Models for the simulation of the motion behavior of groups of pedestrians

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1 Introduction

This document describes three existing models for the simulation of the move of pedestrians, those of Reynolds (the boids model), Helbing *et al.* (refered as the HMFV's model), and Fajen&Warren (FW model). All these models produce robust and adaptive collective behavior that can be used to simulate the motion of agents evolving on plane surfaces, such as non-playing characters (NPC) in video games or pedestrians in an urban virtual environment.

Nevertheless none of these models has been yet fully validated for small groups of pedestrians. To be validated, the output of these models should be compared to experimental data, that are actually missing. All these models hold parameters which values are far to be known. The present study aims at comparing the output of these models in different spatial configurations of the environment.

2 Nature of the studied models

Table 1 outlines the main characteristics of the studied models. It enlightens their common grounds and main differences. These models share the same point of view on pedestrians' behavior. Displacements are studied at the scale of the moves (in a 2D environment) of individuals (the agents). They try to account for the evolution over time of the positions and directions of move of each agents in order to analyse whether some *patterns* occur in the distribution (macro- or meso-level) of these two micro-level state variables. This aspect of the modeling of pedestrians is called the *steering model*.

Helbing's and Warren's models explicitly refer to the Attraction-Repulsion theoretical framework. Underlying hypotheses of Reynolds's one are also compliant to this framework (to a certain extend). All of them are IBSEM (Individually-based, Spatially Explicit Models), kind of multiagent models.

3 Methodology

3.1 Notations

For sake of comparison, we use the same notation system for all the studied models.

Index i refers to the current agent and j to the object (or agent) it may interact with. For sake of simplicity we omitted the i subscript when there was no ambiguity (idem for t which denotes the current time). Models are presented here for displacements on a horizontal plan (2D). Only Reynolds's model would be suitable for simulating movements in 3D.

The mass of the agent is m $[kg]$, its position at time t is $\vec{x}(t)$, its velocity $\vec{v}(t)$. $v(t)$ $[ms^{-1}]$ is the agent's speed (magnitude of the velocity). Its orientation $\varphi(t)$ $[rad]$ is defined as its current

	Reynolds (1987)	Helbing et al. (2002)	Fajen and Warren (2003)
Theoretical framework	–	Attraction–Repulsion	Attraction–Repulsion
Perspective	Computer Animation	Crowd modeling	Cognitive psychology
Individuals	any type	pedestrians	pedestrians
Purpose	steering control	steering control	steering law
Nature	heuristic	social forces	dynamical coupling
Comput. models	IBSEM	IBSEM	IBSEM
Scale	all (meso)	crowd (macro)	individual (micro)
Process	flocking	Panic	individual steering/avoidance
Physical model	simple vehicle	point-mass	not explicit
Components			
Attraction to goal	yes	in Lakoba	yes
Repulsion from others	yes	yes	no
Attraction to others	yes	no	no
Syncing	yes	in Lokoba (velocity)	no
State variables	$\vec{x}, \vec{v}$	$\vec{x}, \vec{v}$	$\vec{x}, \varphi, \dot{\varphi}$
Random (noise)	No	No	No

Table 1: Main properties of the studied models.

direction of motion; $\dot{\varphi}(t)[rad.s^{-1}]$ denotes the angular velocity of the agent, and $\ddot{\varphi}(t)[rad.s^{-2}]$ its angular acceleration.

In the context of the interaction between an agent i and an object j, $d_{ij}(t)$ is the distance between the two entities. $\vec{n}_{ij}(t)$ denotes the normalized vector corresponding to the line joining the center of agent i to object j. It defines the normal component of the interaction. $\vec{t}_{ij}(t)$ denotes the normalized vector orthogonal to $\vec{n}_{ij}(t)$; it defines the tangential component of the interaction (if exists).

$\mathcal{A}$ is the set of agent in the system and $N_{\mathcal{A}}$ the cardinal of this set (number of agents). $\mathcal{O}$ denotes the center of mass of the agents; $x_{\mathcal{O}}(t)$ is its position at time t. When necessary, a refers to an agent, g a goal, o an obstacle and w a wall (spatial entity).

3.2 Elements of comparison

The main objective is to analyse the dynamics of collective behavior of pedestrians resulting mainly from their inter-individual interactions. All the models do not address exactly the same behavioral components (=sub-models) governing the displacements of groups—or crowds—of pedestrians. Nevertheless they share some assumptions and propose similar sub-models.

