Predicting Evacuation Capacity for Public Buildings

Pejman Kamkarian[1] and Henry Hexmoor[2]
[1]Electrical and Computer Engineering Department, Southern Illinois University, Carbondale, IL 62901, U.S.A.
[2]Computer Science Department, Southern Illinois University, Carbondale, IL 62901, U.S.A.

Keywords: Networks of Bayesian Belief Revision, Public Space Safety, Crowd Evacuation.

Abstract: This paper demonstrates a solution for analyzing public space evacuation rates. Evacuating from a public building in a reasonable amount of time is reliant upon how safe the space is in terms of achieving a minimum time to move people outside. In order to increase the safety of evacuation in public spaces, we employed the Bayesian Belief Network method. To have a better estimation pattern, we have to focus on important physical environmental features as well as crowd formation and specifications in a public space.

1 INTRODUCTION

Locations and geometric information are essential attributes for the study of public space safety that guide superior interior layout and designs for indoor spaces. At the intersection of architectural concerns and crowd specifications, assuring safety is a ubiquitous concernin regards to how crowds react to arising situations which can be caused by some other symptoms related to life threatening triggers such as fire, earth quake, burglary, terrorist attacks, and bomb threats. In linguistic terms, the term 'crowd' is a mass noun. Although it shares some properties with other mass nouns such as air and water, it has some behavioural differences from them.

Crowds often use spaces and pathways in unintended ways. This usage stems from collective group behaviors that emerge from an individual's propensity to spend the least amount of effort to vacate the premises. Resulting effects are unpredictable. Although, in some cases, such as attempting to exit through exit doors, minimizing distances to an exit is not a guiding principle, whereas minimizing travel time to an exit is more likely.

Crowd density is important as the number of people in a unit of indoor space which is not homogenous. Our primary objective is to develop a device to be able to predict the safety of a public space. We wish to use Bayesian Belief Networks to provide building designers with a capability to simulate and experiment in order to have a safer environment. We intend that our model will be a useful tool that supplements guidelines for future building design codes.

Although no design improvement can prevent disasters, careful designs can mitigate and significantly reduce frequency of occurrence. Our approach is multipronged. We explore the nature of crowds as well as the structural properties of buildings and then suggest a methodology for the designing and managing of indoor environments. In order to produce a better estimate of a public space safety, we must investigate the behavior of the crowd during various situations. We also need to consider salient features of the crowd, such as the average age and health status, which can affect crowd dynamic movement and hence should be considered.

We need a model that explains how and why crowds may encounter emergencies. We also need to build a model that explains disparate types of crowd behaviors that are possible in various public places, such as stadiums and transportation stations (Still, 2000). Virtual egress analysis and simulation System are fundamentally an intractable problems. By a process of behavioral rule, elimination behaviors are reduced to four interactive rules pertaining to objective, utility, constraint, and assimilation. These four attributed rules produce crowd behavior that is regular in contrast to the chaos of ordinary life. We outline a few interactions between a crowd and its environment. We also outline the development, validation, and early results of a technique for determining the character and critical dynamics relating to a collapsing building. Our aim is not to

Kamkarian P. and Hexmoor H..
Predicting Evacuation Capacity for Public Buildings.
DOI: 10.5220/0004217704330440
In *Proceedings of the 5th International Conference on Agents and Artificial Intelligence* (ICAART-2013), pages 433-440
ISBN: 978-989-8565-39-6

reproduce a model which is able to precisely make decisions for a certain situation, or a specific public space. Instead we strive to produce graphical representations of patterns to demonstrate the general reasons that may cause dangerous situations in a prototypical public space.

The speed, density, and space utilization maps allow us to qualitatively and quantitatively analyze the use of space over time. This in turn facilitates a greater understanding of the nature of the dynamics of the crowd with respect to space requirements. Some physical specifications of indoor public spaces, such as the exit door width or locations of installed ground facilities, should be considered.

For example, the exit door width could then be increased to make crossing easier without flocking, which can produce congestion that exceeds the ultimate yield point for the area. Consideration should also be given to the potential usage of interconnected gates, also called concourses, by spectators at events, such as public transportation arenas. Usage can be considerable if the event spans multiple hours, if inclement weather conditions are present, or if a large population is attending.

