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Crowd simulation for dynamic environments based on information spreading and agents' personal interests

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Abstract

In this work a novel crowd simulation framework that incorporates information of the dynamic environment is introduced. It supports knowledge spreading and allows the simulated agents to behave according to their personal needs that are affected by the surroundings. Each agent has their own personal interests and needs, which affects its goals and interactions with the environment. Genetic algorithms are used to simulate the dynamic behaviour of the environment and the knowledge spreading. As a result more accurate and realistic simulations are obtained improving a wide range of industrial and research applications that require accurate crowd simulation and modelling.

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Keywords: crowd simulation; dynamic environment; genetic algorithm; pedestrian behaviour simulation;

1. Introduction

Crowd and pedestrian simulation are widely used for entertainment, education, emergency training, architectural design, urban planning, traffic engineering and numerous other applications. In most simulations a large number of agents are usually represented. The agents are expected to behave with human like actions, inside virtual surroundings avoiding obstacles and interacting with the environment or other agents. The modelling methods for crowd simulation can be separated into macroscopic and microscopic. Specifically, the movement features of the whole crowd are the main characteristic of the macroscopic algorithms, Treuille et al. (2006). Microscopic methods such as Nguyen et al. (2005) operate on an individual level and are focused on including psychological and social behaviours, interaction among pedestrians, and individual decision making processes.

There are multiple approaches that could be taken to solve the problem of realistic crowd simulations. Many approaches focus on collision avoidance, knowledge of the environment, group or individual decision making, and the personal interests of each agent. In this paper we mainly focus on the individual decision making based on personal interests and the knowledge of the environment. In this section, we briefly review the work carried out by some of the research groups that use these approaches.

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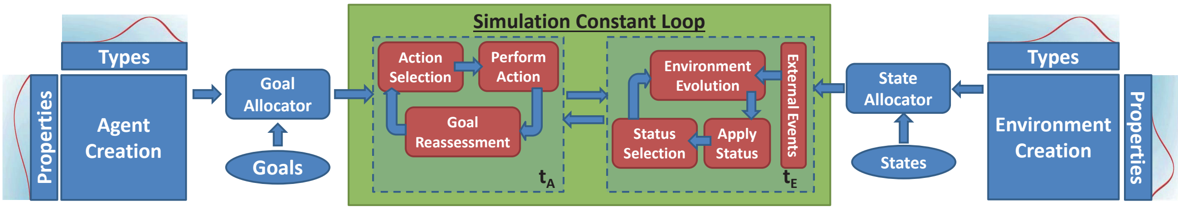

Fig. 1: A diagram of the proposed crowd simulation framework.

An approach using decision making based on the environment was taken in Golas et al. (2013); Ondrej et al. (2010); Almeida et al. (2013). It focuses on situation-based decisions of the agents. Unlike in our simulation, these papers do not take into the account the personal interests of the agents and focuses more on the probabilistic behaviours. The simulation would be different depending on many factors that affect personal behaviours of the agents depending on the environment, their social status and even time of the day. These factors were not taken into the account.

The collision avoidance method is widely used among the crowd simulations. Hybrid Long-Range Collision Avoidance for Crowd Simulation paper is taking such approach. This approach tackles how pedestrians should avoid each other once faced in close ranges. It does not take into the account the environment or individual based behaviours, Ulicny and Thalmann (2001); Pellegrini et al. (2012); Sung et al. (2004). Each agent will behave similarly if given the same situation, resulting in an unrealistic looking simulation.

Crowd simulation was influenced by the agents' socio-psychological state in Cherif and Chighoub (2010); Patil et al. (2011) focusing on their individual actions, and based on their surroundings. Their focus is more on the agents' personal space and on keeping distance from other agents and avoiding them, while going to their selected destination, without considering the realism in their behaviours or the changes in their environment.

In the above papers, one of the main problems is that information for the dynamic environment is not incorporated and the knowledge spreading in not simulated. The proposed method improves the quality of the crowd simulation, by incorporating dynamic area information which is accessed by the agents and which accordingly changes their behaviours. Each agent has their own personal interests and needs, which affect their goals and interactions with the environment. Another addition is that the information that is spreading among the agents is simulated based on the events that occur in the surroundings. Genetic algorithms are used to simulate the dynamic behaviour of the environment and the knowledge spreading defined as the information exchange process between the agents and the environment. The agents will learn the environment over time based on their personal characteristics and goals (e.g. age, employment status, physical needs, personal interests) using reinforcement learning. A list of events and environments are supported (e.g. shopping, street musician, gunfire, rush hour) and the crowd reaction is evaluated over these scenarios.

