Crowd Simulation Incorporating Thermal Environments and Responsive Behaviors

Abstract

Crowd simulation addresses algorithmic approaches to steering, navigation, perception, and behavioral models. Significant progress has been achieved in modeling interactions between agents and the environment to avoid collisions, exploit empirical local decision data, and plan efficient paths to goals. We address a relatively unexplored dimension of virtual human behavior: thermal perception, comfort, and appropriate behavioral responses. Thermal comfort is associated with the ambient environment, agent density factors, and interpersonal thermal feedback. A key feature of our approach is the temporal integration of both thermal exposure and occupant density to directly influence agent movements and behaviors (e.g., clothing changes) to increase thermal comfort. Empirical thermal comfort models are incorporated as a validation basis. Simple heat transfer models are used to model environment, agent, and interpersonal heat exchange. Our model’s generality makes it applicable to any existing crowd steering algorithm as it adds additional integrative terms to any cost function. Examples illustrate distinctive emergent behaviors such as balancing agent density with thermal comfort, hysteresis in responding to localized or brief thermal events, and discomfort and likely injury produced by extreme packing densities.

1 Introduction

We are all familiar with the role environment temperature has on our personal human comfort. Recently virtual reality accessories have begun to appear that provide the user with thermal sensations (Ranasinghe, Jain, Karwita, Tolley, & Do, 2017). Comfort considerations often precipitate adaptive behaviors in real people. Conversely, human body heat can influence nearby air temperature. Harvesting body heat to warm a building has already been used in Stockholm’s Central Station (Casey, 2011). Energy management and efficiency are beneficial societal goals. The simulation of virtual agents has been used in many applications, such as games (Silverman, Johns, Cornwell, & O’Brien, 2006b; Silverman, Bharathy, O’Brien, & Cornwell, 2006a), virtual environments (Pandzic et al., 2001), and evacuation scenarios (Helbing, Farkas, & Vicsek, 2000). In realistic scenarios, virtual agent behaviors should reflect analogous human responses to thermal
conditions. Agents in close proximity to the user’s avatar or in densely packed situations should experience and possibly react to the additional body heat with appropriate comfort-increasing behaviors. Existing simulators explore several psychosocial aspects such as interpersonal distances and discomfort in higher densities, but to our knowledge thermal comfort has not been used in the context of virtual agent simulation. We therefore seek to add a thermal presence dimension to both user and virtual agent experiences.

In this article, we describe a method to assess personal thermal comfort based on the symbiotic relationship between occupant density and the thermal environment (Fanger, 1970). This is a new paradigm for comfort in crowd simulation; yet our method can be readily combined with other crowd motion control mechanisms. To demonstrate that, we linked thermal comfort to the more commonly used notion of occupant density (density comfort) (Fruin, 1971; Hughes, 2002; Treuille, Cooper, & Popović, 2006). A significant aspect of our approach is the use of a temporal window to integrate both thermal and density comfort measures over time. This distinguishes our simulations from reactive and instantaneous behaviors, which compute movements from perceptions, local configurations, or path extrapolations. We run two coordinated simulations: one for the thermal environment and one for the agents. This integrated cosimulation produces novel and realistic emergent human crowd behaviors. Because both simulations run in real time, this thermal environment may be perceived by as well as affected by a virtual reality user.

Our framework is summarized in Figure 1. It starts with an “agent map” that includes a uniform grid matching our 3D simulation environment, in which each cell stores the information and instances of the agents in the cell. The positions of the agents, who act as moving heat sources, are used as input to our heat transfer model that computes the air temperature combined with other heat sink/sources in the environment, generating a “temperature map.” The temperature map, along with other environmental aspects (e.g., humidity, air speed), are used to calculate the thermal comfort level of each agent. The agent map is also used to compute a density comfort model based on agents’ locations, which is combined with the thermal comfort map and integrated along a temporal window to obtain the “overall” comfort of each agent, whether live or virtual. When agents feel discomfort, they will react aiming to improve their comfort level. Although there are many reaction possibilities, we have chosen two main actions: changing clothes, which is triggered by and impacts only the individual’s thermal comfort level, or changing location, which is based on the local thermal context of the environment and nearby agents. When agents need to change location, a crowd simulator is used to move the agents, and their new positions are used as inputs to update the heat transfer model. Hence, the proposed model is a closed-loop system, in which the presence of human or virtual agents affects the environment and in turn the environment is used to initiate motion in the affected agents. Our method is fast enough to be applied in games, real-time simulations, and VR applications.
The main contributions of this work are: 1) the utilization of human thermal comfort models based on environment temperature, interpersonal agent heat exchange, agent activity type, and thermal feedback into the environment; 2) the use of a temporal integration window to model human exposure and response to thermal conditions; 3) a similar integration to assess density comfort with respect to surrounding agents; and 4) the blended use of these thermal and density comfort measures in an agent decision process to directly influence agent movements toward more comfortable conditions. The presence of both thermal and comfort factors yields more natural, contextually sensitive behaviors than either one considered in isolation.

This article is organized as follows: in the next section we review related crowd simulation literature. Section 3 presents the thermal model. Section 4 presents our approach to the cosimulation of agents and the thermal environment, as well as the integration with a density term. Section 5 describes results obtained. Finally, conclusions and directions for future work are presented in Section 6.

