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An agent-based crowd behaviour model for real time crowd behaviour simulation ☆

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ABSTRACT

Crowd behaviour models are divided into agent-based, flow-based and particle-based in terms of whether the behaviour emerges from simulating all people (agents) individually (Koh and Zhou, 2011; Braun et al., 2005; Luo et al., 2008; Pan et al., 2007; Shendarkar et al., 2006; Narain et al., 2009), is programmatically defined a priori using fluid dynamics models (Hughes, 2002, 2003; He et al., 2011), or employ a particle system governed by physical laws (Helbing et al., 2000; Bouvier et al., 1997; Treuille et al., 2006; Cucker and Smale, 2007). In agent-based models, computationally intense problems, such as global navigation, hinder the efficient real-time modelling of thousands of agents. In this paper we present a novel approach to crowd behaviour modelling which couples the agent-based paradigm of allowing high level of individual parametrization (group behaviour between friends, leader/follower individuals) with an efficient approach to computationally intensive problems encountered in very large number of agents thus enabling the simulation of thousands of agents in real time using a simple desktop PC.

1. Introduction

Modelling the behaviour of a large number of individuals is a task associated with high complexity, not only because of the sheer number of individuals often comprising crowds but also because their interactions, movements and general behaviour are the result of highly complex and psychological interdependencies, not suitable for direct one-to-one simulation. The effort, therefore, shifts to emulating the general behaviour of a crowd using basic principles and heuristics that closely resemble reality.

In this respect, there have been mainly two directly opposite poles of attraction for model designers and architects. One possibility is to model each individual (agent) in the crowd separately and expect the crowd's behaviour to emerge as all agents interact (Koh and Zhou, 2011; Braun et al., 2005; Luo et al., 2008; Pan et al., 2007; Shendarkar et al., 2006; Narain et al., 2009; Bouvier et al., 1997; Treuille et al., 2006; Cucker and Smale, 2007) and the other to regard the whole crowd as a continuous and homogeneous fluid governed by the laws of nature as defined and studied by the science of fluid dynamics (Hughes, 2003, 2002; He et al., 2011).

Recent works (Narain et al., 2009) have attempted to combine the much more complex and refined emergent behaviour of agent-based models with the efficiency of flow-based models by proposing hybrid models where agents still exist but from certain pressure/density levels upwards, their behaviour more or less mimics particles in fluids.

Agent-based models are better suited to situations where a high level of realism is desired. Unfortunately, most research is focused on the individual leaving groups dynamics such as people being friends or family members relatively untouched: Helbing and Molnár (1998) have proposed attractive forces which fade over time (agents lose interest) but attractive forces are not always fading such as the attractive forces between members of a family. Furthermore, inside these groups we can usually differentiate leaders from follower individuals. These dynamics can have a considerable effect on the overall emergent behaviour of the crowd.

In this paper, we present our own approach to crowd behaviour modelling with support for group dynamics and different agent personality traits. Our model allows for high parametrization of the individual: each individual has her own physical and psychological traits, ranging from mass, top speed and acceleration to leader or follower personality and has the ability to be part of tightly or loosely bound groups such as family or friends. Furthermore, our model is efficient enough to simulate thousands of agents in real-time on a single CPU.

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1.1. Paper structure

The rest of the paper is organized as follows: in Section 2 we present work which closely relates to ours and in many ways laid the foundations for our model development; in Section 3 we present our model in detail; Section 4 is dedicated to our model's performance; Section 5 discusses the model's qualitative aspects and compares its behaviour to real-life experiments where available and finally Section 6 briefly discusses our conclusions and future work we would like to partake.

2. Related work

Researchers generally prefer and focus on agent-based modelling since it provides a much more refined framework for describing complex human behaviour. They formally describe each individual agent's behaviour and let the crowd's behaviour emerge; the modelling, therefore, is thorough enough to allow realistic agent behaviour while at the same time trying to retain the computational complexity to an acceptable upper limit. Some models incorporate psychological information and factors in the model for better accuracy (Pelechano et al., 2007; Braun et al., 2003; Sakuma et al., 2005) while others omit psychology altogether and only directly simulate in-view agents, leaving the rest to probabilistic methods (Arikan et al., 2001).

One of the main diversifying issues among agent-based models is the underlying movement model for the agents and specifically the way they avoid collisions with obstacles and other agents and the way they decide on a path to their goal. Collision avoidance can be based on Helbing's *Social forces model* (Helbing and Molnár, 1998), *steering behaviours* (Reynolds, 1999), a combination of the two (Moussaid et al.), or even correction of agents' velocities using aggregate movement dynamics from nearby agents (Narain et al., 2009). Global path planning, on the other hand, is achieved by running a path searching algorithm such as A* or Dijkstra on a carefully prepared graph representation or grid (i.e. quadtree) of the environment (Shao and Terzopoulos, 2007; Shendarkar et al., 2006).

