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VEHICLES TRAFFIC SIMULATION USING THE SOCIAL FORCES MODEL

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Abstract. *This article presents a mathematical-computational procedure aimed at simulating the behavior of passenger vehicle drivers moving in a small urban traffic network, a topic of great relevance for the development and future operation of autonomous vehicles. The kernel of the system is a set of second-order differential equations build upon the social forces model, proposed in 1995 by Helbing and Molnár to investigate the dynamics of crowds. These 'forces' are, in fact, vectorial functions that describe the action of human agents, as they move in a given environment. In this article, the dynamic model includes social forces that try to represent the driver's instantaneous intention when driving on urban roads, thus allowing to simulate characteristic traffic actions such as overtaking vehicles and taking care of obstacles. The results of the simulations indicated that the system dynamics is intrinsically capable of avoiding collisions between vehicles and between a vehicle and a fixed obstacle, even in high risk situations.*

Keywords: *social forces, driver behavior, multiagent systems*

1. Introduction

The intense competition between the automotive industries implies that, each year, vehicles equipped with increasingly complex automation resources are released on the market, a trend that should strengthen in the coming years, pari passu with the progress of assistive technologies based on Artificial Intelligence. Autonomous vehicles, capable of operating without any human interference, are already being tested (Dikmen and Burns (2017); Liu *et al.* (2020)) in specialized applications, such as the delivery of goods, for example (Kapser and Abdelrahman (2020)), and it is expected that this will be a constant trend in near future.

To implement a transport system based on autonomous vehicles - level 5 of the SAE classification of vehicle automation levels (Ross and Guhathakurta (2017)) - it is essential to reproduce the negotiation strategies used by drivers to safely deviate from obstacles and, simultaneously, follow optimal trajectories towards the desired destinations.

Like every typical problem in the domain of Complex Systems (Bar-Yam (2002)), the unpredictability of driver's behaviour in traffic requires the use of mathematical models that describe the evolution of the system, whether at the macroscopic, mesoscopic or microscopic scale.

The macroscopy approach is based on Continuum Mechanics, describing the dynamics of the system through partial differential equations similar to the Navier Stokes equations (Hughes (2002)).

In the mesoscopic approach, it is assumed that each element of the system moves in space in a stochastic way; therefore, equations analogous to those of the Kinetic Theory of Gases and computational methods based on Boltzman meshes, are applied to descrive the evolution of the system (Johansson *et al.* (2008)).

In the microscopic approach, each element of the system moves autonomously according to predetermined rules built from mathematical criteria and methods. In the literature, microscopic models based on cellular automata (Burstedde *et al.* (2001); Han and Ko (2012)) and on rules generated by Game Theory are very frequent (Bui and Jung (2018); Wu *et al.* (2018)). However, the social forces model (Helbing and Molnar (1995)) has proven effective in describing the decision-making mechanism of human agents moving competitively in a constrained environment. These 'forces' are, in fact, vector functions of a repulsive nature, derived from a monotonically decreasing potential function. Due to these characteristics, they are able to avoid collisions and attract the agents to the desired positions.

These models had their genesis in a seminal article by Helbing and Molnár (Helbing and Molnar (1995)), who proposed a set of mathematical functions, called social forces, which seek to measure the degree of motivation to perform certain actions by human agents that move in clusters.

It is important to emphasize that the social forces model proposed by Helbing and Molnár (1995) described the behaviour of pedestrians in a crowd. Huang *et al.* (2012) and, more recently, Yoon and Ayalew (2019), extended the use of social forces model to represent the actions of drivers driving on highways and city streets

The present paper aims to show that the social forces model proves to be effectively robust in preventing crashes even when drivers perform risky maneuvers. All results reported here are based on the version of social forces adapted by Huang *et al.* (2012) to model the actions of drivers in traffic.

2. The social forces model

In this model, the psychological sensations of the human agents, relative to the phenomenon under study, (such as, for example, fear of a collision or desire to reach a certain place) are defined as 'social forces'. Assuming that the agents have unitary 'mass', the social forces, when vectorially added together according to a law analogous to Newton's second law, give rise to a system of second order nonlinear differential equations. The social forces model provides for several categories of 'forces'.