2 Related Work

Many different methods exist for crowd simulation (Pelechano, Albleck, & Badler, 2008; Thalmann & Musse, 2013). Crowd models may be characterized as microscopic (agent-based) or macroscopic (density or statistics-based). In an agent model each individual perceives and reacts to the world according to various local rules (Reynolds, 1987; Pelechano, Albleck, & Badler, 2007; Guy, Chhugani, Kim, Satish, Lin, Manocha, & Dubey, 2009), social forces (Helbing & Johansson, 2011; Chenney, 2004; Treuille et al., 2006), following behaviors (Lemercier et al., 2012), or velocity obstacles (van den Berg, Lin, & Manocha, 2008a; van den Berg, Patil, Sewall, Manocha, & Lin, 2008b; Patil, Van Den Berg, Curtis, Lin, & Manocha, 2011; Kim, Guy, & Manocha, 2013). Data-driven approaches replace mechanistic rules with databases of real crowd behaviors (Lee, Choi, Hong, & Lee, 2007; Lerner, Chrysanthou, & Lischinski, 2007; Paravisi, Werhli, Jacques, Rodrigues, Bicho, & Musse, 2008; Courty & Corpetti, 2007; Pettré, Ondřej, Olivier, Cretual, & Donikian, 2009; Hu, Ali, & Shan, 2008; Ju, Choi, Park, Lee, Lee, & Takahashi, 2010). Macroscopic approaches aim to govern the global behavior of crowds using environment descriptions (Yersin, Maim, Ciechomski, Schertenleib, & Thalmann, 2005; Pettré, Grillon, & Thalmann, 2008), space colonization (de Lima Bicho et al., 2012), or continuum fluid-like flows (Treuille et al., 2006).

All of these approaches share the basic goal of creating realistic crowd behaviors in response to various stimuli: the environment geometry, the positions of other agents, collision avoidance, and goal points. In these algorithms, agent decisions are instantaneous and predictive, since reactive behaviors are needed to avoid future collisions, reach goals, and achieve formations. Here we adopt a temporal exposure window that integrates recent thermal and density information for use in agent comfort assessment and decision-making.

In addition to the temporal exposure window, we propose a new term for comfort in crowd simulations. The term comfort has been used with various meanings, but the most common has been associated with human density. Fruin (1971) defined the level of service concept where density and speed relationships are guidelines for comfort and safety in different spaces. In the context of crowd simulation, several authors (Helbing & Johansson, 2011; Kulpa, Olivier, Ondřej, & Pettré, 2011; Best, Narang, Curtis, & Manocha, 2014) relate the local density of the agents to their actual speed. Hughes (2002) and Treuille et al. (2006) describe comfort as a subjective quantity related to occupant density: pedestrians are assumed to reach an objective while interacting with each other to avoid forming over-dense areas. Other authors (van Toll, Cook, & Geraerts, 2012; Hoogendoorn, van Wageningen-Kessels, Daamen, Duives, & Sarvi, 2015) use density-based discomfort measures to estimate the cost of reaching a certain destination. Here we present a new measure of comfort related to the agent’s thermal experience, which can be added to any agent-based crowd algorithm or directly conveyed to a VR user. Thermal comfort opens a novel input dimension, adds environmental realism to
decisions, and thus improves observed motion and behavior in thermally interesting contexts. A thermal model has been used to evaluate comfort in pedestrian simulation (Fukuyo, 2004). A social forces model (Helbing et al., 2000) is used to simulate pedestrians in a specific environment, using two possible air-conditioning setups. Then, based on the presimulated occupancy and air-conditioning configuration, thermal model factors are calculated. Agents do not change the air temperature, nor do they change their movements based on thermal comfort. In their work, the simulation and the thermal model are completely decoupled.

While thermal models and occupant behaviors have been considered in recent simulations for building energy assessment and management (Kashif, Ploix, Dugdale, & Le, 2013; Parys, Souyri, & Woloszyn, 2014), they do not consider groups of individuals or movement behaviors instigated by occupant density and comfort.

3 The Thermal Model

People are quite sensitive to their thermal environment. Thermal comfort has been studied for years by environmental engineers (Fanger, 1970). There are six primary factors that impact thermal comfort:

1. Metabolic rate \( M \)
2. Clothing insulation \( I_{cl} \)
3. Air temperature \( t_{a} \)
4. Mean radiant temperature \( t_{r} \)
5. Air speed \( v \)
6. Humidity \( r_{h} \)

The first two factors depend on the individual. The metabolic rate is the rate of transformation of chemical energy into heat and mechanical work, usually measured in met units (one met = 58 W/m\(^2\)), where W is watts. Averaged measurements of typical activities can be used to estimate \( M \). For instance, \( M \) can range from 0.7 during sleep to 8.0 in some competitive sports such as wrestling (ASHRAE, 2004). The clothing insulation factor \( I_{cl} \) quantifies the thermal insulation provided by a specific garment, given in clo units (1 clo = 0.155m\(^2\)°C/W) (ASHRAE, 2001). Typical values for \( I_{cl} \) range from 0 clo (no clothing) to 2 clo (heavy outer garments). The other four factors are environmental. The air temperature (measured in °C) is obviously a key factor in thermal comfort. The mean radiant temperature \( t_{r} \) is defined as the uniform temperature of an imaginary enclosure in which the radiant heat transfer from the human body is equal to the radiant heat transfer in the actual nonuniform enclosure (ISO, 1998), and it is also measured in °C. The air speed (in m/s) and humidity (%) complete the six-factor list. All of the factors interact when evaluating thermal comfort: cold temperatures can be tolerated on a sunny day, and hot weather feels better when the air is dry rather than humid. Crowded situations can affect radiant heat transfer by providing desirable warmth or causing discomfort imposed by extra thermal load from close neighbors.

