Supplementary Material of Varied Realistic Autonomous Vehicle Collision Scenario Generation

Maria Priisalu[1], Ciprian Paduraru[2], and Cristian Smichisescu[1,3]

[1] Lund University, Sweden
{maria.priisalu,cristian.sminchisescu}@math.lu.se
[2] University Of Bucharest, Romania ciprian.paduraru@fmi.unibuc.ro
[3] Google Research

1 Additional experimental results

1.1 Qualitative results of the ATCG model

In Fig. 1 it can be seen that ATCG produces natural-looking and varied initial locations for AVs and pedestrians (all external agents in dark blue color). Some of the pedestrians (in green circles) manage to avoid collisions with the AVs and others do not (red circles).

The policy of the ATCG agents can be seen in Fig. 2. Note that the ATCG's policy is more dispersed than that of ATS as seen in Figure 7 of the main paper. This is due to the Gaussian smoothing in the prior of APILA, introducing the estimated pedestrian density $\mu^{\mathcal{D}}$ as factor in APILA's prior μ^p and introducing the sum of the standard deviations of the initial location coordinates $r_\sigma(\boldsymbol{x}_0)$ in the total reward of APILA. See section §1.2 below.

The Table 2 in the main paper the AV and the ATCG have been trained alternatively, here in Table 1 we only train the ATCG and keep the AV model constant. The ATCG is able to find collision scenarios for the *base AV* model independently of pedestrian behavior model. The *Collision seeking* and *Collision avoiding* pedestrians result in the highest rewards for APILA and AVILA.

1.2 Ablation study of APILA

The APILA is adapted from ATS [1] by introducing smoothing μ_n^{TTC} with 2D Gaussian filter (G) on the ATS's prior μ_n^{TTC}, by including the estimated pedestrian density $\mu^{\mathcal{D}}$ in the prior μ^p and by the introduction of the reward term $r_\sigma(\boldsymbol{x}_0)$. The effect of these ablations on APILA can be seen in Table 2. Note that ATS [1] only places out pedestrians, and AVILA is novel. The policy of the ablation in Table 2 without G,$\mu^{\mathcal{D}}$ and $r_\sigma(\boldsymbol{x}_0)$ can be seen in Figure 7 of the main paper. The visual inspection of Figure 7 of the main paper shows that without smoothing pedestrians crowd the AV. To avoid placing all pedestrians near the AV smoothing was introduced, and the resulting pedestrians' initializations are shown in Fig. 1 and Fig. 2 and Figure 8 of the main paper. Smoothing (G) decreases APILAs collision rate but increases the pedestrians' average pedestrian density value (average $\mu^{\mathcal{D}}$), as seen in Table 2. After smoothing more pedestrians get

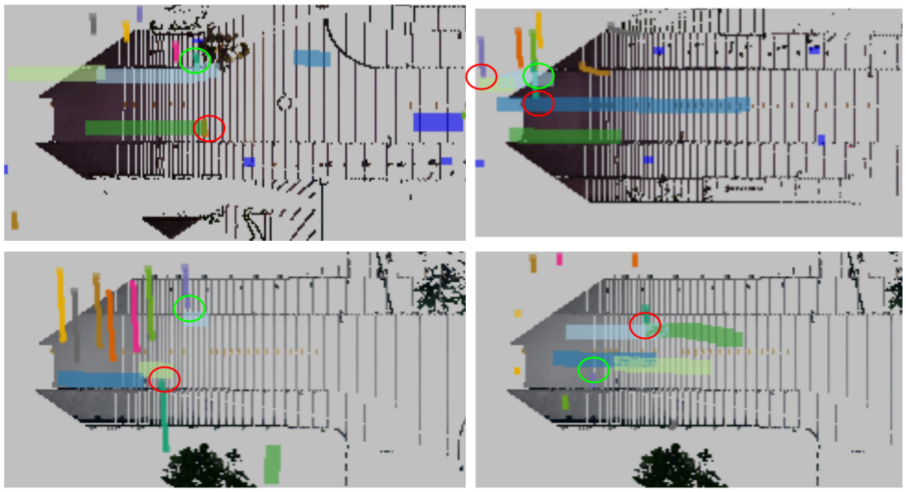

Fig. 1. Four sample scenarios showing multiple cases where the AV and pedestrians manage to avoid collisions (shown with green circles) and cases where they collide (shown with red circles). The top lane of cars is moving to the left and the bottom lane to the right.