This novel crowd simulation framework incorporates information of the dynamic environment, supports knowledge spreading and allows the agents to behave according to their personal needs that are affected by the surroundings. As a result more accurate and realistic simulations are obtained improving a wide range of industrial and research applications that require accurate crowd simulation and modelling.

2. Proposed methodology

In this work a novel approach for crowd simulation is presented considering not only the human behaviour but also the dynamic nature of the environment. Therefore, in the proposed methodology the simulation mechanisms consider both the personal characteristics of the pedestrians and the information provided by the environment operating in a dynamic way. These two entities exchange data and details about their status based on an information spreading model. The overall approach is shown in Fig. 1, indicating the main parts of the simulation system. In the following sections each of the components of the simulation algorithm is analysed.

2.1. Agents simulation model

Let us define crowd as a large number of people gathered together in a disorganized way and consider two types of crowd formation. In the first case, a crowd has a common purpose, such as at a sports event, which is known as a psychological crowd. The second type of crowd is formed when many people are in the same area (e.g. town or shopping center) but they have individual aims or goals. In the proposed simulation algorithm the crowd consists of many agents and each one has their own personal interests and needs, which affect their goals and interactions with the environment. In order to realize this, different types T of agents were considered and a set of properties P was introduced. The selected types include the following categories: businessman, tourists, elder, teenager, and adult resident, while the main features that could affect their behaviour are speed, knowledge of the area, distraction level, hunger and shopping desire. For each agent type different weights were selected for their properties, using a normal distribution.

$$w_P(x, \mu_P, \sigma_P) = \frac{1}{\sigma_P \sqrt{2\pi}} e^{-\frac{(x-\mu_P)^2}{2\sigma_P^2}} \tag{1}$$

where $P \in \{1, ..., N_P\}$ with N_P to indicate the total number of properties selected in the current simulation. w_P corresponds to the obtained weight for the P feature. In the same process weights w_T are assigned also to all the types of agents T generating the initial characteristics of the simulated crowd.

The selected weights w_P^i and w_T^i for a given agent i affect its behaviour in different ways. Considering that an agent of type businessman and with low weight for the distraction level the probability to alter their path due to environmental destructions will be low too. In the general case, this is the conditional probability $p(A|T, P)$ of this action A to occur given the type and the properties of the agent.

Since the primary population of the crowd has been selected, based on the initial and conditional probabilities a goal is allocated to each agent. Then we move to the simulation loop for the agents, where the selected action is performed, a new state is evaluated reassessing the assigned goal and if it is required a new behaviour is selected. This loop repeats every t_A and runs constantly during the whole simulation. For the goal reassessment stage, the weights for the agents are updated based on the state of environment and the global features/properties. In more detail, the (μ_P, σ_P) parameters are updated using the information from the environment (e.g. time, local features, etc.), following a set of predefined rules. This approach allows the agents to adapt to the environment and adjust their behaviour based on the current state and their desires. In the action selection stage, a simple decision making system is introduced that is based on the obtained weights and the most appropriate action is selected. This process also contains a random term to allow some unpredictability to the overall simulated behaviours. The last part actually performs the selected action based on simple path finding algorithms and locomotion techniques. All the selected actions are simulated following a set of basic tasks and rules based on probabilities allowing the design of more complex behaviours considering always in a certain level an element of unpredictability.