Since different people subject to the exact same set of conditions may feel different levels of thermal comfort, there are mathematical models that map a set of conditions to a statistical model of thermal sensation. The Predicted Mean Vote (PMV) model (Fanger, 1970) maps the six key factors for thermal comfort onto a numerical thermal sensation scale ranging from −3 (cold) to +3 (hot), where 0 is the neutral (ideal) feeling. The thermal sensation scale is used by environmental engineers for designing HVAC (heating, ventilating, and air-conditioning) systems for buildings, aiming to keep the PMV within the comfortable range \(-0.5 < PMV < 0.5 \) (ASHRAE, 2004). Although the PMV has been devised for indoor environments, it can also be adapted for outdoor scenarios by adjusting the mean radiant temperature accordingly (Staiger, Laschewski, & Grätz, 2012). In fact, the most important meteorological parameter affecting human energy balance during sunny weather conditions is the mean radiant temperature (Matzarakis, Rutz, & Mayer, 2007).

Given values for the six parameters, the PMV is computed as

\[
PMV = (0.303e^{-0.036M} + 0.028) L(M, I_{cl}, t_{a}, t_{r}, v, r_{h}),
\]

where \( L \) is the thermal load on the body, defined as the difference between the rate of metabolic heat generation
and the calculated heat loss from the body into the environment, which is a function of the six primary factors, and can be found in Fanger (1970); ISO (1998). The PMV formulation was based on the mean responses of several test subjects (Fanger). Populations with different cultural backgrounds might perceive thermal effects differently: people living near the equator are more resilient to heat and less to cold, while the opposite is expected for people living in cold climates. To cope with such differences, one can add an (empirically determined) offset value $\tau$ to the PMV, which should be negative for people used to hot environments, and positive for people living in cold ones. This can even be extended to individualized agent preferences.

The Predicted Percentage of Dissatisfied (PPD) is the expected percentage of people thermally dissatisfied in a given environment. Based on studies that surveyed subjects in a controlled indoor chamber, Fanger (1970) devised a relation between the PPD and the PMV, given by

$$PPD = 100 - 95e^{-0.03353PMV^4 - 0.2179PMV^2}.$$  (2)

Although the PPD indicates the percentage of people dissatisfied in a given environment, it can be also viewed as the probability of an individual agent feeling uncomfortable in the same environment within a time window (see Section 4.4). The next section describes our computational approach which builds on these models.

4 The Thermal Environment Model

Our method for thermal comfort can be integrated with any agent or crowd simulator to influence the motion of individual agents. In fact, the crowd simulation is a changeable module in our framework, as illustrated in Figure 1.

We added our thermal and density comfort formulation into an agent simulator which provides steering, collision avoidance, goals, and animated body movements (Shoulson, Marshak, Kapadia, & Badler, 2014), and runs in real-time for modestly complex environments in Unity3D (Uni, 2017). Agents change their behaviors in response to the integrated comfort terms. At each simulation timestep, the air temperature is updated based on heat propagation from known (and possibly varying) environmental sources and sinks, as well as from any occupants. Based on the air temperature and the other five parameters from Section 3, thermal comfort is computed for each agent. Agents use the thermal and density comfort terms to select motions and actions which improve their comfort level. In order to avoid discretized and instantaneous decisions (which can generate unrealistic vacillating, jerky, or cyclical behaviors), we use a temporal exposure window that integrates thermal information over a time span so that the decision process is more coherent. Finally, the resulting agent conditions are fed back into the heat transfer model. This is detailed in the next section.

4.1 Computation of the Air Temperature

Since the simulation must compute agent behaviors based on their thermal comfort, we must generate and simulate the relevant environmental factors of humidity, air temperature, air speed, and mean radiant temperature. Although sophisticated models could be used, we treat humidity, air speed, and mean radiant temperature as user-provided variables, and use a simplified heat transfer model for the air temperature.

Since our emphasis is on agent behaviors, we adopt a simplified heat transfer model. We use a 2D model for the air temperature $T(x, y, t)$ guided by diffusion with possible heat sources or sinks:

$$C \frac{\partial T}{\partial t} = \frac{\partial}{\partial x} \left( k(x, y) \frac{\partial T}{\partial x} \right) + \frac{\partial}{\partial y} \left( k(x, y) \frac{\partial T}{\partial y} \right) + Q(x, y, t),$$  (3)

where $C$ is the volumetric heat capacity of the air ($J/(m^3\,^\circ C)$), $k(x, y)$ is thermal conductivity ($W/m\,^\circ C$), and $Q$ is the rate of heat generation/consumption ($W/m^3$) caused by sources/sinks. Although the thermal conductivity of homogeneous media (such as air) are usually constant, we adopted a spatially varying version so that walls and other thermally insulating objects
in the interior of the room can be approximated. For that purpose, one should select smaller values for $k(x, y)$ at the location of these objects, allowing the simulation of more complex environments. For the boundaries of the room, we can either use Dirichlet conditions (controlled temperature) or Neumann conditions (partial or total insulation).

