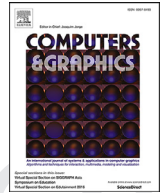




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Technical Section

## Using real life incidents for realistic virtual crowds with data-driven emotion contagion<sup>☆</sup>

Ahmet Eren Başak<sup>a</sup>, Uğur Güdükbay<sup>a,\*</sup>, Funda Durupınar<sup>b</sup>

<sup>a</sup> Department of Computer Engineering, Bilkent University, Ankara 06800, Turkey

<sup>b</sup> Computational Biology Program, Oregon Health & Science University, Portland, OR 97239, USA

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### ABSTRACT

We propose a data-driven approach for tuning, validating and optimizing crowd simulations by learning parameters from real-life videos. We discuss the common traits of incidents and their video footages suitable for the learning step. We then demonstrate the learning process in three real-life incidents: a bombing attack, a panic situation on the subway and a Black Friday rush. We reanimate the incidents using an existing emotion contagion and crowd simulation framework and optimize the parameters that characterize agent behavior with respect to the data extracted from the video footages of the incidents.

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### 1. Introduction

Crowd psychology has attracted the attention of scholars for more than a century. In his seminal work, “The Crowd: A Study of the Popular Mind”, Le Bon [1] describes the salient aspects of crowd psychology as impulsiveness, irrationality, emotionality and mental unity. This phenomenon is also known as *collective (mis)behavior*. Social psychology literature introduces various theories to explain the reasons for collective crowd behavior, including social contagion [1,2], predisposition [3–5] and emergent-norms [6] theories. Brown [7] describes an elaborate taxonomy of crowds and classifies crowds under two general categories as *audiences* and *mobs* depending on the existence of observable unified behavior, instead of the reasons bringing crowd members together. In both categories, crowd members share a common goal unlike pedestrians on a street who happen to be coincidentally at the same place at the same time. What distinguishes mobs from audiences is their active and emotional disposition, which leads to “mob”ility. This feature makes mobs more interesting to study (and simulate) as they display more diverse and interesting behaviors than audiences. Therefore, we focus on mob simulations in this work.

One of the most influential factors that causes collective mob behavior is emotion contagion. Emotion contagion is the

phenomenon of having the feelings and responses of one person influencing and manipulating the emotions of others in a group of individuals [8]. Within this continuous feedback mechanism, we generally observe that emotions and resulting behaviors converge to a single active response over time, thus converting audiences to mobs. Because of this feature, systems that model emotion contagion mostly focus on mob behaviors.

We need a universal, objective, quantitative and reusable method for validating crowd simulation models, not just in terms of the steering behaviors of individuals but the authenticity of the group behavior as a whole. We can then formally define future improvements to existing simulation systems and compare different systems under different scenario cases. Crowd simulation literature includes various techniques to evaluate the behavior of virtual agents such as learning parameters from crowd videos [9–11]; determining metrics to compare different simulations [12–14]; and referring to human expert opinions [15]. In this work, we propose a data-driven approach to mimic real crowd behaviors by learning the parameters that affect crowd behavior and to validate crowd simulation systems according to their fidelity to real life behaviors. We apply this approach to the epidemiological emotion contagion framework proposed by Durupınar et al. [16]. We explain how to learn the characteristics of emotion contagion from a real-life event video and how to improve and optimize the emotion contagion model by Durupınar et al. using the results of this analysis. To this end, we investigate the agent behavior before and after the incident and recreate the incident in a virtual environment.

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\* Corresponding author.

E-mail addresses: [eren.basak@bilkent.edu.tr](mailto:eren.basak@bilkent.edu.tr) (A.E. Başak), [gudukbay@cs.bilkent.edu.tr](mailto:gudukbay@cs.bilkent.edu.tr) (U. Güdükbay), [durupina@ohsu.edu](mailto:durupina@ohsu.edu) (F. Durupınar).

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52 The contributions of this paper are as follows:

- 53 • We propose a data-driven, quantitative and reproducible  
54 pipeline for learning parameters from real crowd videos for  
55 synthesizing virtual crowds.
- 56 • We explain how real-life incidents can be utilized for evaluation  
57 and improvement of crowd simulations.
- 58 • We clarify the properties of suitable material for this process  
59 and demonstrate how to process videos of real-life incidents for  
60 virtual environment creation.
- 61 • We analyze three contemporary incidents and apply our pro-  
62 posed approach to an existing emotion contagion and crowd  
63 simulation system.

64 A preliminary version of this research has appeared as a con-  
65 ference paper [17]. Different from [17], which analyzes only one  
66 scenario, this extended version includes a comprehensive set of ex-  
67 perimental results for three different scenarios. We introduce new  
68 error metrics to evaluate the proposed approach and include new  
69 figures illustrating our approach and its experimental results, as  
70 well as new sets of graphs about the experimental results. We also  
71 re-organize and extend the related work to fully cover the state-  
72 of-the-art on the subject.

73 The rest of the paper is organized as follows. In Section 2,  
74 we discuss the related work in emotion contagion, crowd simu-  
75 lation and empirical evaluation studies. In Section 3, we provide  
76 a brief overview of existing emotion contagion models and Dur-  
77 rupinar Emotion Contagion Model that we base our studies on. In  
78 Section 4, we explain the proposed parameter learning framework  
79 and necessary steps to analyze crowd videos before using them  
80 for the optimization process. In Section 5, we explain the incidents  
81 that we studied, how we extracted data from them, how we recre-  
82 ated them in a virtual environment and how we simulated them  
83 using Durupinar model. In Section 6, we demonstrate and discuss  
84 the results of our parameter estimation mechanism on the stud-  
85 ied incidents. Finally, we summarize our work in Section 7, draw  
86 conclusions and discuss future improvement ideas.