Development of our pattern spans beyond our current project. The crowd consists of many individuals. Each simulated person computes his least effort at every step in order to accomplish his goals and other objectives of interest. Our aim is to maximize utility in the context of applicable constraints. Each entity has the capacity to react according to its internal attributesas well as the changes in the environment as the simulation proceeds. The dynamics of the crowd are an emergent phenomenon that is not programmed explicitly.

In case of a group of people at an indoor public space, as one of their natural actions, they may move randomly in any allowed available public space. Having no specific pattern of moving individuals sometimes leads to having a large group of people in the same space. This can be dangerous especially if the position that the mentioned group of people occupies is vulnerableor is sensitive to overweighting. In such cases, lacking a suitable strategy to make people aware about moving to any other safe positions in the space leads to a disaster, especially in public space such as inside a tower or any upper levels of a building.

In this paper we demonstrate the Bayesian Belief Networks as a significant solution to predict the random movements of people through the indoor space and predict the probability of gathering a large group of them at any vulnerable points. The Bayesian Belief Network performs this task by having general specifications of the environment as well as the people present in it.

Probabilistic reasoning and Bayesian Belief Networks are widely used to predict behaviours in many computational systems, such as in (Trautman and Krause, 2010) that produced robotic navigation routes amongst crowds using the least probabilistically obstructed regions in dense crowds.This is solving a classic robotic slow decision making problem. Probabilistic evacuation of a crowd escaping fire is simulated in (Pires, 2005) where human cognitive processes are modelled. A good survey of common crowd modelling and simulation techniques is found in (Shendarkarb et. al., 2008). In section 2 we will address a few guiding principles. Section 3 outlines main tenets of constructing a Bayesian Belief Network for the purpose of predicting building safety. Sections 5 and 6 respectively describe a general methodology and a specific example. Our paper culminates with Section 7 offering concluding remarks.

2 AN OVERVIEW OF PHYSICAL ENVIRONMENTS AND CROWD PROPERTIES

In order to predict a special pattern of gathering for a group of people in a givenindoor location, possessing a general knowledge of the public space is essential. Some public spaces have more capacity for allowing people to move and gather than others. In order to have a good estimation ofplacing a large group of people at a particular location, considering various capacities is essential. We must consider the position and placement of obstacles that are normally fixed in the environment because they can affect the crowd distribution patterns. We must also know other facilities that are installed inside the environment for people to use, such as vending machines or performance stages. We need to consider the geographic location of the building and also the type of buildings or floors around the indoor structure. We will briefly discuss modelling each environmental key feature separately in ourupcoming section on constructing a Bayesian Belief Network.

2.1 Crowd Properties

Shortcut exploitation is a fundamental human characteristic that we rely on as one of our guiding principles. Another relevant human characteristic is competitive nature, which will become important in egress and ingress considerations. For instance, in an evacuation, individuals will compete with one another in progressing towards exits exploiting optimal available paths. Our pattern will be a predictive device for discovering the reasons that may be caused by human characteristics in terms of the collapsing of public spaces. Although guiding principles dictate salient properties and behaviours, they can hinder proper conclusions. Our pattern is used to propagate microscopic human behaviours to discover emergent properties. It will replace the current macroscopic analyses that do not scale up well.

3 BAYESIAN BELIEF NETWORKS

Humanshavethe ability to recognizing relations between different general attributes such as geographic locations, cultural, and racial values and norms (Davies and Russell, 1987). Generally there are two kinds of relations: near-deterministic and probabilistic. The relations between attributes, such as the place of birth and racial origin, are classified as near-deterministic because an Asian person who is born in an Asian country is very likely to have the same racial makeup as his/her Asian parent. All other relations that are not crucially deterministic are classified as probabilistic. For example, a person who lives in Australia and is of Caucasian descent will likely speakEnglish.

Bayesian Belief Network concentrates on dependencies among existing attributes in a very effective way. Instead of considering all possible dependencies among attributes, it focuses only on significant dependencies among all attributes available in a domain. Generally, that provides a compact representation of joint probability that is distributed among all available attributes consequently. While designing belief networks, considering the most succinct and complex possible graph representation is essential. In terms of a graphical representation of belief networks that consists of inter-connected networks,this is known to be a NP-hard problem (Cooper, 1987).