A fundamental aspect to our work is that the heat propagation model is cosimulated with the agent models: agent behavior is affected by thermal conditions and they, in turn, transfer heat into the environment. Typical human heat generation values can vary from 81 W (sleeping) to 1630 W (sprinting). In dense crowds, the heat produced may even warm the environment. Ackerman (2012) noted that buildings in Paris, Stockholm, and Minnesota have been using human thermal energy to improve thermal comfort on cold days or to channel the surplus energy to nearby buildings. Despite the tight relationship between the heat propagation and agent simulation models, it is important to note that they are independent. The two simulations have separate codebases and they communicate with each other to cosimulate the entire system. Hence, different heat propagation models and agent simulators could be readily combined.

We use the locations of the agents given by the simulator as circular heat sources to build the term $Q(x, y, t)$ in Equation 3. Each agent is a source with constant heat generation $Q_0$. If there is semantic information about an agent’s activity (e.g., standing, walking, running, exercising, dancing, cooking, etc.), the approximate heat produced can be assigned using a conversion table (ASHRAE, 2004).

There are many numerical methods to solve the parabolic PDE given by Equation 3 (Hundsdorfer & Verwer, 2013). Since evaluation of the equation is tightly integrated with the agent simulator (which employs a small time step $\Delta t$), we used a simple explicit Euler solution method based on forward finite differences in time and central differences in the spatial coordinates. For a thermal discretization grid with $M \times N$ cells, the complexity of each iteration is $O(NM)$, which adds very little computational burden to the agent simulator.

4.2 The Thermal Comfort Model

The PMV and PPD are computed for each agent to quantify its thermal comfort level. The six factors from Section 3 are implemented as follows:

1. Metabolic rate (M): We use metabolic rates related to standing (1.6 met) and walking at 2, 3, 4, and 5 km/h (1.9, 2.4, 2.8, and 3.4 mets, respectively) for each individual agent in the simulation (ISO, 1998).

2. Clothing insulation ($I_{cl}$): We use three possible clothing levels for each agent: $I_{cl}^{\text{min}} = 0.4$ clo (light clothes), $I_{cl}^{\text{med}} = 1.2$ (medium), and $I_{cl}^{\text{max}} = 2.0$ clo (heavy jacket), based on the clothing insulation chart presented in ASHRAE (2004).

3. Air temperature ($t_a$): As noted in Section 4.1, it is provided by the diffusion heat equation, impacted by heat source/sinks and the location of virtual agents.

4. Radiant temperature ($t_r$): Since the mean radiant temperature is very difficult to estimate, we separate it into two components. The first component $t_{r0}$ is due to the environment: for indoor scenarios, it is set equal to the air temperature, as in Matzarakis, Mayer, and Iziomon (1999); for outdoor (sunlit) environments, it is defined by the user to account mostly for solar radiation, either extracted from real-life data or estimated based on atmospheric and environmental parameters (Matzarakis et al., 2007). The second component is due to the influence of other surrounding agents if they are sufficiently close to have direct, interpersonal, radiant heat transfer, which increases the first one. To model this direct heat transfer, we only consider agents located within the “intimate” proxemic distance (0.45 m) proposed by Hall (1959). This influence should decay with increased interpersonal distance (inverse square law) and depend on their mutual “form factor”: that is, it is maximal when two agents face each other’s front (or back), and diminished as their body orientations near 90°. The model for a given virtual agent with $i$ surrounding intimate space agents is
where $t_r$ is the environmental mean radiant temperature, $d_i$ is the center-to-center distance, and $\theta_i$ is the angle to the $i^{th}$ intimate distance agent, $\epsilon$ is an offset parameter that controls the minimum radiant temperature gain for a given distance when $\theta = 90^\circ$ (i.e., agents in lateral locations), and $\gamma$ is the weight that controls the temperature increase with respect to the air temperature. Assuming an average radius of 0.2 m for each agent, the possible distances $d_i$ lie in the range [0.4, 0.85].

5. Air speed ($v$) and Humidity ($r_h$): These are user-specified parameters, and kept spatially and temporally constant in all simulations (at present).

The PMV index of Section 3 is derived for steady-state conditions, but it can be applied during minor fluctuations of the variables by using temporal averages. In ISO (1998), individual averages of the variables over a period of 1 hour is suggested. In ASHRAE (2004), different temporal windows are suggested for each variable. In particular, a window of at least three-minute duration containing at least 18 equally spaced samples in time is suggested for the air temperature. We adopt this latter approach for all variables. Instead of averaging each parameter individually, however, and then computing the PMV, we directly compute the average of the PMV values, which is then used to obtain the PPD.

### 4.3 The Density Comfort Model

If agents are guided solely by the thermal discomfort presented so far, virtual agents can potentially gather at high densities near thermally comfortable zones. However, it is well known that people tend to preserve their personal space (Hall, 1959), avoiding high densities if at all possible. Furthermore, real-life experiments show that there is an intricate relationship between crowd density and thermal comfort. For instance, Griffitt and Veitch (1971) reported that several positive mood aspects (e.g., concentration, social affection, vigor, comfort) decrease in denser crowds, while negative aspects (such as fatigue) increase. They also show that similar behaviors happen when the temperature is increased from normal (73.4°F/23°C) to hot (93.5°F/34.2°C), concluding that people in hot crowded places report comfort levels significantly more negatively than in low-density and thermally comfortable temperature rooms. Although this behavior may seem natural, it is hard to assess universally if people would prefer low-density and thermally uncomfortable scenarios rather than high-density and thermally acceptable rooms.

