Velocity-based models for crowd simulation

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Abstract. Velocity-based models belong to the category of microscopic crowd simulation models. They recently appeared in the crowd simulation literature. They mathematically formulate microscopic interactions as a function of agents' states and their derivatives. In the case of collision avoidance, this property provides agents with the ability to produce anticipated smooth reactions, with great impact on simulation results.

Keywords: crowd simulation, microscopic models, velocity-based models.

1 Introduction

Velocity-based models correspond to a new type of numerical models of microscopic interactions for crowd simulation. This category enables solving interactions (collision avoidance) with anticipation. To allow anticipation, a velocity-based model formulates interactions not only as a function of agents' states (positions), but also as a function of their derivatives (velocities). The basic principle of velocity-based models is to decompose, for each agent, the reachable velocity domain (all the global motions an agent can perform) into two components: the admissible, and the inadmissible velocity domains. The admissible velocity space is the set of velocities at which an agent can move without risk of future collision. At the opposite, a risk of collision appears when the agent moves at a velocity belonging to the inadmissible domain. This poster summarizes 3 examples of velocity-based models.

2 Comparative description of 3 velocity-based models

2.1 The Paris model

The Paris model [Paris 2007] proposes a discrete approach to estimate the admissible velocity domain. Each agent's motion is controlled by the direction of walking θ and its walking speed s. Let us consider an example of interaction between two agents, A and B. We describe below how the motion of A is controlled by the model with respect to the motion of neighbor agent B. The future positions of B are predicted from the linear extrapolation of the current position and velocity vector (current time is time t_0). In Fig. 3., left image, the current position and velocity of A and B are shown, as well as the future positions of B at times t_1, t_2 and t_3.

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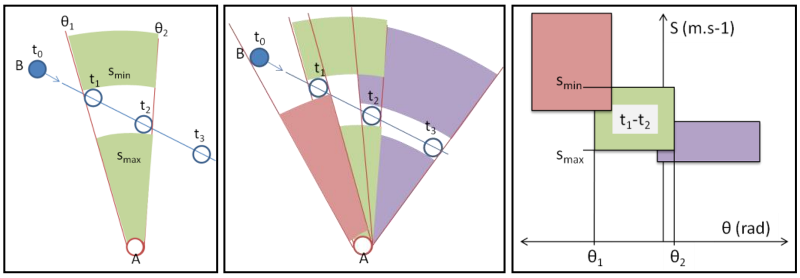

Fig. 1. Illustration of the Paris model.

Several time intervals are considered. For each time interval $[t_i,t_{i+1}]$, the angular sector covered by the predicted motion of B and relative to the position of agent A is computed. In Fig. 3., the left image displays the angular sector covered by B between t_1 and t_2. The angular sector is delimited by θ_1 and θ_2. Agent A may enter into collision with B in the time interval $[t_i,t_{i+1}]$ if, and only if, A moves in a direction belonging to this angular sector. For each time interval and corresponding angular sector, we additionally compute s_{min} and s_{max}, which are respectively the minimum speed at which A should move to pass in front of B, and the maximum speed at which A should move to give way to B. In the example of Fig. 3, if A moves in a direction $\theta \in [\theta_1,\theta_2]$ at a speed $s \in [s_{max},s_{min}]$, there is a high risk of future collision.

Steps 1-3 are repeated for each neighbor agent and for each time interval. Portions of inadmissible velocities (belonging to intervals $[s_{max},s_{min}]$ and $[\theta_i$ and $\theta_{i+1}]$) are successively reported into the control space (Fig. 3., right image: the space left blank corresponds to the admissible velocity domain). By construction, the admissible velocity domain is deduced. The model uses a cost function to deduce the best solution belonging to this domain.

2.2 The Tangent model

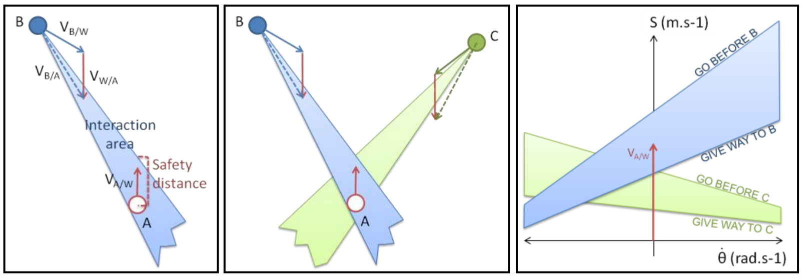

Fig. 2. Principles of the Tangent model.