The target social force attracts the agents to their destinations, following a path defined by circular areas, whose centers form a set of n points $\vec{r}_\alpha^1, \vec{r}_\alpha^2, ..., \vec{r}_\alpha^n$, where $\vec{r}_\alpha^n$ is the final destiny.

Supposing that $\vec{r}_\alpha^k$ is the next goal to the agent in position $\vec{r}_\alpha(t)$, then its desired direction $\vec{e}_\alpha$ is defined by:

$$\vec{e}_\alpha := \frac{\vec{r}_\alpha^k - \vec{r}_\alpha(t)}{||\vec{r}_\alpha^k - \vec{r}_\alpha(t)||} \tag{1}$$

and the target social force $S\vec{F}t$ is given by

$$S\vec{F}t = \frac{1}{\tau} \cdot (v_0 \vec{e}_\alpha - \vec{v}_\alpha) \tag{2}$$

where v_0 is the desired speed, $\vec{v}_\alpha$ the current velocity, and τ a scale parameter of the agent.

Object social forces avoid collision between agents or between an agent and an edge belonging to any fixed obstacle. These forces are given by the gradient of a monotonically decreasing potential function:

$$S\vec{F}o := -\beta_1 e^{-\frac{||\vec{r}_p(t+\Delta t)||}{\beta_2}} \frac{\vec{r}_p \cdot \vec{v}_\alpha}{||\vec{r}_p \cdot \vec{v}_\alpha||} \frac{\vec{r}_p}{||\vec{r}_p||} \tag{3}$$

where β_1 and β_2 are scale and sensibility parameters, respectively, $\vec{r}_p = \vec{r}_\beta - \vec{r}_\alpha$ is the relative distance between the agent and the obstacle, and Δt is the agent's forecast time. The factor $\frac{\vec{r}_p \cdot \vec{v}_\alpha}{||\vec{r}_p \cdot \vec{v}_\alpha||}$ was included in the expression 3 to amplify the magnitude of the forces when two agents move toward a collision.

In Equation 3, if the obstacle is static, then $\vec{r}_p(t + \Delta t) = \vec{r}_p$; if the obstacle is dynamic, then $\vec{r}_p(t + \Delta t) = \vec{r}_p + \vec{v}_p \Delta t$, where $\vec{v}_p = \vec{v}_\beta - \vec{v}_\alpha$ is the relative velocity between the agent and the obstacle.

Then, by introducing into Newton's second law the expressions 2 and 3, one finally arrives at the differential equations of the system:

$$\frac{d^2 \vec{r}_\alpha}{dt^2} = \sum_B S\vec{F}o + \sum_\beta S\vec{F}o + S\vec{F}t + \vec{n} \tag{4}$$

where B are static obstacles, β is any other agent, $\vec{r}_\alpha$ is the agent's position, and the term $\vec{n}$ represents the inherent uncertainty of this model.

In this simplified first version model, agents are treated as material points of unity mass. Clearly, this is a radical simplification, but it has proved necessary to facilitate the investigation of the effects of social forces on the system. In future versions of the model, vehicle dimensions will be considered and more refined kinematics models (as, for instance, the one described in Li *et al.* (2012)), will be adopted.

3. Definition of Scenarios

To properly implement the social forces model, simplified scenarios were simulated so that the isolated action of each of the forces could be analyzed.

Scenario 1 aims to investigate the ability of a driver to modify the direction of the vehicle when it is heading towards a fixed obstacle. In scenario 2, two vehicles are moving towards each other; thus, one can examine how repulsive forces act to avoid collision with moving obstacles. In scenario 3 the effect of the target social force is analyzed; to do so, an abrupt curve is considered and 'desired areas' along the road are defined.

After verifying the behavior of the social forces model in the simple scenarios 1, 2 and 3, more realistic traffic geometries were investigated.

Scenario 4 is designed to simulate the overtaking process: on a two-lane highway, vehicle A, that is behind B, maneuvers so as to get in front of B. Scenario 5 is intended to examine a high-risky situation: on a two-lane highway, a driver loses control of the vehicle, and it enters into the neighboring lane in an uncontrolled manner. Finally, scenario 6 investigates the behavior of drivers who, at an intersection with no traffic lights, each head in their desired direction and desired speed.