Despite the existence of many density-based models for crowd simulation (Hughes, 2002; Treuille et al., 2006; Best et al., 2014; van Toll et al., 2012), we are not aware of anything analogous to the thermal PPD for measuring the percentage of people that feel uncomfortable as a function of the local density. In fact, even the concept of local density is ambiguous in discrete distributions, and it is usually approximated as the ratio of the number of agents within a region to the area of the region or a distance-weighted average of the neighbors, as in Best et al. (2014). As noticed by Hall (1959), people tend to maintain certain distance limits from neighbors depending on their relationship. For example, only people with an intimate relationship are expected to be within one’s intimate personal space: when strangers are in that region, the person feels much less comfortable. The same happens with the personal, social, and public spaces, but with progressively less “intrusion discomfort.”

We use a simple model to estimate the local discomfort with respect to the local density, analogous to the thermal PPD. For clarity, the thermal PPD given in Equation 2 will be denoted by $PPD_t$, and the density PPD will be denoted by $PPD_d$. The measure $PPD_d$ essentially exploits the progressive intrusion effect based on Hall’s interpersonal distances (Hall, 1959), given by

$$PPD_d = 100 \frac{n_i + \beta n_p}{M_i + \beta M_p},$$

where $n_i$ and $n_p$ are the number of agents in the intimate and personal spaces, respectively, $M_i$ and $M_p$ are the maximum number of agents in these two regions, and $\beta$ is the decay factor for the personal space.

Like the thermal $PPD_t$, the density $PPD_d$ is also averaged in time, since the discomfort sensation changes
gradually, rather than instantaneously, with the density. High densities may be tolerated for a short time, but discomfort increases rapidly when the situation persists. Although the temporal windows that guide the density and thermal PPD adaptation do not need to be the same, we used the same 3-minute window with 18 equally spaced samples for both. The two PPD values are then used to guide agent behaviors, as described next.

4.4 The Individual Decisions

Agents are influenced by both local density and thermal comfort, encoded by \(PPD_d\) and \(PPD_t\), respectively. There are many ways to explore the two comfort levels in the context of agent simulations. For instance, a density-based penalty is used in Hughes (2002), Treuille et al. (2006), Best et al. (2014), and van Toll et al. (2012) so that high-density regions tend to be avoided. We now explore how the thermal and density discomfort levels may be used for active agent decision-making. Recall that the PPD is the probability that an agent will feel discomfort; it is not an absolute metric for behavioral thresholds.

Although the thermal comfort might be combined with density models for path-planning (so that agents tend to avoid thermally uncomfortable and high-density regions), in this work we use the comfort measures at an even higher level. In our simulations, the virtual environment is divided into spatial contexts with semantic information (e.g., “place to eat”), and agents have goals in these contexts. At all times, a first level that explores only \(PPD_t\) is used to evaluate the thermal comfort of each individual. The main assumption of adaptive thermal control is that if a change occurs such as to produce discomfort, people react in ways that tend to restore their comfort (Nicol & Humphreys, 2002), such as opening windows or changing clothes. To avoid dealing with complex building and heat transfer models for now, agents cannot take an active role in modifying the environment. Agents do, however, modify their clothing: an agent adds a piece of clothing when it is too cold, and removes a piece of clothing when it is too hot, as long as there are layers to add or remove. Specifics on this process appear later in this section.

The second decision level considers a joint PPD blend of both thermal and density comfort factors when an agent reaches its goal. A precise formulation of this joint PPD is difficult, since the interplay of these two comfort terms has personal, preferential, contextual, and even cultural factors. However, it should be monotonically increasing in both \(PPD_t\) and \(PPD_d\), so that low values of these variables lead to higher comfort levels.

We use a simple linear weighted average to generate the combined \(PPD_c\), given by

\[
PPD_c = \alpha PPD_t + (1 - \alpha) PPD_d,
\]

where \(\alpha \in [0, 1]\) controls the blend. The weight \(\alpha\) can be set taking into account individualities, so that agents who feel uncomfortable staying closer to other agents could present smaller \(\alpha\) values, while agents more sensitive to thermal aspects could present larger \(\alpha\) values. Note that when \(\alpha = 1\), only the thermal comfort is considered; only the density is evaluated when \(\alpha = 0\). One possibility for the practical inclusion of cultural aspects in our method is to use the personal distance, as proposed by Hall (1959) in order to set \(\alpha\) relative to density comfort. A recent study on personal space employing a projective technique was conducted in 42 countries (Sorokowska et al., 2017). Participants had to respond by graphically marking which distance they would feel comfortable with when interacting with three categories of people: a) a stranger, b) an acquaintance, and c) a close person. The number of countries assessed in this study (Sorokowska et al.) promotes proxemic preferences and differentiation across cultures. This information could help parametrize \(\alpha\) in our method.

When an agent is uncomfortable according to \(PPD_c\), the agent tries to move to another position that improves comfort, that is, decreases the \(PPD_c\). This movement is effected in one or possibly two stages. First, the simulator probes a neighborhood within the same context around the agent and computes the \(PPD_c\) at all points, choosing the location of the minimum value as the next goal for the agent. The default size of this area in our implementation is \(3 \times 3\) meters, but that can be readily changed. This process might be repeated up to \(N_t\) times, leading to a fixed-iteration gradient descent approach in which the agent moves toward a
local minimum of $PPD_c$. If after $N_i$, location changes the agent is still uncomfortable, the second stage of movement is invoked. In this stage the agent moves (navigates) to a random position in another context with the same semantic level. For instance, if an agent is in a “restaurant” and after some time cannot find a comfortable position, the agent will go to another “restaurant” context, as illustrated in Figure 2.

