Statistical Inference on Emergency Egress Analysis Considering Blocking Effects on Crowd Movement

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Abstract— **In building emergency evacuation, the perception of hazard can stress the crowd, arouse their competitive behaviors, and trigger disorder and blocking as they pass through a narrow passage (e.g., narrow exit). This is a serious concern threatening evacuees' survivability and egress efficiency. How to effectively manage risk of such undesired situations is a critical problem in evacuation planning. Based on advanced simulation, behavioral studies and psychological findings on crowd evacuation, this paper establishes a probabilistic graphical model for egress risk analysis, especially considering egress blocking effect on crowd movement. In this model, a hazard event (e.g., fires) is the cause of crowd escape. The undesired event of disorder and blocking is then characterized as an outcome of excessive stress on evacuees due to surrounding hazards, resulting in a drastic decrease of crowd movement in a probabilistic fashion. Several unknown parameters exist in this model, and they have clear psychological meanings, such as the social bond of evacuees, the stress level of crowd in a hazardous condition, etc. Based on this probabilistic graphical model, statistical inference can be implemented and the unknown parameters in the model can be estimated.**

I. INTRODUCTION

Evacuees were pushing against each other trying to get to the front door as fast as possible, but they were trampled underfoot and the doorway was simply blocked. This tragedy happened in a Bangkok nightclub fire on January 1st 2009, and as the fire spread through the entire building within 10 minutes, 61 people were killed and more than 200 injured in the horrible moments of intense heat, smoke, pushing, shoving and crushing (Mydans, 2009). Similar scenes of disorder and blocking were observed in the Rhode Island nightclub fire in February 2003 (Grosshandler et al., 2005) and many other building emergencies. How to effectively prevent or mitigate such disasters becomes an important and urgent issue.

As identified by recent egress research, a fundamental cause of such disorder and blocking is the psychological stress that is aroused by the emergency hazard (Proulx, 1993 and 1997). Due to such stress, people move or try to move considerately fast to escape from danger. However, if they cannot move as desired, in particular, when a bottleneck such as a doorway or a corridor limits their speed of motion, they may compete with each other, and disorders and blocking may happen. However, such an important feature has long been ignored in traditional egress models. Over the past decade, advanced simulation has been developed for egress analysis where the pedestrians were microscopically modeled with certain psychological factors captured. Such advanced simulation well demonstrated the blocking phenomenon in the results, and it provides a large amount of data for further analysis. Based on such simulation and related pedestrian models, a probabilistic graphic model is established in this paper for advanced egress analysis. This graphical model critically characterizes the inter-relationship among the hazard status, passage capacities, crowd movement and certain psychological factors, and unknown parameters in this model have clear psychological meanings, such as the social bond of evacuees, the stress level of crowd, etc. Based on this probabilistic graphical model, statistical inference can be implemented and the unknown parameters in the model can be estimated.

II. AN EGRESS MODEL WITH BLOCKING EFFECTS

Based on recent advances in psychology, behavioral studies and pedestrian modeling and simulation, a probabilistic graph is established in this section. In this section, a key concept, the desired flow of crowd, is first presented as the macroscopic counterpart of the desired velocity in Helbing, Farkas, and Vicsek, 2000. It reflects the inner drive of crowd movement in terms of flow dynamics (Section A), and it rises as crowds are stressed by the hazards of fire and smoke (Section B). The outcomes of disorder and blocking are then modeled as the desired flow rate exceeds the allowable rate as specified by the passage capacity, resulting in a drastic decrease of crowd movement in a nonlinear and probabilistic fashion. Through this model, interdependencies among crowd flows, emergency events and passage capacities are characterized, and how to guide crowd to use the passages with proper capacities is then identified as an important issue (subsection C).

