A Spatio-temporal Probabilistic Model of Hazard and Crowd Dynamics in Disasters for Evacuation Planning

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Abstract. Managing the uncertainties that arise in disasters – such as ship fire – can be extremely challenging. Previous work has typically focused either on modeling crowd behavior or hazard dynamics, targeting fully known environments. However, when a disaster strikes, uncertainty about the nature, extent and further development of the hazard is the rule rather than the exception. Additionally, crowd and hazard dynamics are both intertwined and uncertain, making evacuation planning extremely difficult. To address this challenge, we propose a novel spatio-temporal *probabilistic* model that integrates crowd with hazard dynamics, using a ship fire as a proof-of-concept scenario. The model is realized as a *dynamic* Bayesian network (DBN), supporting distinct kinds of crowd evacuation behavior – both descriptive and normative (optimal). Descriptive modeling is based on studies of physical fire models, crowd psychology models, and corresponding flow models, while we identify optimal behavior using Ant-Based Colony Optimization (ACO). Simulation results demonstrate that the DNB model allows us to track and forecast the movement of people until they escape, as the hazard develops from time step to time step. Furthermore, the ACO provides safe paths, dynamically responding to current threats.

Keywords: Dynamic Bayesian Networks, Ant Based Colony Optimization, Evacuation Planning, Crowd Modeling, Hazard Modeling.

1 Introduction

Evacuating large crowds of people during a fire is a huge challenge to emergency planners and ill-conceived evacuation plans have resulted in many potentially avoidable deaths over the years [1]. However, accurately evaluating evacuation plans through real world evacuation exercises is disruptive, hard to organize and does not always give a true picture of what will happen in the real situation. These challenges are further aggravated by the uncertainty of how a hazard will evolve; requiring evacuation plans to be dynamically adapted to the situation at hand.

Formal crowd models have previously been found useful for off-line escape planning in large and complex buildings, frequented by a significant number of

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people [9-15]. The focus is typically either on crowd behavior or hazard dynamics, for fully known environments. However, when a disaster strikes, uncertainty about the nature, extent and evolution of the hazard is the rule rather than the exception. Additionally, crowd- and hazard dynamics will be both intertwined and uncertain, making evacuation planning extremely difficult. To address this challenge, we propose a novel spatio-temporal probabilistic model that integrates crowd dynamics with hazard dynamics. The overall goal is to build an integrated emergency evacuation model comprising hazard and threat maps, crowd evacuation, and path planning.

The research reported here is conducted as part of the *SmartRescue* project, where we are also currently investigating how to use smartphones for real-time and immediate threat assessment and evacuation support, addressing the needs of both emergency managers and the general public. Smartphones are equipped with ever more advanced sensor technologies, including accelerometer, digital compass, gyroscope, GPS, microphone, and camera. This has enabled entirely new types of smartphone applications that connect low-level sensor input with high-level events to be developed. The integrated crowd evacuation- and hazard model reported here is fundamental for the smartphone based reasoning engine that we envision for threat assessment and evacuation support.

We take as our case study the emergency evacuation of passengers from a ship, triggered by a major fire. Managing uncertainty in such a scenario is of great importance for decision makers and rescuers. They need to be able to evaluate the impact of the different strategies available so that they can select an evacuation plan that ensures as ideal evacuation as possible.

The organization of this paper is as follows: Sect. 2 presents the ship scenario, forming the environment for our approach. We then introduce the novel integrated hazard- and crowd evacuation model in Sect. 3, covering a detailed DBN design for intertwined modeling of hazard- and crowd dynamics, including congestion. A pertinent aspect of this approach is that we apply Ant-Based Colony Optimization (ACO) to configure the DBN with optimal escape paths. In Sect. 4, we present and discuss simulation results that demonstrate that the DNB model allows us to track and forecast the movement of people until they escape, as the hazard develops from time step to time step. Furthermore, the ACO approach provides safe paths, dynamically responding to current threats. We conclude the paper in Sect. 5 by providing pointers for further research.