As will be shown in Section 5, this method produces an emergent behavior observed in real life: people may avoid standing close to each other to improve their thermal comfort, for example, while waiting at a sunny bus stop on a hot day. Conversely, people might get closer to each other to get warmer on a cold winter day. Note that existing simulation models may penalize higher density regions, but here this is exactly what is needed: to use interpersonal body heat to improve overall crowd comfort.

In both levels, decisions are synchronized with the update of $PPD_t$ and $PPD_d$, that is, every 10 seconds. PPD values report the percentage of people who are uncomfortable within the temporal window (3 minutes). More precisely, every 10 seconds the decision process for each agent generates a random number $r$ in the range $[0, 1]$, and the agent “decides” to be “uncomfortable” if

$$r < p_r = 1 - \left(1 - \frac{PPD}{100}\right)^{1/n},$$

where $n = 18$ is the number of samples within the temporal window, and PPD is either $PPD_t$ in the first decision level, or $PPD_c$ in the second. After $n$ consecutive decisions (i.e., the length of the temporal window used), the probability of having only negative decisions (i.e., keeping the current status) is $(1 - p_r)^n = 1 - PPD/100$, which is exactly the expected fraction of “comfortable” people. Hence, if we have $N$ agents subject to the same conditions, a percentage PPD of them will “decide” to be uncomfortable, which is exactly the original concept of PPD.

5 Experimental Results

This section presents some results obtained with our method. Our algorithms were implemented using Unity’s Scripting API for C#. We used native game objects to represent our agents, with collider components for collision avoidance, and a NavMesh component for describing the navigation map where the agents move.

For simulations, we primarily use a 3D model of an enclosed market that contains various small but distinctive spaces, numerous obstacles, and heat sources and sinks. The Unity NavMesh graph connects all interest points. Any location in the environment can be assigned as a target for the agent.
The constants used in the market simulations are: air speed $(v) = 0.1 \text{ m/s}$ and relative air humidity $(r_h) = 40\%$, and for the thermal comfort model $\gamma = 0.1$ and $\epsilon = 0.5$ for mean radiant temperature, which leads to an increment of up to $1^\circ\text{C}/1.8^\circ\text{F}$ on average with respect to the environmental radiant temperature $t_{r0}$ in very dense situations (6 agents within the intimate space). This increment depends on the distance and orientation of the neighboring agents, as described in Equation 4. Note that temperature changes over time are computed by the simulation, so the incremental radiant term only changes if the intimate space agent configuration changes. In addition, we used $M_i = 6$, $M_p = 12$, and $\beta = 0.2$ as the default parameters for the density discomfort level given in Equation 5, so that the “intimate” discomfort dominates. As for parameter $\alpha$ that controls the weight between the thermal density discomfort terms in Equation 6, we used different values to show that the behavior of agents vary depending on $\alpha$. We also used $N_i = 3$, meaning that each agent tries to find a more locally comfortable position three times before deciding to move to another context, as described in Section 4.4.

Our results follow in four main parts. The first describes the impact of the clothing factor and temporal exposure window on human behaviors. The second presents the influence of the thermal and comfort factors, both individually and combined, in the decision process. The third one presents the “feedback-loop-effect”, in which the heat generated by several people in a room affects the air temperature, changing their thermal comfort and causing agents to move, which in turn changes the room temperature. The final example focuses on the impact of dense crowds in a very hot environment, using a simulated scenario loosely inspired by the tragic 2015 Hajj disaster (Alaska, Aldawas, Aljerian, Memish, & Suner, 2017).

5.1 Impact of Clothing Factor and Temporal Exposure Window

In the first decision level, the thermal comfort model affects an agent’s clothing choice. In this scenario, the initial air temperature is set to $25^\circ\text{C}/77^\circ\text{F}$, and a few heat sources are present (so that the temperature is spatially varying). An agent with clothing factor 2 (maximum) starts far from a heat source, approaches, and keeps close to it. Figure 3 shows plots of the air temperature, the thermal PPD of the agent, and the chosen clothing factor along its path. As can be observed, the agent is initially thermally comfortable, but the $PPD_t$ increases as the perceived air temperature increases. After 128 seconds, the agent takes off the heavy jacket, keeping a medium clothing factor of 1.2. The temperature keeps rising, and after another 70 seconds the agent switches to the lightest clothing factor (0.4). It is important to note that there is no discontinuous transitions in $PPD_t$ after each clothes change, due to the temporal exposure window.

To further evaluate the impact of the temporal window, we simulate an indoor environment with no heat sources or sinks, with an initial indoor air temperature of $22^\circ\text{C}/71.6^\circ\text{F}$, and agents with medium (comfortable) clothing. Agents are close to a door, which opens for 60 seconds and then closes, letting cold ($−5^\circ\text{C}/23^\circ\text{F}$) outside air in. To show only the comfort we turned off agent decision-making, so they are not going far from the door. Without the temporal window, most agents feel thermally uncomfortable immediately after the door opens (see Figure 4[a]). With temporal integration, the discomfort level increases smoothly (see Figure 4[b]) up to the moment when the door closes. The colored “auras” in Figure 4 map the PMVs from $-3$ (cold, shown as dark blue) to $+3$ (vivid red), and green denotes optimal thermal comfort (PMV equal to zero). The horizontal bars over the heads indicate the
Figure 4. Effect of temporal exposure window on thermal comfort: no integration in (a) and with integration in (b). Snapshots (2D view on the top, oblique 3D view on the bottom) were taken when door closed.

local density, from low density (green) to high density (red).