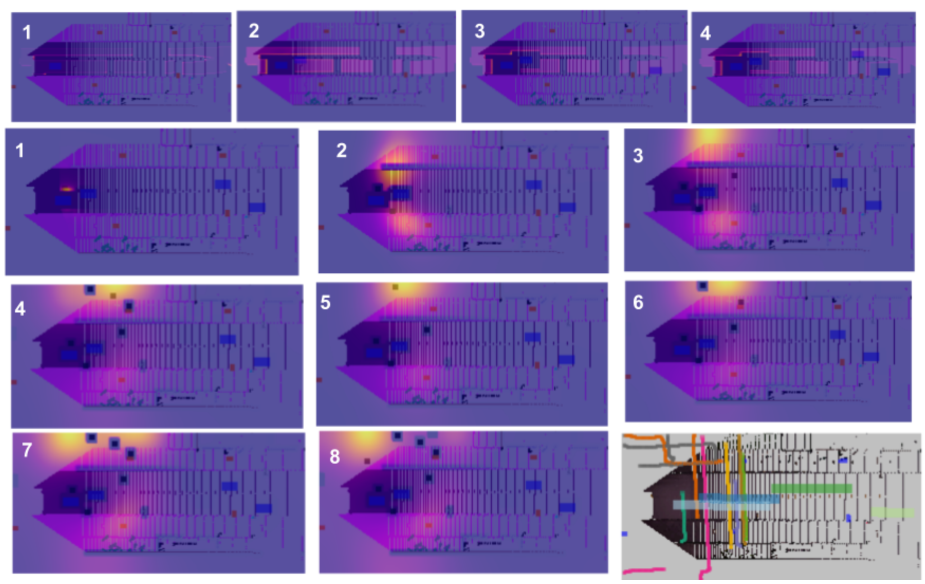

Fig. 2. A sample scenario depicting no collision but varied and realistic initialization of pedestrians and AVs by ATCG. The first row shows AVILA's policy for placing out 4 AVs, second to fourth row show APILA's policy for placing out the first to 8th pedestrian. The trajectories of all of the agents are shown in the fourth row third column.

Table 1. Performance of ATCG trained with various pedestrian models and with the *base AV* model.

Metric	**Constant velocity**	**Distracted SPL**	**SPL**	**Collision avoiding**	**Collision seeking**
R_μ APILA's	0.6($\pm$0.3)	0.8($\pm$0.5)	0.5($\pm$0.4)	**1.0**($\pm$0.6)	**1.0**($\pm$0.1)
R_ν AVILA's	-7.6($\pm$0.6)	-9($\pm$2)	**-7.0**($\pm$0.6)	**-6.7**($\pm$0.9)	-**8**($\pm$3)
# collisions	**1.0**($\pm$0.2)	**0.7**($\pm$0.3)	**1**($\pm$0.2)	**0.87**($\pm$0.06)	**0.9**($\pm$0.4)

Table 2. Ablations of APILA.

$\mu^{\mathcal{D}}$	$r_\sigma(\boldsymbol{x}_0)$	G	$\uparrow R_\pi^+$ collision free	$\uparrow$# collisions	$\uparrow$ average $\mu^{\mathcal{D}}$
			1.5($\pm$ 0.3)	**0.5**($\pm$ 0.1)	0.32($\pm$ 0.2)
✓			3.2($\pm$ 0.4)	**0.5**($\pm$ 0.1)	0.25($\pm$ 0.08)
	✓		2.8($\pm$ 1.6)	**0.4**($\pm$ 0.2)	0.3($\pm$ 0.1)
		✓	**6.3**($\pm$ 0.9)	0.1($\pm$ 0.1)	**0.51**($\pm$ 0.07)
	✓	✓	4.0($\pm$ 0.9)	0.3($\pm$ 0.1)	**0.52**($\pm$ 0.08)
✓	✓	✓	**4.9**($\pm$ 0.3)	0.27($\pm$ 0.06)	**0.56**($\pm$ 0.06)

initialized on the sidewalk and further away from the AV where more pedestrians can naturally be found. The pedestrian density map $\mu^{\mathcal{D}}$ inclusion provides APILA prior knowledge of typical pedestrian distributions in the given scene. The reward $r_\sigma(\boldsymbol{x}_0)$ encourages variation among the initial locations of the pedestrians. Both the inclusion of $r_\sigma(\boldsymbol{x}_0)$ and $\mu^{\mathcal{D}}$ increase the collision rate and decrease the tendency of pedestrian agents to stay near areas often visited by pedestrians. The decrease in collisions brought about by smoothing is countered by the inclusion of $\mu^{\mathcal{D}}$ and $r_\sigma(\boldsymbol{x}_0)$. This is likely because both $\mu^{\mathcal{D}}$ and $r_\sigma(\boldsymbol{x}_0)$ encourage variation among the initial locations of the N pedestrians, leading the model to find more scenarios that lead to collisions. We propose to include all of the model components $\mu^{\mathcal{D}}$,G and $r_\sigma(\boldsymbol{x}_0)$ to balance between likely and collision-prone scenarios, but the choice may vary due to the application.

