Behavior Design for Heterogeneous Traffic Flow of Autonomous and Human-driven Vehicles

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Introduction:

We investigate spontaneous platoon formation in heterogeneous traffic flow consisting of human-driven (HVs) and autonomous vehicles (AVs) in different behavior scenarios through simulation experiments. Our study reveals that platoons may form spontaneously, and platooning properties are associated with the behaviors of AVs. We conduct the simulation experiments through a parsimonious Cellular Automata model (we develop a software for this purpose), which captures the different characters of AVs and HVs as well as their interactions. AVs are endowed with neighbor awareness and opportunistic behaviors. We observe that, intriguingly, even with this relatively simple model, AVs form into platoons without centralized control. Such phenomena may relate to the intrinsic incentives that AVs perceive and their ability to tell neighbor vehicle types. Our findings indicate the potential of regulating future heterogeneous traffic flow through decentralized agent behavior design.

Cellular Automata Model for Traffic Flow:

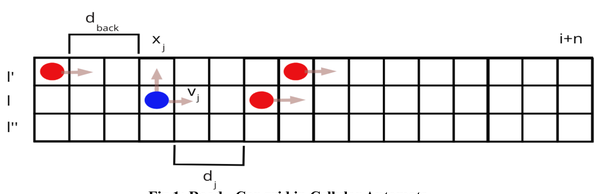

Fig 1: Road - Car grid in Cellular Automata

Cellular Automata (CA) is a computational model where each agent occupies a cell, and has its behavior is determined by its own state and the state of other agents in its neighborhood. Nagel and Schreckenberg (1992) were the first to use this technique to model traffic flow. Their model comprises a system of vehicles which evolve over linear time in accordance to rules:

Longitudinal Update Rule:	Multi-lane Update Rule:
∗Rule 1: Acceleration, $v_j \to min(v_j+1, v_{max})$ Rule 2: Braking, $v_j \to min(v_j, d_j)$ Rule 3: Randomization, $v_j \to v_j - 1$ (with probability p_s) Rule 4: Motion, $x_j \to x_j + v_j$	∗Rule A: Incentive criterion , $v_{l'} > d_j$ ∗Rule B: Safety criteria , $d_{back} > v_{max}$ Rule C: Decision, $l \to l'$ (with probability p_l) Rule D: Longitudinal Update Rule

Fig 2: Rules for CA models for traffic flow

Each update of the system, requires all the vehicles to follow these rules simultaneously, with each vehicle first deciding whether to change lane before deciding how much to move forward; this order of decision making is fundamental to the CA model.

Simulation and Analysis Software:

We have developed a GUI software capable of simulating different heterogenous traffic flow scenarios with different AV behaviors. To create our model, we used principles of OOP with the main objects being two Abstract Data Structures: Road and Car. The software allows the user to track different key parameters of traffic flow and later creates a .txt file of those recorded parameters. This data is sent to the analysis part of the software to generate various plots and statistics for the user. This software is written entirely in Python3.

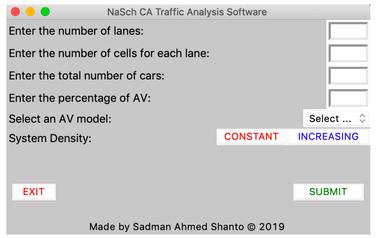

Fig 3: Graphical User Interface of the software

Autonomous Vehicles Behavior Design:

In our project, we adapt the Nagel-Schreckenberg Cellular Automaton model to introduce a model of mixed traffic flow of HVs and AVs that captures three potential behaviors of AVs – *opportunistic, neighbor awareness* and *baseline* behavior. We distinguish between the two class of vehicles in our simulation by assigning different behavioral parameters - *braking probability, lane changing probability, maximum speed* - and methods - *traversal velocity functions*- to each vehicle type and model.

Opportunistic model: AVs require well defined instructions in the form of algorithms and optimization functions to make decisions while driving. This level of algorithmic control on the decision making of AVs imply that such vehicles can achieve idealized traffic flow parameters that cannot be attained by HVs, which behave erratically. This type of *erratic* behavior does not apply to AVs, who make their decisions of accelerating/deceleration and lane changing solely based on safety and opportunity.

$$P(braking) = 0; P(lane\ change) = 1;\ v^{av}(t+1) = min(v^{av}(t)+1, s_{lv}, v^{av}_{max}, v_{sl})$$

Neighbor Awareness model: AVs can communicate with each other and the surrounding using V2X technology. We hypothesize that these "*neighbor aware*" AVs would behave differently depending on the type of vehicle they are trailing. An AV trailing another AV can maintain a shorter headway due to their inter-connectivity and, hence, can maintain a higher speed; such phenomenon would not be seen if the leading vehicle is a HV.