2.2. Simulation model for the environment

The second part of the simulation framework is focused on the environment and the approach is similar to the previous case. A set of types of environment is available indicating a certain behaviour, feature or characteristic of that location. For example, a type could be a shop, a restaurant, an information point, a phone booth, or an event such as the presence of a street artist in a specific area, a charity work, a fight or a gun fire. Each one of these types has specific properties mainly related to their range, time duration and severity. Additionally, there are several global parameters that are fixed and provided by the user such as current time and weather conditions, which affect both the environment and the agents. Since the initial state of the environment is defined we move to the simulation loop that operates at a different frequency in comparison to the agents loop. During this iterative process the selected status is applied to the environment, the environment itself is updated using a genetic algorithm generating new states based on the current conditions, some global events (e.g. weather) and the effects of the agents actions. In order to provide an example consider the scenario of a street artist, whose presence may alter the behaviour of the agents that will stop and watch the event. If this change to the agents goals is common it will affect the environment itself and the new

Algorithm: Evolutionary algorithm

```
Initialise the environment with N states generated based on the initial weights (probability
density functions)
Rank the states by fitness
repeat
        for the number of new states to be created
                Generate a new state
                        Create one new state i by crossover
                        Mutate i
                Calculate fitness
                        Calculate fitness(i) as the classification rate
        end for
        Generate next generation's set of states
        Rank the set of states by fitness
        Select next generation's set of states with elitism
until generations without changes > Threshold
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Fig. 2: An example of the genetic algorithm used to simulate the evolution of the environment.

generation of the types of the environment will have higher probability to contain one or more street artists. In the opposite case, where very few agents stop, this type of environmental states or events will gradually be less likely to occur. This evolutionary algorithm could be extended to optimize not only the amount of a given type but also the location and the time to occur if these features are meaningful for a particular scenario. The evolutionary algorithm that was utilized is shown in Fig. 2.

3. Evaluation process and metrics

In order to evaluate the proposed crowd simulation algorithm two scenarios were considered, the behaviour of the agents during a shopping activity and the case when a street artist is present. In our experiments the aim is to evaluate the simulation accuracy and not the computational complexity of the algorithm. The main issue of this task is that obtaining the ground truth is either a time consuming process or due to ethics and privacy restrictions the required data are not available. For example, in some cases, the ground truth is obtained using mobile device tracking techniques Wang et al. (2012) and in other cases the estimation of the number of collisions occurring during the simulation process is utilized as a performance metric alongside with the required CPU or GPU processing power and time, Ricks and Egbert (2013). As it was mentioned above, all these approaches for crowd and urban interactions simulation evaluation either do not consider the realism parameter focusing on the performance or are applicable only to a small subset of scenes and scenarios.

The suggested evaluation approach allows the comparison of crowd simulation algorithms providing a similarity measurement. The requirements of this method are the use of real videos of an observed scene captured using standard CCTV cameras, and of the 3D environment including the knowledge of the available exits and entrances. During the first step of the proposed metric, a 3D replica of the observed scene is designed using basic primitives, while for the texturing samples from the real video sequence are selected. Since the 3D scene is available the camera location and orientation are adjusted to be the same as in the real scene; and the entering and exiting locations are specified. Thus, the real and the simulated video sequences are used to extract features in order to measure their level of similarity. These features are obtained from the optical flow (e.g. histogram of oriented optical flow HOOF) in both sequences, Chaudhry et al. (2009). The optical flow methods proposed by Sun et al. (2010) is utilised in this work.

