Adaptive Behavioral Modeling for Crowd Simulations

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Abstract
In this study, we design an adaptive behavioral model for a dynamic virtual environment. We model the dynamic environment with behavior maps which are constructed with information theory quantities. These maps are capable of capturing the dynamic nature of the environment by changing temporally and spatially. Subsequent to building this model, agents’ responses to these maps are represented with a set of formulations. In our test studies, we have observed that our model successfully produces realistic and diverse behaviors by incorporating effects of the environment.

Keywords: crowd simulation, information theory, behavioral modeling

1 Introduction
Realistic behavior of agents in crowd simulations is still a challenging problem due to the number of factors determining agents’ behavior which are not easy to represent mathematically. In agent-based behavioral models, an agent responds to other agents and events using static and predefined behavior rules, whatever the environment conditions are. However, dynamic conditions which are inherent in the environment greatly effect an agents’ behavior and existing models are not capable of adapting themselves to these conditions.

In order to model the effects of the crowd on agents, we need a quantification to represent the activities of the crowd and model the effects of the crowd on individual agents. A good model has to be adaptive to changes in the dynamics of the crowd both spatially and temporally. In our model, we develop behavior maps which convey information on probabilistic and statistical properties of agents’ activities. Information theory quantities, i.e. information entropy and Kullback-Leibler divergence are used to produce behavior maps. As behavior maps are updated spatially and temporally; agents adaptively respond to their environment with the contribution of these maps. This contribution is represented with numerical entities and agents’ responses are calculated with a set of formulations.

2 Related Work
There have been many studies on agent-based crowd models to create human-like behaviors. Seminal works of Reynolds used behavioral models considering local rules to create emergent flocking (Reynolds, 1987) behaviors. Pelechano et al. (2007) created an improved model by using psychological and geometrical rules with a social and physical forces model. There are studies which
model the virtual environment as maps to guide agents’ behaviors. Shao and Terzopoulos (2007) modeled the environment with topological, perception and path maps to generate autonomous agents.

3 Behavior Maps
A behavior map spans over the virtual environment, and records all the agents’ activities. This map, $B$, is a 2D grid, consisting of $w$ rows and $h$ columns. Physical properties of an agent, $a_i$, can be described as $a_i = \{u, \vec{v} : u, \vec{v} \in \mathbb{R}^2\}$ where $u$ defines the position and $\vec{v}$ defines the velocity. The activity of an agent is described by its position, the direction and the magnitude of its velocity. Activities of an agent are mapped to the corresponding cell in $B$. We compute behavior maps by using probabilistic analysis methods incorporating quantities from information theory. Information entropy from information theory field (Shannon, 1948) provides an insight about how likely a system produces varied outcomes. Namely, it is a measure of uncertainty of a random variable. The other concept we have utilized is Kullback-Leibler divergence (KL) (Kullback, 1997) which is a non-symmetric metric expressing the difference between two probability distributions. Figure 1 displays behavior map construction.

We need to have probability mass functions (pmf) regarding to the activities in the scene to make use of information theory quantities. The first pmf, $P_{\vec{v}}$, defines the velocity direction distribution. Consider an agent with normalized velocity $\vec{v}$, then this vector is added as a sample to one of the $n$ bins of $P_{\vec{v}}$, where the value of $n$ effects quantization resolution. The second pmf, $P_{\|\vec{v}\|}$, defines the velocity magnitude distribution. Agents’ speed is quantized into $m$ categories and speed of an agent is added as a sample to one of these categories.

3.1 Entropy Map
Entropy values represent behavioral patterns of the crowd. Entropy values denote whether agents move independently or in a pattern. To build the entropy map, $E$, we begin by considering a random variable, $X_{i,j}$ ($i,j$ indicating location on $E$), drawn according to pmf $(P_{\vec{v}}(t-n\Delta t)\rightarrow t\vec{v})_{i,j}$. Then, $E$ can be defined as:

$$E^t = \{H(X_{i,j}) : 0 \leq i < w, \ 0 \leq j < h\}$$

(1)

, where $H(X_{i,j})$ is the entropy of $X_{i,j}$.

3.2 Expectance Map
In order to quantize the expectance of the current activities on the scene, we compare the current probability distribution on the scene with $P_{\vec{v}}$. We employ Kullback-Leibler divergence to compute the difference between two probability distributions. KL calculations are called as expectance maps. Let $P_{\vec{v}}^t$ define the current probability distribution of the crowd, and $P_{\vec{v}}((t-n\Delta t)\rightarrow (t-\Delta t))$ define the cumulative distribution of activities, expectance map $KL$ is defined as:

$$KL^t = \{(D(P_{\vec{v}}((t-n\Delta t)\rightarrow (t-\Delta t)\|P_{\vec{v}}^t))_{i,j} : 0 \leq i < w, \ 0 \leq j < h\}$$

(2)

A high KL value represents that current activities taking place at that location can be regarded as surprising, while in areas with lower KL values, the current status of the crowd is as expected.