Bayesian Belief Networks are investigated and developed by many researchers (Pearl, 1986). It was later called by many different terms such as thecausal networks (Good, 1961-62), probabilistic causal networks (Cooper, 1984), probabilistic influence diagrams (Howard and Matheson, 1984); (Shachter, 1986), and probabilistic cause-effect models (Rousseau, 1968). At the early usage of this application, it was applied to medical diagnostics. For example, in terms of a technical aid supporting medical experts, it was applied to a database which consisted of many different symptoms and related diseases in order to predict the kind of disease based on a brief description of the observed symptoms (Barnett et. al., 1998). This method became more dominant henceforth. Microsoft has announced its competitive advantages as including its expertise in Bayesian Belief Networks (Helm, 1996). As future examples of using Bayesian networks we can point to robotic help and guidance (Berler and Shimony, 1997), software reliability assessment (Neil et. al., 1996), data compression (Frey, 1998), and fraud detection (Ezawa and Schuermann, 1995). One broad usage of Bayesian Belief Networks is applying it to product design. We use products because of their functions and properties. They are subject of artefacts (Roozenburg and Eekels, 1995). Using Bayesian Belief Networks for customizing products leads to build a product based on the customer's need. For example, producing a same car would be varied if customers asked to have a fast car in terms of speed or having a car in order to be able to carry heavy and large objects.

A Bayesian Belief Network is a graphical representation of probabilistic relationships between a set of discrete attributes of the considerable research. It consists of a directed acyclic graph such that each node specifies a variable and the arcs between nodes represent the independent relations between variables. In such a graph, each variable is conditionally independent of any combination of its parent nodes (Frey, 1998). Each node has its own conditional probability table which consists of all possible states based on all possible states of its parent nodes. For those nodes without any parent, we will use an unconditional probabilities table.

In artificial intelligence, there are several application classes that represent the probabilistic relationships between different attributes using a directed graph (Duda et. al., 1976); (Weiss et. al., 1978). As a solution to represent uncertain knowledge, Bayesian Belief Networks became acceptable and popular among artificial intelligence communities in the late 1980's (Lauritzen and Spiegelhalter, 1988); (Pearl, 1988). Later, the Bayesian Belief Networks were applied in varies of sciences, such as expert systems of diagnostic systems.

4 CONSTRUCTION OF A BAYESIAN BELIEF NETWORK

In order to demonstrate our Bayesian Belief Network, we considered two separate work areas: (a) indoor public space specifications, including both indoor and some outdoor, and (b) the features of people who are present in the space. We then applied both indoor public space and the people features on a unit of Bayesian Belief Networks pattern.

4.1 Implementation

Generally, we have divided the employed attributes of a building safety crowd evacuation into two categories including (a) physical public space specifications, and (b) Crowd specifications.

4.1.1 Physical Properties

Exploring physical specifications of building safety, while investigating crowd safety evacuation is essential. Most of the time, people are located in a closed, covered area when they are gathered for a certain event. They are sharing a common activity, which is often related to the reason fortheir gathering as a crowd. The following six features are deemed detrimental.

Terrestrial sustainability: We considered natural or other sources that can cause vibration for the indoor space as an important factor. There are two general sources that can affect a public space to be vibrating. In terms of determining the safety of the building, considering such sources are essential. The first group of sources are natural and related to the area's geometric specifications that a public space is built upon, such as the distance from any faults or volcanoes. The second group of vibration sources are created by human activity, such as a metro or train facility. In addition to these, considering the average weather status of the area is another key feature that can affect the rate of vibration for the structure. A public space that is located in a severe weather area that has stormy weather frequently and is prone to more vibrations than a structure that is located in an area with a calm weather.

Flow capacity: We divided this feature into two categories, the evacuation safety rate for (a) examined indoor public space, and (b) for the general building that the examined public space is located inside. For indoor public space, we focused on obstacles in terms of the number, installation positions and also the average size of them. Each public space has a number of emergency exit doors as well as normal entrances that should be taken into account. To have an estimate of safety for a general building's evacuation rate, we considered on all existence obstacles that are located somewhere between the indoor space and the main entrances of the building. The numbers of such objects, as well as the installation positions and the average size of them, were the factors that we considered for this category. As another key feature, we investigated the type of the building such as a flat, an apartment, a tower and so on. In case of being inside an apartment or a tower, considering the level that public space is located leads to having a better estimation for the evacuation safety rate.

Overall exit capacity: Each door, based on its location and width, has a different capacity to allow passing a number of people through it at any moment. We considered this feature for not only the examined public space, but for all entrances that are located between the interior space and the outside.