It is important to emphasize that the scalar parameters in equations 2 and 3 were defined by trial and error process, until the simulation results proved to be credible. In this way, different scenarios responded better to different sets of parameters. This is the weak point of the social forces model, as already stressed in the literature (Kretz *et al.* (2018); Bassoli and Vincenzi (2021)). In future versions of the model, those parameters will be estimated with the aid of optimization techniques and by confronting real and simulated traffic data.

In all scenarios, the tracks are defined by a set of interconnected straight lines and the repulsion forces to fixed obstacles are calculated assuming the smallest distance between the agent's position and the edges of the obstacle.

Naturally, in a real implementation of an autonomous vehicle system, this information should be provided by proper sensors that detect obstacles and estimate distances (Campbell *et al.* (2018))

4. Implementation

All the procedural and object oriented resources of Python have been used to implement the traffic simulation code, whose main elements (see Figure 1) are described in the following.

There are 3 classes defined in this implementation. "Agent" represents the punctual vehicles that are subject by social forces, and their movement characterize the heterogeneous system. "Border" is the delimitation of the roads, defined by straight lines. And "desired_area" is a circular space that the agent want to achieve.

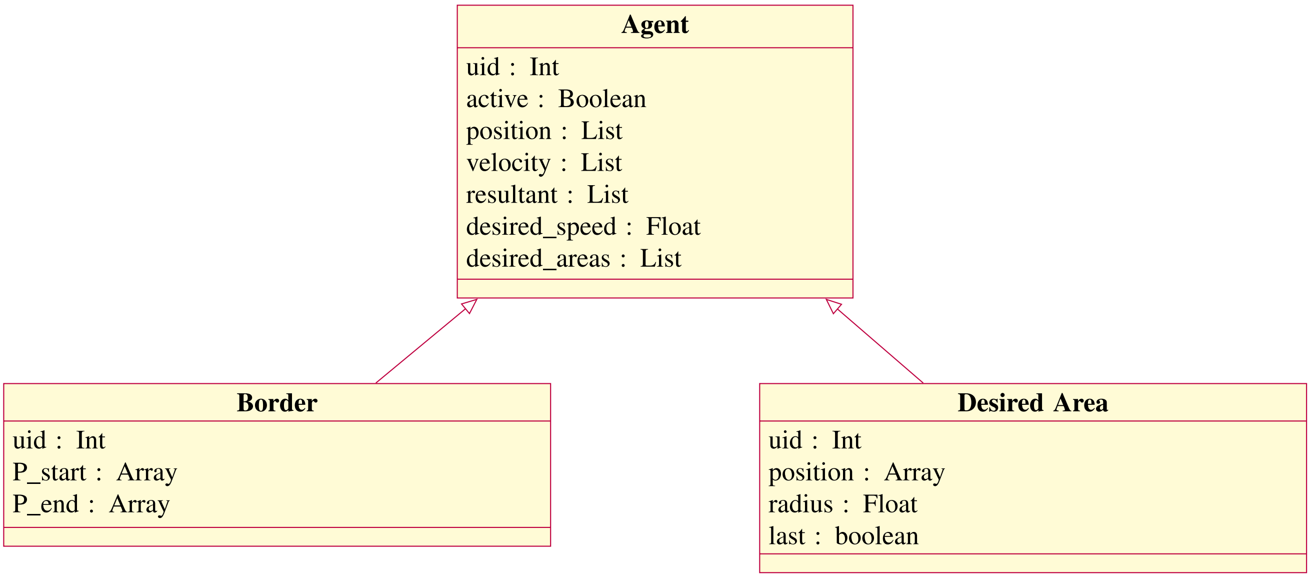

Figure 1. Object diagram

The "agent" object has these attributes: a) Uid: agent's identity; b) Active: on if the agent has already arrived to its destiny, off otherwise (and its velocity is turned to identically null); c) Position: agent's coordinates; d) Velocity: agent's V_x and V_y velocity components; e) Resultant: F_x and F_y components of the resultant force acting on the agent; f) Desired speed: an input of the target social force; g) Desired Areas: a list composed by objects *Desired Area* to set the path and the destiny that the agent must run.

