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Prediction in Social Path Following

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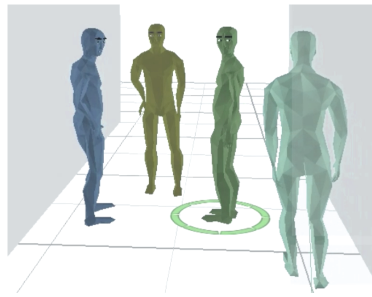

Figure 1: *A conversation group reacts to a passer-by and rearranges to avoid a collision in a tight space.*

Abstract

Path following in games mostly focuses on avoiding collisions with dynamic physical objects that appear along a chosen path to a given destination. Some work also attempts to humanize the abstract path returned by a path finding algorithm through methods like smoothing. Games typically do not consider social factors during path following, even though many depict social environments. Social path following considers the social environment in particular, carving a trajectory that reflects awareness of other human beings and their social activities. This includes awareness of territories that have social significance but no concrete physical form, such as the space between those having a conversation. This paper describes work that extends a state-of-the-art predictive method for path following with social awareness, predicting and avoiding social collisions. The work builds on a platform for social simulation, which already models social territoriality and gaze behavior. The results appear promising and highlight the importance of perceiving and dealing with the social space along with the physical one.

CR Categories: I.3.3 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation I.2.1 [Artificial Intelligence]: Applications and Expert Systems—Games;

Keywords: simulation, path following, social behavior, territoriality

1 Introduction and Motivation

In virtual simulations, such as games, characters need to move around the environment. To simplify the problem, the environment is represented in two dimensions and the motion is managed using a three-layer architecture [Reynolds 1999]: action selection, steering and locomotion. In particular we are interested in the second layer since it relates to path following in a dynamic environment.

We want to construct a convincing path for an agent walking from a start position to a goal position. A high density of other moving agents, complex structures inside the environment and real-time constraints make this quite complex. The shortest path can easily be produced from the global environment through specific algorithms and data structures, but sometimes it is not enough. In fact it does not take into account collisions with dynamic obsticles, realistic motion, congestions and social rules. However, it presents a first approximation and a good start. We use the popular A* algorithm to provide the shortest path through an automatically generated navigation mesh representing the static environment. After this path is found, the focus shifts to addressing path following.

Path following is about adjusting the path without applying strong corrections, avoiding collisions and considering all forces that rule the environment. Therefore social path following means that agents are affected by social forces such as human territories [Scheflen and Ashcraft 1976], social behaviors and body language. We expect a realistic path, without inconsistencies while maintaining good performance. Our method builds on [Karamouzas and Overmars 2010], which uses a velocity-based approach to perform the collision avoidance, adjusting speeds/orientations at each time step. The algorithm is composed of three phases: 1) perception of agents and obstacles through the peripheral vision of the agent setting up a list of neighbors and time contacts; 2) building ranges of available speeds and orientations; 3) discretization of ranges, finding the best combination considering a heuristic function about energy consumption, deviation angle and risk of collision.

We extend this approach by predicting social intentions and movements. We adopt a probabilistic model, monitoring typical behaviors of others that would indicate the start of a conversation between them [Bennett et al. 2010] (approaching space, mutual gaze [Cafaro et al. 2009] and salutation). Each agent becomes aware of approaching spaces and what territories to avoid in order to escape "awkward" social situations (e.g. finding yourself in the middle of someone elses's conversation). To prevent stuck situations, we also simulate social negotiation of space: a sort of a silent agreement, a reciprocal understanding of intentions that forces agents to help each other. Finally, exactly like humans in the real world, we add social protocols and some randomness that make movements even more realistic and unique.

Our model can be applied in a variety of simulations, including

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crowded environments. It is adaptive, so variables and parameters are set up automatically based on available system resources. It is possible to simulate different kinds of people, creating profiles adding more/less energy consumption, social awareness, speed or amplitude of orientation. We developed several scenarios to test and to show the results of our method.