The movement model is usually complimented by a psychological and emotional state model which endows agents with the ability to react to stimuli differently depending on their psychological and emotional state: Modelling here is based on Belief-Desire-Intention (BDI) models (Shendarkar et al., 2006; Rao and Georgeff, 1992), decision networks (Yu and Terzopoulos, 2007), Bayesian networks (Hy et al., 2004; Pearl, 1988; Ball and Breese, 2000) and even fully layered frameworks embodying an agent's situational awareness and consequence foreseeing into the model (Luo et al., 2008).

Finally, many researchers have incorporated environmental perception into their models. Various methods have been proposed for the propagation and perception of auditory (Monzani and Thalmann) and visual (Funge et al., 1999; Noser et al., 1995; Kuffer and Latombe, 1999; Renault et al., 1990) stimuli; others have proposed models for combined audio, visual and haptic sensory inputs (Conde and Thalmann, 2004). Most of them are, generally, computationally expensive.

3. A model for real time crowd behaviour simulation

3.1. Overview

We propose an agent based model with fully autonomous agents using a three-layered approach: at the higher level is the *cognitive layer* which models the emotional state of each agent, using a set of preset emotions and a quantification of the intensity each emotion is being "felt" by the agent. These emotions are affected by the agent's interaction with the virtual world (*"Was that an explosion I heard? Why are these people running?"*) and events in the virtual world have an impact on them. To achieve this, human perception is modelled through perception limitation structures such as visibility graphs and by using specific excitement modifiers communicated between agents, each agent can influence those nearby (those who see him poll him for influence modifiers to be applied to their own states). An agent in panic, for example, will broadcast high values of stress and fear to be added to the states of agents listening who will update their states accordingly. The combined intensities of these emotions affect the lower layer, the *strategic* layer: this is responsible for the decision making process of the agent and is implemented using hierarchical state machines: *"Now that I have completed my check-in, where should I proceed to?"*.

At the bottom of the stack rests the *movement* layer. This is responsible for realizing the actual movement of the agent towards her goal, as set by the strategic layer while avoiding structural obstacles and pitfalls as well as collisions with other agents. Our is a *social forces – flow-field – aggregate dynamics* model (Helbing et al., 2000; Narain et al., 2009; Patil et al., 2011).

3.2. Movement model

At the core of our movement model is the refined social forces model proposed by Helbing et al. (2000) extended to allow flow-field based navigation and aggregate dynamics built-in.

For each agent α and given a specific time $t, \vec{r}_\alpha(t)$ is the agent's absolute position vector on the world (the point of her center of mass), m_α is her mass, $\vec{v}_\alpha(t)$ her actual velocity vector and r_α her body's radius. Furthermore, depending on the state she is in, she has a desired speed $s_\alpha(t)$.

3.2.1. Self-force

The self-force represents the force an agent applies on herself in order to reach her destination, while travelling at her desired speed $s_\alpha(t)$. This force can be broken down into two components:

(i) the *goal self-force* which is a force in the direction of the shortest path to the agent's destination and
(ii) the *aggregate self-force* which is a force exerted on the agent because of the general movement of a dense crowd she is in.

3.2.1.1. Goal self-force. Agents in our model are pre-endowed with complete information on the shortest path to their next waypoint within a virtual room. This is exploited by agents applying a force on themselves pushing them forward in the direction of the shortest path to their destination, called the *goal self-force*. The intensity of the force depends on the difference between their current velocity $\vec{v}_a(t)$ and their desired velocity $s_\alpha(t)\vec{e}_G(\vec{r}_\alpha(t))$:

$$\vec{f}_\alpha^{goal}(t) = \frac{m_\alpha}{\tau_\alpha}(\vec{v}_\alpha(t) - s_\alpha(t)\vec{e}_G(\vec{r}_\alpha(t))) \tag{1}$$

where τ_α is a *relaxation time* controlling the agent's acceleration and $\vec{e}_G(\vec{r}_\alpha(t))$ is the direction (vector) of the shortest path from point $\vec{r}_\alpha(t)$ to point G, where G is α's goal.

3.2.1.2. Rapid Flow-Field Computation algorithm. Since the shortest path computations are considerably expensive and cannot be re-calculated continuously for every agent separately we have developed a Rapid Flow-Field Computation (RFFC) algorithm for fast calculation of the directions of the shortest paths from any given point to any goal. Specifically, a grid is overlaid on the simulated area and for each cell and each possible goal, we pre-compute the direction agents should follow for shortest access to said goal.