The Tangent model was designed to better simulate the human perception of others' velocity [Pettré09]. The model is described from the example of motion control for agent A during interaction with agent B (see Fig. 4.). The velocity vector of B relatively to A, $V_{B/A}$, is first computed. By linear extrapolation, $V_{B/A}$ allows to estimate the distance at which B will pass A. When the crossing distance is too low, A has to perform an avoidance maneuver. To avoid a future collision, the relative velocity vector $V_{B/A}$ must lie out of the interaction area. Agent A can adapt this relative velocity by playing on its own velocity vector $V_{A/W}$ (we cannot assume that A controls B's motion). Fig. 4, illustrates these two components of the relative velocity vectors. In the example Fig. 4, one can see that A can for example decelerate: the $V_{A/W}$ component of $V_{B/A}$ would then be shorter and collision avoided. Equally, A could turn to the right.

2.3 The Vision model

The two previous models assume that agents, i.e., simulated human walkers, are able to integrate a large quantity of information about neighbors' motions. This information is progressively projected into the control space to deduce the admissible velocity domain. Even though the Tangent model also models motion perception error to better simulate the timing of an interaction, real humans do not process information this way to control their locomotion. They control their walk mainly according to their visual perception of their environment. The objective of the Vision model, in comparison with the two previously proposed models, is to better simulate this perception-action loop.

The neuroscience field stated that humans, during avoidance of static or moving obstacles, successively answer two questions: will a collision with the obstacle occur? When will this collision occur? They react accordingly. The manner in which humans process their optical flow to answer these questions is still under debate but some theories state that two variables are directly exploited by humans for motion control: first, $\acute{\alpha}$, the derivative of the bearing angle, and second, ttc, the time-to-collision. When an obstacle is always visually perceived under the same angle (i.e., $\acute{\alpha} = 0$), and is growing in the image formed on the retina (ttc>0), a risk of future collision is detected. The imminence of the collision risk is determined by ttc as well.

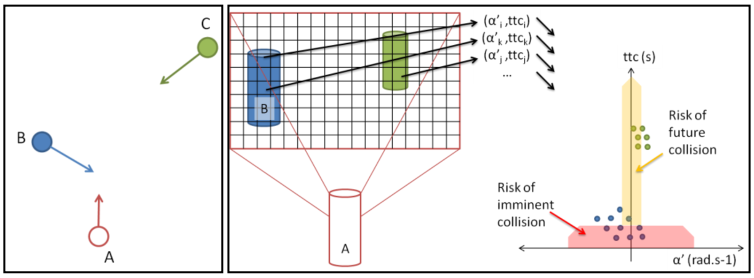

Fig. 3. Principles of the Vision model.

The Vision model reproduces this perception action loop. The principle of the model is illustrated in Fig. 5, from the example of an interaction between an agent A and two other agents (B+C), as shown in the left image of the figure. To start, we compute a digital representation of the environment from the perspective of agent A (right image). This representation is computed similarly to classical graphical rendering techniques. A matrix represents the perceived image, each pixel is computed based on rastering techniques. The comparison stops here, we do not compute the pixels' graphical properties (color, intensity). Instead, for each pixel p_i, two values are computed: $(\acute{\alpha}_i, ttc_i)$, the time-derivative of the bearing angle and the time-to-collision. Agent motion control is performed according to a simple perception-action simulation loop. Pixels with low $\acute{\alpha}$ values correspond to a risk of future collision. When such pixels are perceived, the agent turns to change this situation. Pixels with low ttc values correspond to an imminent risk of collision (even with large $\acute{\alpha}$ values because of the body envelope). When pixels with such low values are perceived, the agent decelerates.

3 Discussion and Conclusion

In this abstract, we shortly described three different velocity-based models. They propose three different methods to compute the admissible velocity domain and to finally control the agents' motion.

The fundamental basis of velocity models should also be put again into question. A simple linear extrapolation of trajectories based on current position and velocity is sometimes a bad prediction, especially during maneuvers (a small deviation may completely change the trajectory prediction between two time steps): in crowded places where people constantly adapt their motion, is using a velocity model useless? Probably not, because computations are constantly re-evaluated. But smarter predictions, at the level of real human abilities, would probably make this new type of model even more realistic and useful.

4 References

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