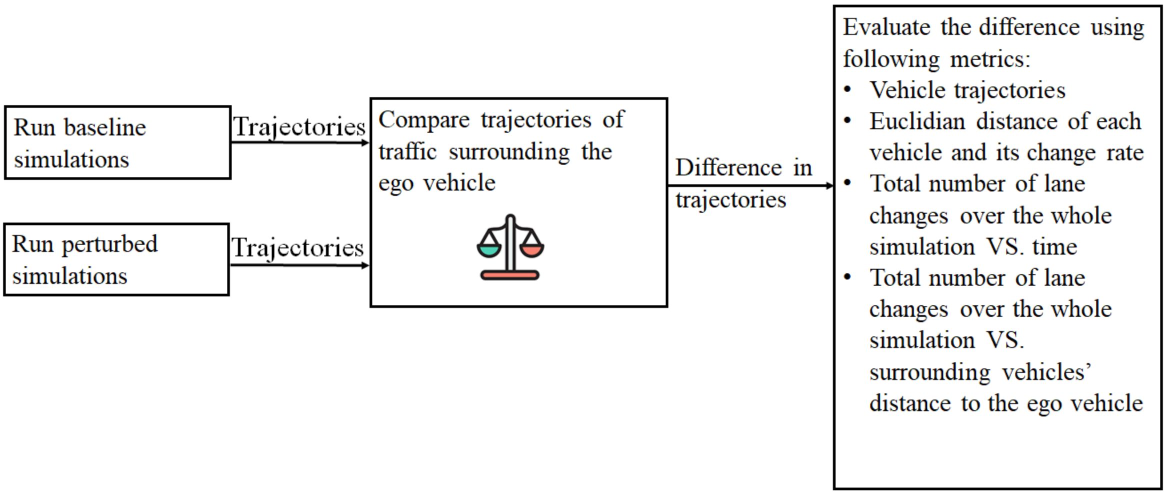


Figure 3 Analysis flow of ROI of ego vehicle on surrounding traffic.

The purpose of evaluating ROI using different metrics is to demonstrate that the ROI can be viewed from different perspectives and the results might not necessarily be the same with different metrics. The following metrics have been investigated:

- Difference in trajectories: this metric evaluates the difference of trajectories of traffic surrounding the ego vehicle.
- Euclidian distance: this metric computes the Euclidian distance of one vehicle's trajectories in baseline and perturbed simulations, where $EuDis$ is Euclidian distance, S_{bl} is station of baseline, S_{per} is station of perturbed, $\mathrm{x_{bl}}$ and $\mathrm{y_{bl}}$ are coordinates in baseline and $\mathrm{x_{per}}$ and $\mathrm{y_{per}}$ are coordinates in perturbed simulations.

$$EuDis = \begin{cases} \sqrt{\left(x_{bl}-x_{per}\right)^2+\left(y_{bl}-y_{per}\right)^2}, if\ S_{bl} \geq S_{per} \\ -\sqrt{\left(x_{bl}-x_{per}\right)^2+\left(y_{bl}-y_{per}\right)^2}, Otherwise \end{cases}$$

- Rate of change (ROC) of Euclidian distance: this metric computes the rate of change of Euclidian distance. $ROC = \frac{dEudis}{dt}$, where ROC is rate of change of Euclidian distance.
- Total number of lane changes over the whole simulation space versus time: this metric computes the total number of lane changes over the whole simulation versus time. The lane change over a period of time can be computed using the equations below, where $LaneChange$ is the lane changes indicator for one vehicle, $\Delta\mathrm{t}$ is a period of time, i is vehicle ID, N is the maximum vehicle ID during the period of time and $N_{LaneChange}$ is the total number of lane changes over a period of time.

$$LaneChange(\Delta\mathrm{t})_i = \begin{cases} 1, Lane\ change\ occurs \\ 0, Otherweise \end{cases}$$

