Future Virtual Particle Method for Pedestrian Navigation

Castiglione Gonzalo, Agustin Marseillan, Daniel Parisi

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Abstract

We present a novel method to simulate virtual pedestrians based on the social force model. In our model, each pedestrian has a point in front of him called Future Virtual Particle (FVP) which represents where the pedestrian is headed to and at what speed.

keywords:
pedestrian, collision avoidance, future virtual particle, force model

1 Introduction

1.1 Motivation and previous work

Navigation of biological, sinthetic or virtual agents is a relevant problem in several fields such as pedestrian dynamics, moving robots and animation of characters for videogames and motion pictures.

Modelling and simulating the displacement of agents through arbitrarily complex environments may be stated in an hierarchical structure of mechanisms depending mainly on the distance from the agent. This level has been named, from closer to further, as operational (walking, lowest level physical-computational model for displacement), tactical (way-finding, route choice) and strategic (general activity planning) [Hoogonen and Bovy 2004]. These levels are not independent, factors affecting one level may impact in the following and vice-versa, for example, the route choice may vary due to congestion of agents produced from previous route choice and walking behavior. Also, obstacles can impact on the operational level or tactical level depending on the particular geometry of the environment. The particular mechanism we want to address is the avoidance of obstacles being fixed or moving (another agent) which involves operational and tactical aspects of the navigation.

A general approach is to take an existing operational model and equip it with a higher level model which allows better and smoother collision avoidance behavior. Existing low level models can be taken from pedestrian dynamics field and in general this models can be classified into rule based and force based, discrete and continuous space description, etc. [Schadschneider 2009].

A famous example of continuous and force based model is the Social Force Model [Helbing 1995, 2000]. In this model the dynamic for virtual pedestrians is derived from the Newton equation's considering the total force exerted over each agent is the result of three forces: Contact, Social and Driving Force. While the driving force points towards the final objective of each pedestrian, the social force is repulsive and acts as a kind of collision avoidance force. However this social force term introduces several artifices in some configurations [see for example Lakoba et al. 2005, Parisi et al 2009].

Cellular automaton models make use of a spatial grid, which can be occupied or empty, along with a set of rules determining the evolution and conflict resolution of virtual pedestrians moving over the cells of the grid. An emblematic cellular automaton model is the one proposed by Kirchner and Schadschneider [2002].

Hybrid models have also been proposed such as the Contractile Particle Model [Baglietto and Parisi, 2011] in which a continuous description of the space is combined with a set of simple rules governing the dynamics of the system.

The basic operational model -as the ones described above- can be improved if higher level mechanisms were added to manage more complex issues as efficient avoidance. Some recent examples can be found in the literature.

Karamouzas et al. (2009) proposed a method for collision avoidance modifying the social force model, basically, replacing the social force term by a new "evasive" force which tends to avoid future collisions. The magnitude and direction of this force is calculated considering the predictions of these possible collisions.

Kretz et al. 2011 have arrised the point that the key ingredient in social force model is the driving force instead of interaction force, so in this work the authors propose a method for dynamically adjusting the desired velocity following the gradient of a field given by a time map, in other words, the desired velocity is chosen as the quickest path to the objective taking into account the geometry and other agents (collision, congestion, jams, etc.). Also mounted on the SFM, MoussaÃ¯d et al. [2011] presented a model using "cognitive heuristics" to determine the norm and direction of the desired velocity for each agent dynamically during the evolution of the system.

In the same line, we also proposed that the navigation capacity of virtual agents should be concentrated in the on-line decision of the desired velocity. Both direction and magnitude calculation of the desired velocity are the key differences with the SFM.

The method proposed could be mounted on different basic displacement models like the SFM or the CPM, in the present work we have chosen the first one.

1.2 Social Force Model

The Social Force is a model presented by Helbing [1, 2] in several publications. This paper will focus on the latest version of the model [2]. In his model, each pedestrian i occupies a circular area of redius r_i and is governed by thee forces.

$$\vec{F_i} = \vec{F_{D_i}} + \vec{F_C} + \vec{F_s}$$

This forces are a measure for the internal motivations of the individual to perform certain actions.

