New approaches to evacuation modelling

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Summary of the workshop part of the 12th Symposium of the International Association for Fire Safety Science

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Abstract. This document presents the contributions of the Workshop "New approaches to evacuation modelling" that took place on the 11th of June 2017 in Lund, Sweden within the Symposium of the International Association for Fire Safety Science (IAFSS). The scope of the workshop was to get insights into the building fire evacuation modelling world from experts in areas other than fire safety engineering. The workshop included contributions from five experts in different fields, namely 1) Psychology/Human Factors, 2) Sociology, 3) Applied Mathematics, 4) Transportation, 5) Dynamic simulation and biomechanics. This report presents a collection of the position papers which summarize the presentations given by the experts, the comments, questions and answers session after each presentation and the final workshop discussion.

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1. Introduction

Evacuation model developments for fire safety engineering applications have reached a crossroads. Model developers could continue tuning parameters and performing validation studies for the existing sub-models used to represent the main behavioural and physical components of evacuation (i.e., pedestrian movement, route choice, etc.) or begin incorporating features based on fields outside of fire safety engineering. In recent years, scientists in research fields outside of fire safety engineering have conducted research which is often very relevant to evacuation modelling. What is the potential of models/methods/data/theories from other fields to be integrated in evacuation models? What are the current gaps in evacuation modelling which need to be addressed? What are the needs of the users/practitioners? The workshop "New approaches to evacuation modelling" brought together a set of international experts from various disciplines outside of fire safety engineering with evacuation modelling experts in order to discuss fresh ideas for the evacuation modelling world. The modern concept of evacuation research is to consider it as its own discipline whereby evacuation experts need to be educated in a variety of fields outside of fire safety engineering, e.g., psychology, mathematics, etc. More collaborations between specialists in each discipline as well as more education for fire safety engineers are therefore needed to consolidate and expand the evacuation modelling field.

This workshop represented an ideal platform for a dialogue between evacuation model developers, model users, fire safety practitioners, authorities and researchers who are involved in disciplines that could significantly contribute to evacuation modelling.

The structure of the workshop included five presentations conducted by international scientists who are experts in various areas outside of fire safety engineering, namely 1) Psychology/Human Factors, 2) Sociology, 3) Applied Mathematics, 4) Transportation, 5) Dynamic simulation and biomechanics. This report includes a collection of position papers which summarize the main concepts discussed in each presentation and reflect the opinion of the authors of each presentation. The scope was to provide ideas, recommendations, suggestions, models, data, theories and methods that could be implemented in existing and future evacuation models for fire safety engineering applications. It is important to note that the papers presented in this document have not been peer reviewed and as such represent the opinion of the authors. After each presentation, a Questions & Answers (Q&A) session was led by two experts from the evacuation modelling community. The scope was to comment on the potential implementation strategies of the proposed ideas. The associated Q&A sessions are presented in this report at the end of each paper. At the end of all contributions, an open discussion session took place in which the workshop participants had the opportunity to present comments and questions directly to the workshop panelists and/or experts from the evacuation modelling community. A summary of this discussion is presented in the last section of this report along with the conclusions.

2. Workshop programme and participants

The workshop "New approaches to evacuation modelling" took place from 09.00-12.00 on the 11th of June 2017. The programme of the workshop is presented in Table 1.

Table 1. Workshop schedule.

Time	Topic	Presenter
9.00-9.05	Welcome	Enrico Ronchi
09.05-9.35	Psychology/Human Factors	Max Kinateder
09.35-10.05	Sociology	Erica Kuligowski
10.05-10.35	Applied Mathematics	Alessandro Corbetta
10.35-10.50	Coffee break	
10.50-11.20	Transportation	Adam Pel
11.20-11.50	Dynamic simulation and biomechanics	Peter Thompson
11.50-12.00	Open discussion	

Each presentation covered an area outside of fire safety engineering. Presentations lasted 15 minutes each and they were followed by 15 minutes of discussion led by two evacuation modelling experts. The evacuation modelling experts were Dr Enrico Ronchi (Workshop leader) and Prof Ed Galea. Their biographies are presented below.

Workshop leader and evacuation modelling expert
Enrico Ronchi, Lund University (Sweden)
Enrico Ronchi is an Ass. Senior Lecturer at the Department of Fire Safety Engineering, Lund University. Dr Ronchi holds a Ph.D. at the Polytechnic University of Bari (Italy) in evacuation modelling. During his career Enrico has been a guest researcher at NIST (USA), University of Würzburg (Germany), University of Cantabria (Spain), Waseda University (Japan) and Imperial College London (UK). Enrico has participated in several research projects in the area of evacuation modelling and he is currently the leader of the ISO task group on their verification and validation.

Evacuation modelling expert
Ed Galea, University of Greenwich (UK)
Professor Ed Galea is the founding director of the Fire Safety Engineering Group (FSEG) of the University of Greenwich in London where he has worked in the area of evacuation modelling for over 25 years. Prof Galea serves on a number of standards committees concerned with fire and evacuation for organisations such as IMO, ISO and the SFPE Task Group on Human Behaviour in Fire.

2.1. Workshop programme

The detailed workshop programme is presented below.

09.00-9.05 Welcome and Workshop Objectives
Enrico Ronchi, Lund University (Sweden)
An introduction on the objectives and format of the workshop was provided by the workshop leader, Enrico Ronchi.

09.05-9.35 Psychology/Human Factors
Presentation: The Human in Human Evacuation Modelling: Visual Perception, Social Influence, and Emotional States
Max Kinateder, Dartmouth College (USA) (collaborating with Youssef Shiban, Germany)
Dr Kinateder is a postdoctoral researcher at Dartmouth College working on perception and action in emergency situations. Most of his research circles around questions on why and how people do (not) evacuate in emergency situations. He is interested in investigating the psychological mechanisms that shape evacuation behavior (e.g., perception and action, decision-making, risk perception) and research methods (e.g. Virtual Reality) that allow the investigation of causal mechanisms in evacuation behavior.
Discussion with panel comments/questions led by the evacuation modelling experts

09.35-10.05 Sociology
Presentation: A Multi-disciplinary Perspective on Representing Human Behavior in Evacuation Models
Erica Kuligowski, NIST (USA)
Dr Kuligowski is the leader of and sociologist in the Wildland-Urban Interface Fire Group at the National Institute of Standards and Technology. Dr. Kuligowski holds a Ph.D. in Sociology from the University of Colorado at Boulder, as well as a B.S. and M.S. in Fire Protection Engineering from the University of Maryland, College Park. Her research interests are human behavior in emergencies, including preparedness, response and recovery behaviors, emergency communications, behavioral modeling, and the modeling of social systems.
Discussion with panel comments/questions led by the evacuation modelling experts

10.05-10.35 Applied Mathematics
Presentation: Overhead pedestrian tracking for large scale real-life crowd dynamics analyses
Alessandro Corbetta, Eindhoven University of Technology (Netherlands) (collaborating with Federico Toschi, The Netherlands)
Dr Alessandro Corbetta is a post-doctoral researcher at the group of Turbulence and Vortex Dynamics, at Eindhoven University of Technology. His academic interests involve statistical dynamics of pedestrian crowds, large scale pedestrian tracking, mathematical modeling and high-performance computing. Dr. Corbetta received a Ph.D. in Applied Mathematics from Eindhoven University of Technology and a Ph.D. in Structural Engineering from Polytechnic University of Turin, Italy. He has been visiting researcher at Los Alamos National Laboratory, USA, working on high performance computing and computational plasma physics.
Discussion with panel comments/questions led by the evacuation modelling experts