2 Related Work

Many have addressed the path planning problem. We refer the reader to [Duives et al. 2013] for an exhaustive view of the state of the art and a comparison and classification of general simulation models. In particular this analysis evaluates each approach in dense environments. Simulating social interactions we are mostly interested in new methods based on social forces and behaviors. Craig W. Reynolds provided a solid foundation for this work with his contributions on steering behaviors [Reynolds 2000], [Reynolds 1999]. Understanding motion dynamics, shared rules and stimuli that affect interactions of animals, as well as humans, he proposed mental models and forces to drive reactive agents. Even today, his contribution is an essential starting point for many researchers such as [Ratsamee et al. 2012], [Yamaguchi et al. 2011], [Popelová et al. 2011]. Similar approaches are [van den Berg et al. 2008], [Karamouzas and Overmars 2010] that further emphasize the adjustment of orientation and speed. Mainly these models are focused on solving the collision avoidance in any context through a continuous cycle of perception-reaction, giving autonomy and independence to each agent and ensuring good performance at the same time. Even though robust, a possible drawback is a simulation of too rigid and mechanical movements without integrating social forces and not considering human-like behavior and territories. A social forces algorithm is proposed in [Baig et al. 2014]. Taking into account the sociology literature, the procedure is composed of three modules: path planning, awareness of density crowds and personal reaction bubble. The idea is to drive agents considering motivation, interaction, repulsive and resistive forces differentiating collision types and providing priority.

Another type of approach consists of a data driven model to manage the motion [Lee et al. 2007], [Paris et al. 2007]. The simulation is ruled by a central brain that after getting information from videos of real pedestrian builds trajectories and paths. In this way the system is able to cluster virtual humans and to provide learning rules that include social and psychological factors. Even if [Paris et al. 2007] has similar features to the velocity-based approaches (prediction and best motion calibrated from motion capture data), these approaches do not fit our context perfectly in which each agent is independent and the model is based on perception and reaction phases.

More recently some techniques have been presented to address an aspect of the social problem. They are based on the idea that most people in a crowd actually move in groups walking together [Moussaïd et al. 2010]. Usually the group is composed of 2 to 4 members, there is no rigid patterns of formation and the speed depends on the density of pedestrians. The approach consists of considering groups as single units and the motion is the result of pedestrian motivation, repulsive force with other pedestrian and repulsive force from boundaries. [Karamouzas and Overmars 2012] extend this research trying to model macro/microscopic behaviors: for each time step agents follow the group path but solve its own path following problem autonomously. [Karamouzas et al. 2013] adopt minimization of space and time and is based on a linear programming technique to resolve congestions and prevent deadlocks. Note that a weak point of these methods is not to consider the full dynamic nature of the social space, e.g. by already grouping people together into conversations.

3 Approach

Before going into details of our approach, we need to remember the set up of our simulation: several agents navigate, perceive and interact; the virtual environment is represented by a two dimensional plane; the time is discrete and for each time step a new velocity vector is computed; obstacles that hamper movements are walls or other virtual agents; the first approximate path is computed once using the **A* algorithm**. Our approach builds on the work of I.Karamouzas and M.Overmars [Karamouzas and Overmars 2010]; summarizing the algorithm it consists of three main steps in which agents retrieve other colliding agents, define the range of admissible speed/orientation, find the optimal solution through an heuristic function. We extend these three phases by adding social behaviors and forces.

3.1 Basic Algorithm

During the first step, agents perceive potential colliding obstacles using central and peripheral visual sensors. In other words, by knowing the positions and interpreting velocities of others, the agents predict collisions and build a limited list of potential colliding agents, ordered by expected time of contact. A collision is predicted using the inequality of Euclidean distance:

$$\|(x_j + v_j t) - (x_i + v_i t)\| \leq (r_j + r_i) * incr$$

where x, v, t, r represent respectively positions, desired velocities, time and radii of agent personal spaces.

The second phase determines the set of speeds U_i and orientations O_i that avoid contact with the retrieved colliding agents. In these

$$\Delta\theta_i^{\max}(tc) = \begin{cases} \frac{\delta_{\max} - \delta_{mid}}{e^{tc}} + \delta_{mid}, & \text{if } 0 \leq tc < tc_{\min} \\ \delta_{mid}, & \text{if } tc_{\min} \leq tc < tc_{\text{mid}} \\ \delta_{mid} \frac{tc_{\text{mid}} - tc}{tc_{\max} - tc_{\text{mid}}} + \delta_{mid}, & \text{if } tc_{\text{mid}} \leq tc \leq tc_{\max} \\ 0, & \text{if } tc_{\max} < tc \end{cases}$$

$$O_i = \{\mathbf{n}_\theta \,|\, \theta \in [\theta^{des} - \Delta\theta_i^{\max}, \theta^{des} + \Delta\theta_i^{\max}]\}$$

$$U_i = \begin{cases} u \,|\, u \in [0, u^{\max}], \\ u \,|\, u \in [u^{pref}, u^{pref} \pm \Delta u_i^{\max}], \\ u \,|\, u \in [u^{pref}, u^{pref} \pm \Delta u_i^{\max}], \\ u^{pref}, \end{cases}$$