The studied models share the following assumption: no verbal nor nonverbal communication, no social relationship between the agents, no "abnormal" conditions (ie., by default they consider relaxed individuals).

3.3 Scenarios

The study focuses on simple scenarios, easy to reproduce and to observe, that are relevant regarding the scale of observation (meso level) and covered by the studied models. Singh et al. (2009) have proposed such scenarios (most of them had been studied before). This set of scenarios was named SteerBench.

The simulated system is compounded of groups of pedestrians which do not know each others and who are moving towards the same location (their goal). Some scenarios consider subsets of pedestrians having different goals (for instance to simulated the crossing of pedestrians' lanes). Notice that all the scenarios from SteerBench are not relevant for all the models.

Each agents (at least some of them) are supposed to have a goal: a point they want to reach. It is a kind of external forcing parameter. The implemented models may produce very specific and unrealistic behaviors when agents are very close to their spacial goal. Theses conditions shall be excluded from the analysis. To avoid these undesirable side effects, agents can be destroyed as soon as they have reached their goal (or at least when very close to it).

3.4 Indicators & Metrics

It remains pretty difficult to qualify emergent behaviors and it is true for the emergent moves of pedestrians. Some authors have proposed some indicators suitable for the analysis and the comparison of steering models.

Flocking behavior. From Wood (2010). The different *phases* of a flock can be characterized by the polarization and the angular momentum about the group centre $\mathcal{O}$.

Polarization of a group of agents : average of the velocity of the group of agents.

$$p(t) = \frac{1}{N_{\mathcal{A}}} |\sum_{i \in \mathcal{A}} \vec{v}_i(t)|$$

Angular momentum :

$$p(t) = \frac{1}{N_{\mathcal{A}}} |\sum_{i \in \mathcal{A}} \vec{r}_{i\mathcal{O}} \times \vec{v}_i(t)|$$

with $\vec{r}_{i\mathcal{O}} = d_{i\mathcal{O}}.\vec{n}_{i\mathcal{O}}$.

Spatial sorting From Wood (2010). It characterizes the distribution of the velocity within the flock. Used two *connected velocity correlation functions*.

Velocity–radius

If positive, the fast individuals are on the outside of the group, otherwise *slow individuals are on the outside.*

$$\langle vr \rangle = \frac{1}{N_{\mathcal{A}}} \sum_{i \in \mathcal{A}} v_i.d_{i\mathcal{O}} \; - \langle v \rangle_i.\langle x_{\mathcal{O}} \rangle_i$$

Velocity–angle

If positive the fast individuals are towards the rear of the group, otherwise *they are towards the front of the group.*

$$\langle v\theta \rangle = \frac{1}{N_{\mathcal{A}}} \sum_{i \in \mathcal{A}} v_i.\theta_{i\mathcal{O}} \; - \langle v \rangle.\langle \theta_{\mathcal{O}} \rangle$$

with $\theta_{i\mathcal{O}} = \varphi_{\mathcal{O}} - \psi_{i\mathcal{O}}$. $\varphi_{\mathcal{O}}$ is the heading of the center of the group and $\psi_{i\mathcal{O}}$ the bearing of the center of the group for agent i: $\widehat{\vec{r}_{i\mathcal{O}}, \vec{v}_i}$.

4 Reynolds's model

4.1 Context

The model was designed in an engineering perspective for the purposes of game development or computer animation (Reynolds, 1987). This model is dedicated to the realtime simulation of the coordination of collective motions of situated agents, named *boids*. The result of Reynolds's work is the OpenSteer library (Reynolds, 1999), which is distributed as an open source software at `http://opensteer.sourceforge.net/` (last update: 2004).

4.2 Overview

Reynolds uses the term *steering behavior* to refer to the control of the trajectory of agent's motion. The overall problem of simulating the motion of an agent is organized in 3 layers. The upper layer is responsible for the elicitation of the agent's goal (strategic layer). The steering (sub-)models *per se* govern the intermediate layer (tactic layer), and aim at calculating dynamically the path the agent is actually following to reach its goal. The lower layer is dedicated to the body animation (locomotion), according to the velocity and the orientation calculated by the steering model.