**5.2 Comfort Factors**

One of our main contributions is the thermal comfort model. We compare and evaluate linear combinations of the thermal and density comfort models, as presented in Equation 6. By adjusting parameter \( \alpha \), the simulated agents assign more weight either to the thermal or to the density-based comfort terms, and differing behaviors ensue.

In order to evaluate just the joint discomfort function, we turned off the clothes changing decision (first layer), and evaluated just the motion pattern. We modeled an outdoor scenario containing two contexts: one sunlit open region and a smaller room with a roof. All simulations were initialized with 10 agents in the larger room and 30 in the smaller one, as shown in Figure 5(a). As in Figure 4, the character’s outline “aura” denotes the thermal comfort. Additionally, the color bar on top of the character indicates the density comfort, where green indicates comfortable densities, while yellow and red denote progressively more discomfort.

The initial air temperature was set to 21°C/69.8°F, with a cloudy sky at the beginning of the simulation that changes to sunny. Based on the RayMan software (Matzarakis et al., 2007), we estimated the mean radiant temperature of 25°C/77°F when cloudy, which then rises to 48°C/118°F when the clouds dissipate (approximately 8 seconds after the beginning of the simulation).

With this initial setup, we first simulate with \( \alpha = 1 \), meaning that all decisions are based only on thermal comfort. As the clouds dissipate and the radiant temperature increases in the open context, agents get progressively less thermally comfortable. Eventually, they all move to the shaded region, as shown in Figure 5(b). We observe that they do not respect their proxemics, which is expected since density was not taken into account.

When simulating the same scenario with \( \alpha = 0 \), only the density comfort is considered. Since the initial density is relatively high in the smaller context, agents tend to move away from each other, and some of them eventually move to the sunny uncovered context. By the end of the simulation, 23 agents remained in the smaller (shady) context, and 17 ended up in the larger
Figure 5. Simulation results using different weights $\alpha$ for the thermal and density discomfort levels. Images on the top are 2D views of the environment, and the bottom images are 3D views.

(sunny) one, as shown in Figure 5(c). The two agents in the sunny region that are thermally comfortable (green outline “aura”) had just moved from the shaded region, and after some time they would become thermally uncomfortable due to the temporal integration window.

The final example was performed using $\alpha = 0.5$, so that equal weight was assigned to thermal and density comfort levels. The final frame of the simulation, shown in Figure 5(d), indicates that some agents in the sunny region move to the shaded context, but keep a more homogeneous distribution than the initial configuration, which means that they respect each other’s proxemics due to the density term. Since the final comfort is a balance between thermal and density factors, a few agents end up “comfortable enough” in the hot sunny region.

5.3 The Feedback-Loop-Effect in Crowded Scenes

One important aspect of our model is the feedback-loop-effect in which people generate heat (which is particularly noticeable in denser crowds and indoor spaces) and are also affected by the thermal consequences. To illustrate this effect, we consider a square room with dimensions $20 \times 20$ m$^2$, in which the initial ambient temperature is set equal to the (constant) boundary temperature $T_b$, and evolves in time due only to body-generated heat.

In the first scenario, we start with a comfortable temperature of $T_b = 23^\circ$C/73$^\circ$F and a dense crowd of 450 agents distributed within a circular region with a radius of 4 meters in the center of the room, leading to a local density of 9 people/m$^2$, which is very high (Fruin, 1971). We then compute the heat propagation and the average thermal discomfort for all agents considering i) nonresponsive agents, who stay still; and ii) reactive agents, who move radially toward the room boundaries (and thus decrease the local density). The top image of Figure 6(a) shows the average discomfort level ($PPD_t$) for both static (dashed curve) and reactive (solid curve) agents, where the color of the curve indicates the local density. For nonreactive agents, the local temperature increases considerably over time, so that the average thermal discomfort level ($PPD_t$) rises above 90% when the temperature exceeds 36$^\circ$C/97$^\circ$F. On the other hand, the reactive agents move away from each other, which alleviates heating (maximum temperature reaches 28$^\circ$C/82$^\circ$F in the center of the room) and positions them closer to the comfortable temperature at the boundaries. As a consequence, the average $PPD_t$ remains below 20%. The final configuration of both static and reactive agents, as well as the corresponding discomfort maps, are illustrated in the bottom left and bottom right of Figure 6(a), respec-
tively. As can be observed, the final configuration of responsive agents improves both thermal and density comfort levels, which is the expected behavior for real humans.