10.35-10.50 Coffee break

10.50-11.20 Transportation
Presentation: Evacuation Modelling in the field of Transport
Adam Pel, Delft University of Technology (Netherlands)
Dr Adam Pel is assistant professor at the Transport and Planning department at Delft University of Technology. In his research he uses data analytics, mathematical modelling, and simulation and optimisation techniques to study the design, operations and control of road transport systems. He leads multiple research and industry-funded projects that particularly address the resilience of road transport systems, including evacuation choice/response behaviour, travel and driving behaviour under emergency conditions, transport/evacuation planning, traffic flows and traffic management measures, and transport network connectivity and integrity.
Discussion with panel comments/questions led by the evacuation modelling experts

11.20-11.50 Dynamic simulation and biomechanics
Presentation: An analysis of human biomechanics and motor control during evacuation movement
Pete Thompson, Autodesk (UK) (collaborating with Denise McGrath, Ireland)
Dr Thompson is a Principal Engineer at Autodesk, an expert in dynamic simulation with a Ph.D. in computer simulation of crowd flows from the University of Edinburgh (UK). Dr Thompson is currently working on the implementation of the concepts of biomechanics of human movement into crowd evacuation simulation modelling. This work is conducted together with Dr Denise McGrath, lecturer at UCD (Ireland), expert in Biomechanics focusing on the interactions between human movements and the environment.
Discussion with panel comments/questions led by the evacuation modelling experts

11.50-12.00 Open discussion and final remarks
Dr Enrico Ronchi and Prof Ed Galea moderated an open discussion in which the workshop participants could address questions directly to the workshop panelists. Final remarks of the workshop will be discussed.

2.2. Workshop participants

The following participants took part in the workshop:

Yuki Akizuki
Karen Boyce
Dorota Brzezinska
Alessandro Corbetta
Arturo Cuesta
Rita Fahy
Edwin Galea
Emanuele Gissi
Ahreum Han
Jan Hora
Sian Hwa Lek
Max Kinateder
Erica Kuligowski
Mineko Imanishi
Zach Liew
Brian Meacham
Yoshikazu Minegishi

Yoshifumi Ohmiya
Adam Pel
Michael Plagge
Enrico Ronchi
Tomonori Sano
Masayuki Sato
Wuiguo Song
Michael Spearpoint
Manuela Tancogne-Dejean
Manabu Tange
Peter Thompson
Rahul Wadhwani
Jonathan Wahlqvist
Jonghong Wang

3. Papers and questions/answers sessions

This section includes the five papers presented at the workshop along with the Questions & Answers session. The full references of the papers are:

Kinateder, M., & Shiban, Y. (2017). The Human in Human Evacuation Modelling: Visual Perception, Social Influence, and Emotional States. In *Workshop New Approaches to Evacuation Modelling* (pp. 12–21). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

Kuligowski, E. D. (2017). A Multi-disciplinary Perspective on Representing Human Behavior in Evacuation Models. In *Workshop New Approaches to Evacuation Modelling* (pp. 24–36). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

Corbetta, A., & Toschi, F. (2017). Overhead pedestrian tracking for large scale real-life crowd dynamics analyses. In *Workshop New Approaches to Evacuation Modelling* (pp. 38–50). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

Pel, A. J. (2017). Evacuation Modelling in the field of Transport. In *Workshop New Approaches to Evacuation Modelling* (pp. 52–63). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

McGrath, D., & Thompson, P. (2017). An analysis of human biomechanics and motor control during evacuation movement. In *Workshop New Approaches to Evacuation Modelling* (pp. 65–76). Lund, Sweden: Department of Fire Safety Engineering, Lund University.

The Human in Human Evacuation Modelling: Visual Perception, Social Influence, and Emotional States

Max Kinateder[a] & Youssef Shiban[b]

[a]Dartmouth College, Department of Psychological and Brain Sciences, Hanover NH, USA
[b]University of Regensburg, Department of Clinical Psychology and Psychotherapy, Regensburg, Germany

ABSTRACT

Fire evacuation models aim to predict emergency evacuation process by modelling human behavior. Despite evacuation models undeniable contribution to building safety, important aspects of human factors are still under-represented in current evacuation models. This workshop contribution discusses three examples of how basic research on human perception, emotion and behavior can inform evacuation models. First, perception is the key process by which building occupants collect information about their environment. Yet, perceptual processes are often oversimplified in evacuation models. Using the example of visual perception of smoke, we aim to illustrate how a modeling of perceptual processes could contribute to current evacuation models. Second, evacuation models are mainly simulating social systems using physics based approaches and as such include so called behavioral facts (e.g., movement to the familiar or social influence). This section tries to link laboratory findings on social influence with behavioral facts in evacuation. Third, stress and fear are controversial topics in evacuation research; Many evacuation theories favor an approach that underlines the ability of humans to make rational decision in emergency situations and occupants' emotional states are often ignored. While "panic" has certainly been debunked as a myth, emotional states might still influence occupants' evacuation decision-making and behavior. This section describes the current state of research on how stress and fear affect spatial navigation and human behavior in crowds.

KEYWORDS: human behaviour, fire evacuation, visual perception, social influence, stress, fear

1. Introduction

Fire evacuation models serve two purposes. First, they are engineering tools that help to assess the safety of buildings, where the main concern for the users is to reliably estimate the Required and Available Safe Egress Time (RSET/ASET) as well as predict congestion levels and potential design issues (Purser & Bensilum, 2001). Second, evacuation models are also research tools that contribute to a better understanding on human behavior in fire; specifically, they allow researchers to generate new hypotheses that then can be tested empirically. For both purposes, evacuation models will become more effective the better we understand human perception and action in emergency situations. Recent developments in basic research and modelling has significantly pushed the boundaries as to what aspects of human behavior in fire can be modelled, ranging among others from biomechanics (Thompson & McGrath, 2015), physiological/metabolic processes (Delin et al., 2016; Kuklane & Halder, 2016), to cognitive aspects (Kinateder, Kuligowski, Reneke, & Peacock, 2015; Kuligowski, Gwynne, Kinsey, & Hulse, 2017).

However, there seems to be some disconnect between basic research and model development. One potential reason for this might be that it is difficult to translate findings from a basic laboratory experiment into valid predictions on how people would react in a wide range of emergency situations. One challenge is the sheer variety of possible emergency scenarios. Another is that occupant evacuation behavior becomes more difficult to predict as crowd density attenuates (i.e., the less crowd movement resembles flow patterns).

In the following sections, we discuss aspects that influence *individual* occupant evacuation behavior and attempt to connect them to existing approaches in evacuation modeling. All aspects conceptually understand evacuees as agents embedded in a sociotechnical system, where constraints from the social and physical environment as well as characteristics of the evacuees themselves shape behavior. Researchers then can ask the following questions: What information is available to an evacuee at what time? How is this information processed? And how does it affect behavior?

The first of three aspect discussed below is *perception* and refers to the process that allows an organism to successfully act in its ecological niche. There are many aspects of perceptual research that are relevant to fire evacuation (e.g., auditory perception or olfaction); we will focus on visual motion perception and try to outline what parts of visual information are available to a human observer and how these are connected to behavior. The second aspect is *social influence* with a focus on low density scenarios (i.e., scenarios in which behavior is not completely restrained by physical forces). In the third section, the influence of intense emotions such as fear on spatial behavior will be discussed, hopefully finding common ground between observation that evacuees "don't panic" (Fahy, Proulx, & Aiman, 2012) and the findings from basic research that show how stress and fear bias decision-making.

