EUROGRAPHICS 2021 / N. Mitra and I. Viola
(Guest Editors)

Volume 40 (2021), Number 2

Dynamic Combination of Crowd Steering Policies Based on Context - Supplementary Material

B. Cabrero-Daniel[1], R. Marques[2], L. Hoyet[3], J. Pettré[3], and J. Blat[1]

[1]Universitat Pompeu Fabra
[2]Universitat de Barcelona
[3]Inria, Univ. Rennes, CNRS, IRISA

1. Computational time

As explained in the main text, in the case of two algorithms having the same performance (once tuned) in a particular context, the system prefers the one that is less computationally expensive in terms of simulation time. The order of algorithms is defined by the empirical results presented in Figure 1.

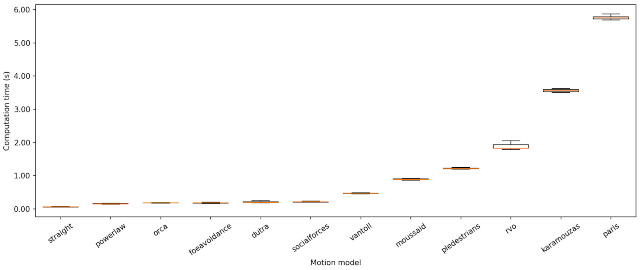

Figure 1: Average time it takes the crowd simulator to generate a 30 seconds trajectory using each of the used steering algorithms.

2. Increase in quality

Table 1 shows, for each context, the increase of simulation quality (in terms of QF) between using the best steering algorithm (with default parameters) and the best steering policy. These results confirm the importance of optimizing the algorithm parameters in order to find a suitable policy for each context. Such an analysis is also present in the work of [**?**]. However, contrary to them, in our approach no reference data is needed, provided that the QF is already tuned. Our work presents different strategies for using the information in Table 1 to improve the quality of crowd simulations.

3. Steering algorithm tuning

Each of the character steering algorithms, implemented in velocity space [vTGG*20], used in this work need appropriate parameter values. The algorithms are tuned, that is adjusting the parameter values, using QF [CDMH*21]. Below, you can find the appropriate parameter values for each of the contexts.

	Density level		
	$0.5ppm^2$	$1ppm^2$	$2ppm^2$
F0	PL (94%, +13%)	RVO (93%, +12%)	ORCA (93%, +12%)
F10	Kar (93%, +13%)	ORCA (93%, +14%)	RVO (92%, +14%)
F50	ORCA (91%, +13%)	Kar (90%, +14%)	RVO (85%, +11%)
F90	RVO (92%, +14%)	Kar (91%, +17%)	ORCA (81%, +11%)
F130	ORCA (91%, +15%)	Kar (89%, +18%)	ORCA (79%, +12%)
F170	PL (90%, +16%)	ORCA (89%, +20%)	ORCA (78%, +15%)
BF0	RVO (93%, +19%)	ORCA (91%, +24%)	ORCA (81%, +21%)
BF10	Mou (90%, +17%)	ORCA (85%, +21%)	RVO (74%, +18%)
BF50	Mou (87%, +16%)	Mou (78%, +16%)	SF (72%, +20%)
BF90	SF (90%, +19%)	Mou (79%, +19%)	SF (72%, +23%)
Unstr.	Mou (86%, +18%)	ORCA (82%, +25%)	TTCA (75%, +30%)

Table 1: Context to steering algorithm map. In brackets (and separated with commas), the average quality of trajectories simulated with the best tuned algorithm for each context and the increase in quality with respect to the same steering algorithm with default parameter values.

The best parameters for the Universal Power Law for unidirectional flows crossings at 0 degrees with density 0.5 char/m^2: neighbour interaction range, $\tau_0 = 2.6$; goal reaching force scale, $w_g = 1$; and $k = 1.5$.

The best parameters for the Universal Power Law for unidirectional flows crossings at 0 degrees with density 0.5 char/m^2: neighbour interaction range, $\tau_0 = 2.6$; goal reaching force scale, $w_g = 1.6$; and $k = 1.5$.

We use ORCA for many of the defined contexts. In the case of a unidirectional flows crossing contexts we use the following time horizon, t_{max}, values:

- At 50 degrees with density 0.5 char/m^2: $t_{max} = 5.2$.
- At 130 degrees with density 0.5 char/m^2: $t_{max} = 5.9$.
- At 170 degrees with density 0.5 char/m^2: $t_{max} = 3.4$.
- At 10 degrees with density 1 char/m^2: $t_{max} = 6.6$.
- At 170 degrees with density 1 char/m^2: $t_{max} = 3.28$.
- At 0 degrees with density 2 char/m^2: $t_{max} = 3.9$.
- At 90 degrees with density 2 char/m^2: $t_{max} = 2.8$.
- At 130 degrees with density 2 char/m^2: $t_{max} = 4.5$.
- At 170 degrees with density 2 char/m^2: $t_{max} = 2.55$.

In the case of bidirectional flows crossings, we use ORCA with the following t_{max} values:

- At 0 degrees with density 1 char/m^2: $t_{max} = 4.29$.
- At 0 degrees with density 2 char/m^2: $t_{max} = 3.94$.
- At 10 degrees with density 1 char/m^2: $t_{max} = 3.6$.