Regarding its steering behavior, an agent is represented as a *Simple Vehicle*, which is a point-mass approximation of its body. Each agent has a linear velocity but no momentum of inertia. The agent's motion results from the forces generated by the agent that apply on this point-mass.

4.3 Purpose

Reynolds proposed his boids model to produce plausible coordinated motions for fish schools, herds of gnu, or crowds of pedestrian ... The model was not specifically designed to simulate the behavior of pedestrians. The model is not grounded on any psychological theoretical framework, but is more a simplified physical model on which heuristics have been applied.

4.4 Conceptual model

4.4.1 State variables and scales

Agents are assimilated to point-mass: they have a mass m, a position $\vec{x}(t)$, and a velocity $\vec{v}(t)$. Their physical capabilities are constrained by a maximum speed $V_{\max}[ms^{-1}]$ (its preferred speed). The magnitude of the force applied to the agent is bounded by $F_{\max}[N]$.

4.4.2 Process overview and scheduling

We do not consider here all the behavioral components of the OpenSteer library, but only those relevant to the context of the present study. The two first sub-models control the steering to a stationary goal, and the next three ones the flocking behavior (boids model).

Seek the goal. This sub-model acts to steer the agent toward a given static position it wants to reach (its next spatial goal).

$$\vec{S}_i^{seek} = V_s.\vec{n}_{ig} - \vec{v}_i \tag{1}$$

Arrival. This component controls the magnitude of linear velocity of the agent. When the agent is far from the goal ($d_{ig} > D_g$), its speed equals $V_{\max}$ and it is decreasing linearly to zero when the distance falls down under D_g.

$$V_s = \min(1, \frac{d_{ig}}{D_g}).V_{\max} \tag{2}$$

Separation.

$$\vec{S}_i^{sep} = \sum_{j \in \mathcal{N}_s} \frac{-1}{d_{ij}}.\vec{n}_{ij} \tag{3}$$

Cohesion.

$$\vec{S}_i^{coh} = \frac{1}{card(\mathcal{N}_c)} \sum_{j \in \mathcal{N}_c} d_{ij}.\vec{n}_{ij} \tag{4}$$

	Designation	Value	Unit	Eq.
m	mass of the agent	1	kg	
$V_{\max}$	magnitude of the preferred (max) velocity	2.0	ms^{-1}	2
$F_{\max}$	magnitude maximum force applied to the agent	8.0	N	
D_g	distance to a goal at which the agent's speed decreases		m	1
α_g	weight of the influence of a stationary goal	1	–	6
$r_{\mathcal{N}_r}$	radius of the neighborhood for the separation interaction	5	m	3
$\theta_{\mathcal{N}_r}$	field of interaction for separation	$-.707$	rad	3
α_s	weight of the influence for the repulsion	12	–	6
$r_{\mathcal{N}_a}$	radius of the neighborhood for the alignment interaction	7.5	m	5
$\theta_{\mathcal{N}_a}$	field of interaction for alignment	.7	rad	5
α_a	weight of the influence for the alignment	8	–	6
$r_{\mathcal{N}_c}$	radius of the neighborhood for the cohesion interaction	9.0	m	4
$\theta_{\mathcal{N}_c}$	field of interaction for cohesion	$-.15$	rad	4
α_a	weight of the influence for the cohesion	8	–	6

Table 2: Parameters for the Reynolds's model.

Alignment.

$$\vec{S}_i^{ali} = \frac{1}{card(\mathcal{N}_a)} \sum_{j \in \mathcal{N}_a} (\vec{v}_j - \vec{v}_i) \tag{5}$$

Scheduling. At every frame of the simulation, for every agent, for each of its behavior, the system calculates a new desired direction of movement, which is assimilated to a *steering force* generated by the surrounding elements in the agent's vicinity. The actual agent's move is the result of a weighted sum of all the forces generated by the different interactions.

The resulting *steering force* is:

$$\vec{S}_i = \alpha_g.\vec{S}_i^{seek} + \alpha_s.\vec{S}_i^{sep} + \alpha_c.\vec{S}_i^{coh} + \alpha_a.\vec{S}_i^{ali} \tag{6}$$

The magnitude of the steering force is caped to $F_{\max}$ and the agent's speed to $V_{\max}$. Its new position is computed using a forward Euler integration scheme. The new heading of the agent is computed using the vector of displacement.