Let us assume that $I_R(u,t)$ and $I_S(u,t)$ are the image frames of a real and the corresponding simulated scene, respectively. The motion vectors for each pixel location in each frame are estimated using the above optical flow techniques, which are shown in (2) and (3)

$$M_R(u,t) = \mathfrak{F}(I_R(u,t), I_R(u,t-1)) \tag{2}$$

$$M_S(u,t) = \mathfrak{F}(I_S(u,t), I_S(u,t-1)) \tag{3}$$

Fig. 3: Examples of real sequences from market places used in our evaluation process, (left). Examples of simulated sequences showing the crowd behaviour, (right).

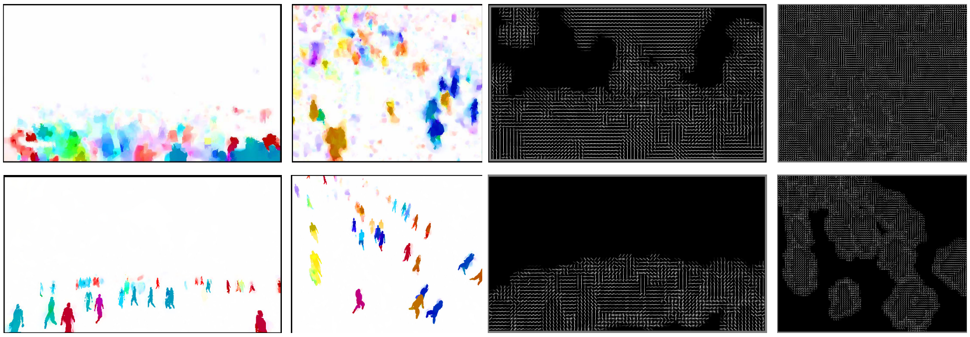

Fig. 4: Examples of the selected features (MVs and HOOF) for real and simulated sequences.

Since the motion vectors are available the histogram of oriented optical flow (HOOF) is calculated both for the real and simulated scenes.

$$f_R^{HOOF} = HOOF(M_R) \tag{4}$$
$$f_S^{HOOF} = HOOF(M_S) \tag{5}$$

Finally, the flux of the features in (4)-(5) is represented by the surface integral of the given vector field.

$$\Phi(\mathbf{u}, t) = \sum_u \sum_t f dudt \tag{6}$$

Based on (6), we obtain Φ_R^{HOOF}, Φ_S^{HOOF}, that correspond to the proposed metric. In order to measure the similarity and rank the algorithms the Bhattacharyya distance was utilized, which can be applied either on the whole sequence or on smaller blocks allowing speciotemporal adaptation of the proposed features and metrics.

4. Results

In our experiments sets of real sequences from shopping centers and similar locations were used, showing pedestrians to move, stopping to watch the shops, entering them and reappearing after a short period of time. Also the scenario of a street artist present in the area was considered showing the simulated crowd behaviour in that case. Fig. 3 shows examples of the real and the simulated scenes used in our experiments that demonstrate the crowd behaviour in shopping centers and market streets. Since the sequences are available the features are extracted and examples of the obtained optical flow in a colour coded representation are shown in Fig. 4. Also images of the HOOF in both cases, real and simulated scenes are shown in Fig. 4. In our comparative study a method based on the work in Liu et al. (2012) was developed that was not designed to consider the environment in the decision making system of the system in comparison with the proposed simulation algorithm. All the results are summarised in table 1 and Fig. 5 showing that the proposed approach provides more accurate and realistic simulations. Finally, one more example of the case of the street artist is shown in Fig. 6 (left), while an example of the genetic algorithm for the environment is visualised in Fig. 6 (right) showing the different types of states in each block indicated with different colour during the optimisation process.

Table 1: The average errors for all the scenes.

Error (Bhattacharyya)	Liu et al. (2012) Simulation	Proposed Simulation
Scene 1	0.79924	0.79681
Scene 2	0.80039	0.79769

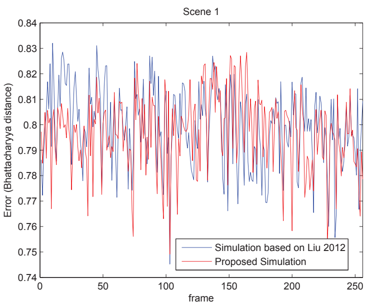

Fig. 5: Bhattacharyya error for each frame in Scene 1.

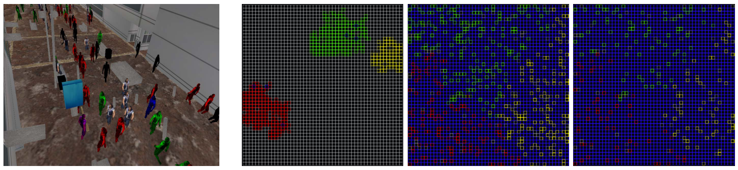

Fig. 6: An example of the simulated crowd behaviour in the presence of a street artist (left). The evolution of the dynamic environment during the optimisation process (right).

5. Conclusions

In this paper a novel crowd simulation method was proposed that allows the simulated agents to adjust their behaviour based both on their individual goals and the surroundings. The suggested approach initialises the population using specific probability density functions generating different types of agents with different characteristics and interests. Regarding the environment a genetic algorithm was used to evolve the types and the states of the areas present based on external events or the behaviours of the simulated agents. Experiments were performed demonstrating these behaviours and an approach based on visual features was used to evaluate the proposed simulation method.

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