2. Visual perception in fire emergencies

In most evacuation models, agent behavior is based at least to some extent on what agents "see" in a given situation. In many cases, agents have complete "knowledge" of the spatial layout. For examples, agents can be "aware" of obstacles in front of them and dynamically react to the behavior of other agents. The process of how humans navigate by extracting visual information from the environment is referred to as visually guided locomotion and has been studied extensively (Gibson, 2014; Warren, 2006; Warren, Kay, Zosh, Duchon, & Sahuc, 2001) and applied to pedestrian behavior in crowds (Rio, Rhea, & Warren, 2014; Rio & Warren, 2013). Vision is a crucial source for information for human locomotion, and, for example, gaze behavior (i.e., where a person looks) while walking over complex terrain is immediately connected to gait behavior and foot placement (Matthis & Fajen, 2014). At the core of the computational vision science approach to perception is an understanding on how the visual system extracts and processes information from the physical environment. Unfortunately, most evacuation models oversimplify visual perception and thus risk misrepresenting how building occupants might react to an approaching fire. For example, many evacuation models completely ignore dynamic visual features such as smoke or use the physical extinction coefficient (complex refractive index) to describe how far people can see through smoke (Ronchi, Gwynne, Purser, & Colonna, 2012). In the following section, we will use the example of smoke perception to illustrate how perceptual processes could be better conceptualized in evacuation modelling. We would like to emphasize that vision was one example, there are many other aspects of perception (e.g. auditory, tactile, or olfactory) that are also relevant to occupant evacuation behavior.

Marr (1982) proposed to backtrack perceptual processes from the physical properties of the environment to identify how that information is processed and represented along the visual pathway in the brain. On an extremely coarse level, the visual system extracts motion information from the visual field by processing lawful spatiotemporal patterns of light falling on the retina. A way to describe such patterns is by quantifying the change of light intensity over space and time (Adelson & Bergen, 1985). Filters (i.e., neurons whose receptive fields are attuned to specific gradients) in the visual system are attuned to various kinds of motion (e.g., according to orientation in the visual field) and summary statistics the filtered signals give rise to coherent perceptual phenomena (for more detailed reviews, see for example Burr & Thompson, 2011; Nishida, 2011). One source of motion information during fire evacuation might come from smoke and flames, but what are the visual features of moving smoke? Correctly timing the motion of a looming plume of smoke can provide vital information for survival during fire emergencies. For example, building occupants might base their decision to evacuate on density and speed of smoke in a building fire. Visual properties of smoke certainly depend on its mechanical/physical properties and follow lawful behavior; Approaching smoke is a visually rich stimulus that provides the observer with a range of potential motion cues and can be classified as fluid non-rigid motion (Aggarwal, Cai, Liao, & Sabata, 1998). As an object moves through an observers visual field, it creates characteristic patterns of motion vectors, often referred to as optic flow (Gibson, 2014) that are accessible to the visual system. Several flow based motion cues are available to the observer, allowing to extract simple (e.g., speed and angle of moving contrast gradients) to complex (e.g., looming of a smoke plume) motion patterns. Kawabe, Maruya, Fleming, and Nishida (2015) showed that local motion speed is a visual cue that allows observers to accurately judge fluid characteristics (e.g., viscosity). Given that smoke can be mathematically described in similar terms as fluids, it seems plausible that human observers can extract this information to estimate global speed and direction of moving smoke. Unlike rigid objects, however, smoke continuously changes its shape and contrast. This creates perceptual uncertainty, which in turn might lead to bias in how humans speed and orientation of moving smoke. Studies on motion perception in fog show that reducing contrast uniformly in the visual field (i.e., like looking through a fogged-up windshield) reduces perceived speed (Snowden & Hammett, 1998). If, however, contrast is reduced non-uniformly (decreased contrast with larger distance), speed is overestimated, indicating that the spatial distribution of contrast affect how speed is being perceived (Pretto, Bresciani, Rainer, & Bulthoff, 2012). Like contrast, motion coherence can bias perceived speed of a moving stimulus. In one study, peripheral background noise (i.e. dots moving incoherently) to a central coherently moving set of dots biased participants to overestimate the stimulus speed as a function of noise level (Chuang, Ausloos, Schwebach, & Huang, 2016). Next to basic motion cues, the visual system is able to identify more complex visual motion patterns such as optical expansion (flow based) and the change in size (not flow based) to specify approaching movement (Schrater, Knill, & Simoncelli, 2001). Unlike a rigid moving object, smoke might contain less precise optic flow and more local size change information due to its expanding and contracting shape.

Another question is how smoke impairs vision during navigation. Smoke typically is not uniformly distributed and its density varies in space. That is, for example, depending on the relative height of smoke in the environment, occupants' vision will be affected differently. Some research indicates that artificially impaired vision reduces navigation, way-finding abilities and spatial learning (Gauthier et al., 2008) as well as walking speed (Fridolf, Andrée, Nilsson, & Frantzich, 2013). That is, occupants' ability to detect exit signs and navigate egress routes depend not only on their knowledge of the spatial layout but also on the visual information available in a given moment.

Although the current example uses perception of moving smoke and may appear overly specific, it illustrates how visual information could guide agent behavior. Many aspects of the visual environment are known to the model developer (e.g., the layout of the environment or the distribution and movement of smoke). Consequently, agent behavior could be modelled based on the rules by which physical features in the environment are translated into visual percepts.

3. Social influence in low density crowd situations

Most evacuations happen in a social context in which individual occupants influence one another. Physics and agent based crowd evacuation models have been very successful in predicting crowd behavior and the overall evacuation process (Helbing & Molnar, 1995; Kuligowski, 2016).

However, factors influencing agent decision-making and behavior in low density situations are still not well understood. In ambiguous emergency situations, occupants seek information and the behaviour of other occupants may be considered as a useful source of information. Studies show that occupants often engage into various preparatory actions before evacuating (e.g. gathering belongings, making phone calls) (Hulse, Day, & Galea, 2013). Then, they have to decide where and how they want to reach their destination. Unfortunately, not all occupants pick an adequate destination or the optimal route (Fridolf, Nilsson, & Frantzich, 2011; Nilsson, Johansson, & Frantzich, 2009). There is evidence in the literature that during dangerous situations people influence each other with regard to where to and how they navigate (e.g. Kinateder, Müller, Mühlberger, & Pauli, 2012; Kinateder et al., 2013; Nilsson et al., 2009). As this might be the case for all occupants in the situation, behavioural uncertainty may lead to delayed or inadequate evacuation decisions (Darley & Latané, 1968; Kinateder & Warren, 2016). Social influence can potentially affect pre-evacuation time (time from a first alarm cue onset to evacuation behavior) and exit choice (choice of evacuation destination) (McConnell et al., 2010).

Another aspect of social influence is cooperation. Observations from fire evacuations report that many occupants display pro-social behavior in fire emergencies. The *tend and befriend* hypothesis assumes that especially female individuals respond to acute stress, such as emergency situations, with pro-social behavior (Taylor et al., 2000). Interestingly, cooperation during evacuation from dangerous situations may lead to slower evacuation (Heliövaara, Kuusinen, Rinne, Korhonen, & Ehtamo, 2012).

Outside evacuation modelling, pedestrian movement and mutual influence of crowd members has been studied empirically. For example, the *behavioral dynamics framework* integrates an information-based approach to perception with a dynamical systems approach to action and has been successfully used to model pedestrian movement (Warren, 2006). It is one of the few pedestrian models in which various aspects of pedestrian movement have been experimentally validated at the level of individual pedestrians (e.g. Rio & Warren, 2012). This approach is particularly interesting, as it allows to predict global patterns of crowd behaviour (e.g., grouping behavior) based on the local interactions of individual occupants.