Parameters. Table 2 summarizes the parameters for all the sub-models. No values were specified for those parameters in Reynolds (1987, 1999). The values given here have been retrieved from the source file of OpenSteer (plugins Boids and Pedestrian). Typically, $\mathcal{N}_s \subset \mathcal{N}_a \subset \mathcal{N}_c$.

4.5 Design concepts

Each agents (at least some of them) are supposed to have a goal: a point they want to reach. It is a kind of external forcing parameter. The implemented models may produce very specific and unrealistic behaviors when agents are very closed to their spacial goals. Theses conditions shall be excluded from the analysis. To avoid undesirable side effects, agents can be destroyed as soon as they have reached their goal (or at least very close to it).

4.6 Details

4.6.1 Initialization

The agent's velocity is initialized to $V_{\max}$. The initial direction of move depends on the simulation scenario.

4.6.2 Submodels

Stationnary goal The interaction is computed as the combination of 1 and 2:

$$\vec{S}_{ig}^{seek} = \min(1, \frac{d_{ig}}{D_g}).V_{\max}.\vec{n}_{ig} - \vec{v}_i \tag{7}$$

Boids. In the general case, the interaction between agent i and j is computed as :

$$\vec{S}_{ij}^{boid} = (\alpha_s \xi_{ij}^s \frac{1}{d_{ij}} + \alpha_c \xi_{ij}^c d_{ij}).\vec{n}_{ij} + \alpha_a \xi_{ij}^a (\vec{v}_j - \vec{v}_i) \tag{8}$$

where $\xi_{ij}^n(t) = 1 \iff j \in \mathcal{N}_n(i)$ (neighborhood of i at time t, regarding interaction of type n) and 0 otherwise.

At last the resulting steering force is:

$$\vec{S}_i = \alpha_g.\vec{S}_{ig}^{seek} + \frac{1}{card(\mathcal{A})}.\sum_{j\in\mathcal{A}} \vec{S}_{ij}^{boid} \tag{9}$$

The magnitude of this force is then truncated to $F_{\max}$. The magnitude of the corresponding velocity is also truncated to $V_{\max}$.

5 Helbing's model

5.1 Context

Helbing et al. (2002) analysed the properties of crowds behavior under different conditions. They concluded their analysis by: *"In summary, one could say that fluid-dynamic analogies work well in normal situations, while granular aspects become important in panic situations."*. In this article, which is an extended version of (Helbing et al., 2000), they presented the results obtained using the early version of the social force model (Helbing and Molnár, 1995) for different typical situations: pedestrian lanes ... Their model accounts for the dynamics of the self-organization of pedestrians crowds at a micro-level.

5.2 Overview

The agent's interactions with its environment generate *forces* which drive the agent to move by modifying its velocity and its direction of move. The different motivations of and influences on a pedestrian i are described by separate so-called *force terms.*

It is a continuous-space model. Each pedestrian is considered as a Newtonian particle (sic) (Lakoba et al., 2005). The model aims at unifying the resulting effects of the physical forces that exert on the agent with so-called *social forces*, within the general law: $\vec{F} = M.\vec{\Gamma}$

Lakoba et al. (2005) introduced some conceptual modifications to the HMFV's model:

1. the social force depends on the density of the crowd,

2. repulsion forces are different whether two interacting agents are in face-to-face or face-to-back spatial configuration,

3. selection of the direction of motion is based on the agent's knowledge about the position of the obstacles and exits.

They have also proposed a more "realistic" value for the B, the fall-off of the social force, and a more efficient implementation for the computation of the force that avoids two pedestrians to overlap.

5.3 Purpose

The model was developed to simulate panic escape for large crowds of pedestrians. Individuals move on an horizontal plan; the environment may contain walls and exit doors agents try to reach. The model is not supposed to be executed in real-time.

5.4 Conceptual model

5.4.1 State variables and scales

The model considers pedestrians as particles having a mass and occupying a circular area. For the computation of its movement, the agent is viewed as a particle (point, mass) on which forces are applied.

Each pedestrian holds a location $(x(t), y(t))$ (m), a direction of move (rad), a velocity $v(t)$ (ms^{-1}). Individuals have a mass m (kg), a body radius r (m).

Elements from the environment are walls (stationary obstacles) and doors (stationary goals). Walls are represented as spatial entities, exits by points. Agents known the absolute positions of these elements.