Figure 2: *Building ranges of speeds U_i and orientations O_i. From [Karamouzas and Overmars 2010]*

formulas (Fig.2) tc represents the time of contact with the most threatening agent, Θ^{des} and u^{pref} are respectively the desired orientation and speed, u^{max} is the maximum speed for agents, Δu_i^{max} is the minimum between u^{pref} and the difference of u^{max} and u^{pref}, $\Delta\Theta_i^{max}$ has the same meaning for orientation. The other variables are actually constants: tc_{max}, tc_{mid} and tc_{min} are intervals of time to give priority to collisions, δ_{mid} and δ_{max} are different amplitudes of the orientation angle.

In order to find a good balance between performance and realism, we need to discretize the sets of orientations and speeds (Fig.3). It is done automatically by the system considering the density/complexity of the environment [Karamouzas and Overmars 2010]. Finally for each step the new velocity vector is computed using an heuristic function that mimimizes energy consumption, deviation angle and risk of collisions. The next section shows the

Approach	Mutual Gaze	Salutation	Conversation
True	True	True	1.0
True	True	False	0.7
True	False	True	0.8
True	False	False	0.1
False	True	True	0.95
False	True	False	0.15
False	False	True	0.3
False	False	False	0.0

Table 1: *Table containing all possible perceived events and the heuristic probability that the perceived agents are about to have a conversation*

complete formula that has been revised in order to include social behavior.

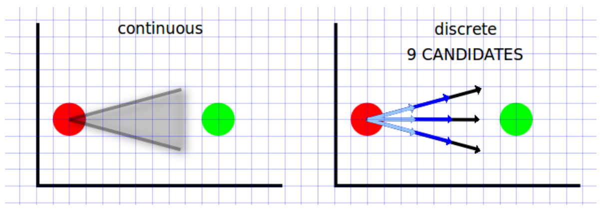

Figure 3: *Transforming ranges from continuous to discrete*

3.2 Prediction

Our agents are powered with social awareness that makes them able to understand territories and to predict social intention. Perceiving velocity vectors (movements related to a single time step) is the essential condition for running the basic algorithm but just by predicting future social interactions we can really improve the behavioral realism. This process is done by interpreting typical signals that appear before a conversation identifying people that are approaching each other. Thus, for each time step, each agent needs to monitor:

- **approach:** Checking if two or more partners are approaching each other. Since sometimes paths are not simple lines due to moving obstacles, using linear regression we can build a line that approximates the motion and intentions of agents. The procedure is able to manage two different situations: 1) two agents that are approaching each other; 2) one agent standing and the other one is approaching.
- **mutual gaze:** A simultaneous, sometimes non-continuous eye contact. A mutual gaze of two/three seconds during the approaching phase usually suggests that people are acquaintances and are going to be engaged in a conversation.
- **salutation:** Recognizable from specific gestures, smiles or a few words. Since right now our simulator does not allow us to simulate this feature the close salutation is approximated by identifying a progressive decreasing of speed during the approaching phase.

Collecting this information makes it is possible to build a probabilistic model that predicts future conversations from perceived signals. Table 1 summarizes our heuristic model showing the probability of a conversation starting between to perceived agents based on all possible perceptions of their activities.

Generating a random value or using a threshold value and comparing it with the assigned probability, the current agent decides whether to consider it a future conversation or not. As result of this procedure we have a new social behavior that consists of respecting human territories avoiding crossing approaching spaces and to interrupt future interactions. It can be used as new cost to the heuristic function (Fig.4):

$$\mathbf{v}_i^{new} = \underset{\mathbf{v}^{cand}\in FAV_i}{\arg\min}\ \{\overbrace{\alpha\left(1-\frac{\cos(\Delta\phi)}{2}\right)+\beta\frac{\left|\|\mathbf{v}^{cand}\|-\|\mathbf{v}_i\|\right|}{u^{max}}}^{\text{Energy}} + \underbrace{\gamma\frac{\|\mathbf{v}^{cand}-\mathbf{v}_i^{des}\|}{2u^{max}}}_{\text{Deviation}} + \underbrace{\delta\frac{tc_{max}-tc}{tc_{max}}}_{\text{Collisions}} + \underbrace{\eta\frac{dist_{max}-dist}{dist_{max}}\cdot\frac{tc_{max}-tcAS}{tc_{max}}}_{\text{Social Territory}}\}$$

Figure 4: *Formula modified from [Karamouzas and Overmars 2010], taking social territory into account when computing the cost of each velocity*

Here v^{cand} represents all candidates from discrete speeds and orientations, v_i is the previous velocity vector, α, β, γ, δ and η are weights assigned to energy (orientation and speed), deviation, collisions and social territory avoidance costs. Minimizing the total cost means finding the best velocity vector to model the motion.