The first term is known as the "Driving Force". It's calculated as follows:

$$\vec{F_{D_i}} = m_i \frac{v_{di}\vec{e_i} - \vec{v_i}}{\tau} \tag{1.1}$$

$$\vec{e_i} = \frac{\vec{x}_i^k - \vec{x}_i(t)}{||\vec{x}_i^k - \vec{x}_i(t)||} \tag{1.2}$$

$\vec{F}_{D_i}$ represents the force that a pedestrian i keeps towards his desired velocity of motion.
v_{di} is the desired speed for the pedestrian i.
$\vec{e}_i$ is the desired direction of motion of the pedestrian i.
$\vec{v}_i$ is the current velocity of the pedestrian i.
$\vec{x}_i(t)$ is the actual position of the pedestrian i at the time t.
x_i^k is the closest point from the goal (represented as an area) to pedestrian i.

Figure 1.1 shows an example of a pedestrian currently moving in direction of $\vec{v}$ but adjusting its trajectory towards X.

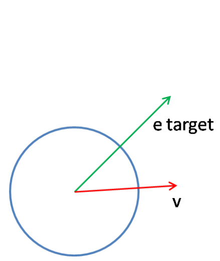

Figure 1.1: Driving force

The second term is known as the "Social force". It's calculated as follows:

$$\vec{F}_{S_i} = \sum_{j=1, j\neq i}^{N_P} Aexp(-\frac{\epsilon_{ij}}{B})\, \vec{e}_{ij}^{n} \tag{1.3}$$

$\vec{F}_{S_i}$ represents the fact that a pedestrian keeps a certain distance to other pedestrians and borders.
N_p is the number of existing pedestrians.
A and B are constants determined by simulations.
ϵ_{ij} is the distance from x_i towards x_j.
$\vec{e}_{ij}^{n}$ is the unit vector from x_i towards x_j.

Figure 1.2 shows 1.3 graphically.

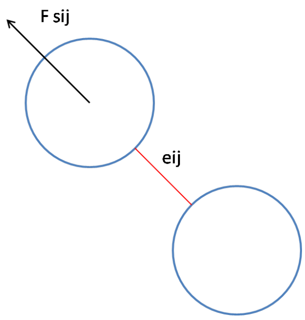

Figure 1.2: Social Force

The third term is known as the “Granular force”. It’s calculated as follows:

$$\vec{F}_{G_i} = \sum_{j=1, j\neq i}^{N_P} [-\epsilon_{ij} k_n \vec{e_{ij}^n} + v_{ij}^t \epsilon_{ij} k_t \vec{e_{ij}^t}]\, g(\epsilon_{ij}) \tag{1.4}$$

$\vec{F}_{G_i}$ represents the physical force that a pedestrian suffers when colliding with another object (pedestrian or wall).
k_n and k_t are the normal and tangential friction coeficient respectively.
g is ???

Figure 1.3 shows 1.4 graphically.

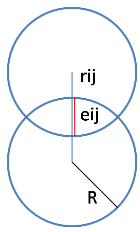

Figure 1.3: Colliding pedestrians

Afterwards $\vec{F_i}$ is calculated on each simulation step for each of the pedestrians and applied until all of them had reached their goal.
Fixed parameter values:

Name	Value
A	$2000\,[N]$
B	$0.08\,[m]$
k_n	$1.2\,10^5\,[\frac{N}{m}]$
k_t	$2.4\,10^5\,[\frac{kg}{m/s}]$
τ	$0.5\,[s]$

While this model doesn’t present a very real behaviour for pedestrians, it worked as a starting point for numerous projects.

1.3 Future Virtual Particle Model

Given that the SFM adds a fictional force on pedestrians, navigation doesn’t resemble reality for high pedestrian densities. Also, SFM didn’t have the same values as well known metrics for real-case scenarios such as the flow of pedestrians going out a door and the fundamental diagram.

Because of this, we present a new model in which the social force from equation 1.1 affecting directly on each pedestrian is eliminated and replaced with a desire force facing a short term objective. This force is created using equation 1.2 replacing r_i^k with the vector facing the closest point on the short term objective area.