4. Defensive behavior and evacuation: the role of stress and fear

Fire evacuation models attempt to describe how humans react in life threatening situations. Some aspects of evacuation behavior such as general threat detection behavioral responses to threatening situations have been extensively studied in psychological research. Surprisingly, the influence of fear or stress that occupants may experience during evacuation only plays a minor role in evacuation modeling. Emotions are directly linked to human (and animal) defensive behaviors and cause qualitative shifts in a set of decisions and behavior related modalities in order to increase an organism's chance of survival. Established behavioral models identified a cascade of defensive behavior and describe three stages of how an organism's autonomic responses, protective reflexes, and brain responses change systematically depending on threat proximity (Löw, Weymar, & Hamm, 2015). This section gives a brief overview of the current state of research on how emotional states in general and stress/fear in particular relate to evacuation behavior.

The defense-cascade model describes three distinct stages of defensive behavior (Fanselow, 1994). In the *pre-encounter stage*, no threat has been detected yet but a threat has been previously experienced in similar situations leading to increased vigilance. Conceptually, hearing a fire alarm could be classified into this stage, as most people have experienced fire alarms before, however mostly in non-threatening drill situations. Individuals who experienced a severe fire emergency in the past might be more vigilant when they hear a fire alarm and prepare to engage in avoidance behavior. Indeed, having experienced the 1993 bomb attack on the World Trade Center was associated with faster evacuation decisions during the evacuation from the World Trade Center on September 11, 2001 (Averill et al., 2005), however, it is unclear as to how this experience affected total evacuation times (Day, Hulse, & Galea, 2013). As soon as a threat has been detected, the organism moves on to the *post-encounter defense stage*, in which attention is focused on threat cues, and physiological and behavioral defensive responses are generated (Campbell, Wood, & McBride, 1997; Fanselow, 1994; Lang, Davis, & Ohman, 2000; Maren, 2001; Morgan & Carrive, 2001). Threat cues in fire emergencies could be perceiving fire cues (flames, smoke) or observing fearful behavior from other occupants. Finally, in the *circa-strike stage* the threat is most imminent and the organism engages in active behavioral strategies accompanied with increased physiological activation (Kim et al., 2013; LeDoux, 2012). In the case of a fire evacuation, this would be an extreme situation in which threat of fire is imminent and occupants are exposed to smoke and flames or other threats. In this case, most occupants are more susceptible to fear related biases in decision-making a perception. Each of the three stages may appear during a fire evacuation and depending on the scenario, different fear reactions can be hypothesized. Although, there is a lack of empirical evidence it is possible that in most evacuation scenarios, occupants will find themselves in the pre-encounter or post-encounter defense stage, as the most common evacuation triggers are fire alarms or initial fire cues (Xiong, Bruck, & Ball, 2016).

Fear and stress influence various cognitive processes such as attention and behavior that are relevant to evacuation behavior. Basic research on fear processes may help to understand the role of fear in evacuation. For instance, cognitive biases are well documented in fearful situations and are consistently found in highly fearful participants and in patients suffering from specific phobias such as pathological fear of heights. Several studies have shown that fear influences *attention* (e.g. by narrowing it) towards threatening objects (Cisler, Ries, & Widner, 2007; Mogg & Bradley, 2006; Ohman, Flykt, & Esteves, 2001; Watts, McKenna, Sharrock, & Trezise, 1986), and that when experiencing strong fear, attention is quickly engaged with the fearful object (Mogg & Bradley, 2006) and slow to disengage (Fox, Russo, Bowles, & Dutton, 2001; Fox, Russo, & Dutton, 2002). Furthermore, fear inducing cues are hard to ignore and can distract from the task at hand (Gerdes, Alpers, & Pauli, 2008; Okon-Singer, Alyagon, Kofman, Tzelgov, & Henik, 2011). In an evacuation scenario this could explain, why fearful occupants are more susceptible to "ignore" exit signage when confronted with more salient fire cues.

Fear can also influence how occupants see their environment. Regions in the brain that are relevant for processing emotional (e.g., fearful) content have strong connections to the human visual system (Amaral, Behniea, & Kelly, 2003; Phelps, Delgado, Nearing, & LeDoux, 2004; Vuilleumier & Driver, 2007). Specifically, the level of amygdala activation under threat has been found to correlate to the level of activation in visual cortex (Ahs et al., 2009; Larson et al., 2006). Such changes in activation in visual cortex could potentially explain links between fear and biases in perceptual tasks. Such biases include, overestimating the size of feared stimuli (Stefanucci, Gagnon, Tompkins, & Bullock, 2012; Stefanucci, Proffitt, Clore, & Parekh, 2008) or reporting that feared objects are larger, faster, or closer than they actually are (Clerkin, Cody, Stefanucci, Proffitt, & Teachman, 2009; Teachman, Stefanucci, Clerkin, Cody, & Proffitt, 2008; Vasey et al., 2012).

Furthermore, fear might shape spatial navigation. In fearful behavior, usually referred to as avoidance in humans, a fearful person tries to increase the distance between feared stimulus or situation. Interestingly, research on rodent behavior has shown that fearful rats exploring a square field tend to avoid open spaces and stick closer to walls compared to non-fearful rodents (Simon, Dupuis, & Costentin, 1994). A recent study has confirmed this for human exploration behavior (Walz, 2013).

Note that fear and stress can bias evacuation behavior is not in contrast to the fact that so called "panic" rarely occurs (Fahy et al., 2012). Humans are able to engage in pro-social behavior and make rational decisions when they experience fear; However, emotional states can introduce systematic biases in decision-making and spatial behavior. Understanding, if and how much fear is typically caused by various aspects of fire evacuation scenarios, and how that fear is linked to evacuation behavior is still unclear and needs to be subject to future research but bears the potential to explain certain behavioral phenomena frequently observed in evacuation.

5. Summary and outlook

Using the examples of visual perception, social influence, and emotional states, we hope to illustrate how basic research on human behavior can inform evacuation model development. How could these insights be implemented in evacuation models? One potential approach would be to simulate perceptual processes to inform agents about the environment. This would have the benefit that agents could navigate novel spaces with incomplete prior and current knowledge of the environment. These perceptual processes could be conceptualized at varying degrees of detail, and, for example, modelers could specify agents' visual field, how agents respond to dynamic changes in the environment (e.g., changes in visibility), or even complex interactions between biomechanical constraints, eye-movement, environment and behavior. An even more complex approach would be to model a wide range of perceptual abilities depending on the agent profile expected in a given situation (e.g. age or physical ability). Social influence and fear could be implemented as a source of biases or variance that change the probability distributions of certain behaviors in one way or the other.

This paper touched on aspects that are partly implemented in current evacuation models. For example, many evacuation models integrate behavioral facts and cognitive processes (e.g., risk perception) into their models. However, validation and verification of evacuation models is still problematic (Ronchi, Kuligowski, Nilsson, Peacock, & Reneke, 2016). The point here is to link behaviors that could be or are already simulated in evacuation models to research that has been rigorously validated and tested in controlled empirical settings. This approach potentially does not only allow to develop more precise models of occupant evacuation behavior, but also offers a route to understand why certain behavioral facts occur (e.g., *why* are occupants moving to the familiar?).