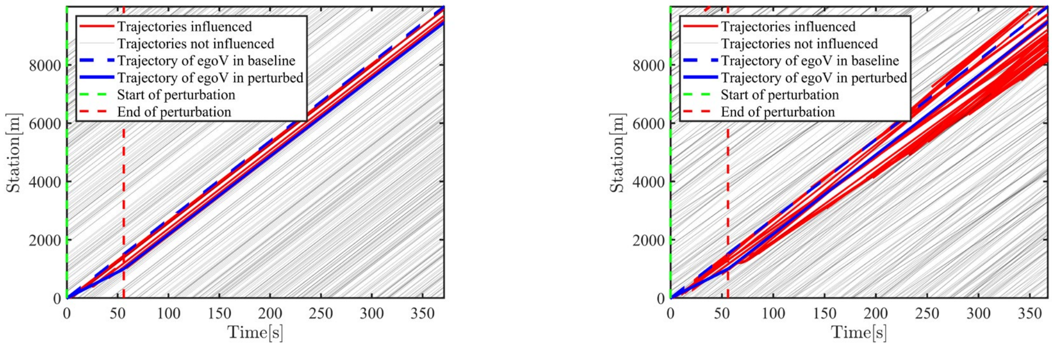
$$N_{LaneChange}(\Delta t) = \sum_{i=1}^{N} LangChange(\Delta t)_i$$

- Total number of lane changes over the whole simulation versus distance to ego vehicle: this metric computes the total number of lane changes over whole simulation versus distance to ego vehicle that can be computed using the equations below, where $\Delta Dego$ is a range of distance of surrounding traffic to ego vehicle.

$$LaneChange(\Delta\mathrm{Dego})_i = \begin{cases} 1, Lane\ change\ occurs \\ 0, Otherweise \end{cases}$$

$$N_{LaneChange}(\Delta Dego) = \sum_{i=1}^{N} LangChange(\Delta Dego)_i$$

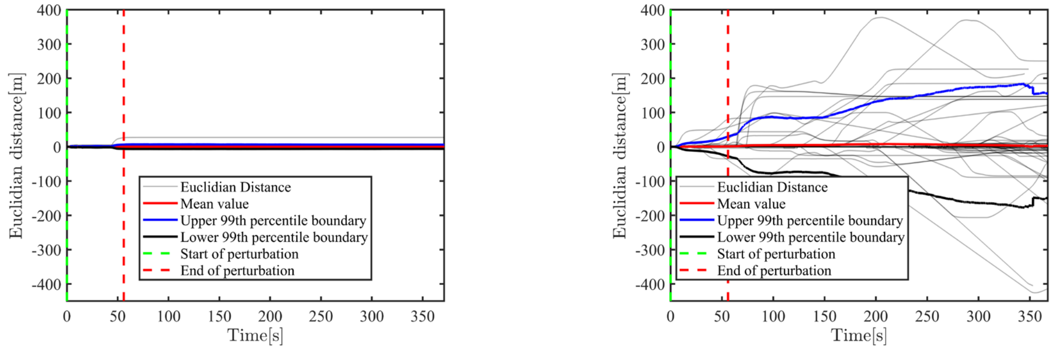
3. Analysis and Results



(a) *(b)*

Figure 4 (a): Station versus time: "frozen" mode; (b): Station versus time: "warm" mode.

Figure 4 shows the time-space diagram comparing the baseline and perturbed simulations in "frozen" and "warm" modes. This figure works for assessing ROI using the first metric specified in section 2.2, which is difference in vehicle trajectories. The trajectories that are the same between the baseline and the perturbed simulations are shown in gray. They indicate that these vehicles are not influenced by the perturbation, which is a speed change of -20 mph on the ego vehicle for 1 km happening at the beginning of the perturbed simulation. The trajectories that are different between the baseline and the perturbed simulations are shown in red, which on the contrary, indicate that these vehicles are influenced by the perturbation. As shown in subplot (a), in "frozen" mode, the ROI by difference of vehicle trajectories is confined by the trajectories of ego-vehicle itself from baseline and perturbed simulations. In other words, surrounding vehicles in front of the trajectory of ego-vehicle from baseline, and behind the trajectory of ego-vehicle from perturbed simulation, are not influenced by the perturbation. By contrast, subplot (b) shows in "warm" mode, surrounding vehicles in front of the trajectory of ego-vehicle from baseline, and behind the trajectory of ego-vehicle from perturbed simulation, are influenced by the perturbation. Figure 4 demonstrates that "warm" mode traffic, which has a larger speed variance, has a larger ROI by difference of vehicle trajectories.