2 The Model

2.1 Hipotesis

The main effects that govern the motion of a pedestrian are the same as Helbin's:

1. The pedestrian wants to reach his goal in the shortest possible path.
2. The pedestrian's movement is influenced by other pedestrians. Depending on the distance between the two of them and the predicted trajectory, the pedestrian will feel the need to change his route to be able to avoid the other pedestrians. It is because of this effect that pedestrians will need to recalculate their route as new pedestrians get closer to them.
3. Movement speed will be influenced by needs.

2.2 Geometrical definition

A pedestrian is defined as follows:

- Circular shape

  Represents the space that this pedestrian occupies. Circle's radio is generated randomly to represent different types of pedestrians. The range of values is distributed uniformly in $[0.25, 0.29][cm]$.

- Long term objective

  Represented by a static area. When it is touched by a pedestrian, it is considered as accomplished. Multiple objectives can by defined in a list, in this case, each of them must be reached in order.

- Short term objective

  Called future virtual particle (FVP), it represents a point at a relative distance from the pedestrian's center. It's a dynamic objective.

  It is defined as a $1\,[kg]$ mass. Not collisionable.

- Desired speed

  Represents the speed the pedestrian would walk if he was alone. Varies with a uniform distribution between $[1.2, 1.4]\,[m/s]$.

- Reaction distance (RD)

  Maximum distance between a pedestrian and his FVP, it represents the distance at which a real pedestrian would react from an obstacle.

Figure 2.1 shows a pedestrian geometrical definition:

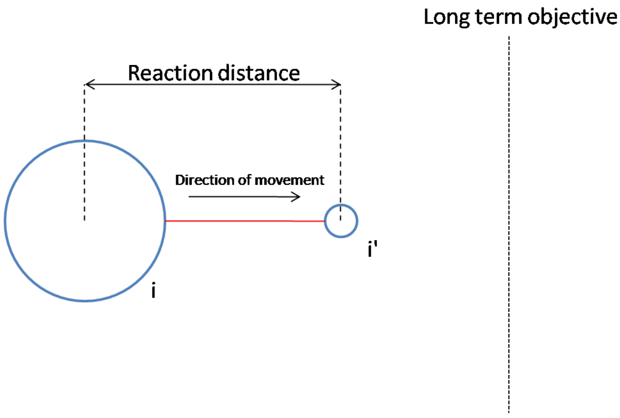

Figure 2.1: Pedestrian top view

Pedestrians will be named after a letter (i.e: i or j) and the same letter with a apostrophe will represent it's FVP (i.e: i' or j')

Figure 2.2 shows all the vectorial definition that will be used:

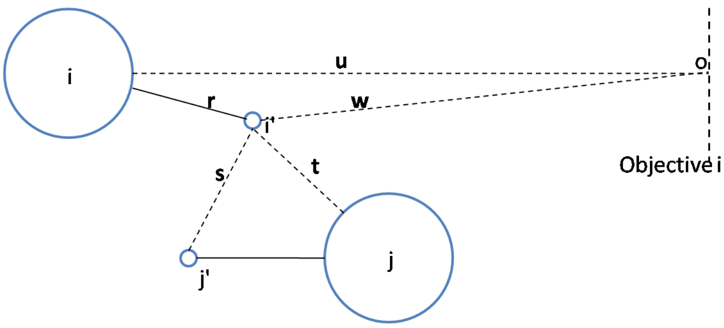

Figure 2.2: Vectorial definitions

2.3 Dynamics of the FVP Model

In this section all the forces acting on the FVPM will be defined

2.3.1 Forces

- Dynamic of the FVP

  Each pedestrian has to reach the long term objective at some point, to ensure this, the FVP needs to be aligned with the shortest path to the long term objective $\mathbf{o}$. On the other hand, there are sometimes obstacles in the way, which will make this impossible, in this cases, the route will have to change depending on the situation.