A. The Blocking Effect on Crowd Movement

Existing egress research clearly indicates that disorder and blocking occur at the bottleneck in a structural layout (e.g., the doorway). Thus, our study will focus on crowd movement at such bottlenecks rather than in open areas, and the key egress scenario to be modeled is, how crowd move from one area to another via a bottleneck rather than how they move within the areas. As a result, in this section, the crowd movement will be modeled in an elementary layout as shown in Figure 2, where two areas, v_1 and v_2, are connected by a passage. To model the blocking effect at a macroscopic level, a novel concept – the desired flow rate, will be first established based on the desired velocity concept in Helbing, Farkas, and Vicsek, 2000.

The desired velocity in Helbing, Farkas, and Vicsek, 2000 specifies two aspects of the motion that an individual desires to realize – the direction and speed. As a multitude of such individuals move collectively through a passage as shown in Figure 2, this microscopic concept will be transformed to the macroscopic level by taking average of such individual speeds and directions. For the average direction, as individuals move in a passage, their desired moving directions are almost at a tangent to the passage way because they are passing it through. As a result, the average direction of crowd movment can be abstracted as along with the tangential direction of the passage. As for the desired speed on average, it is then measured by the tangential desired speeds averaged among all the individuals and is denoted by $|\vec{v}^d|$. Such averaged direction and speed are then represented in flow dynamics, and the new concept of desired flow rate q^d is obtained based on the fluid physics: q^d is the product of the average desired speed $\vec{v}^d$, the crowd density ρ, and the width *l* of the passage.

$$q^d = \vec{v}^d l\rho. \quad (1)$$

Based on the fluid physics, the desired flow rate captures the average speed of crowd movement by its magnitude, and the average direction by its sign. Its magnitude $|q^d|=|\vec{v}^d|l\rho$ denotes the average number of people who demand immediate motion in escaping and thus desire to move through a passage per time unit (see the blue dots in Figure 2). The sign, $\mathrm{sgn}(q^d)=\mathrm{sgn}(\vec{v}^d)$, represents the direction of their desired movement. With the direction of a passage specified (e.g., the arrow direction in Figure 2), q^d is positive if the crowd desire to move along with this direction, and negative if they desire to move oppositely. In the perspective of psychology, such desire of crowd motion is due to the perceived stress in emergencies, and especially related to the perception of hazards (e.g., fire or smoke). Thus, q^d, as an indicator for demand of crowd movement, can be also viewed as a measure of the stress on evacuees.

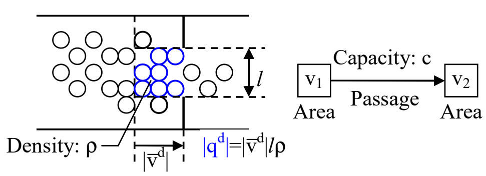

Fig. 2. Crowd Flow Dynamics at a Passage

What will happen as such demand of crowd travel keeps on increasing in emergency egress? Existing research indicates that, when such demand exceeds a bottleneck (exits, doorway) capacity, a disaster may rise as disorder and blocking in crowd movement (Kachroo, et al., 2008). Thus, the blocking effect is modeled as the desired flow rate exceeds the allowable rate as specified by the passage capacity, resulting in an undesired decrease of crowd movement. Here, the parallel to q^d, which describes the desire of movement in a psychological sense, is flow rate q, which reflects the physical motion that the crowd is able to realize. Similarly, the magnitude of q denotes the number of individuals who physically pass through a passage per time unit, and the sign of q denotes the direction of such flowing. In particular, crowd physical movement is motivated by their psychological desire. Thus the actual crowd flow q is directed by the desired flow q^d, and this implies $\mathrm{sgn}(q) = \mathrm{sgn}(q^d)$. The capacity of a passage is $c=\max\{|q|\}$, the maximal number of people who can pass through the passage per time unit. With the above flow-based concepts, the blocking effect is modeled as: when the desired flow rate is below the passage capacity, crowd can move as fast as desired, and q is equal to q^d. If the desired flow rate exceeds the passage capacity, the probability of disorder and blocking will increases with the increase of the overage, resulting in a decrease of the crowd flow rate in a nonlinear and probabilistic fashion in Figure 3.

Compare the above curve (Figure 3) with that in simulation of Helbing, Farkas, and Vicsek, 2000 (Figure 1), it is clear that the two curves are in the same shape, and this can be viewed as a justification of our macroscopic modeling. The following probability distribution exemplifies the curve in Figure 3.