2 Ship Fire Scenario and Modeling Approach

2.1 Ship Scenario

We use an onboard ship fire as an application scenario for our model. Fig. 1(a) depicts the ship layout and 1(b) shows the layout as a directed graph. The ship consists of compartments, stairways, corridors and an embarkation area. A, B and C are the compartments, each with doors connecting them to D - a corridor. D_1, D_2 and D_3 represent the corridor area that directly links to the different compartments. E is an embarkation area (muster or assembly area) where in an emergency, all passengers gather before being evacuated and abandoning the ship. S_1 and S_2 are the stairways connecting the corridor to E. In (b) the directed graph edges specify the possible direction of movement for the passengers, including the option of remaining in one's current location, for instance due to congestion in adjacent rooms/stairways, panic or confusion, debilitating health conditions, or simply obliviousness to the hazard.

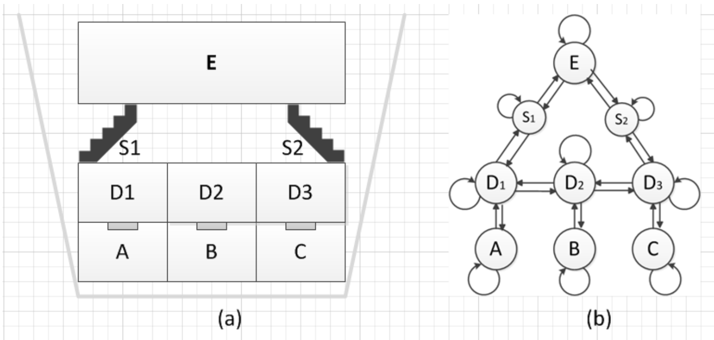

Fig. 1. Hypothetical ship layout (a), represented as a directed graph (b)

2.2 Modeling Approach

A novel aspect of our approach is that we integrate crowd dynamics with hazard dynamics and model the entire emergency evacuation process using a Dynamic Bayesian Network (DBN) [2]. A DBN integrates concepts from graph theory and probability theory, capturing conditional independencies between a set of random variables, $X = (x_1, \dots, x_n)$ [3] by means of a directed acyclic graph (DAG) [4]. Each directed edge in the DAG typically represents a cause-effect relationship. This allows the joint probability distribution of the variables to be decomposed based on the DAG as follows, with pa_i being the parents of x_i in the DAG:

$$P(x_1, \dots, x_n) = \prod_{i=1}^{n} p(x_i \mid pa_i) \tag{1}$$

Thus, the full complexity of the joint probability distribution can be represented by a limited number of simpler conditional probability distributions.

To capture temporal dynamics, variables are organized as a sequence of time slices (1, …, t), $Z_{i:t} = (Z_1, \dots, Z_t)$. This organization allows us to forecast both hazard and crowd behavior, $P(Z_{t+n}|Z_{1:t})$, where $n > 0$ indicates how far into the future the forecasting is projected [2]. A compact definition of a DBN consists of the pair $(B_1, B \rightarrow)$, where B_1 is a traditional Bayesian network that defines the prior distribution of state variables $p(Z_1)$. $B \rightarrow$ is a two slice temporal BN (2TBN) that defines the transition model $p(Z_t|Z_{t-1})$ as follows:

$$p(Z_t|Z_{t-1}) = \prod_{i=1}^{n} p(Z_t^i|Pa(Z_t^i)) \tag{2}$$

Here, Z_t^i is the i-th node at time step t. $Pa(Z_t^i)$ are the parents of Z_t^i, which can be from a previous time slice. The structure repeats itself, and the process is stationary, so parameters for the slices $t = 2,3 \ldots$ remain the same. Accordingly, the joint probability distribution for a sequence of length T can be obtained by unrolling the 2TBN network:

$$p(Z_t|Z_{t-1}) = \prod_{t=1}^{T}\prod_{i=1}^{N} p(Z_t^i|Pa(Z_t^i)) \tag{3}$$

We now proceed to proposing how the above DBN framework can capture hazard- and crowd dynamics in an integrated manner, using the SMILE reasoning engine as the implementation tool. Furthermore, we will illustrate our simulation findings using the GeNIe modeling environment. Both SMILE and GeNIe were developed by the Decision Systems Laboratory at the University of Pittsburgh and are available at http://genie.sis.pitt.edu/.