  To model this situations, two types of forces act over the FVP:

  - Internal force

    This force will guide the pedestrian on the shortest path $\mathbf{ox_i}$ and minimize the time needed to reach the long term goal. This force is modeled using two springs:

The first spring starts on $x_{i'}$ and ends on the point at distance RD on vector $\mathbf{x_i o}$ with a spring constant K_1. This spring represents how much the pedestrian wants to reach his target. A larger spring constant will force a more straight path, but possible with more collisions on its way. In order to avoid an oscillatory movement (i.e: with a single pedestrian), a damping γ was added to this spring.

The second spring starts on x_i, ends on x_i' and has a steady distance of RD with a spring constant $K_s(\theta)$ where θ is the angle between $\mathbf{u}$ and $\mathbf{r}$. With this spring the FVP will tend to always be at RD distance from the pedestrian. Because a pedestrian always tries to reach his goal in the shortest possible path (hypothesis 1), if it has to take a big detour of his ideal path, it will try to reduce his velocity drastically in order to avoid making a long travel. To recreate this, the spring constant has to be dependant of the deviation angle.

$$K_s(\theta) = \frac{K_2}{\theta}$$

Given pedestrian i, the equation for his internal force is:

$$F_{internal}(i) = K_1 * (|r| - RD) + K_2(\theta_i) + K_2(\theta_i) * (???) \tag{2.1}$$

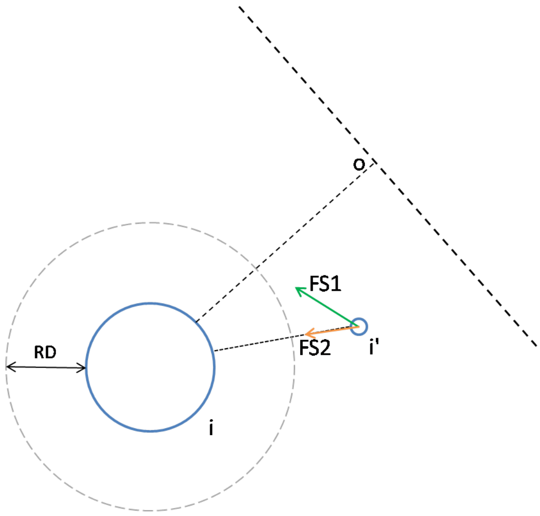

Figure 2.3: Pedestrian internal forces

– Avoidance forces

This force will produce avoidance movements when obstactes are detected on the path. The magnitude of this force is calculated using two factors:

The first factor is calculated for each of the pedestrian j ($j \neq i$) who is in the range of sight of pedestrian i. This restriction is verified using the following condition:

$$\mathbf{r_{ii'}} \bullet \mathbf{r_{ij'}} < 0$$

This filter represents the fact that a pedestrian (in most cases) does not make decisions based on obstacles behind him. Hence, they are ignored. The formula for the external forces that the FVP i feels is defined as follows

$$F_{ext}(i) = \sum_j F_{i',j'} + F_{i'j} = \sum_j (\alpha_{ff} e^{-dist(i',j')/\beta_{ff}}) + \sum_j (\alpha_{fp} e^{-dist(i',j')/\beta_{fp}})$$

where α_x and β_x are predefined constants.

The first term of the sum acts as a repulsion force between i and j FVPs, resulting in the avoidance of a future collision. The second term uses this same principle but calculates the repulsion force between $j's$ FVP and i. Repulsion against walls is calculated in the same way, by using the closest point between the FVP and the wall and special values for α_{fw} and β_{fw} for the calculation.

Figure 2.4 shows the external forces that a pedestrian i suffers because of another pedestrian (j) and also the direction in which i desires to move.