The effect of varying the pedestrian behavior policy on APILA can be seen in Table 3, utilizing a goal-driven collision avoiding pedestrian such as SPL results in a comparable number of collisions with using a constant velocity pedestrian model. We also report the metric $H(\pi^-)$ collision - the pedestrian behaviour policy's entropy during its collision course. The constant velocity pedestrian results in a lower average μ^D than the other pedestrian behavior models, as the other models are trained to tend to stay in areas frequented by pedestrians. Utilizing randomly distracted pedestrians [1] does not lead to an increase in collisions, likely because the pedestrian's distracted behaviour is unstructured and thus not learnable for APILA, as also confirmed in [1]. The collision seeking pedestrian attains a higher entropy during collisions and is thus more unpredictable in near-collision scenarios causing the collision frequency to drop, while the collision avoiding pedestrian's entropy is low making the pedestrian's motion easier to predict even

Table 3. The constant velocity pedestrian model results in a decreased number of collisions. APILA can generate collisions independently of the pedestrian behaviour policy. The SPL model produces the most pedestrian-like behaviour.

Metric	**Constant velocity**	**Distracted SPL**	**SPL**	**Collision avoiding**	**Collision seeking**
R_π^+ collision free	1.8(±0.1)	3.1(±1.5)	**4.9**(±0.3)	2.5(±0.6)	3.7(±0.8)
# collisions	**0.2**(±0.1)	**0.4**(±0.2)	**0.27**(±0.06)	**0.3**(±0.1)	0.13(±0.06)
average $\mu^{\mathcal{D}}(x_t)$	0.48(±0.08)	0.45(±0.04)	**0.56**(±0.06)	0.31(±0.01)	0.5(±0.2)
$H[\pi]^-$ collision	0	0.08(±0.02)	**0.05**(±0.03)	**0.04**(±0.01)	0.1(±0.1)

if the pedestrian attempts to avoid collisions. Most notably APILA can generate collisions independently of the pedestrian behaviour policy.

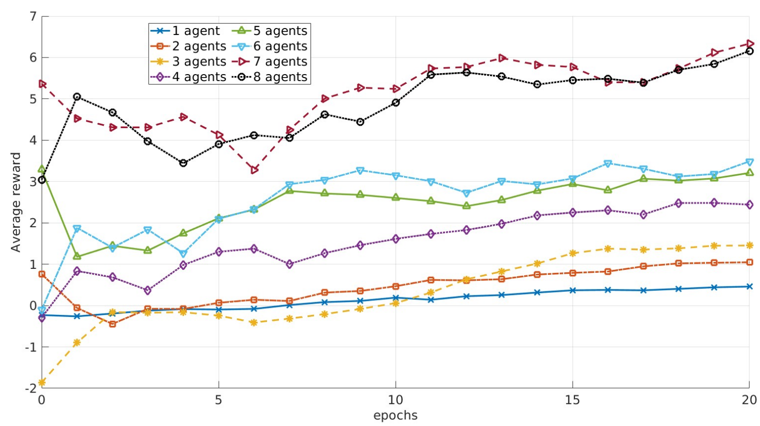

Fig. 3. APILAs model trained with 7 and 8 pedestrians start learning with a higher reward and continue to increase in reward with an increasing number of epochs.

As expected increasing the number of pedestrians implies a higher collision frequency giving a higher reward value, as seen in Fig. 3.

1.3 Ablations of AVILA

In Fig. 4 the average number of collisions between AVs and pedestrians is shown. It can be seen that a larger number of AVs results in general in a larger number of collisions. Three AVs appear to be optimal for the given dataset. It could be that beyond this the AVs have trouble avoiding collisions with one another when trying to avoid pedestrians.

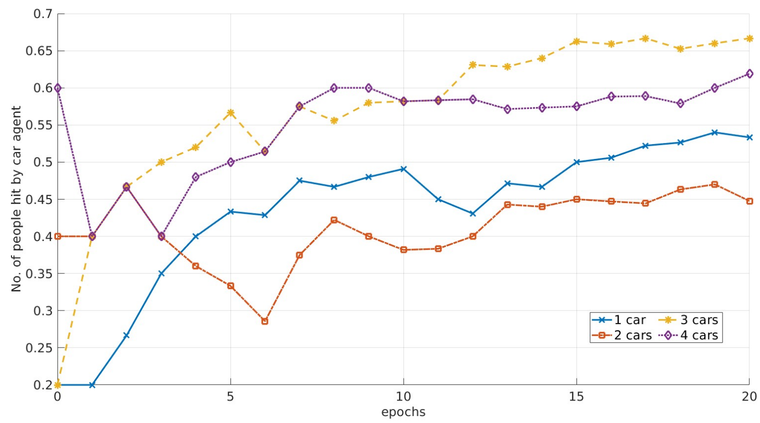

Fig. 4. Three AVs produce the largest amount of collisions between the AVs and pedestrians on the validation set.

References

1. Priisalu, M., Pirinen, A., Paduraru, C. & Sminchisescu, C. *Generating Scenarios with Diverse PedestrianBehaviors for Autonomous Vehicle Testing* in *PMLR: Proceedings of CoRL 2021* (Nov. 2021).