To prevent a deadlock or stuck situations we developed a new human behavior that consists of negotiation of space in accordance with social rules. A typical example is two opposite flows of people using the same gate. We simulate the non-verbal communication transmitted through gaze and body language to request and give others more space, similar to what we see in the real world. This behavior is the result of two different components:

- **active:** Predicting a possible congestion, the agent requests more space gazing continuously at the individual that obstructs its movement expecting a reaction.
- **passive:** Perceiving a continuous gaze, the agent simply increases the space dedicated to the passageway. If it is engaged in a conversition, the reaction produces a rearrangement of the formation.

3.3 Fine Tuning and Profiles

Getting information about the environment, the number of virtual agents and their positions, our simulation is able configure the parameters to balance believability and performance. The main variables affected are the size of the list containing colliding agents (*proportional*), the discretization interval (*inversely proportional*) and the weights assigned to social rules used in the heuristic (*inversely proportional*). The algorithm has been implemented with specific protocols: for example agents prefer to avoid obstacles going on the right or they are able to balance the heuristic costs according to the environment properties. Moreover the general procedure is affected by stochastic factors, something similar to a random force [Baig et al. 2014], that improves believability by producing multiple unique behaviors.

Finally, it is possible to build customized profiles of agents (Fig.5), setting up certain abilities, in order to simulate different types of locomotion and stereotypes of people. For example, a rushed agent does not care about collisions and wants to reach a destination as soon as possible; so we need to give more priority to the deviation cost and reduce the orientation angle. A stealthy agent has exactly the opposite behavior: it gives more priority to collisions (effectively avoiding them) and has more time to reach the destination.

default profile	tc_{max}	8	δ_{max}	90°	α	1	δ	1
	tc_{mid}	6	δ_{mid}	30°	β	0.05	η	0.8
	tc_{min}	2.5	incr	1.5	γ	1	dist	0.1
rushed profile	tc_{max}	8	δ_{max}	50°	α	1	δ	0.1
	tc_{mid}	6	δ_{mid}	20°	β	0.05	η	0.1
	tc_{min}	2.5	incr	1	γ	3	dist	0.1
stealthy profile	tc_{max}	12	δ_{max}	150°	α	1	δ	4
	tc_{mid}	6	δ_{mid}	30°	β	0.05	η	0.8
	tc_{min}	5	incr	3	γ	1	dist	0.1

Figure 5: *Examples of profiles*

4 Results

We implemented our approach in our CADIA Populus social simulation platform [Pedica and Vilhjálmsson 2010], resulting in a series of short prototype scenarios. The platform is based on the perception-reaction model, it provides human behaviors and face-to-face interaction including typical gestures, animations and territorial dynamics. It is written in Python and runs on the Panda3D engine. Moreover in this demo each agent has a default profile and in almost every scenario we use a camera that shows the scene from the top. The scenarios are all available in an accompanying video for judging the believability. [1]

4.1 Overtaking

The first situation (Fig.6) demonstrates two characters that have the same destination but different speeds. The character that starts further left changes its orientation to avoid the character in front, and continues adjusting its trajectory towards the desired destination without cutting across the path of the other character. This is a typical pedestrian situation.

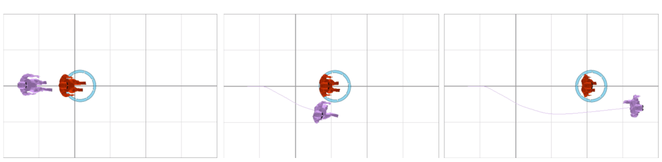

Figure 6: *First scenario: Pedestrian overtaking another*

4.2 Avoiding the Player

In the second scenario (Fig. 7) one character is driven by social path following and the other one is controlled by the player, who can set random destinations by clicking on the screen. The autonomous character does its best to stay out of the player's way.