We use the Social Forces model for contexts with bidirectional flows crossings at 50 degrees and density 2 char/m^2 ($t_{max} = 1.46$), at 90 degrees with density 0.5 char/m^2 ($t_{max} = 0.64$), and at 90 degrees with density 2 char/m^2 ($t_{max} = 0.64$).

We use the steering algorithm by Moussaid et al. [MHT11] in the following bidirectional flows crossing scenarios:

- At 10 degrees with density 0.5 char/m^2: neighbour interaction range, $d_{max} = 2.98$.
- At 50 degrees with density 0.5 char/m^2: $d_{max} = 2.5$.
- At 50 degrees with density 1 char/m^2: $d_{max} = 4.7$.
- At 90 degrees with density 1 char/m^2: $d_{max} = 3.9$.

RVO is also preferred in a variety of different contexts. In the case of unidirectional flows crossings, depending on the distribution of directions and density we use:

- Crossing at 90 degrees with density 0.5 char/m^2: $\omega_i = 1.55$.
- Crossing at 0 degrees with density 1 char/m^2: character avoidance strength factor, $\omega_i = 1.68$.
- Crossing at 10 degrees with density 2 char/m^2: $\omega_i = 1.72$.
- Crossing at 50 degrees with density 2 char/m^2: $\omega_i = 0.8$.

In the case of bidirectional flow crossings we use the following parameter values for RVO:

- Crossing at 0 degrees with density 0.5 char/m^2: $\omega_i = 1$.
- Crossing at 10 degrees with density 2 char/m^2: $\omega_i = 1$.

The TTCA algorithm, based on the method by Dutra et al. [DMCN*17], is preferred in an N directional crowd (unstructured context) with density 2 char/m^2. In this case we use $\sigma_a = 2.16$ and $\sigma_s = 1.73$.

The steering algorithm by Karamouzas and Overmars [KO11] is used in four unidirectional flows crossings contexts.

- At 10 degrees with density 0.5 char/m^2: neighbour interaction range, $t_{max} = 5.4$; $\kappa_1 = 0.5$; $\beta = 1$; $\gamma = 1$; and $delta = 8$.
- At 130 degrees with density 1 char/m^2: neighbour interaction range, $t_{max} = 5.4$; $\kappa_1 = 0.5$; $\beta = 1$; $\gamma = 1$; and $delta = 8$.
- At 50 degrees with density 1 char/m^2: neighbour interaction range, $t_{max} = 5.4$; $\kappa_1 = 0.5$; $\beta = 1$; $\gamma = 1$; and $delta = 8$.
- At 90 degrees with density 1 char/m^2: neighbour interaction range, $t_{max} = 5.4$; $\kappa_1 = 0.5$; $\beta = 1$; $\gamma = 1$; and $delta = 8$.

In the video examples, provided as Supplementary Material, trajectories simulated using the PLEdestrians steering algorithm use the following parameter value set: neighbour interaction range, $t_{max} = 3$; minimum admissible TTC, $t_{min} = 0.5$; $w_a = 2.23$; and $w_b = 1.26$.

We use the parameter names for each of the algorithms that appear in the original works, whenever possible, and/or the ones used in [vTGG*20]. Unless stated otherwise, the neighbour interaction range for all the algorithms is 3.5 meters. Characters farther than this value will not be taken into account in to compute the next velocity, v_{next}, for characters. All policies using a sampling method to find the next velocity for characters (i.e., ORCA, Moussaid, PLEdestrians, Paris, Karamouzas, and RVO) use a relaxation time equal to 0.5. None of the policies used in this work take into account the contact forces (the coefficient is equal to zero) that apply when characters collide into each other.

References

[CDMH*21] CABRERO DANIEL B., MARQUES R., HOYET L., PETTRÉ J., BLAT J.: *A Perceptually-Validated Metric for Crowd Trajectory Quality Evaluation*, vol. 4. Association for Computing Machinery, New York, NY, USA, sep 2021. URL: `https://doi.org/10.1145/3480136`, `doi:10.1145/3480136`. 1

[DMCN*17] DUTRA T., MARQUES R., CAVALCANTE-NETO J., VIDAL C., PETTRE J.: Gradient-based steering for vision-based crowd simulation algorithms. *Computer Graphics Forum 36* (05 2017). `doi:10.1111/cgf.13130`. 2

[KO11] KARAMOUZAS I., OVERMARS M.: Simulating and evaluating the local behavior of small pedestrian groups. *IEEE Transactions on Visualization and Computer Graphics 18*, 3 (2011), 394–406. 2

[MHT11] MOUSSAÏD M., HELBING D., THERAULAZ G.: How simple rules determine pedestrian behavior and crowd disasters. *Proceedings of the National Academy of Sciences 108*, 17 (2011), 6884–6888. 2

[vTGG*20] VAN TOLL W., GRZESKOWIAK F., GANDÍA A. L., AMIRIAN J., BERTON F., BRUNEAU J., DANIEL B. C., JOVANE A., PETTRÉ J.: Generalized microscropic crowd simulation using costs in velocity space. In *Symposium on Interactive 3D Graphics and Games* (New York, NY, USA, 2020), I3D '20, Association for Computing Machinery. URL: `https://doi.org/10.1145/3384382.3384532`, `doi:10.1145/3384382.3384532`. 1, 2