First Aid recovery capacity: In emergency cases, proper extinguisher tools that are installed on reasonable locations can help people stay alive and safe for a longer time before being they can evacuate from dangerous situations. For example, in case of fire, using existing fire extinguishers near the fore source will help people stay alive inside the area for a longer time before evacuation.

Structural integrity: To have a better building safety estimate, considering the materials that public space is made of as well as the age of the structure are essential, especially in case of using old materials that may expose people inside at higher risk than a new building with new and superior material would.

*Space occupancy rate:*This factor can be determined by the type of using the public space as well as the shape and the variety of installed facilities inside. A theatre or a conference room witha variety of rows of chairs may house more people at any moment than a storage room or an area consisting of a sort of different offices.

4.1.2 Crowd Properties

Considering movement rate, which is related to the average age of the crowd as well as their average health status, and the crowd's normal distribution at each moment leads us to a better estimation of the crowd's evacuation safety rate. As we hypothesize, in a kindergarten class, the average age of the majority of occupants will be below 10 years, whereas in a conference room, it will be above 10. In a hospital, as another instance, the average health status is weak, whereas in a sports complex, health can be assumed to be good.

5 NETWORK TOPOLOGY

We focused and classified all factors that are key features for building our Bayesian Belief Network structure. The proposed pattern may be varied while considering different areas with different situations. The Figure 1 represents the overall topology of our general BBN network.

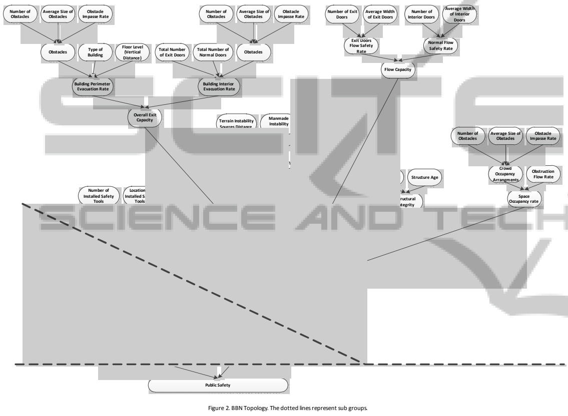

Figure 1: BBN topology.

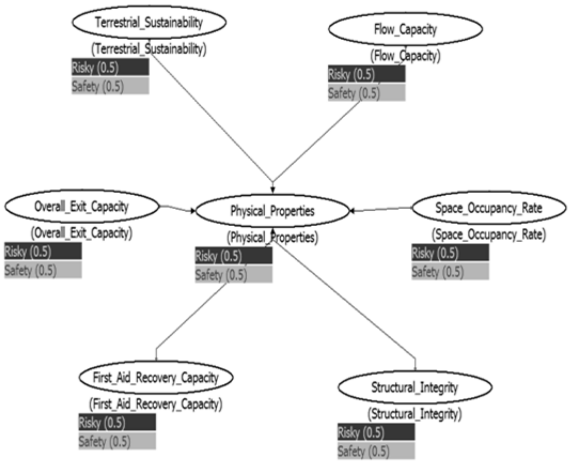

Figure 2: Physical properties portion of BBN.

We constructed our model based on two general sub graphs that are the children of the main BBN root pattern. Figure 2 shows the physical properties of the sub graphs, whereas Figure 3 shows the crowd property's sub graph.

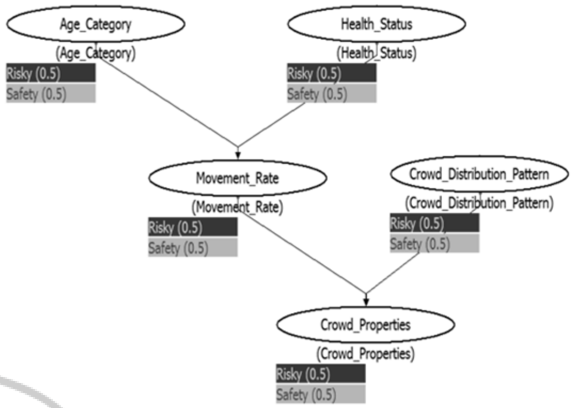

Figure 3: Crowd properties BBN.

6 VALIDATIONS

We simulated a large ballroom public use space on our campus. The building contains four floors and our simulated ballroom is a frequently used space on the second floor, housing international and orientation events. Figure 4 depicts the floor plan of the second floor, including our ballroom.