In (Lakoba et al., 2005), the model has been applied for the simulation of 100 people during 60 seconds. Simulations lasted between 20 minutes to 1 hour.

5.4.2 Process overview and scheduling

Hereafter $\vec{n}_{ij}$ denotes the normalized vector corresponding to the line joining the center of agent i to agent j. It defines the normal component of the force. $\vec{t}_{ij}$ denotes the normalized vector orthogonal to $\vec{n}_{ij}$; it defines the tangential component of the force.

Velocity and direction of move. The agent is supposed to have both a desired velocity $v^0(t)$ and a desired direction of move $\vec{e}^0(t)$. The agent applies a kind of *internal force*, broken down into an acceleration (*driving term*) and a *friction term*:

$$m_i \frac{1}{\tau}.(v_i^0(t).\vec{e}_i^0(t) - \vec{v}_i(t)) \tag{10}$$

where $\vec{e}^0(t) = \frac{1}{||\vec{v}^0(t)||}.\vec{v}^0(t)$. It controls the agent's trajectory when it moves alone in a obstacle free environment. τ is called the relaxation time. Eq. 10 could also be writen as:

$$m_i \frac{1}{\tau}.(\vec{v}_i^0(t) - \vec{v}_i(t)) \tag{11}$$

Collective motion. From Lakoba et al. (2005), agents adapt their velocity according to their neighbors and thus generate an internal force:

$$\vec{f}_i^{pref} = -m_i.\tfrac{1}{\tau}(\vec{v}_i(t) - \vec{v}_i^g(t)) \tag{12}$$

$$\vec{v}_i^g = (1-p).V^0.\vec{e}_i + p\tfrac{1}{\text{card}(\mathcal{N}_i)} \textstyle\sum_{j \in \mathcal{N}_i} \vec{v}_j \tag{13}$$

where:
V^0 is the speed of the agent when alone

$\mathcal{N}_i$ is the set of the agent's neighbors
p a "panic parameter". The size of the neighborhood is defined by a radius $r_{\mathcal{N}}$.

When $p = 0$, Eq. 10 and 12 are identical.

Territorial effect: repulsive interactions. These interactions generate social forces among neighbors. Several variants have been proposed for this behavioral component. Intrinsically it is based on the following term:

$$\vec{f}_{ij}^{soc} = Ae^{\frac{(r_{ij}-d_{ij})}{B}}.\vec{n}_{ij} \tag{14}$$

Eq. 14 does not account for the anisotropy of this interaction, namely agents do not interact with agents behind them in the same way they do for agents in front of them. The force term from Eq. 14 is scaled as follows:

$$\vec{f}_{ij}^{soc} = Ae^{\frac{(r_{ij}-d_{ij})}{B}}(\lambda_i + (1-\lambda_i)\frac{1+\cos(\psi_{ij})}{2}).\vec{n}_{ij} \tag{15}$$

where $\cos(\psi_{ij}) = -\vec{n}_{ij}.\vec{e}_i$; $\lambda_i \in [0, 1]$

Attractive interactions. The attraction force that drives an agent toward an element g of its environment has the same shape as Eq. 15:

$$\vec{f}_{ij}^{att} = A_g e^{\frac{(r_{ig}-d_{ig})}{B_g}}(\lambda_i + (1-\lambda_i)\frac{1+\cos(\psi_{ig})}{2}).\vec{n}_{ig} \tag{16}$$

where B_g is smaller than B in Eq. 14 and A_g is negative, larger than A and time dependent. d_{ig} is the distance between the center of the agent and the surface of the object g.

Physical forces for panicking pedestrians. They apply when the agent collides with another group member(s) or obstacle(s). These physical forces typically come into play in "panic situations". The force is broken down into a normal component $\vec{f}^{push}$ (*pushing*) that counteracts body compression and a tangential one $\vec{f}^{frict}$ (*sliding friction*):

$$\vec{f}_{ij}^{push} = k\eta(r_{ij} - d_{ij}).\vec{n}_{ij} \tag{17}$$

where $\eta(x) = H(x).x$ (H is the Heaviside function).