$$v^L_{max} = \begin{cases} v_{aa}, if\ AV-AV \\ v_{ah},\ if\ AV-HV \\ v_h, if\ HV \end{cases}$$

$$v_{aa} > v_{ah} \geq v_h$$

$$v^{av}(t+1) = min(v^{av}(t)+1, s_{lv}, v^L_{max}, v_{sl}) - \delta(P(braking));\ \delta(P(braking)) = [0,1]$$

Neighbor Awareness and Opportunistic model: Such AVs shows both *Opportunistic* and *Neighbor Aware* behavior.

$$P(braking) = 0; P(lane\ change) = 1;\ v^{av}(t+1) = min(v^{av}(t)+1, s_{lv}, v^L_{max}, v_{sl})$$

Baseline Model: In this model AVs behave *exactly* like an HV, with their behavior being indistinguishable from one another. Traditional CA rules described in Fig. 1 were implemented to encapsulate such behavior in addition to the following constraints imposed by the uniformity of the two classes.

$$v(t+1) = min(v^{av}(t)+1, s_{lv}, v_{max}, v_{sl}) - \delta(P(braking));\ \delta(P(braking)) = [0,1]$$

Baseline Headway Model: Such AVs behave like the *baseline* model with the exception that these AVs can maintain smaller headways than HVs, i.e. $v^{av}_{max} > v^{hv}_{max}$.

$$v(t+1) = min(v^{av}(t)+1, s_{lv}, v_{max}, v_{sl}) - \delta(P(braking));\ \delta(P(braking)) = [0,1]$$

Simulation Experiments:

We conduct two simulation experiments with the purpose of studying the impact of the five AV behaviors on the overall traffic flow and better understand any emergent patterns of collective behavior. In both the experiments, we consider a circular road with three lanes (periodic boundary conditions) with each lane comprising of 100 cells. The vehicle objects follow their respective set of behavior rules. For each simulation, the road starts from empty state. N Vehicles are then distributed randomly on the road with zero initial velocity; the vehicle type is determined stochastically upon allocation, following a binomial distribution with the probability of a vehicle being an AV (i.e. percentage of AVs) being 30%.

For the first experiment, we simulate the traffic flow for each of these models for the same number of simulation time steps (1200) for three different densities: 0.08, 0.2 and 0.6. These densities are normalized such that a state density of 1 represents jam density.

For the second experiment, we increase our system density linearly till it reaches the jam density. We allow the simulation to run for a fixed number of time steps (100) for each system density before incrementing it

Parameter	Neighbor Aware	Opportunistic	Neighbor Aware and Opportunistic	Baseline Headway	Baseline
$p_l(HV)$	0.6	0.6	0.6	0.6	0.6
$p_l(AV)$	0.6	1	1	0.6	0.6
$p_s(HV)$	0.4	0.4	0.4	0.4	0.4
$p_s(AV)$	0.4	0	0	0.4	0.4
v_{aa}	5	4	5	4	3
v_{ah}	4	4	4	4	3
v_h	3	3	3	3	3

Fig 4: Table of parameter values used in the five test cases of Experiment 1 and 2

Self-Organization Phenomenon:

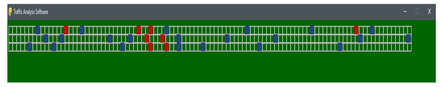

Fig 5: A screen capture of the simulation showing a cluster of 6 AVs (red). [Periodic Boundaries]

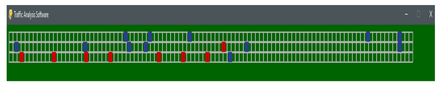

Fig 6: Another screen capture from the simulation showing self-organized lane of 7 AVs (red) .[Periodic Boundaries]

Upon observation of several different simulation cases, we discovered that AVs under certain models and situations displayed strong self-organized phenomenon. There were two types of self-organized events that were most prominent: *AVs moving closely together but in different lanes* and *AVs moving closely together in the same lane.* We hypothesize that the formation of clusters is natural due to the opportunistic nature of AVs, modeled through both its gap seeking and braking behavior. We study the effects of such self-organization on overall traffic flow and how different AV behaviors affect such phenomenon.