4 Response to Behavior Maps
In our crowd simulation engine, agents have internal properties called behavioral constants and behavioral state. Behavioral constants can be regarded as personality attributes of an agent and behavioral state determines at what level behavioral constants effect agent’s behavior. Throughout the simulation, behavioral state is altered adaptively by behavior maps. These two properties modify agents’ responses through certain formulations.
To display diversity in agents’ behaviors, we incorporate composite agents into our model. A composite agent is a special agent equipped with a proxy agent, $r_i$, to model a number of emergent behaviors realistically (Hengchin et al., 2008). Definition of an agent has to include internal properties, in addition to the physical properties. Definition of an agent $a_i$ is extended as:

$$a_i = \{\text{type, } u, \vec{v}_p, d, s, \delta, (f_1, \ldots, f_n), \beta : \vec{v}_p \in \mathbb{R}^2; f_n, \beta, d, s \in [0, 1]\}$$  \hspace{1cm} (3)

These parameters are: 1) type: Indicates whether an agent is composite agent or proxy agent. 2) $\vec{v}_p$: Indicates the velocity an agent prefers to move. 3) $d$: Distance to set between $r_i[u]$ and $u$. The longer the distance, the further $a_i$ can proceed with less collisions. 4) $s$: Size of the area $r_i$ occupies 5) $\delta$: Indicates the range in which an agent considers possible collisions. 6) $f_n$: Indicates a behavior constant. Each constant can be utilized to mimic certain personality attributes. 7) $\beta$: Indicates the behavior map value.

Agents’ responses to behavior maps are formulated as:

$$a_i[\beta] = kB_{i,j}; \quad f'_0 = \beta f_0; \quad f'_1 = \beta(1 - f_0)$$

$$a_i[\vec{v}_p] = (\vec{v}_p + f'_1 \vec{v}_b)f'_0 m_0$$

$$a_i[d] = f'_0 d_0; \quad a_i[s] = f'_0 s_0; \quad a_i[\delta] = 1/\beta d_0$$  \hspace{1cm} (4)

$f'_0$ value modifies the proxy agent $r_i$, as $f'_0$ gets higher, $d$ and $s$ values are amplified. $f'_0$ value also increases the speed of an agent in areas with high $B$ value. $f'_1$ value, on the other hand, amplifies the deviation from optimal velocity $\vec{v}_p$. The final response is the change in $\delta$ value that is inversely proportional to $\beta$ values.

5 Results & Test Cases

We tested our methods through a number of scenarios. Our test environment is built on top of the modified version of multi-agent simulation system called RVO proposed by Van Den Berg et al. (2008). We create a crowd containing 200 agents. Crowd contains three groups of agents with specific behavioral constants. First of these groups constitutes of 20 agents with high $f_0$ and low $f_1$ values which can be considered either as aggressive agents. Second of these groups contain 20 agents with low $f_0$ and high $f_1$ values which can be considered as calm agents. The last group consist of 160 standard agents which do not display any adaptive behavior. Figure 2 displays snapshots from test scenarios.

In our tests with entropy maps, aggressive agents move directly to their goal, as their preferred velocity is not affected from higher $\beta$ values. However, in areas with lower entropy all the agents behave identical and do not search for a more “safe” (collision-free) velocity in areas with low entropy, where $\delta$ values are lowered by $\beta$. In simulations that are run with KL maps; aggressive
agents clear their way aggressively and move directly to their goal in areas with high $KL$ value. On the other hand, agents in the second group behave unexpectedly and this response mimics panicking behavior when an unexpected event happens. To address the general case for a dynamic virtual environment, we combined all three models into a single one. We calculate a weighted average response by adjusting the contribution of each behavior map.

6 CONCLUSION
In this paper, we proposed an adaptive behavioral model for crowd simulations. Our model incorporates the dynamics of a virtual environment through building an analytical model of crowd's activities and formulates agents’ responses. We ran our model over a number of scenarios and observed that agents’ behaviors are adaptively altered under certain environmental conditions. Results show that our methods add complexity and diversity in agents’ behaviors, thus improve realism. These methods can be integrated into either scripted behavioral models to increase their behavioral variation or autonomous agent systems to improve their realism.

REFERENCES