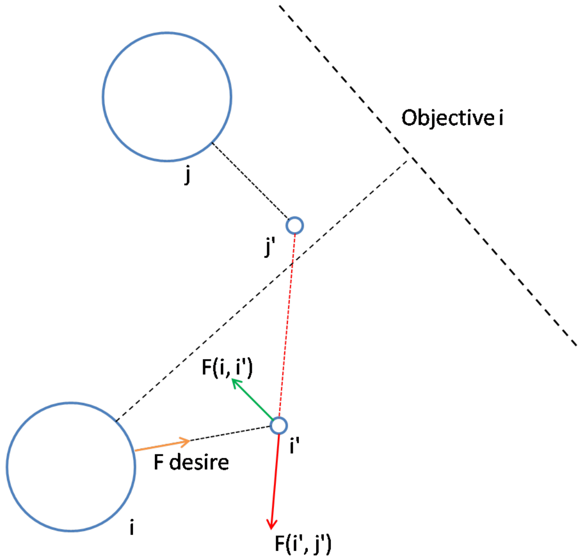

Figure 2.4: External forces affecting future i'

After this, the final $F_{i'}$ is computed by adding all the terms. $F_{i'} = F_{ext}(i) + F_{i\,s1} + F_{i\,s2}$.

To avoid high symetry situations, a low noise $P = 10\%$ is added to F. There are two ways to apply this noise:

- Radial noise:
  - A value p is taken randomly from a uniform distribution $[-P,\, P]$ and calculate: $FL_{i'} = F_{i'} * p$
  - Angular noise:
    - A value $sgn = \{-1,\, 1\}$ is taken randomly from a uniform distribution and a value p from $[-P,\, P]$. Then $FA_{i'} = rotation(F_{i'},\, \pi * sgn) * p$ is calculated.

  At last, we find $F'_{i'} = F_{i'} + FL_{i'} + FA_{i'}$ and apply movement equations.

- Dynamic of the pedestrian

  The pedestrian always wants to move in the direction his FVP is pointing and its magnitude is defined as F_d or desire force:

$$F_{desire_i} = m_i \frac{\frac{|\vec{ii'}|}{|\vec{r}_{max}|}\vec{e_i} - \vec{v_i}}{\tau}$$

  Where $\tau = 0.5$

  **It is important to note that the only deviation from the SFM in this equation is the $k\vec{e_i}$ term. As described above, this model focuses on improving the SFM through dynamically adjusting the desired velocity.*

2.3.2 Algorithm

The pedestrian movement is calculated in four steps:

1. Calculate forces for each FVP.

2. Update positions for each FVP.
3. Calculate forces for each pedestrian.
4. Update positions for each pedestrian.

3 Calibration

3.1 Metrics

The results where compared to the SFM [2]. The test scenarios where crossing and hallway for they present the main types of symmetry (90 degrees and 180 degrees respectively).

The metrics used where:

1. Number of collisions

   The total amount of collisions between pedestrians.

2. Total duration of collisions:

   The sum of the duration of each collision.

3. Average walking speed:

   The average of the average speed of each pedestrian.

4. Average travel time:

   The average time that a pedestrian needed unit it reached the goal.

5. Average travel distance:

   The average distance that a pedestrian traveled unit it reached the goal.

6. Average turn angle:

   The average angle turned by a pedestrian unit it reached the goal.

3.2 Values

To calibrate the model, runs varying parameters were made. A wide spectrum of values was covered, testing every combination of every possible one. After seeing clear preferences towards certain values, the values were refined within that scope. After numerous iterations of this process, the values that best suit these metrics are$\alpha = 800$ y $\beta = [0.65, 085]$ uniformly distributed.

//TODO todos los demas parametros

4 Results

Values	1	2	3	4	5	6
$\alpha = 1000$, $\beta = [0.4, 0.5]$	(1.800, 0.748)	(34.600, 8.333)	(1.024, 0.016)	(1.910, 0.022)	(2.392, 0.005)	(111.062, 19.122)
$\alpha = 2000$, $\beta = 0.08$	(5.333, 2.625)	(12.333, 8.340)	(1.052, 0.003)	(1.876, 0.003)	(2.391, 0.002)	(106.185, 13.778)

Table 1: Metrics comparing SFM vs FVPM. Average of 10 runs.

// Poner Graficos indicando distancias y esquemas del future y la particula.

5 Conclusions

// agregar al final futuras opciones que se abren con este trabajo

References

[1] Helbing, Dirk; Molnár, Péter (1995). "Social force model for pedestrian dynamics".

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[3] I. Karamouzas (2009). "A Predictive Collision Avoidance Model for Pedestrian Simulation"