3 Spatio-temporal Probabilistic Model of Hazard- and Crowd Dynamics

In this section, we describe the rescue planning model and the integrated evacuation model. The rescue planning model is a brute force search of all possible escape paths to find paths that minimize hazard exposure for the full range of hazard scenarios. We apply the ACO algorithm to efficiently find optimal paths for large disasters.

The application of BNs for decision support in maritime accidents has been discussed by Datubo et al. [5]. Their focus is to model and simulate accident scenarios such as fire, flooding and collision. The purpose is to identify optimal decision policies, including alarm- and evacuation strategies, based on maximizing expected utility under different hazard scenarios. Our approach is quite different from Datubo et al.'s work, since we are focusing on tracking both passenger and hazard, dealing with the uncertainty that arises when one has to rely more or less on limited sensor information. In addition we forecast crowd behavior and hazard development for the purpose of producing real-time risk maps, evacuation paths, and dynamically identifying the optimum movements of passengers as the hazard evolves.

3.1 Rescue Planning

Rescue planning can be regarded as a combinatorial optimization problem using graph traversal as a starting point. We let each location i be connected with a vertex v_i, and let each potential flow from location i to j be represented by an edge $e_{i,j}$. In addition to a common graph representation, we let each vertex v_i have a hazard $\hbar_i$, so that the hazard values $\hbar_i \in \boldsymbol{H}$ are probability values representing the likelihood of hazards. Thus, the vertices, edges and hazards are a constructed graph with hazards $G(\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{H})$.

Further, we let one of the vertices, $v_n \in \boldsymbol{V}$, represent the escape area, while $v_0 \in \boldsymbol{V}$ represents the starting locations for passengers. We then define a search space $\boldsymbol{S}$ as a finite set of discrete decision variables, so that any $s \in \boldsymbol{S}$ is a possible route from v_0

to v_N. We further define a function f representing the hazard probability of s. The objective is therefore to find an $s^* \in \boldsymbol{S}$ so that $f(s^*)$ is minimized. This way $f(s^*)$ can be read as an inverse survival rate by choosing the escape route s^*.

By calculating the escape route for every possible combination of $\hbar_i \in \boldsymbol{H}$ in the scenario in Fig.1, we can generate at least one escape route. Our approach is thus similar to the problem of finding the shortest path between two nodes in a graph, for which many optimization algorithms exist [7]. However, we are focusing on finding multiple paths that both address congestion and minimizes hazard exposure.

ACO has some attractive properties, namely that ACO algorithms can efficiently handle dynamic situations, stochastic optimization problems, multiple objective optimization, parallel distributed implementations and incremental optimization [6]. For route-based escape planning this is particularly useful since we expect:

- the parts of the layout graph for escape to change dynamically as the hazard evolves,
- decisions to be based on stochastic information as the hazards are represented by stochastic functions,
- to face multiple objectives such as multiple escape nodes, and
- parallel distributed implementations for online and offline computation, supporting for instance smartphone based sensing and computing.

Finding the shortest path in a graph $G(\boldsymbol{V}, \boldsymbol{E})$ using ACO works as follows: Artificial ants move from vertex to vertex. When an ant finds a route s from v_o to v_N, the ant deposits pheromones in all $v_i \in s$. The amount of pheromone deposited depends on the quality of the solution. Consequently, the shorter the found path, the more pheromone per vertex is deposited. Furthermore, each ant is guided by a stochastic mechanism biased by the amount of pheromone on the trail; the higher the amount of pheromone, the more attractive the route will be to the ant. Thus, the ants walk randomly, but with a preference towards higher pheromone routes. In this way, the ants incrementally build up a promising search space.

For rescue planning, we propose a slight adjustment to the ACO. Instead of deposited a constant amount of pheromone, we let the ants deposit pheromones equivalent to the inverse of the "size" of the perceived hazard in s, i.e. $1 - f(s)$. Thus, when an artificial ant arrives at v_N will have a combined probability value from the hazard probabilities from the visited vertexes as $(s) = 1 - \prod_{V_i \in s}(1 - \hbar_i)$. Hence, a low $f(s)$ signifies a low probability of a perceived hazard in route s, meaning more pheromone will be deposited. In Sect. 4 we provide empirical support for ACO finding the path with the smallest probability of hazards; a minimized $f(s)$.