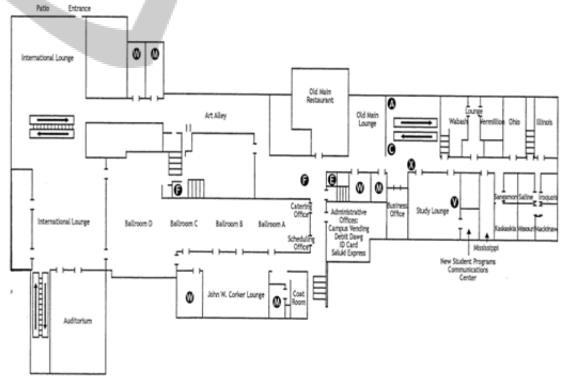

Figure 4: Layout of Ballroom D at the SIUC campus.

We explored the ballroom in order to assign it a safety rating. During active events, the non-occupied space between the ballroom and the outside doorway is 40% of total space. The average size and occupancy with obstacles is about 50% of the empty space, which is distributed in a normal fashion for the available space.

We constructed the conditional probability table (CPT) for obstacles where we considered both values for nodes B, and C, as safety and hence, the obstacle node value becomes 0.9 or 90%, which is classified as a safety situation.

Our student centre building has four floors, which classifies it as a multilevel building. Because ballroom D is located at the second floor, the value of the Type of Building node is determined to be risky. The floor level vertical distance is classified as risky as well.

Regarding the CPT for building perimeter evacuation capabilities, the building perimeter evacuation rate is classified as a safety node, with a 50% chance of safety. In terms of considering indoor space during events, about 50% of space is occupied by different obstacles, installed with a normal distribution, with the average size of 50%.

With regards to the CPT for obstacles, such node indicates safety value. There are also two exit doors as well as two normal entrance doors available inside the space. We consider those values as two nodes: total number of exit doors and total number of normal doors, hence they indicate a safety value. Regarding CPT for the building's interior evacuation rate, it has a safety value of 90%. Based on the total number of exit doors and their width, as well as the number of normal interior doors, referring CPTs for exit doors' flow safety rate and normal flow safety rate, exit doors are classified as safe nodes. Hence, regarding CPT for flow capacity, the IO safety rate shows a safe value based on its parent nodes. This node has a chance of 90% for safety. There are no first aid recovery tools installed inside the public area. The number of installed safety tools' node, as well as their location values on the CPT, will be set as risky. As a result of parent nodes, the first aid recovery capacity node becomes risky, which indicates a risky situation for this part of the BBN tree. In this case, this node has only a 10% chance of safety. During data gathering for the installed facilities, such as chairs, the available empty space is less than 30% of the total area. Based on the number of facilities installed inside the area, their position, and their average size, the CPT for Crowd Occupancy arrangements indicates a risky situation. The average size and installed positions both will be set to safe. This leads to CPT computations for the obstruction flow rate node, which is a safe node with 70% chance of safety. This place is built for gathering purposes with enough space inside. We classified the crowd occupancy arrangements as a safe node. Having the values of both nodes, the obstruction flow rate node and the crowd occupancy arrangement node, on the relative CPT for space occupancy rate, leads us to have the space occupancy rate as a safety value with a 90% chance of safety. The following figure 5 shows the yearly average climate status of the examined area.

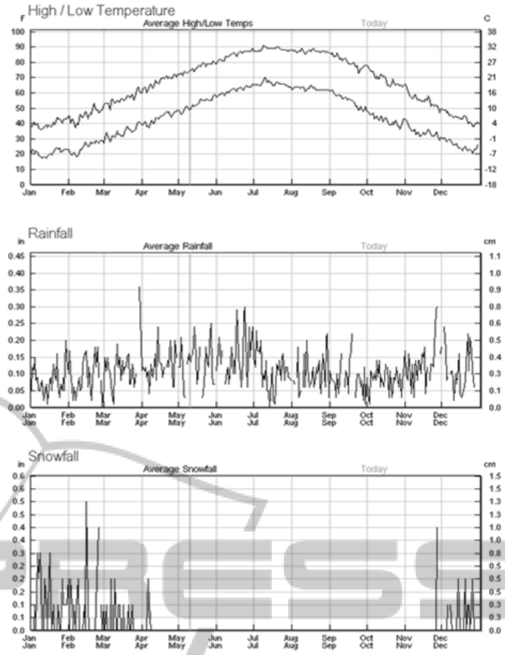

Figure 5: The yearly average climate status of the Carbondale.