[1] http://secom.ru.is/videos/SocialPathFollowing

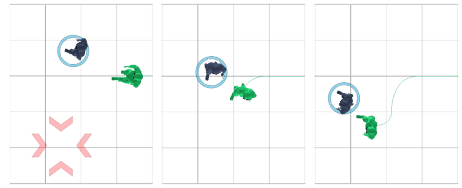

Figure 7: *Second Scenario: Avoiding a dynamic player character*

4.3 Crowds

The third scenario (Fig. 8) is useful for putting strain on the collision avoidance by introducing crowded circumstances: groups of pedestrians have opposite destinations, their positions are very close and their movements converge in a specific area of the environment (congestion). The results seem fairly believable. Running this scenario more times, each execution always produces different paths and dynamics, exactly what we expect in the real world.

Figure 8: *Third Scenario: Crowd collision avoidance*

4.4 Predicting Conversation

In the fourth scenario (Fig. 9) we have a couple of future conversants that are approaching each other and a character that wants to reach a destination on the other side of the approaching line. The moving agent monitors the social behaviors of the other characters and after perceiving a future interaction it avoids the social territory that is forming. In this case we can notice that the agent decides to avoid the obstacles by passing on the left because it predicted the future positions of the conversants and this movement consumes less energy than going on the right.

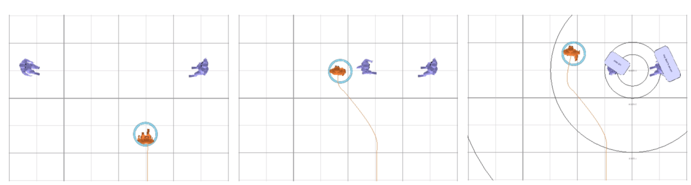

Figure 9: *Fourth Scenario: Detecting and avoiding dynamic social territory*

4.5 Negotiating Space

The last scenario (Fig.10) and (Fig.11) shows a non-verbal negotiation of space. There is a narrow corridor delimited by walls, a stable conversation and a moving character that needs to go to the other end of the corridor. Perceiving a small passageway, through gaze, the walking character requests more space; the nearest conversant notices the behavior and moves accordingly, avoiding the awkward situation of having the approaching character crash through the conversation. Actually this last behavior is made even a bit more interesting and complex by the social simulation platform, which drives the conversation group. It executes a common attention rule in the group: if one of the conversants sees someone approaching, it triggers the others to also look at the agent [Pedica and Vilhjálmsson 2010].

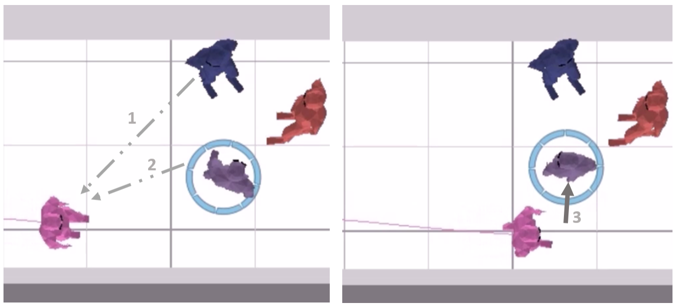

Figure 10: *Last scenario: non-verbal negotiation of space. Showing a series of gazes (1 and 2) and a final movement (3)*

Figure 11: *Last scenario: non-verbal negotiation of space. Showing a series of gazes (1 and 2) and a final movement (3) from first person perspective*

5 Conclusion and Future Work

We presented a model that looks to theories of social behavior to address the path following problem. We believe that increasing social perception, knowledge and ability of agents is the right way to build believable motion. It needs to strike a good balance between protecting/respecting social territories and reaching goals and desired destination. Building on state-of-the-art velocity- based methods, our approach is flexible through parameterization.

Whe have included a few chosen examples that visually demonstrate the power of our approach, but a more thorough evaluation, including direct comparisons and quantitative analysis, is part of future work.

Looking at the related work for inspiration, a few clear improvements can be made. First of all we could optimize certain data structures, such as the navigation meshes, to ensure better performance of the algorithm. We could think about how to include motion in groups and its dynamics, as described in [Moussaïd et al. 2010]. Another improvement is a full prediction of congestions, as sort of "escape behavior" that can be activate just in critical situation. An interesting way to improve the approach is developing a social A* Algorithm, working in the path finding module, trying to build an heuristic function based on social costs.

Finally, we intend to integrate this work with our latest social simulation framework called *Impulsion*, which is based on behavior trees and has been implemented in the Unity 3D engine [Pedica and Vilhjálmsson 2012].

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