Furthermore, this class has these implicit methods: a) *check_agent_in_area*: check if the agent has already achieved its destiny, the final *desired_area*. This function returns a boolean variable that is useful for changing the status "Active" of the agent; b) *desired_direction*: uses the center of the next desired area to set the agent's velocity direction. This direction is given by Equation 1, and used to calculate the target social force (see Equation 2)

The *desired area* object is a circular area, defined for each agent. A set of these areas form a path that the agent must follow, until reaching the *final area*, his destination. This object has the following attributes: a) Uid: areas's identity; b) Position: coordinates of the circular area's center ; c) Radius: circle radius value; d) Last: set on if the desired area is the agent's final destination, and off otherwise;

The *border* object represents the edge of the road. It has a method to calculate the distance between agent and border, and these following attributes: a) Uid: Border's identity; b) P_start: x and y coordinates of the first point that defines the edge ray; c) P_end: x and y coordinates of the second point that defines the edge ray;

All of these objects interact with each other through procedural functions and data structures that store sets of instantiated objects of each class.

Equation 4 was solved by using the Runge Kutta 4th order method with a step size $h = 0.01$, assuming agents as punctual, and the term $\vec{n}$ was assumed null. The algorithm was implemented in Python 3.0, using Anaconda Spyder 3 as IDLE and its libraries Matplotlib to graphic plotting and Numpy to manage and operate vectors.

5. Results

The obtained results are discussed in the next topics.

5.1 Scenario 1 - Testing the colision avoidance behavior

In the first Scenario, one agent departs from the middle of the road to an edge to test the anti-collision behavior for static obstacles, with initial velocity $\vec{v}_0 = 10i + 1j$m/s.

In Figure 2 it can be seen that the agent changed its trajectory as it approached the border of the runway. Since the minimum distance between the agent and the edge during the entire simulation was 3.29m, one can verify the efficacy of the repulsive force for static obstacles in avoiding collision.

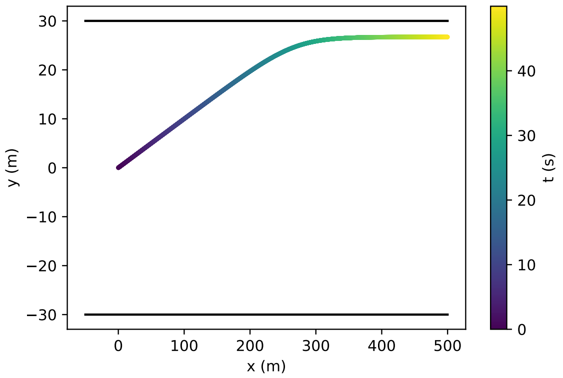

Figure 2. Scenario 1: Agent movement

5.2 Scenario 2 - Front collision

Scenario 2 simulates two agents moving in the same directions in a road, but in opposite way, one against the other, in similar initial conditions. The aim of this scenario is to examine the anti-collision behavior for dynamic obstacles of the agents.

In Figure 3, the agents move against each other, and deviate to opposite sides on the imminence of collision, where the agents are 2.73m apart.

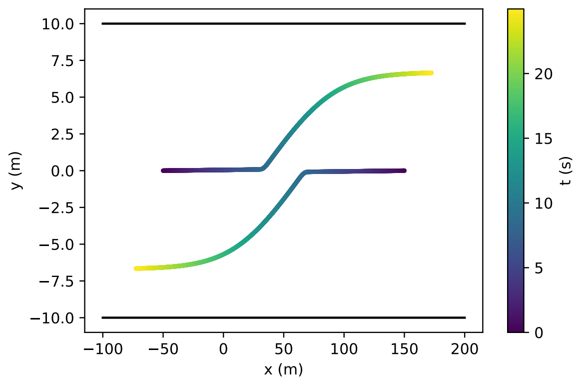

Figure 3. Scenario 2: Agents movement

5.3 Scenario 3 - Target Social Force

This simulation was performed to assess the target social force, therefore an agent is forced to maneuver in an abrupt curve, following a predefined path, thanks to the action of the *desired areas* (illustrated in Figure 4 as pink circles) associated with certain positions in the road network.