In Helbing et al. (2002), the friction term was:

$$\vec{f}_{ij}^{fric} = \kappa\Delta_{ji}.\vec{t}_{ij} \tag{18}$$

where $\Delta_{ji} = (\vec{v}_j - \vec{v}_i).\vec{t}_{ij}$

In Lakoba et al. (2005) this term was:

$$\vec{f}_{ij}^{fric} = \kappa|\vec{f}_{ij}^{push}|.\vec{t}_{ij} \tag{19}$$

$$= \kappa k\eta(r_{ij} - d_{ij}).\vec{t}_{ij} \tag{20}$$

Scheduling The model assumes the vectorial additivity of all the forces generated by the behavioral components: the forces computed for each behavioral components are summed and then applied to the agent. The state variables are updated on a fixed schedule.

Parameters. Table 3 summarizes the values of the parameters for each sub-models. No values were specified in Helbing et al. (2000, 2002). These values come mostly from Lakoba et al. (2005).

Moussaïd et al. (2011) defined $r_i = m_i/320$. For a 80 kg individual, the radius is .25 m.

Lakoba et al. (2005) introduced an anisotropic gain in the social force, scaled by the λ parameter.

	Designation	Val.	Unit	Eq.
m	Mass of the agent	80	kg	
r	Radius of the agent	.35	m	
τ	Relaxation time	.5	s	10
A	Strength of the social force between agents	2.10^3	N	14
B	Fall-off length of the social force between agents	.08	m	14,15
k		1.2×10^5	kgs^{-2}	
κ		2.410^5	$kgm^{-1}s^{-1}$	
λ		$[0, 1]$	–	
V^0	Preferred velocity		ms^{-1}	
$R_{\mathcal{N}}$	radius of the agent's neighborhood	2–3	m	
A_g	Strength of the attraction toward a goal		N	16
B_g	Fall-off length of the attraction toward a goal		m	16

Table 3: Parameters for the Helbing's model.

5.5 Details

5.5.1 Initialization

Idem for Reynold's model.

The force coming from the "resulsive interaction" may be very high when agent are very close together. Thus it is safe to initialize the simulation with inter-invidividual distances that correspond to low values of this social force.

5.5.2 Submodels

We do not consider here the behavior named "panicking pedestrians"; It will not be implemented.

Steering to the stationary goal This component controls the desired direction of move $e^0(t)$, which is used in Eq. 10. It is a forcing parameter. We can assume that the magnitude of the desired velocity is constant and identical for all the agents: $v^0(t) = v^0$. This parameter correspond more or less to $V_{\max}$ of Reynold's steering model.

Repulsion from neighbors. This component is governed by the social forces presented in section 5.4.2.

Attraction to neighbors. This component is not explicit in the model. It can be implemented using the "Attractive interaction" submodel.

Syncing. This component controls the velocity of the agents when in group (cf. "collective motion").

6 Fajen & Warren model

6.1 Context

The model was proposed by Fajen and Warren (2003, 2007), which have been working in the field of cognitive psychology. The model was first dedicated to the study of the locomotion of isolated pedestrians. The objective was to characterize how individuals interact with the objects in their environment, and how these interactions *shape* the agents' behavior. This approach is grounded in the theory of the ecological approach of cognition. Their authors named it the *behavioral dynamics*.

6.2 Overview

The behavioral dynamics approach conceptualized by Warren (2006) is an ecological, emergent, and distributed approach to behavior . Based on the ecological approach to perception and action (Gibson, 1986), the individual is seen as coupled to its environment through information and control variables, such that action is governed by behavioral strategies or control laws. The locomotor trajectory is not prescribed by an internal planning process, but emerges from the interactions of the individual agent with its environment. The temporal evolution of behavior is thus not determined by either the agent or the environment alone, but control is distributed across both, through the conjunction of the agent-environment state, given the task constraints and the effective control laws. As such, control lies in the agent-environment system and is distributed and self-organized (Gibson, 1986).

The coupling between the agent and the environment is both mechanical, through forces exerted by the agent, and informational, through information fields in the environment that specify the state of affairs to the agent. From that coupling emerges a pattern of behavior, with a dynamics characterized by stable states, bifurcations, hysteresis, attractors and repellers. As such, the approach characterizes the agent-environment interaction as a dynamical system, and the unfolding behavior as a trajectory in the state space of the system. It is this emergent behavior that is called the behavioral dynamics (Warren, 2006).

6.3 Purpose

These models aim to account for human behavior when individuals interact with the objects of their environment. They are dedicated to isolated pedestrians steering to stationary (or moving) targets and avoiding stationary (or moving) obstacle(s).