Based on the area's yearly average weather status, this area is located in a windy/stormy position for most days of the year, so we will classify the Weather Instability Sources node as risky. The distance from this area to the train rails is less than 3 kilometers. Hence, we considered a risky value for the Manmade Instability Sources node. The following figure 6 shows the geographic details of the examined region.

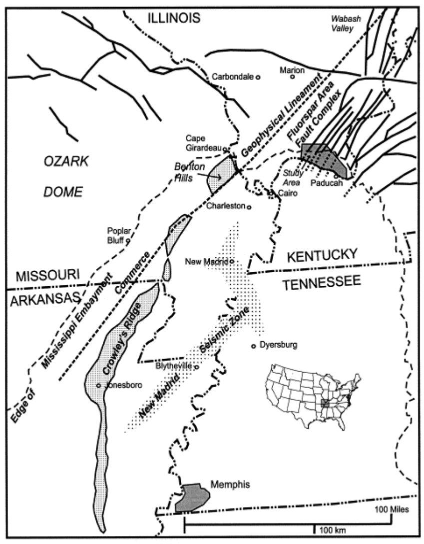

Figure 6: Earth fault close to Carbondale (New Madrid).

Based on the map in Figure 6, the building is far from major earth quake faults and mountains with volcanoes. Therefore, we considered the value of the Terrain Instability Sources as a safe node. Regarding CPT for Terrestrial Sustainability, and based on the values of parent nodes, Terrestrial Sustainability value becomes safe with a 50% chance for safety.

The majority of the building is constructed with concrete, which permits us to assign a safety node for Material Used. It was built on 1925, so the Structural Age will be set as risky. In regards to CPT for Structural Integrity, the value of structural integrity has a value of safe with a 50% chance of safety. Usually, the majority of age for people within the building is between 15 to 50 years of age. The majority of health status is also healthy for the people who gather inside this place. The values of both age category and health status nodes are safe values. For CPT of movement rate, the child node movement rate becomes safe. It has a 90% chance of safety. When forming a crowd, they usually have a 50% distribution over the whole area, which means a normal distribution. The crowd distribution Pattern node, hence, shows a safe value with a 90% chance of safety. Regarding crowd properties, and based on the parent nodes for the crowd properties node, it presents a safety value and a 90% chance of safety.

Regarding to parent nodes values of the physical properties node, it indicates a safety value, a 90% chance for safety.

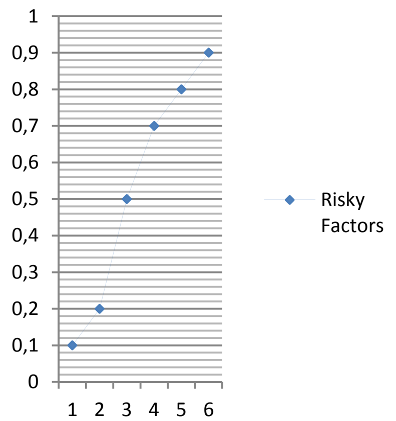

Figure 7: The CPT diagram for Physical Properties node.

Figure 7 shows risky factors to rate proportions. Of all safety factors discussed in the previous section, if only one indicated as an unsafe situation, the unsafely rate for the whole system become 0.1. In other terms, there is a 90% chance of safety. The safety rate for the whole system decreases by increasing the number of unsafe factors, as indicated in Figure 7.

As determined by the final measurements, regarding CPT, and based on the values of the parent nodes, physical properties and crowd properties, the value of the child node of the public safety node will be determined. This node reflects a safety measure and a 90% chance for safety.

7 CONCLUSIONS

This paper explored the Bayesian Belief Network as a mechanism for evaluating potential risks that can be generated due to unpredictable crowd movements at any position of a building. Bayesian Belief Network is able to predict the probability of gathering a large group of people at a particular position by focusing on general attributes of the examined environment as well as the people who are in it. Therefore, it is essential to have such a mechanism in case of forming a large group of people in the examined indoor public spaces, especially when the space is located in upper levels of the building. It helps security agents to consider the vulnerability and strengths of a public space. This can prevent the arising of any potential risk that can occur because of emergencies, such as overweighting. In order to evaluate efficacy of our methodology, we are gathering data for a real world set of buildings on our campus and early results are promising.