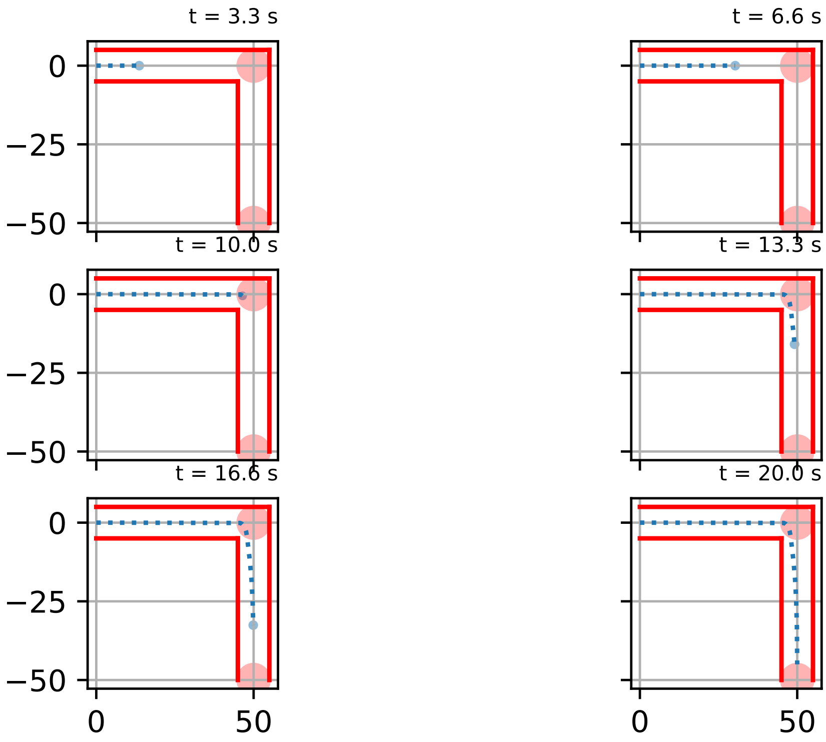

Figure 4. Scenario 3: Agents movement

5.4 Scenario 4 - Overtaking in a road

In this scenario, a lane change overtaking is simulated. Three agents are placed on a street. The blue agent drives at a much faster speed than the others, but is behind then. Figure 5 illustrates the overtaking process, showing that, after some time, the agent manages to overtake the other vehicles with great speed.

Although successful, the simulation shows how dangerous this behavior can be, since the agents came to be excessively close, within a distance of 0.5m.

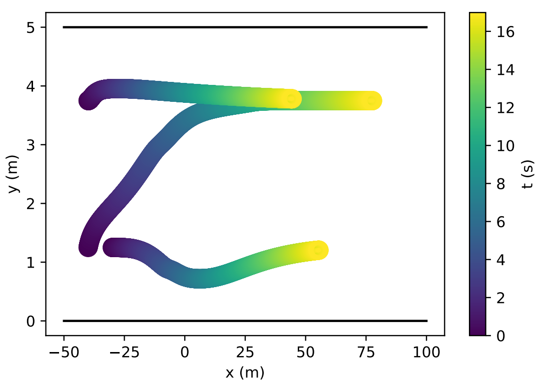

Figure 5. Scenario 4: Agents movement

5.5 Scenario 5 - Two way road

This scenario seeks to simulate agents moving in two opposite directions in a highway. The random conditions for $n-1$ agents are consistent with the rules of traffic: their velocities are aligned with the direction of lanes. However, one of the agents that moves from right to left exhibits anomalous and unexpected behavior, invading the opposite lane.

Figure 6 illustrates the movement of the agents, and it can be seen that the agent exhibiting anomalous behavior managed to get back on trail after some time. Its important to highlight that all the agents got very close to each other, featuring a very dangerous move.