3.2 Integrated Evacuation Model

The integrated evacuation model (IEM) is designed to keep track of the location of people, their flow between locations, as well as the corresponding hazard status of the locations, from time step to time step. The overall structure of IEM is shown in Fig. 2. The IEM consists of a *Hazard Model*, a *Risk Model*, a *Behavior Model*, a *Flow Model* and a *Crowd Model*. Each model encapsulates a DBN, with the *Hazard Model* being detailed in Fig. 3 for example purposes (the other models have a similar structure).

For each location X, the *Hazard Model* contains a variable $Ha_X(t)$ that represents the status of the hazard, for that location, at time step t. These variables capture the dynamics of the hazard, which for fire involves its development and spreading from location to location. The *Hazard Model* for our particular scenario thus consists of nine hazard nodes, each referring to a particular part of the ship layout from Fig. 1. We model the fire hazard based on physical fire properties, abstracting the progressive stages of fire using the states: *Dormant*, *Growing*, *Developed*, *Decaying*, and *Burnout*. Note that depending on the nature of the barriers separating locations, a *Developed* fire may potentially spread to neighboring locations, triggering a transition from *Dormant* to *Growing* in the neighboring location.

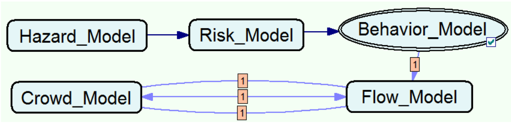

Fig. 2. Macro view of DBN model for Integrated Evacuation Model (IEM)

As illustrated in Fig. 2, the *Risk Model* at time step t depends on the *Hazard Model.* For each location X, the Risk Model contains a variable $R_X(t)$ with three states: *Low Risk*, *Medium Risk*, and *High Risk*. Briefly stated, the *Risk Model* maps the state of each node in the *Hazard Model* to an appropriate risk level, to allow a generic representation of risk, independent of the type of hazard being addressed. For simulation purposes, the dormant fire stage is considered to be *Low Risk*, while a fire in the *Growing* or *Burnout* stage introduces *Medium Risk*. Finally, if the fire is *Developed,* then we have *High Risk*.

Risk levels, in turn, are translated into a *Behavior Model*, with optimal response to each possible risk scenario being determined by ACO for normative crowd behavior in larger scenarios. We develop descriptive models based on studies of crowd psychology models. The *Behavior Model* is simply a single DBN variable, $B_X(t)$, with each state mapping to a particular flow graph (global evacuation plan), as defined in Sect. 3.1. For instance, one particular flow graph could suggest the escape routes: "A-D_1-S_1-E", "B-D_2-D_1-S_1-E" and "C-D_3-S_2-E". Such paths are selected based on pre-computed risk assessments, based on overall survival rate. Note that we study both the ideal evacuation and typical evacuation of the crowd for each hazard scenario.

The *Flow Model* in Fig. 2 manages the flow of incoming and outgoing people along each edge in the layout graph in Fig. 1, represented by three mutually supporting variables for each location X. The variables $I_X(t)$ interleaves incoming flows by alternating between neighbor locations, while $O_X(t)$ routes the incoming flow into an outgoing flow by selecting an appropriate destination location. Finally, the variable $S_X(t)$ is used to calculate the resulting number of people in location X, having $I_X(t)$ and $O_X(t)$ as parents. *In other words, our DBN can keep track of the actual number of people at each location by just counting!* This organization allows us to model the flow of incoming and outgoing people from different locations, as well as congestion, flow efficiency, and crowd confusion, all within the framework of DBNs. Here, flow efficiency reflects how quickly the evacuation process is implemented, and how quickly people are reacting. Confusion models suboptimal movement decisions, and can potentially be extended to be governed by local factors such as smoke, panic, and so on.

Finally, the *Crowd Model* keeps track of the amount of people at each location *X* at time step *t*. It also serves as storage for the crowd movement calculations performed by the *Flow Model*. Currently, we apply a rough counting scheme that for each location *X* keeps track of whether the location is *Empty*, contains *Some* people or contains *Many* people, using the variable $C_X(t)$. Basically, an *Empty* location or one that only contains *Some* people, can receive *Some* people from a neighboring location, while a location with *Many* people must be unloaded before more people can enter. This can easily be extended to more fine granular counting and flow management as necessary for different application scenarios.