REFERENCES

Barnett, G. O., Famiglietti, K. T., Kim, R. J., Hoffer, E. P., Feldman, M.J., 1998. DXplain on the Internet. In *American Medical Informatics Association 1998 Annual Symposium.*

Berler, A., Shimony, S. E., 1997.Bayes Networks for Sonar Sensor Fusion.*In Geiger, D, Shenoy, P (eds) 1997.*Proceedings of the Thirteenth Conference on Uncertainty in Artificial Intelligence Morgan Kaufmann.

Cooper, G. F., 1984. NESTOR: A computer-based medical diagnostic aid that integrates causal and probabilistic knowledge.*In Ph.D. dissertation.*Medical Information Sciences, Stanford University.

Cooper, G. F., 1987. Probabiistic inference using belief networks is NP-hard.*In Technical Report KSL-87-27, Medical Computer Science Group.*Stanford University.

Davies, T. R., Russell, S. J., 1987. A logical approach to reasoning by analogy. In *IJCAI 10.* pp. 264–270.

Duda, R. O., Hart, P. E., Nilsson N. J., 1976.Subjective Bayesian methods for rule-based inference systems.*In Proceedings of the 1976 National Computer Conference (AFIPS Press).* pp. 1075-1082.

Ezawa, K. J., Schuermann, T., 1995.Fraud/Uncollectible Debt Detection Using a Bayesian Network Based Learning System: A Rare Binary Outcome with Mixed Data Structures. *In Besnard, P, Hanks, S (eds) Proceedings of the Eleventh Conference on Uncertainty*. in Artificial Intelligence Morgan Kaufmann.

Frey, B. J., 1998.Graphical Models for Machine Learning and Digital Communication.*In MIT Press.*

Good, I.J., 1961-62.A causal calculus (I & II).*In British Journal of the Philosophy of Science*.pp. 305-318 12: 43-51.

Helm, L., October 28, 1996.Improbable Inspiration.*In Los Angeles Times.*

Howard, R. A., Matheson, J. E., 1984. Influence Diagrams. *In Howard, R. A. and Matheson, J. E. (eds.).*The Principles and Applications of Decision Analysis, (Strategic Decisions Group, Menlo Park, CA). pp. 721-762.

Lauritzen, S. L., Spiegelhalter, D. J., 1988. Local computations with probabilities on graphical structures and their application to expert systems. In *Journal of the Royal Statistical Society.*Vol.50 No. 2 pp.157-224.

Neil, M., Littlewood, B., Fenton, N., 1996.Applying Bayesian Belief Networks to Systems Dependability Assessment.*In Proceedings of Safety Critical Systems Club Symposium, Leeds.*6-8 February 1996 Springer-Verlag.

Pearl, J., 1986. Fusion, propagation and structuring in belief networks. In *Artificial Intelligence 29 241-288.*

Pearl, J., 1988. Probabilistic Reasoning in Intelligent Systems: networks of plausible inference.*In Morgan Kaufmann.*

Pires, T. T., 2005. An approach for modeling human cognitive behavior in evacuation models, In Fire Safety Journal, Vol. 40, No. 2, March 2005, Pages 177–189, Elsevier Pub.

Roozenburg, N. F. M., Eekels, J., 1995. Product Design: Fundamentals and Methods.*In Wiley*.

Rousseau, W. F., 1968. A method for computing probabilities. In *complex situations,* Technical Report 6252-2. Stanford University Center for Systems Research.

Shachter, R. D., 1986.Intelligence Probabilistic inference.*In Kanal, L. N., Lemmer, J. F. (eds.), Uncertainly in Artificial Intelligence (North-Holland, Amsterdam).* pp. 371-382.

Shendarkarb, A., Vasudevana, K., Leea, S., Son, Y., 2008. Crowd simulation for emergency response using BDI agents based on immersive virtual reality, Simulation Modelling Practice and Theory, Vol. 16, No. 9, Pages 1415–1429, Elsevier Pub.

Still, G. K., 2000. Crowd dynamics, *Doctoral dissertation.* University of Warwick, U. K.

Trautman, P., Krause, A., 2010. Unfreezing the Robot: Navigation in Dense, Interacting Crowds, IROS proceedings, pp. 797-803, IEEE press.

Weiss, S. M., Kulikowski C. A., Amarel S. and Safir A.,1978. A model-based method for computer-aided medical decision making. In *Artificial Intelligence.*pp. 145-172.