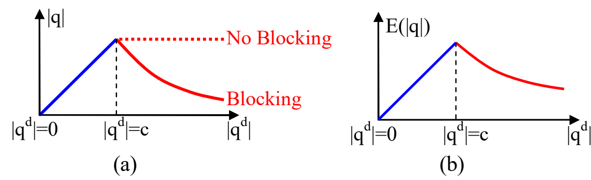

Fig. 3. The Egress Blocking Effect

a) If $|q^d| \le c$, q equals q^d with probability 1, i.e.,

$$\Pr(q \mid q^d, c) = \begin{cases} 1 & \text{for } q = q^d, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

b) If $|q^d| > c$, the probability of disorder and blocking increases as the difference between q^d and c increases, i.e.,

$$\Pr(q \mid q^d, c) = \begin{cases} 1-\exp\left(\dfrac{\alpha}{|q^d|-c}\right) & \text{if } q = \mathrm{sign}(q^d)\cdot c, \\ \exp\left(\dfrac{\alpha}{|q^d|-c}\right) & \text{if } q = \mathrm{sign}(q^d)\cdot c^{Blc}. \end{cases} \quad (3)$$

Here c^{Blc} denotes a small magnitude of crowd flow rate in case of disorder and blocking, and $\alpha<0$ is an unknown parameter affecting the slope of the curve in Figure 3 when $|q^d|>c$. Here the parameter α actually reflects the level of competitiveness of crowd in their movement. As α goes to zero, $E(q|q^d)$ tends to decrease sharply, which implies a increased probability of disorder and blocking. In the contrast, if α becomes a large negative number, $E(q|q^d)$ tends to decrease slowly, implying a decreased probability of blocking. Especially, as $\alpha \to -\infty$, it implies that all evacuees are ideally altruistic. As a result, no probability of disorder and blocking will be induced.

Another point to be mentioned is, although the above flow dynamics can be easily extended to capture the counter-flows of crowds, this paper will not consider this case because in an evacuation process people move toward exits collectively and their moving directions usually converge to be the same rather than opposite. Thus, counter-flow seldom occurs, and it is out of the concern of this paper.

B. The Relation of Hazard and Stress

Existing psychology findings indicate that hazardous threat can stress people and cause their escape. For example, as fire spreads, people may perceive the threat and be more stressed, and thus desire immediate motion more urgently (Ozel, 2001; Staal, 2004). As a result, the demand of egress, as formalized as the desired flow rate q^d, is dependent on emergency status. The following probability distribution will exemplify such relationship between the desired flow q^d and hazard status s^F.

To model the above features at the macroscopic level, the probability method is used where the binomial distribution is adopted to transform an individual probability measure to a collective probability measure. Through this distribution, the microscopic characteristics of pedestrians will be transformed to the macroscopic characteristics of crowd behaviors. Here let probability p_{imp} denote the probability that an individual that demand immediate motion without waiting, and thus try to break the order of egress and move out first. The discrete parameter p_{imp} then is dependent on the fire and smoke status, i.e., p_{imp} increases as fire or smoke get closer to people. Take the elementary layout in Figure 2 for example, the probability measure p_{imp} can be specified as

$$p_{imp} = \begin{cases} p_{imp}^H & \text{if fire/smoke propogates to} \\ & \quad \text{any direct adjacencies of area } v_1 \text{ or } v_2, \\ p_{imp}^L & \text{otherwise.} \end{cases} \quad (4)$$

Then the total number of impatient individuals during the given time period forms the desired flow $|q^d|$, i.e., the number of those demanding immediate motion within the time period. As a result, the desired flow $|q^d|$ is binomially distributed, and the distribution is Bin(|w|, p_{imp}).

$$\Pr(|q^d| = k \mid w, s^F) = C_{|w|}^k (p_{imp})^k (1 - p_{imp})^{|w|-k} . \quad (5)$$

Here k=[0, |w|], and |w| denotes the number of individuals who decide to take certain path for escape. Symbol s^F denotes the fire/smoke status in a given egress layout. Similar to q^d and q, |w| represents the magnitude, and the sign of w represents the direction of escape that is the same of the direction of q^d and q.