In the second scenario, the initial room and boundary temperatures are set to $T_b = 15^\circ C/59^\circ F$, and the same 450 agents are distributed as sparsely as possible within a circular region with diameter of 20 meters (i.e., the room size), so that the initial density is approximately 1.4 people/m$^2$. As in the first scenario, we also consider static (nonreactive) and moving (reactive) agents, who now move toward the center of the room. Figure 6(b) shows the analogous results of Figure 6(a) for this new scenario. We see that reactive agents get more thermally comfortable after some time when compared to static ones, since a denser distribution leads to more local heat accumulation (which is good in this situation, since the initial temperature is low). This example show a tradeoff between thermal and density comfort levels: when one increases, the other decreases. The final state relates again to a very high density (9 people/m$^2$), which humans would probably not tolerate very long. However, we believe that the ideal configuration would lie between the initial and final states, where agents get close enough to each other to get a little warmer, but still keep their density comfort level acceptable. This last behavior is not achieved by typical crowd simulation algorithms, in which increasing local density is always penalized.

5.4 Implemented Scenario Inspired by the 2015 Hajj Disaster

In very cold or very hot environments, the thermal discomfort given by Equation 2 tends to saturate very close to 100%, which is expected. Such extreme temperatures, however, impact more than the comfort level: they cause thermal stress (Matzarakis et al., 1999), which might lead to life-threatening situations such as heat strokes or dehydration (Bouchama & Knochel, 2002). A real-life situation that potentially combines very hot weather with dense crowds is the annual Hajj pilgrimage to Mecca, which is a prototype scenario for crowd analysis and simulation. However, previous approaches (such as Curtis, Guy, Zafar, & Manocha, 2011) focus only on the crowd density, and do not account for the significant thermal effects.

Our last scenario was inspired by and abstracted from the Hajj disaster on September 24, 2015, where
crowds coming from two intersecting paths merged. We could not find the exact temperature at the time of the disaster, but records show that the temperature in Mecca on that day was in the range \([32^\circ, 48^\circ]C\) \([[98.6^\circ, 118.4^\circ]F]\), with a relative humidity of 40\%. We used a conservative initial temperature of 35°C (95°F), since the incident occurred at 9:00 am. The mean radiant temperature was estimated using the RayMan software (Matzarakis et al., 2007) assuming no cloud coverage and an air speed of 0.5 m/s, which leads to \(t_r = 62^\circ C (144^\circ F)\). Regardless of clothing levels and metabolic rates, the estimated PMV would be greater than 5, which corresponds to an “extreme heat” grade of physiological stress according to Matzarakis et al. (1999).

We used Cassol et al. (2015) to simulate 11,000 agents in a T-shape environment analogous to the intersection in the Hajj disaster, with dimensions of the vertical route \(123 \times 20\) m\(^2\) and of the horizontal route \(10 \times 23\) m\(^2\), as illustrated in Figure 7(a). We then repeated the same simulation but randomly selected a fraction of the agents to stop, mimicking heat exhaustion effects, and evaluating the impact on the crowd flow. If only 5\% of the agents stop, the average density varies from 5.42 people/m\(^2\) to 6.62 people/m\(^2\), which by positive feedback would exacerbate physiological failure and thus increase the number of agents affected by thermal exhaustion. If we also consider the radiant temperature produced by nearby agents in crowded scenes, as given by Equation 4, the temperature in the middle of the crowd might reach almost 50°C (122°F), increasing even further the chance of thermal exhaustion (or dehydration). Figure 7(b) illustrates a top-down view of the simulation (density map), along of the temperature map in the simulated scenario.

6 Conclusions

We explored two new factors influencing human-like agent behaviors: temporally integrated thermal and density measures. We demonstrated novel emergent behaviors unlike any evidenced in other agent or crowd simulation systems. For example, our agents can move into a region of higher occupant density to improve their thermal balance, or can spontaneously move away from a group of people to get more comfortable. We adopted standard measures of human comfort as much as possible so that our results would have physiological validity. We combined agent simulations with a simple but effective heat transfer model so that a cosimulation allowed each to affect the other: people create heat, occupation density amplifies heat, heat helps define comfort, and comfort drives movement and clothing changes.

The resulting simulations demonstrate plausible agent behaviors under varied density and thermal contexts. In a virtual environment, these emergent behaviors in the surrounding people may enhance a participant’s sense of presence: simulated agents will spontaneously change local position or clothing to adopt to the ambient context. We do not yet know if the perception of people exhibiting these behaviors will elicit a concomitant sympathetic thermal response in the live subject, but at least it will provide visual evidence of the thermal conditions perceived by others.
Formal validation of the actual local movements of the virtual agents affected by thermal and density factors would be difficult, as the Predicted Percentage of Dissatisfied is, by definition, a probabilistic quantity. Individual tolerances, personal preferences, actual clothing, and social conditions (e.g., surrounded by friends or strangers) may affect movement choices. Accordingly, we based our validation as much as possible on the accepted ISO standards for human response to thermal and ambient environment factors. Our use of this factor in itself adds a novel agent decision-making element that has not been incorporated into other graphical crowd simulators.

One possible next step is to improve the thermal simulations with more sophisticated software tools. This direction may sacrifice real-time interaction, but will gain a system that could be of great value in helping design and improve the energy efficiency of real buildings. We could also further study the interplay between thermal and density comfort for path planning purposes. Other exciting extensions include more detailed and individualized modeling of agent environmental preferences (e.g., seeking an area of higher air velocity in a warm environment), their personal relationships and affinity groupings with others in the locale, interest in and attention to ongoing events (such as a performance or the arrival of an ice-cream vendor), and animated interactions between their modeled clothing and behavioral choices. Finally, incorporating these models into a real-time virtual reality application would create a natural testbed for experiencing the physiological presence of temperature and human crowds.

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