4 Simulations, Results and Discussion

4.1 Simulations of Integrated Evacuation Model

We have run several simulations based on the IEM. In one particularly challenging and representative scenario, we assumed that a fire had started concurrently at locations S_2 and *A* at time step t_1. This means that the shortest escape route from location *B and C* will be hazardous, and people should be rerouted through staircase S_1. We used 50 time slices to forecast and analyze hazard dynamics, as well as the behavior of people reacting to this complex fire scenario. To obtain estimates of the posterior probabilities given the evidence of fire, we applied Adaptive Importance Sampling (AIS). This algorithm is designed to tackle large and complex BNs [7], and is used here for forecasting purposes. For tracking, the use of more advanced variants of this algorithm, which support resampling, such as particle filtering, is appropriate. The obtained results are presented in Fig. 3 and Fig. 4.

Fig. 3 illustrates the development of the hazard probability distribution $H_X(t)$=*{Dormant, Growing, Developed, Decaying, Burnout}* over time, for each location *X*. In brief, the bar charts inside each node in the Hazard Model summarize the probability (y-axis) associated with each phase of the corresponding hazard, for each time step (x-axis). Note how the development of the fire reflects our initial evidence, where we, for instance, can observe when the fire is likely to spread to neighbors, such as location D_1 in time step *7*, and at time step *14* for location D_2. To conclude, our DBN provides us with a global probabilistic threat picture, allowing us to assess the current hazard situation, forecast further development, and relating cause and effect, despite potentially arbitrary and limited evidence. In addition to reasoning about hazards, we can also track and forecast crowd behavior using our DBN. The goal of an evacuation is to transfer people from unsafe to safe areas. Figs. 4 (a), (b) and (c) show the simulation results of people moving along the path A-D_1-S_1. At t_0 we have *Many* people in each of the compartments (*A,B,C*), while corridors and stairways are *Empty*.

As can be seen from Fig. 4, it is not until after time step *36* that the probability that room *A* is completely vacated starts approaching *1.0*. Furthermore, Fig. 4 (b) and (c) show that the probability that the number of people in D_1 and S_1 are increasing initially, as people start arriving from locations *A,B, and C* . In general, under the simulated conditions, where people follow the optimal plan without panicking, most