C. Guidance and Way-Finding

How people select their way in escape is an importance issue affecting how to effectively guide them to the safety. Existing findings indicate that such way selection of people can be viewed as a process of their fusing the external information (i.e., guidance) with their internal processes (e.g., their prior knowledge on the exit location). For the external information received, people will trust more on the personalized guidance (e.g., guidance from a group leader) than the impersonalized ones (e.g., exit signs). For their internal characteristics, they tend to use a path they are familiar with rather than unfamiliar with (Proulx, 1993; Johnson and Feinberg, 1997).

As a general framework to model the above features, the probability method is used where the binomial distribution is adopted to transform an individual probability measure to a collective probability measure. In specific, given a guidance u, each individual is supposed to follow the guidance with a probability p_{cr}. In the perspective of psychology, p_{cr} reflects the credit level of the guidance, or the level of trust that people put on the received guidance, and it is described by

$$p_{cr} = \begin{cases} p_{cr}^H & \text{if u is personalized instruction or} \\ & \quad \text{u guides people to a familiar path,} \\ p_{cr}^L & \text{otherwise.} \end{cases} \quad (6)$$

Let x denote the total number of individuals in an area, and the number of individuals following the guidance, i.e., denoted by |w|, is binomially distributed, Bin(x, p_{cr}).

By combining the probability distributions as given in the above three subsections, a probabilistic graph is constructed as shown in Figure 4. Here each node of the graph represents a factor of our concern, e.g., the fire/smoke status, crowd flow rate, etc, and their interdependencies are described via the probability distributions as presented above. To calculate the crowd flow rate q, the information on guidance u, fire/smoke status s^F and passage capacities c are viewed as inputs to this graphic model, and the crowd flow rate q is a random variable conditioned on the information of u, c, s^F, and x. As a result, the crowd flow rate can be denoted by q=q(u, c, s^F, x). Given information on u , c, s^F and x, the probability distribution of q is specified by

$$\begin{aligned} &\Pr(q \mid u, c, s^F, x) \\ &= \sum_{q^d} \sum_{w} \Pr(q \mid q^d, c) \Pr(q^d \mid w, s^F) \Pr(w \mid u, x) . \end{aligned} \quad (7)$$

In the above probabilistic model, the unknown parameters include the social parameter α, the impatience parameter p_{imp}, and the trust parameter p_{cr}. Each of them has clear a psychological meanings, and the parameter estimation can be done by the data acquired from simulation (e.g., NIST's simulation) or by psychological experiments (e.g., virtual reality experiments). In the following sections and our numerical testing, it is generally assumed that guidance is in good credence, and the individuals are of impatience and tend to behave competitively in escape.

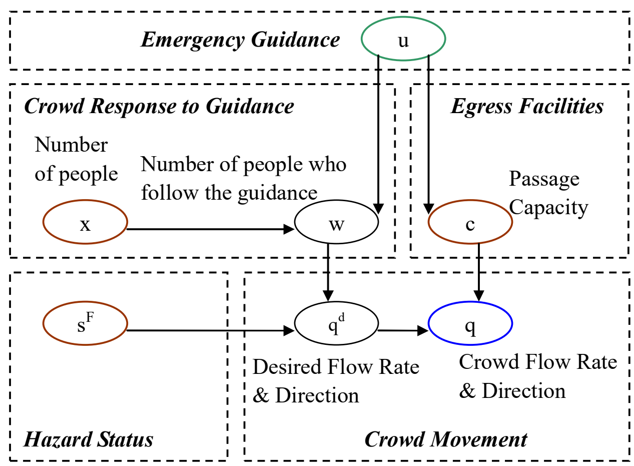

Fig. 4. The probabilistic graph.