(a) *(b)*

Figure 5 (a): Euclidian distance: "frozen" mode; (b): Euclidian distance: "warm" mode.

Figure 5 shows the Euclidian distance comparing vehicle trajectories of the baseline and perturbed simulations in "frozen" and "warm" modes, following the second metric specified in section 2.2. Subplot (a) shows that the after end of perturbation, in "frozen" mode, Euclidian distance of vehicle trajectories between baseline and perturbed simulations is close to zero. While subplot (b) shows that after end of perturbation, in "warm" mode, Euclidian distance of vehicle trajectories between baseline and perturbed simulations grows bigger. The 99th percentile boundaries go up to around +/- 200 meters. Similar to Figure 4, Figure 5 describes that "warm" mode traffic has a larger ROI by Euclidian distance.

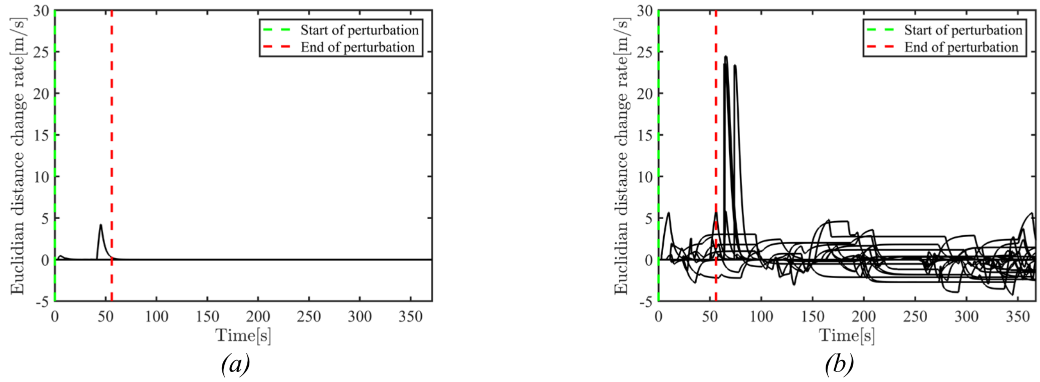


Figure 6 (a): Euclidian distance rate of change: "frozen" mode; (b): Euclidian distance rate of change: "warm" mode.

Figure 6 describes rate of change of Euclidian distance comparing vehicle trajectories of the baseline and perturbed simulations in "frozen" and "warm" modes, following the third metric specified in section 2.2. Figure 6 gives similar information as Figure 5 but from another perspective. Subplot (a) shows that the rate of change of Euclidian distance is zero in "frozen" mode after the end of perturbation. While subplot (b) shows in "warm" mode, it continues to grow after the end of perturbation. It is shown in Figure 6 that "warm" mode traffic has a larger ROI by rate of change of Euclidian distance.