There are obvious limitations to the approach discussed here. For instance, most basic research results have been studied in controlled and isolated settings. Although the strength of the experimental method is its ability to identify causal relationships between variables, it is challenging to transform findings from lab studies into predictions about human behavior in fire without further validating studies. However, evacuation models can only be improved if the underlying psychological and physiological processes are sufficiently understood.

In summary, evacuation models that conceptually simulate occupants as agents embedded in a sociotechnical system can benefit from a deeper understanding of the psychological, social and physical environment. Results from basic research provides surprisingly precise descriptions about how humans could potentially react in fire emergencies.

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Questions and Answers

Following the presentation, a set of comments and questions were asked to the speaker. A summary of these questions and comments along with the answers are provided below.

(Ed Galea): Given the current limited understanding in the area of group behaviour (for instance for what concern exit selection), it is quite difficult to have a model able to represent this aspect. Further research is needed in order to reach this goal. Nevertheless, the use of Virtual Reality (VR) to obtain data on real human behaviour is questionable, i.e. the behaviour observed might not fully correspond to what happens in reality. For this reason, the use of data directly from VR experiments for modelling purpose should be limited. Should VR be used mainly to suggest and evaluate behaviour which could then further tested in other experimental settings with higher level of validity?

(Max Kinateder): VR is indeed different than an evacuation scenario in real life. The issue in Human Behaviour in fire research is that it is often difficult to use case studies (which provides mostly correlation data only). In order to evaluate behavioural aspects in more detail, controlled experiments are needed. For this reason, VR experiments can be used to test hypothesis. It is important to evaluate to which extent then it is possible to generate data comparable to actual behaviours. An example is provided with an experimental study in which participants were participating to an experiment in a real environment (Kinateder & Warren, 2016). A bogus perceptual task was interrupted by a fire alarm in both the real and in the virtual environment. While the magnitude of differences between control, active and passive groups are different, patterns of similar behaviour were observed in both VR and the real experimental environment, advocating for the fact that behavioural data can be to some extent comparable.

(Ed Galea): VR data may be useful indeed, but the main concern is that model developers and users could take results of VR studies and directly implement them in models.

(Max Kinateder): It is important to be clear on the fact that VR experiments are laboratory experiments. It is a responsibility of the model developer to evaluate the limitations in all types of experimental data based on their data collection method. Similarly, model users need to interpret data appropriateness in the context of use.

(Enrico Ronchi): Depending on the type of VR experiments, data may potentially be usable for model development since in some instances it is possible to resemble quite accurately actual behaviour (e.g. in case of evaluation of human response to visual sensory stimuli).

(Ed Galea): For example, group behaviour in VR might depend on the characteristics of the avatars. It is therefore important to consider results from this type of studies carefully before use for modelling purposes.

(Mike Spearpoint): VR studies can also be successfully used for training purposes. For instance they are currently used in earthquake scenarios (Lovreglio et al., 2017). It is though important to carefully evaluate the limitations of the data collected in VR when using data for evaluating behavioural outcomes, but it has potential for training applications.

(Enrico Ronchi): VR can be used to test evacuation system in design in infrastructures that are not existing yet (thus not having the possibility to perform any other type of experiments (Ronchi et al., 2016)). It is possible to use VR to compare qualitatively responses to isolated variables.

(Max Kinateder): The assessment of what can be considered representative data-sets remain for any type of research methods. For instance, even studies involving thousands of people might have their limitation. In any case, there is agreement on avoiding the direct use of VR data for modelling purposes without a careful evaluation. The specific strength of the experimental approach in VR is exactly that it allows researchers to test specific hypotheses by controlling all but a single factor of interest. That way we can test specific hypotheses and draw causal inferences. This is not possible in less controlled settings, because the complexity of a situation, as mentioned by Prof. Galea, can make it impossible to pinpoint the influence of individual factors.

(Enrico Ronchi): In the context of evacuation research, all methods might have issues with validity (i.e. not only VR studies). It is important therefore to assess the trade-offs between different methods rather than analysing the validity issue of a single method

(Erica Kuligowski): Similar validity issues to VR studies might be observed while using behavioural intention questionnaires to assist model development. Limitations have to be identified for all type of research methods and data need to be interpreted for the context of application.

(Ed Galea): If a research method has a validity issue, it is not important how many experiments are conducted. It is important to assess what validation studies have been performed between VR and actual experiments.

(Enrico Ronchi): Examples of validation studies for VR have been performed for simple experiments. Similar patterns can be observed from a qualitative point of view (Malthe and Vukancic, 2012).

(Max Kinateder): It is important to isolate measurable variables when using VR to investigate behaviours.

(Ed Galea): The optical information experiment on visual perception is an interesting study (Kinateder, Pfaff, & Cooper, 2017), but it is important to evaluate its use for fire safety engineering. In most scenarios occupants would not be directly exposed to emerging smoke fronts, so this study might have limited applications for fire evacuation modelling purposes.

(Max Kinateder): Visual perception VR experiments can be used to evaluate not only approaching smoke but also smoke changing its density, thus making it useful to evaluate behaviour of people immersed in smoke. In addition, there are scenarios, for example tunnel fires, in which occupants are confronted with approaching smoke and might decide evacuate too late because they underestimate or overestimate the speed of moving smoke.

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A Multi-disciplinary Perspective on Representing Human Behavior in Evacuation Models

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ABSTRACT
Predicting human behavior is an important aspect of performance-based design. However, our current evacuation modeling tools focus much more on simulating, verifying, and validating the movement of people throughout the building; often neglecting to represent the behavioral component of evacuation. This paper describes the current status of evacuation modeling tools in relation to simulating human behavior and identifies new directions in development that could improve the accuracy, scope, and reliability of model results; namely the inclusion of a comprehensive, conceptual model of human behavior in fire (HBiF). This paper also provides examples of current conceptual models of HBiF, additional research and efforts necessary for conceptual model development, questions for model developers regarding conceptual model implementation, and guidance on when the use of a conceptual model of HBiF would be beneficial.

KEYWORDS: human behavior, evacuation modeling, conceptual modeling, sociology, behavioral modeling, performance-based design

1. Introduction
Behavioral researchers in fire are still fighting the long-standing belief that human behavior during fires is just too complicated to predict. Misconceptions like this can arise from the media's misrepresentation of human behavior during emergencies as panic, wild flight, hysterical breakdown, or so shocked or "out of it" they are unable to respond (Fahy and Proulx 2009; Tierney 2003; Quarantelli & Dynes 1972). Also, human behavior can be deeply confusing to those who do not devote their careers to its understanding. For example, it is counterintuitive that people's first assumption in many disasters, regardless of the intensity of the information perceived, is that nothing unusual is happening, known as normalcy bias (Omer & Alon 1994; Tierney 1993; Drabek 1986; Okabe & Mikami 1982). Additionally, it is puzzling that individuals who seem to have witnessed the same types of cues in an emergency can often react in different ways.

What may seem at first like chaos or random behavior are carefully and logically constructed acts based upon occupants' understandings of the emergency. It is only when we understand how people interpret the situations around them, based upon the information that they perceive from their environment, that we can better understand and predict their resulting behavior.

Predicting human behavior is an important aspect of performance-based design. Life safety consultants, including fire protection (or safety) engineers, authorities having jurisdiction, and code consultants, use computational techniques to assess the safety provided by a building. This is done by using hand-calculations or computer simulation models to calculate how long a population would take to evacuate a building design. If the population reaches safety before conditions in the building become toxic (predicted via fire and toxicity models), by some added safety factor, then the structure is evaluated as sufficiently safe.