## 87 2. Related work

88 We provide a comprehensive review of related work on the  
89 simulation of virtual crowds including emotion contagion studies  
90 and on the comparison of virtual crowds with real crowds in our  
91 previous work [17]. The review refers to various crowd simulation  
92 studies that analyze interactions with the environment [18], the in-  
93 fluence of architecture on crowd behavior [19], data-driven eval-  
94 uation of crowds with trajectory extraction [9–11,14] and scoring  
95 metrics [12,13], emotion contagion models [16,20–23], the role of  
96 appraisal in emotion contagion [15] and how emotion contagion  
97 can be used for simulation of emergency situations [24,25]. In ad-  
98 dition to these, there are other studies that cover the influence of  
99 the environment on the emotions and behavior of crowd members.  
100 For instance, Hoogendorn et al. study the information exchange  
101 and emotion contagion within crowds [26]. They model the change  
102 of information spread with respect to the emotional states of indi-  
103 viduals and simulate an emergency situation to demonstrate their  
104 work. Borodin et al. [27] and Chen et al. [28] apply the concept  
105 of influence among the groups of people to social networks and  
106 show that the responses of key individuals steer the behavior of  
107 the whole group significantly.

108 Heterogeneity is an important aspect of realistic  
109 crowd simulation that has been studied by many groups.  
110 Pereira et al. [29] present a computational model for emotion  
111 contagion in virtual crowds, incorporating personality differences  
112 and interpersonal relationships. They take intimacy between  
113 virtual agents into account for the influence of emotions, where  
114 higher intimacy results in more homogeneous emotional behaviors

115 in crowds. Silverman et al. [30] propose an architecture that  
116 combines an existing pathfinding and cognitive navigation system  
117 (MACES) with PMFserv, which models the changing behaviors of  
118 individuals according to stress, emotions and motivations. Helbing  
119 and Molnar demonstrate the social forces model for explaining  
120 crowd behavior [31], where the characteristics of individuals  
121 in a crowd affect the motion of surrounding pedestrians. In a  
122 later study, they model the panic behavior in crowds mixing the  
123 individualistic behavior and collective instincts [32]. This study  
124 simulates a crowd of people escaping from a smoke-filled room  
125 and proposes an optimal strategy for escaping from such disasters.

126 Evaluation of simulated crowds in terms of their similarity to  
127 real world is another challenge that has been extensively studied.  
128 Fridman and Kaminka [33] demonstrate a crowd simulation model  
129 based on Social Comparison Theory and argue that their model  
130 is suitable for general usage. Furthermore, they propose a method  
131 for evaluating the imitation performance by showing people video  
132 clips of random crowds and as well as simulations, then asking  
133 questions to clarify whether they perceived the video as the be-  
134 havior of unrelated individuals or more like a collective response.  
135 Lin et al. [34] model the crowd behavior evacuating an office build-  
136 ing. In their case study, using the videos taken by the security  
137 cameras, they calibrate the parameters of their model. Similarly,  
138 Tan et al. [35] use an agent-based crowd model for simulating an  
139 evacuation incident and propose a method for representing indoor  
140 space for such simulations.

## 141 3. Emotion contagion approaches

### 142 3.1. ASCRIBE

143 Bosse et al. [24] present ASCRIBE, a computational model of  
144 neural mechanisms of social mutual adaptation for satisfactory  
145 common group decisions. ASCRIBE incorporates a basis for mod-  
146 eling the interaction between the beliefs and emotions of an agent  
147 while also providing mechanisms for the influence of emotions, in-  
148 tentions and beliefs among agents.

149 In its core, ASCRIBE has a model for agents that mirror the  
150 mental states of each other, representing the contagion phe-  
151 nomenon. In this model the amount of influence of a mental state  
152 of one agent on another depends on the *expressiveness* of the  
153 sender agent, *openness* of the receiver agent and *channel strength*  
154 between the subjects, which depends on physical conditions such  
155 as distance and field of view. The combination of the influence of  
156 all the other agents constitutes the overall contagion strength on  
157 an agent. The updated mental state of an agent is calculated as  
158 a combination of the overall contagion and the agent's previous  
159 state. The coefficient of the contagion component determines the  
160 speed of adjustment in an agent's mental state and the conver-  
161 gence of the crowd behavior.

162 The interaction among emotions, beliefs and intentions of an  
163 agent are also incorporated into the ASCRIBE model. In this model,  
164 fear starts affecting information retrieval and amplifies the influ-  
165 ence of the beliefs on behavior if it is above a threshold. The value  
166 given to information by an agent will be affected by the fear and  
167 personality as well, e.g., a pessimistic person with high level of fear  
168 would be significantly affected by negative information; and posi-  
169 tive information would have less influence on the agent's behavior.  
170 Similarly, information influences the emotional state. For example,  
171 negative information has a tendency to increase fear. Finally, be-  
172 liefs and emotions together affect the intentions of an agent.

173 Bosse et al. test ASCRIBE with two scenarios, a synthetic of-  
174 fice evacuation scenario which demonstrates the influence of in-  
175 formation on agents' behavior, and a reanimation of a real-life inci-  
176 dent for demonstrating the model's mimicking potential. The May  
177 4th incident that happened in Dam Square, Amsterdam in 2010

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