Exp 1: Heterogeneous Dynamics Under Constant Traffic Densities:

Low Density Regime		
AV Model	cluster no.	survival time
opportunistic	1.04	17.15
neighbor aware	1.07	7.01
baseline	0.0	0.0
baseline headway	1.05	6.14
neighbor aware and opportunistic	1.04	20.75

Fig 7: Average Values (Low Density)

Critical Density Regime		
AV Model	cluster no.	survival time
opportunistic	2.05	61.95
neighbor aware	1.64	31.45
baseline	1.52	17.75
baseline headway	1.69	23.30
neighbor aware and opportunistic	1.89	97.67

Fig 8: Average Values (Critical Density)

High Density Regime		
AV Model	cluster no.	survival time
opportunistic	4.85	1200.0
neighbor aware	4.81	1200.0
baseline	4.68	1200
baseline headway	4.68	1200
neighbor aware and opportunistic	5.04	1200

Fig 9:Average Values (High Density)

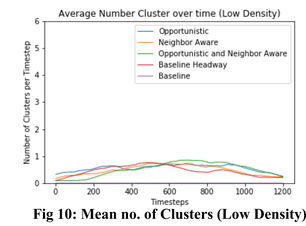

Fig 10: Mean no. of Clusters (Low Density)

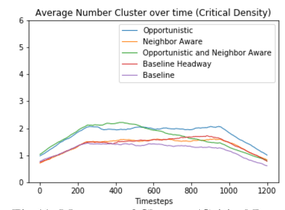

Fig 11: Mean no. of Clusters (Critical Density)

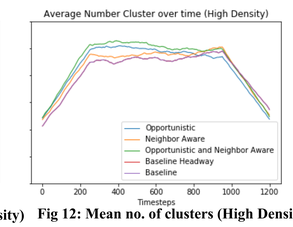

Fig 12: Mean no. of clusters (High Density)

These results verify our initial hypothesis behind the clustering phenomenon *neighbor aware and opportunistic* AV agents benefit the most from trailing other AVs (due to smaller headways) resulting in collective behavior that lead to strong and prominent clustering phenomenon. It further proves that clustering is not a random phenomenon but is unique to systems involving opportunistic intelligent agents that are capable of recognition. In context of our experiment, it means that if AVs are aware of other AVs under ideal occupancy states - low to critical density - they would engage in collective behavior without any centralized command and display clustering phenomenon if they share common incentive of being opportunistic. This implies that is possible to design AV behavior that can form self-organized clusters.

Exp 2: Equilibrium Relation and Dynamics Under Varying Traffic Densities:

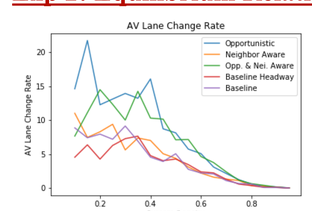

Fig 13: AV Lane Change Rates

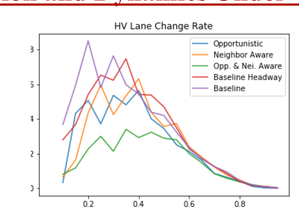

Fig 14: HV Lane Change Rates

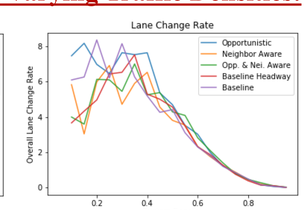

Fig 15: Overall Lane Change Rates

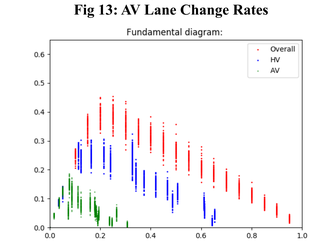

Fig 16: FD of Baseline Model

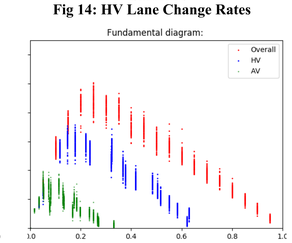

Fig 17: FD of Neighbor Aware and Opportunistic Model

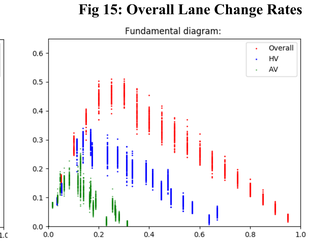

Fig 18: FD of Opportunistic Model

The experiments confirm the impacts of individual AV behaviors on platooning in heterogeneous traffic flow. These findings suggest that the platooning does indeed improve traffic flow by allowing *opportunistic neighbor aware* AVs to seek and trail one another and maintain shorter headways leading to higher speeds for the AV class and more open space for the HV class, which they may use to travel at higher speeds. Such AV behavior also leads to interesting lane change dynamics, where the movement of AVs with respect to HVs mimic those of shepherd dogs herding sheep. The AVs keep the HVs in check by forming prominent self-organized clusters which prevent the HVs from changing lanes.

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