At present, our calculation techniques for evacuation (referred to throughout this paper as "evacuation modeling tools" or "tools") focus much more on simulating, verifying, and validating the ***movement of people*** through the entire building. More specifically on the importance of tracking individuals, their physical movements, and their evacuation timing in the event of a building fire (Fire Model Survey 2015; Kuligowski, Peacock, & Hoskins 2010; Gwynne et al. 1999). While these tools and their underlying calculation techniques are crucial to the engineering community and performance-based analyses, many are missing a key component of building evacuation: the behavioral component. Because the movement and behavioral components are highly coupled, an evacuation modeling tool is incomplete without proper representation of both components.

This paper is written as a discussion piece. Its purpose is to describe the current status of evacuation modeling tools in relation to simulating human behavior and identify new directions in development that will improve the accuracy, scope, and reliability of model results, especially for certain types of fire/evacuation scenarios and project objectives. The first section of this paper describes the current methods that evacuation modeling tools use to represent human behavior in fire. Given there are gaps in current representation, the subsequent section describes the benefits and necessity of a comprehensive, conceptual model of human behavior in fire (HBiF) for incorporation into current evacuation modeling tools. Included in this discussion are examples of current conceptual models of HBiF, additional research and efforts necessary for conceptual model development, questions for model developers regarding conceptual model implementation, and guidance on when the use of a conceptual model of HBiF would be beneficial. The reader should note that this paper is written from multiple perspectives to reflect the author's backgrounds in sociology, social psychology, and engineering, as well as experience as a model user.

2. Current Status in Evacuation Modeling Tools

It would be inaccurate to say that current evacuation modeling tools completely ignore HBiF. Attempts have been made over the years to include aspects of human behavior ranging from simple, user-defined techniques to unique and innovative approaches using "component theories".

2.1. User-Defined Behavioral Representation

Many of the current evacuation modeling tools available today rely on the user to supply a significant amount of information on behavioral representation. This information is required before a simulation is run.

The first example of this user-defined behavioral approach is delay times. Delay time is designed to represent the amount of time individuals or groups will wait or delay until they begin movement to the exits (often referred to as pre-evacuation or pre-movement time). In models, the delay time is a set amount of time or range of times that the user can either assign to a specific group or individual (agent) or request that the model distribute throughout the population (or subset of the population). Many models also offer a default time period or range of times for delay time.

Another example is user-defined behavioral itineraries. These itineraries can simulate the performance of behaviors by an agent or group, aside from simply moving from the original "start" location to the exit for evacuation. Here, the user requests that the modeling tool simulate movement of an agent or group from one location to another, assign a wait time to that agent or group for specific amount of time, and then simulate movement to another location (e.g., either the exit or to another location to wait). Behavioral itineraries are meant to represent a variety of behaviors or actions that can take place during a fire emergency, including rescuing or looking for others, searching for information, and/or gathering personal belongings from a particular location within the building.

While these behavioral approaches are a positive step toward the representation of human response within a simulation tool, the problem is that they rely primarily on the user to determine the population's behaviors ***before*** the simulation even begins (i.e., representation rather than prediction). This places a large burden on the model user; requiring a significant amount of knowledge about evacuation behavior and theory, and based on that knowledge, the pre-determination of behaviors that are likely to emerge during the simulation. Unless the user is clairvoyant, this type of pre-determined behavioral information is impossible to know.

Overall, these user-defined behavioral approaches are useful in forensic analysis purposes, where the fire event has already occurred and the user wishes to re-enact the incident. These approaches are also useful in design cases where the user wishes to test a specific known situation and control the factors and responses of the simulated population. However, they are often used in performance-based design; whereby the user specifies, pre-simulation, the delay timing and/or itineraries of the simulated population, in turn, imposing a large bias on the results produced.

2.2. Behavioral Representation using "Component Theories"

Another method of behavioral representation is through the inclusion of component theories, either as defaults in the modeling tool, embedded input options available for users, or user configuration of the model set-up. In this context, "component theories" are behavioral findings from journal articles, authoritative reports, observations, and/or studies on human behaviour in fire and other emergencies. Each component theory focuses on a particular aspect of the fire emergency and results in one type of behavioral outcome. Component theories are often incorporated within modeling tools as behavioral rules that link one condition to one outcome (e.g., if X, then Y occurs). Examples of component theories (also referred to as "behavioral facts" [Kuligowski et al. 2017]) that are incorporated in some of the current evacuation modeling tools are the following:

- An agent's route choice is based upon the physical environment in the building (Sime 1984); i.e., some set of occupants are more likely to use the more familiar routes in the building for evacuation. Those routes or exits that may be more familiar to agents are the main or front doors of a building, for example.
- An agent or group of agents may transition from walking to crawling when/if the smoke conditions reach a certain limit (Muhdi, Gwynne, & Davis 2009). For example, the limits for smoke conditions may be based on the optical density calculation of the smoke (as provided by the associated fire model).
- The actions of the surrounding population may influence the actions of the simulated agent (Latane & Darley 1970). One example of this is that an agent or group of agents may avoid congested areas of the building. Another example is that an agent may follow others to a specific exit.

The benefits of a behavioral approach using component theories is that it begins to reduce the burden on the user; and instead, involves agency at a more refined level moving us closer to producing genuinely new and unexpected results through the generation of emergent outcomes. Emergent outcomes are those that arise from the model's simulation of the evacuation scenarios, rather than outcomes pre-determined completely by the user. It is important to note that genuinely emergent outcomes can only truly occur at a less refined (higher) level than the pre-determined user intervention – and typically involves interaction between simulated agents / objects. For instance, if the user determines that an agent will definitely use a particular route, then the agent's use of the route is not emergent – no new outcome is generated. The outcome is effectively an attribute of the agent. However, the outcomes produced by the simulated population's use of that route will be emergent (e.g. the length of the queue formed); i.e. outcomes that are not an attribute of the agent. If the agent's route selection is reliant on external conditions (e.g. interaction with other agents, provision of new information, interaction with smoke, etc.), then the agent's action selection is emergent, along with all of the population-level outcomes identified above (e.g. the number of agents using the route, the congestion formed, etc.).

The prediction of emergent outcomes is crucial to life safety analyses, since it is impossible for the user to know, pre-simulation, all possible outcomes of an evacuation scenario (or series of scenarios) for a particular building. The ability to simulate emergence removes the burden from the model user, provides new insights, and increases the accuracy and realism of the results produced. These insights might provide a new perspective on the current scenario being examined or suggest the need to explore new scenarios – both extremely useful user insights.

However, there is a problem with the behavioral approach using component theories. Typically, only a small subset of these component theories is incorporated in any one modeling tool, resulting in a piecemeal representation of HBiF. Piecemeal representations can result in inaccurate modeling results, quite possibly underestimating evacuation timing. Instead, it is necessary is to create and incorporate a more comprehensive and inclusive representation of HBiF within evacuation modeling tools.

3. Improvements to Evacuation Modeling – Conceptual Modeling

To solve these problems, the author advocates for the development of a ***comprehensive conceptual model of human behavior in fire***. With current evacuation modeling tools, the user is required to set up the initial conditions <u>and</u> the evacuee response (either via user-defined inputs or the selection of component theories). The new conceptual model envisioned here is one that requires user-input of *only* the initial conditions, which is often times difficult enough. Initial conditions could consist of the following: building dimensions, exit locations, population numbers and type, and fire location and growth curve(s)[1]. During simulation, these inputs would be used by the conceptual model of HBiF, to predict internal motivations of agents (i.e., risk perception), and in turn, agents' actions and associated delays.