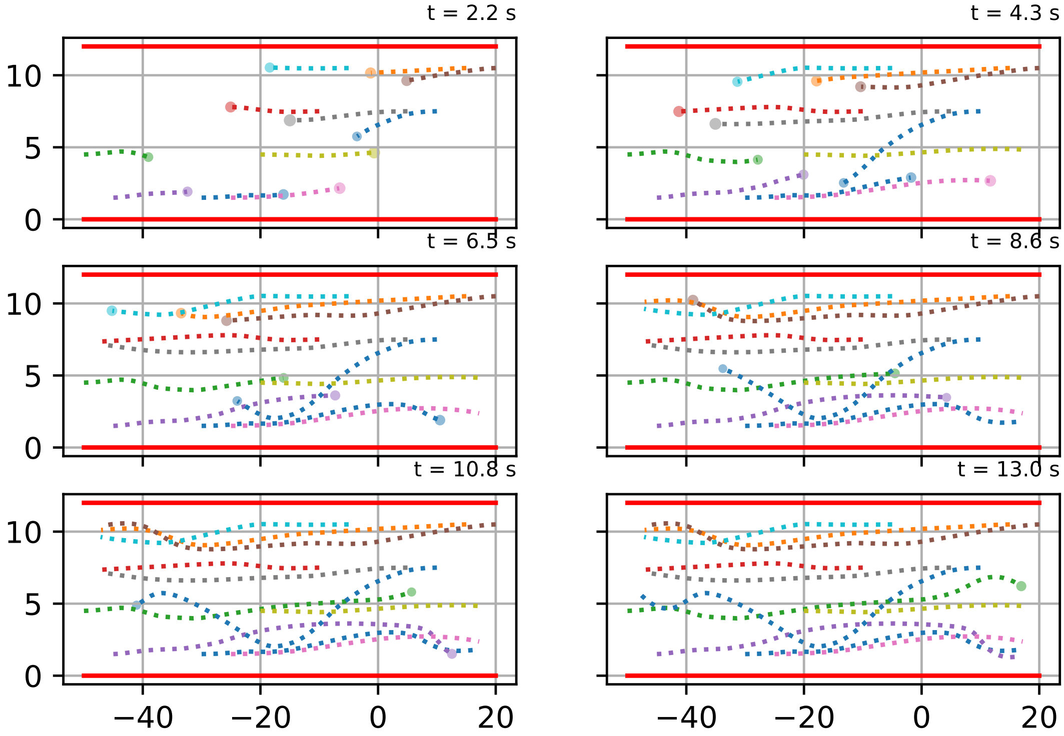

Figure 6. Scenario 5: Agents movement

5.6 Scenario 6 - Crossroads

In this scenario it is simulated a high-risk situation: a crossroads with several vehicles crossing it without traffic lights. All the agents were placed in different starting positions, with different starting velocities, and different desired speeds.

In Figure 7 it is possible to see that the agents get much closer to each other, even reaching a minimum distance of 0.5m. However, a real colision did not occur, since the social forces achieves a very high value when the distance between agents diminishes substantially, with the smallest computed distance of 0.71m.

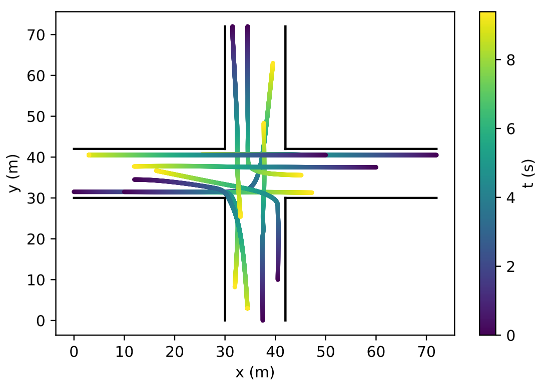

Figure 7. Scenario 6: Agents movement

6. Conclusions

In this article, social forces Helbing and Molnar (1995) were used to describe the behavior of an autonomous vehicle system. Despite the geometric and kinematic simplifications introduced in the model, the simulations indicated that the system dynamics is intrinsically capable of avoiding collisions between vehicles and between a vehicle and a fixed obstacle, even in high risk situations. In the next phase of the project, geometric data and kinematic equations characteristic of passenger vehicles will be introduced in the model. From then on, it will be possible to design an autonomous vehicle management system, where the dynamic model based on social forces will operate as an interface between the measurement system (based on distance sensors embedded in the vehicles and installed along the roads) and the powertrain control system of each vehicle.

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