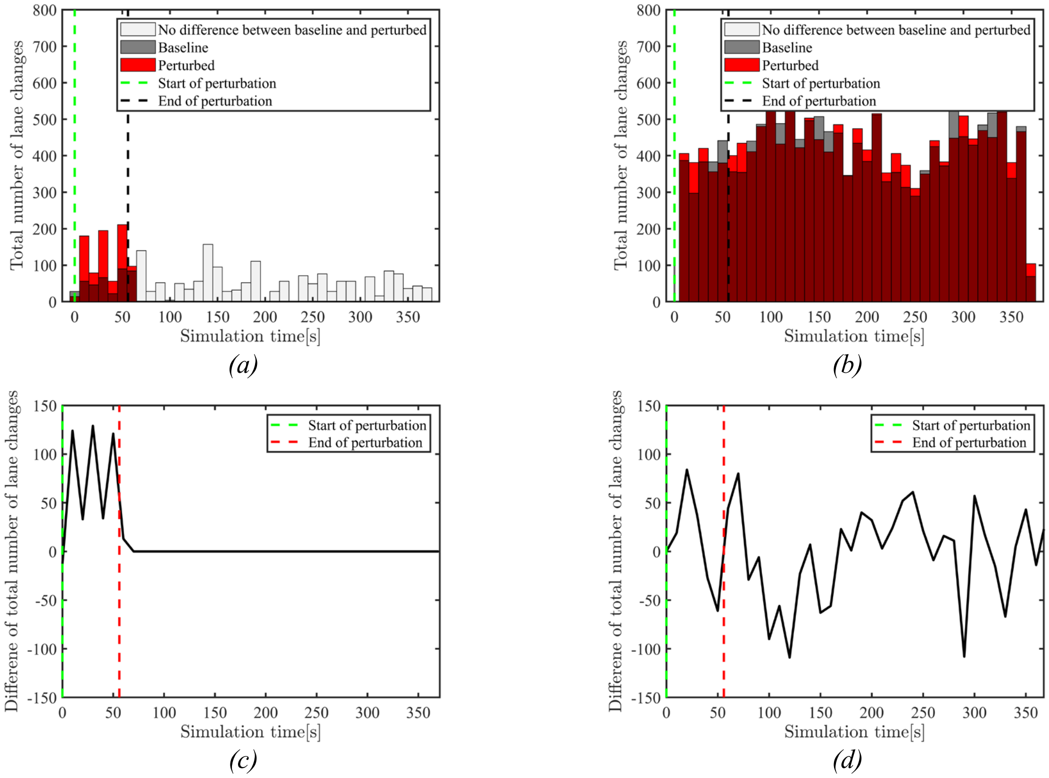


Figure 7 (a): Total number of lane changes over the whole simulation space versus time: "frozen" mode; (b): Total number of lane changes over the whole simulation space versus time: "warm" mode; (c): Difference of total number of lane changes over the whole simulation space versus time: "frozen" mode; (d): Difference of total number of lane changes over the whole simulation space versus time: "warm" mode.

Following the fourth metric, Figure 7 examines total number of lane changes over the whole simulation space versus time comparing vehicle trajectories of the baseline and perturbed simulations in "frozen" and "warm" modes. Subplot (a) shows that in "frozen" mode, ROI by this metric disappears after end of perturbation, while it persists in "warm" mode, as shown in subplot (b). To convey the information more clearly, subplot (c) and (d) show the difference of total number of lane changes over the whole simulation space versus time between baseline and perturbed simulations. It is confirmed in subplot (c) that there is no difference of total number of lane changes after the end of perturbation in "frozen" mode, but there is, in "warm" mode. In addition, subplot (d) shows that the perturbation does not necessarily cause more lane changes in the traffic at a temporal view.