In sum, excessive desire in human activities can sometimes lead to a completely undesired outcome, and this can be seen as vital disasters in emergency egress – disorder and blocking. The model established above focuses on this disastrous effect. It serves as a basis to describe how the situation information (i.e., perceived hazard or received guidance) will affect the psychological factors (e.g., the desired flow rate q^d) and how such factors will further determine the actual flowing of crowd movement. With this model, interdependencies among egress capacities, fire/smoke status, guidance, and crowd flows are characterized in a probabilistic sense to enable predictions of egress with potential disorder and blockings captured, and it is the foundation for us to formulate an optimization problem in the next section.

III. Statistical Inference of Model Parameters

The previous section establishes a probabilistic graphical model for egress analysis. This section will develop a method of statistical inference on unknown parameters in this model. Three unknown parameters include: the social bond factor α, crowd impatience indicator p_{imp}, and trust level parameter p_{cr}. Other model parameters are assumed known, and they include the number of occupants x, fire/smoke status s^F, and crowd guidance u.

Because the unknown parameters are distributed in different arcs in the graphical model, we will use the idea of divide-and- conquer here. As a consequence, the entire graphical model is decomposed in two parts: a sub-graph with parameter p_c and p_{imp}, and the other sub-graph with parameter α. Next, we will first look at the part without unknown parameter α as shown in Figure 5.

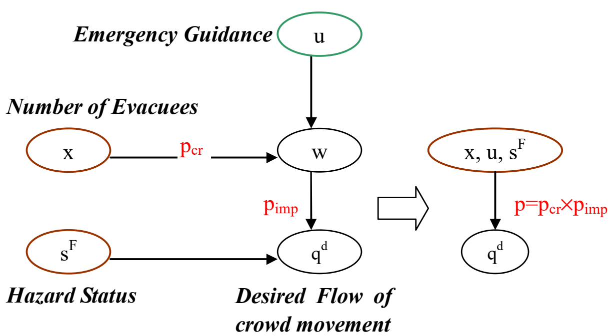

Fig. 5. The probabilistic sub-graph I.

As mentioned in Section II, given x and u, random variable w follows binomial distribution

$$w \sim \mathrm{Bin}(x, p_{cr}) \tag{8}$$

where p_{cr} is the unknown parameter to be estimated. Given w and s^F, random variable q^d follows binomial distribution with parameter p_{imp}.

$$q^d \sim \mathrm{Bin}(w, p_{imp}) \tag{9}$$

Then by mathematical calculation, we derive the probability q^d conditioning on x as

$$q^d \sim \mathrm{Bin}(x, p) \tag{10}$$

where $p=p_{cr} \times p_{imp}$. As a result, the two unknown parameters are combined as one. Considering the conjugate family, Beta distribution is used as the prior of p. That is,

$$p \sim \mathrm{Beta}(a_1, b_1) \tag{11}$$

Then based on the conjugate prior, given data q^d it is easily checked that the posterior distribution of p is

$$p \mid q^d \sim \mathrm{Beta}(a_1+q^d, b_1+x-q^d) \tag{12}$$

If the squared error loss is used, the estimate of the unknown parameter p is directly given by the posterior mean, i.e.,

$$\hat{p} = \frac{a_1 + q^d}{a_1 + b_1 + x} \tag{13}$$

A key question here is whether data q^d can be obtained in reality. The answer is yes. By using psychology knowledges data q^d can be acquired through well-designed questionnaires. For example, consider a building where 500 people locate on weekdays. Each person is given the information about where they locate, where the hazard (e.g., fire or smoke) is probably propagating, and what kind of guidance information (e.g., exit signs) they acquire. They are then asked to select their route for escape. This questionnaire clearly reflects their individual way-selection decisions, more or less independently with each other. Such decisions mainly reflect their desired motion in escape. However, such a survey will not reflect their physical movement realized in a real-world event because each person cannot see other people's way-selection or the actual usage of passage capacities when answering the questionnaire. Thus, the answers from people provide their "virtual" decisions in evacuation, and it gives valuable data to estimate the desired flow rate, but not the actual flow rate. By using the data q^d, the unknown parameter p can be estimated by Bayesian statistics.