6.4 Conceptual model

6.4.1 State variables and scales

The model does not take into account the variation of the speed of the pedestrians. The state variables are the location of the agent $x(t)$, their orientation $\varphi(t)$ and its derivative $\dot{\varphi}(t)$.

6.4.2 Process overview and scheduling

Steering to a stationary goal. In the strategy to reach a stationary goal, the agent tries to have its heading φ and the direction to the goal ψ_g be the same, so that the relative direction to the goal $(\psi_g - \varphi)$ tends to zero. This defines an attractor in state space at $[\varphi, \dot{\varphi}] = [\psi_g, 0]$. The resulting agent's angular acceleration is then given by:

$$\ddot{\varphi} = -b_g\dot{\varphi} - k_g(\varphi - \psi_g)(e^{-c_1 d_g} + c_2) \tag{21}$$

The first component $-b_g\dot{\varphi}$ is the damping term. The term $-k_g(\varphi - \psi_g)(e^{-c_1 d_g} + c_2)$ is the behavioral strategy that makes the agent steer toward its goal g attracted by the fix point $(\varphi - \psi_g) = 0$. The term $(e^{-c_1 d_g} + c_2)$ exponentially decreases with the distance d_g between the agent and the goal, and tends toward the constant c_2, making the goal attractive whatever d_g.

Steering to a moving target. To steer toward a moving target, the agent uses a more general behavioral strategy than for steering to a stationary goal, which is a particular case. For reaching a moving target, the agent uses the "*constant bearing angle*" strategy Warren and Fajen (2008), which makes it keep the direction to the moving target constant, i.e. agent keeps $\dot{\psi}_m$ null. The resulting agent's angular acceleration is then:

$$\ddot{\varphi} = -b_m\dot{\varphi} - k_m\dot{\psi}_m(d_m + c_3) \tag{22}$$

Submodel	Values
Stationary goal (Eq. 21)	$b_g = 3.25$, $k_g = 7.5$, $c_1 = 0.4$, $c_2 = 0.4$
Moving obstacles from Warren and Fajen (2008)	$k_{mo} = 530$, $c_4 = 6$, $c_5 = 1.3$

Table 4: Parameters for Fajen & Warren's model

$(d_m + c_3)$ is a linear distance term, which compensates for the decrease in angular velocity with target distance (d_m); c_3 prevents the target's influence from dropping to zero with distance.

Avoiding a moving obstacle. To avoid a moving obstacle, the agent uses an inverse strategy to the one used to steer toward a moving goal. The idea is for the agent to avoid keeping the direction to the obstacle constant. The contribution of this component to the angular acceleration of the agent is then:

$$\ddot{\varphi} = k_{mo}\dot{\psi}_{mo}e^{-c_4|\dot{\psi}_{mo}|}e^{-c_5 d_{mo}} \tag{23}$$

The term $(\dot{\psi}_i)(e^{-c_4|\dot{\psi}_i|})$ is the heart of the behavioral strategy: maintain variable the angle with the moving obstacle, here described by $\dot{\psi}_i$. The obstacle is less and less repelling as it is more distant to the agent's moving direction, term $(e^{-c_4|\dot{\psi}_i|})$, and that it is geographically distant, term $(e^{-c_5 d_i})$.

Scheduling The model was not originally designed for simulation purposes. It is a synchrone model, which can be reasonably discretized over time and used in a multiagent simulation as in Bonneaud et al. (2012).

All the components may be computed at each agent activation and then their contributions being summed.

6.5 Details

6.5.1 Initialization

Same considerations as for the other models.

6.5.2 Submodels

Seek the goal. This component of the agent's behavior can be implemented using the sub-model "*steering to a stationary goal* (Eq. 21). The variation of the velocity when the agent arrives close to its goal can be simulated using the model proposed in OpenSteer (Eq. 2).

Separation. Eq. 23 gives a solution for an agent to avoid a moving obstacle. It could be a candidate for the modeling how agents keep a distance with their close neighbors.

Cohesion. It results from the tendency for agents to get closer from each over. This component may be achieved by the right balance between "*avoiding a moving obstacle*" (Eq. 23) and "*Steering to a moving target* (Eq. 22).

Alignment The model does not hold a specific component to support this behavioral component. It is interesting to assess whether tis component has to be explicitly introduced into the model or not.

References

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