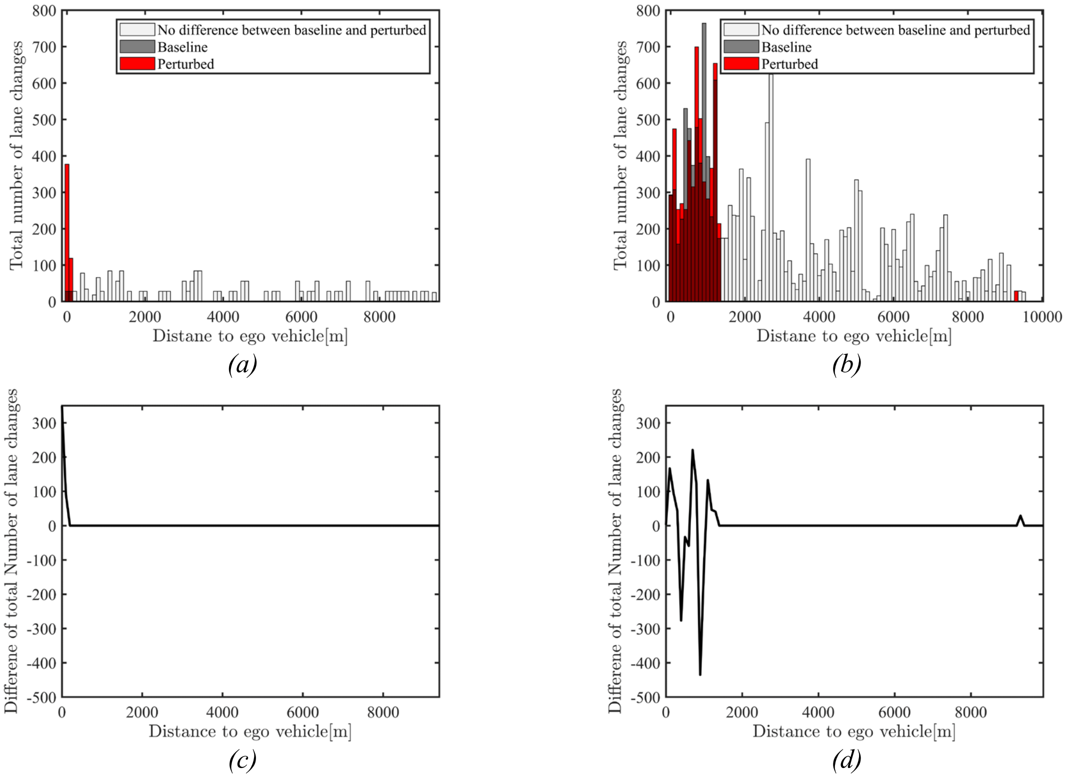


Figure 8 (a): Total number of lane changes over the whole simulation time versus distance to ego vehicle: "frozen" mode; (b) Total number of lane changes over the whole simulation time versus distance to ego vehicle: "warm" mode; (c) Difference of total number of lane changes over the whole simulation time versus distance to ego vehicle: "frozen" mode; (d) Difference of total number of lane changes over the whole simulation time versus distance to ego vehicle: "warm" mode.

Based on the fifth metric, Figure 8 shows total number of lane changes over the whole simulation time versus distance to ego vehicle comparing baseline and perturbed simulations in "frozen" and "warm" modes. While Figure 7 demonstrates the ROI in a temporal view, Figure 8 demonstrates it in a spatial view. Specifically, subplot (a) shows that in "frozen" mode, the ROI by this metric appears very close to the ego-vehicle, while subplot (b) shows that in "warm" mode, the ROI can go up to more than 1000 meters from the ego-vehicle. Similar to Figure 7, subplot (c) and (d) show the difference of total number of lane changes over the whole simulation time versus distance to ego vehicle between baseline and perturbed simulations. Moreover, subplot (d) describes that the perturbation does not necessarily cause more lane changes in the traffic at a spatial view. It is noted that in subplot (b) and (d), there is a small difference between baseline and perturbed simulations near 10000 meters from the ego-vehicle. This might be caused by the accumulation of numerical errors of the simulations. Further statistical analysis will be needed to verify it.

4. Conclusions

This work presented a new concept, Region of Influence, or ROI, indicating the region over which a perturbation into the traffic as an input can influence the whole traffic system in time and space. This work introduced as well a method to characterize the ROI of one vehicle on the surrounding traffic. The method used a macroscopic traffic simulator to perform baseline and perturbed simulations, and evaluated how the perturbation, which was a change of velocity of ego vehicle in this work, could influence the surrounding traffic and how big the ROI was. The results show that overall, speed variance has a strong influence on ROI. The results also show that ROI can have different values when using different metrics. The findings in this study may enlighten the selection of domain when doing traffic simulation, in particular when speed variance is considered as a key factor.

To prototype the method and verify the analysis flow and metrics for ROI evaluation, this work selected relatively short roadways, relatively large perturbations and simple traffic parameters, which may not be representative of realistic driving scenarios. Further statistical analysis will be needed to determine ROI in different driving scenarios.

Acknowledgment

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