As for the parameter α, this is more challenging than p_{cr} and p_{imp} because estimation of α involves the actual flow rate q, and q may only be acquired from the real-world emergency. Thus it will be very difficult for us the get the data q based on a simple questionnaire. A feasible way to acquire data q is by jointly using psychological experiments and computer-based simulation, and also from data acquired in historical events.

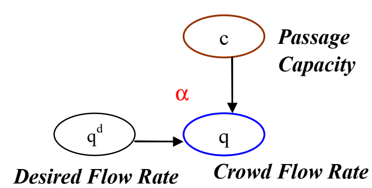

Fig. 6. The probabilistic sub-graph II.

In this paper, we assume the availability of data q^d, c and q. Then the question here is how to get the posterior distribution of α by using the data. Based on the probability distribution as specified in (3), it is clear that if $q^d < c$, then the data does not provide any information about the unknown parameter α. So if $q^d < c$, then the prior $\pi(\alpha)$ will not change in this case. As a matter of fact, our model uses a deterministic dynamics if $q^d < c$ holds, and thus there is no estimation problem when $q^d < c$.

If $q^d > c$, then the data can be used to update our information on α. In specific, $q|\alpha,q^d,c$ is in binary logic. Therefore, the Bernoulli distribution can be used to characterize such a case, where the Bernoulli random variable is normalized as

$$Z = \frac{q - c}{c^{blk} - c} = \begin{cases} 0 & \text{if } q = c \\ 1 & \text{if } q = c^{Blc} \end{cases} \tag{14}$$

As Z=1 is an indicator of blocking in egress. Then it is clear that Z follows Bernoulli distribution as,

$$\Pr(Z \mid \frac{\alpha}{|q^d| - c}) = \begin{cases} 1 - \exp\left(\frac{\alpha}{|q^d| - c}\right) & \text{when } Z = 0, \\ \exp\left(\frac{\alpha}{|q^d| - c}\right) & \text{when } Z = 1. \end{cases} \tag{15}$$

An emphasis here is that q^d and c are assumed to be condition variables, which are deterministically given in this estimation problem. This is somewhat different from the probabilistic view of the desired flow rate q^d in the previous section.

Considering the conjugate family, this paper will specify the distribution of $\exp(\alpha/(|q^d|-c))$ rather than α, and the prior is thus the Beta distribution,

$$\exp(\alpha/(|q^d|-c)) \sim \mathrm{Beta}(a_2, b_2) \tag{16}$$

Based on the above variable transformation, data q, q^d and c will exclusive produce data Z, and the prior distribution of $\exp(\alpha/(|q^d|-c))$ can be updated by using data Z, resulting in the posterior distribution as

$$\exp(\alpha/(|q^d|-c))|Z \sim \mathrm{Beta}(a_2+Z, b_2+1-Z) \tag{17}$$

If the squared error loss is used, the estimate of the unknown parameter $\exp(\alpha/(|q^d|-c))$ is the posterior mean, i.e.,

$$E\left[\exp\left(\frac{\alpha}{|q^d| - c}\right) \middle| Z\right] = \frac{a_2 + Z}{a_2 + b_2 + 1} \tag{18}$$

Then the estimate of unknown α is then simply obtained as

$$\hat{\alpha} = (|q^d| - c)\log\left(\frac{a_2 + Z}{a_2 + b_2 + 1}\right) \tag{19}$$

Then by using the Bayesian inference in the above two sub- graphical model, the estimate of unknown parameters $p=p_{cr} \times p_{imp}$ and α is obtained. The numerical testing is under work now in Matlab, and the results will be added later.

IV. Conclusion

Excessive desire in human activities may sometimes lead to a completely undesired outcome, and this feature is essentially captured in our modeling presented in this paper – excessive crowd demand for escape can lead to the disasters of disorder and blocking in emergency egress. Such egress dynamics is captured in this paper as a probabilistic graphical model. Based on the graphical model and a decomposition method, statistical inference is implemented in two decomposed sub- graphical models, and the unknown parameters in the models are estimated.

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