The benefits of such a model is that it could ***predict***, rather than simply determine based upon user input, human behavior during fire events. This outcome alone would enable a user to identify the behaviors that emerge as the fire scenario unfolds, removing significant burden from the model user and increasing the accuracy of model results. This sub-model, after extensive validation, could be incorporated into current and future evacuation modeling tools.

In the following section, examples are provided of conceptual models of human behavior in fire. Each model features a certain aspect of the evacuation timeline. Of these examples, three are highlighted since they are most relevant to our goal -- to predict decisions and actions taken in a fire emergency. The first is a general model of human behavior in fires developed by Canter, Breaux and Sime (1980) that focuses primarily on evacuation actions or behaviors. The second is a conceptual model developed by Kuligowski (2012; 2011) that focuses only on pre-evacuation behavior from a single fire event -- the 2001 World Trade Center Disaster. The third is a conceptual model developed by compiling a series of component theories from various disciplines into a

[1] If possible, the model results would be strengthened if the user knew additional characteristics about the population that could be supplied as inputs, e.g., had they experienced fires or false alarms in the past, and their relationships with other building occupants.

cohesive platform to predict whether an agent takes protection (or not) in a fire emergency (Kuligowski et al. 2017). None of these have been sufficiently validated; and all require extensive work to achieve completion, but are shown here to identify three different methods by which a conceptual model of HBiF can be developed.

3.1. Examples of Conceptual Models of Human Behavior in Fire

Since the 1960s, examples of conceptual models relevant to certain aspects fire emergencies have been developed (Proulx 1993; Edelman, Hertz & Bickman 1980; Withey 1962). One of the first attempts at development of a comprehensive model of behavioral response in fires was performed by Canter, Breaux and Sime (1980). The authors developed three decomposition diagrams that summarized the sequence of evacuees' behavioral actions; one for domestic fires, one for multiple-occupancy fires, and one for fires in hospitals. Each diagram was developed based upon interviews conducted with 41 people involved in the 14 domestic fires studied, 96 people in the 8 multi-occupancy fires, and 62 people involved in the 6 hospital fires. These diagrams focused on the behavioral acts performed, specifically how frequently they were performed and the sequence in which they were performed along the incident's timeline. What is interesting is that some of these "acts", e.g., "hear strange noises," "misinterpret (ignore)," and "feel concerned/frightened" are actually internal process factors, i.e., perceptions or interpretations of the event or the risk, rather than acts themselves. Essentially, these authors were the first to link internal perceptions and interpretations of the fire event to subsequent evacuation behaviors.

Since the same patterns of behaviors/acts existed across all three diagrams (of varying occupancy type), Canter, Breaux, and Sime (1980) then developed a general model of human behavior in fire. The general model summarizes a number of recurring action sequences. According to the model, once an individual receives information from the event, he/she either ignores or investigates this information (labeled as the "interpret" stage). After investigation, the individual enters the "prepare" stage, where he/she is likely to either instruct others, explore further, or withdraw. Depending upon the behavior(s) taken in the "prepare" stage, the individual engages in behaviors in the final stage ("act"), including evacuate, fight, warn, or wait.

As with any model there are limitations associated with Canter, Breaux, and Sime's (1980) general model of HBiF. The general model contains only sequences of actions; and therefore, does not link any initial conditions, factors, or inputs to any one sequence. Without those conditions, factors, or inputs, it is impossible to translate this summary model into a predictive model. How are we to know what conditions prompt a specific agent to perform one type of behavioral sequence over another? This model; however, provides an important starting point for future work in this area.

Influenced by this work, Kuligowski (2012; 2011) developed a qualitative model to predict pre-evacuation actions of the survivors of the 2001 World Trade Center (WTC) Disaster. Through analyses of transcripts from 245 face-to-face interviews with survivors from both WTC towers, collected by Project HEED (Galea et al. 2006), this model explains individually- (or evacuee-) based actions taken during the pre-evacuation period of a building fire/evacuation event. The goal of this research was to describe evacuation decision processes in greater detail than either research on building fires or studies on community-wide evacuation, focusing on how people perceive and interpret environmental cues and warnings, how they seek confirmation during sensemaking and milling processes, and what they do before moving to safety.

There are five main findings that can be highlighted from this research. The findings are as follows:

- The WTC pre-evacuation period was divided into two main phases: the milling/sensemaking phase and the protective action phase. In the milling/sensemaking phase, WTC occupants engaged in two different actions – continuing to work or seeking additional information. In the protective actions phase, on the other hand, occupants engaged in actions that were focused specifically on protecting themselves or others (i.e., helping others, preparing to evacuate, or defending in place). Both phases took place before moving to the stairs or elevators.

- Risk perception, or the feeling of personal danger, was the main predictor of when individuals decided to evacuate – i.e., the transition from the milling/sensemaking phase to the protective action phase. Both individual and environmental factors were identified as influential of risk perception development.
- Some individuals made their decisions to evacuate before others on their floor. These "early responders", as labeled by Kuligowski (2011), were primarily higher-level managers, fire wardens, military personnel, or individuals with experiences or occupations in emergency situations. These individuals still required the receipt of information that increased their level of perceived risk, but were also more inclined to act first (before others) because they felt responsibility for others and/or had previously experienced/witnessed negative consequences associated with fire or building evacuations.
- Certain factors, such as personal responsibility, social connections, and the actions of others, influenced which protective actions people engaged.

See Kuligowski (2011) for further explanation on the conceptual model. Kuligowski's model is not without limitations, however. The model focuses specifically on the pre-evacuation period of one building event. Additionally, the model does not incorporate any decisions or actions of the decedents. While the findings in the model were verified with theory from other events, the factors that influenced each action performed were specific to an office building fire and subsequent evacuation, thus making it difficult to generalize the findings. This is a start to developing a model to predict actions taken during building fires; however, this effort should be expanded upon to include findings from analysis of other building fires, including fires in different types of structures and with different populations, as well as from analysis of other types of natural, technological or human-caused disasters, not limited to building fires.

The third example of a conceptual model was developed by Kuligowski et al. (2017). This model was developed by compiling 28 component theories from various fire-related and social science disciplines on behaviors that can occur during evacuation, the factors that influence these behaviors, and their outcomes. These component theories have each appeared several times in the literature in some form – either as a finding from research or as an assumption in modelling analysis, or some combination of the two. Yet, until this model was developed, these component theories were isolated: distributed between publications and other sources and used occasionally (or in a piecemeal manner) in current evacuation analysis.

This conceptual model, albeit provisional (based on our current understanding), was constructed based upon a theoretical framework of individual decision-making and response to emergencies – the Protective Action Decision Model, or PADM (Lindell & Perry 2012). The PADM, which is based on over 50 years of empirical studies of hazards and disasters (e.g., Sorensen & Vogt-Sorensen 2006; Mileti & Peek 2001; Tierney, Lindell, & Perry 2001; Drabek 1986), provides a framework that describes the information flow and decision-making that influences protective actions taken in response to natural and technological disasters. When organized into the PADM framework, this effort moves the field closer to a conceptual model of HBiF. See Kuligowski et al. (2017) for the preliminary conceptual model of human behavior in fire. Examples are provided here of 5 of the 28 component theories from Stages 1 and 2 of the PADM; risk identification (i.e., the individual decides if there is actually something occurring that may require attention) and risk assessment (i.e., the individual perceives or feels personal danger):

1. The precision, credibility, consistency, comprehensiveness, intensity and specificity of the external cues will affect the assessment of the situation and perception of risk.
2. Authority of the information source affects the perceived credibility of the information, and in turn the assessment of the situation and risk.
3. Normalcy bias and optimism bias are commonplace. In other words, people often think that nothing serious is taking place, and that nothing bad will happen to them, respectively.
4. Training on and/or experience with a particular incident type may allow a similar incident to be defined more quickly by the evacuee.
5. The actions of the surrounding population can influence the internal processes of the individual.