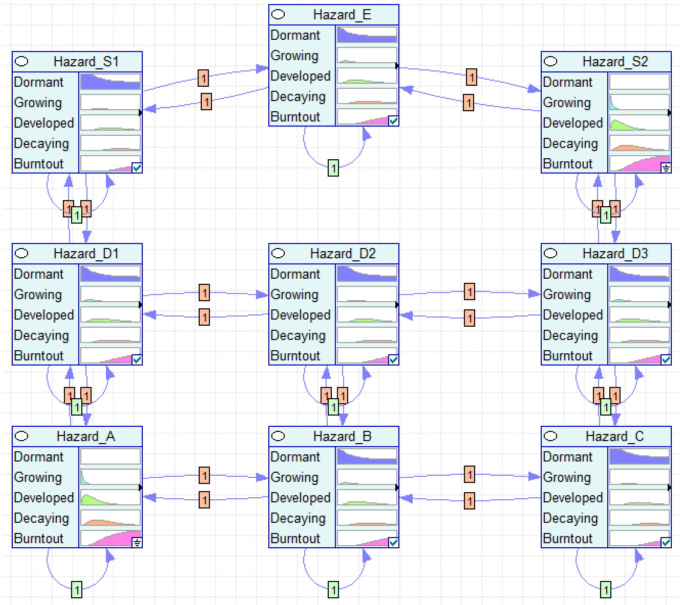

Fig. 3. Inferred probabilistic hazard dynamics for a particular hazard scenario

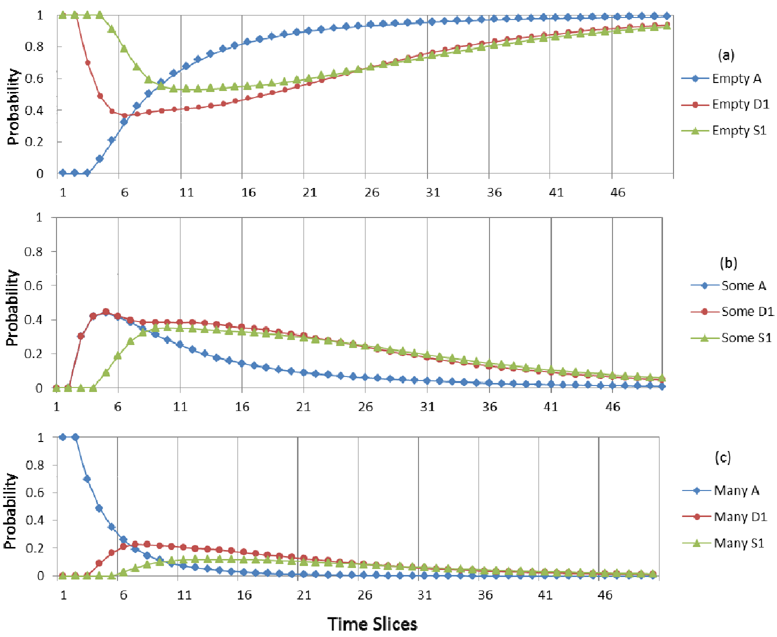

Fig. 4. Crowd dynamics for fire in location A and S_2

people are able to proceed to the exit area. Therefore, from time step 36 it is likely that most people have evacuated, or succumbed to the hazard. To conclude, we notice that the IEM can track and forecast hazard development and people flow, taking into account uncertainty and the intertwined relationship between crowd- and hazard dynamics.

4.2 Route Planning with ACO Approach

Fig. 5 shows the simulation results from the ACO route planning, used for identifying optimal flow graphs for the ship fire scenario shown in Fig. 1. To evaluate evacuation route redundancy, we assigned hazard probabilities randomly and uniformly to either 0 or 1 for each location. The result suggests that low risk routes existed in about 40% of the fire scenarios. The ACO finds these safe routes with probability close to 1.0 using merely 10 ants. The optimal safe routes contain nodes where $f(s)=0$, i.e. nodes were no hazard is present. The results are obtained from the average of 10000 runs. This shows that the adjusted ACO is able to quickly and adaptively find a safe path when it exists.

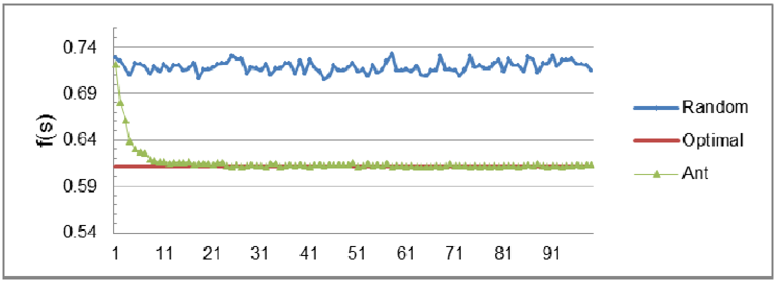

Fig. 5. ACO for Route Planning with 9 Nodes

In addition, a scheme for finding the optimal escape paths for all distributions of hazards has been implemented. The scheme is based on minimizing overall risk, assigning a risk minimizing plan to each hazard scenario. When integrated with the *Behavior Model* of the DBN, the DBN supports dynamically adjusting escape plans that take into account present uncertainty.

5 Conclusions and Future Directions

In this paper we have proposed a spatio-temporal probabilistic model of hazard- and crowd dynamics in disasters, with the intent of supporting real-time evacuation planning by means of situation tracking and forecasting. We have applied brute force and ACO based techniques to identify safest paths, and a DBN for forecasting flow of people and hazard development. Empirical results reveal that ACO is able to quickly find the safest path, using only 10 ants, adaptively for the various hazard scenarios. The IEM allows us to keep track of, and predict, the location of people and hazard status, through each time step, taking into account uncertainty as well as the intertwined relationship between crowd and hazard dynamics. Future directions of the SmartRescue project include calibrating and refining our model based on feedback from a group of practitioners. We also intend to investigate how a collection of smartphones can form a distributed sensing and computation platform. This involves distributed schemes for tracking, forecasting and planning; allowing the IEM and ACO schemes to run seamlessly in the smartphone network.

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