It is important to note; however, that while the component theories are organized by the PADM, additional work is required to connect these theories (and reflect the interaction between them) with all others in the model so that the model works in an integrated manner. This conceptual model should not only consider that the component theories interact in an additive nature, but also in counteractive or even multiplicative ways. For example, component theory #5 (above) states that "the actions of the surrounding population can influence the internal processes of the individual" (Latane & Darley 1970). An example of this could mean that an "observer" agent who witnesses an evacuating population will have a higher perceived risk, and in turn, begin evacuating as well. Component theory #2 (above) states that the "authority of the information source affects the perceived credibility of the information, and in turn the assessment of the situation and risk". Therefore, if a simulated agent is labeled in the model as a "credible source" (e.g., a manager) and the manager begins to evacuate; it is likely that the "observer" agent will perceive a higher level of risk and also begin to evacuate; *representing an additive effect.* On the other hand, if a simulated agent labeled by the model as a "non-credible source" begins to evacuate; the model will be required to reconcile the effect of this non-credible evacuee's behavior on the "observer" agent; *a potential counteractive effect.* Reconciling counteractive and multiplicative interactions between component theories is not a trivial task, but it is necessary for the development of this type of conceptual model.

It is also important to note that all three of these conceptual models focus on the decision-making process and subsequent actions of the individual. However, research in Sociology highlights the importance of group dynamics in emergencies. For example, the Emergent Norm Theory (ENT) of Collective Behavior posits that certain situations, e.g. a fire emergency, prompt people to come together to figure out what is going on and what they should do about it (Turner & Killian 1987; 1972; 1957). In this process, groups spend time discussing the situation, offering suggestions of what to do next, and then, performing these actions collectively. Within this process is the transfer of information, and the assurance that people (and in this case, agents) are not acting individually, but instead, together toward a common goal. Taking collective behavior and ENT one step further, research has shown that individuals help one another during building emergencies, bringing together people in groups at one time or another (Aguirre et al. 2011; Johnson, Feinberg & Johnston's 1994; Turner & Killian 1987). These processes can occur among people who know or do not know one another before the fire event occurs. *Therefore, it will be important to understand and incorporate, in any conceptual model, the role of group dynamics in evacuation decision-making and behavior.*

3.2. Conceptual Model Development

At present, these conceptual models scratch only the surface of the development of a larger, comprehensive model of HBiF. These models provide a path forward for the methods that could be used in its eventual development. However, there is much work still to be done to improve our understanding of HBiF, and without this understanding, a comprehensive model is near impossible. Listed here are just a few examples of areas in the field that require further study (Kuligowski 2016):

- The influence of fire's toxic products and heat on decision-making and behavior (before incapacitation or death occur) in a fire
- An identification of the factors that influence risk perception and how they interact to increase or decrease risk perception levels; Kinateder et al. (2016) provides a starting point.
- The factors that influence the various types of protective actions performed in fires
- The factors that influence the receipt of cues, the ways in which people pay attention to cues, and the comprehension of cues
- The ways in which individual factors, such as gender, disability, age, body size, culture, marital status, past experiences, training and social role, influence decision-making during fires
- The timing associated with the performance of behavior during fires, and the factors that influence this timing
- The influence of urgency or other types of dissemination techniques on the response of individuals during fires
- The influence of group dynamics on individual decision-making and group decision-making during fires
- The role of place (including building type or building characteristics) on decision-making during fires
- The role of psychological states, including stress or anxiety, on decision-making during fires.
- The influence of the fire scenario on human behavior; i.e., could this conceptual model be made sufficiently general to account for human behavior during outdoor fires (e.g., fires that occur at the wildland-urban interface)?

For the field to reach its goal and develop a larger understanding of human behavior in fire, accurate, rigorous, and comprehensive research and theory development must continue. There is still much left to understand, but the ultimate goal of a comprehensive model is in our future.

Additionally, a significant part of conceptual model development is verification and validation. Sokolowski and Bank (2010) describe the modeling process, redrawn as Figure 1. A requirements analysis is used to identify the simuland (or real-world entities of interest to the user). The simuland then leads directly into the conceptual model development, followed by the development of an executable model. The executable model is then run to develop results. It is important to note here that it is *the conceptual model that requires validation efforts*, and the executable model that requires verification. This is important since it seems that, too often, that verification and validation is performed only on the executable model, likely because behavioral concepts are introduced to the executable only in a piecemeal manner (rather than as a fully-formed verified and validated conceptual model).

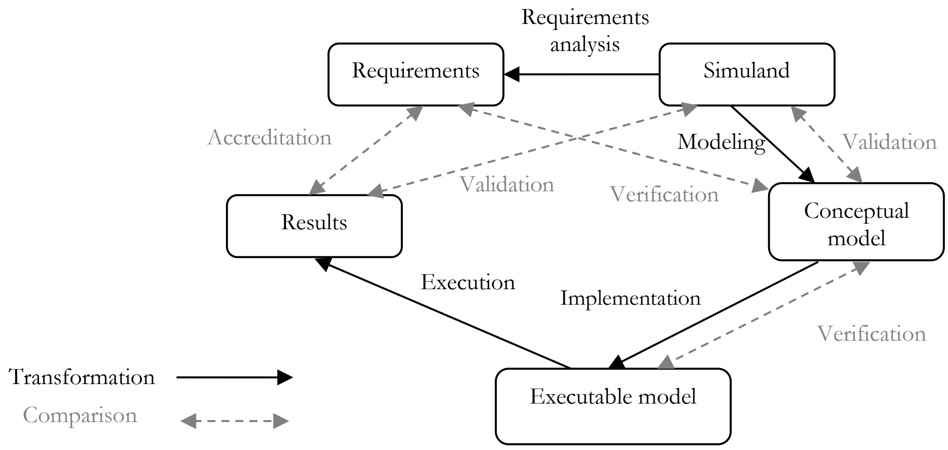

Figure 1: The role of the conceptual model in the entire modeling process [redrawn from Sokolowski and Bank (2010)].

Independent of the method used to create the conceptual model, it will need to be validated using different sets of data from emergency events (including fires in different types of structures and with different populations, as well as from analysis of other types of disasters, not limited to building fires) – to ensure that this model is sufficiently generalized to accommodate all types of fire scenarios.

3.3. Conceptual Model Implementation

Once a validated conceptual model is developed, extensive work will be required to implement it into current or future evacuation modeling tools. Gwynne (2012) has already begun to consider requirements of the agent-based evacuation modeling tools such that a conceptual model of HBiF could be represented, which was extended in Gwynne, Hulse and Kinsey (2016). The authors first describe a simplified behavioral theory of HBiF, and then outline the model functionality required to represent the theory, including external cues and conditions, cue processing, a roles/social network, spatial map, event map, threat perception, agent attributes, and a response or action generator. They end by providing an example of how the evacuee decision-making process can be represented by an agent-based modeling tool.

Since this article is a discussion piece written for the panel on evacuation modeling at the 12th IAFSS Symposium, additional questions are posed here to the evacuation modeling developer community to prompt initial conversation:

- What are your thoughts on the development of a conceptual model on human behavior in fire? Is this a feasible approach to improving evacuation modeling tools? Please explain.
- What do you see as the major barriers to or concerns regarding this approach?
- What information would you require to implement such a model?
- What method(s) can you envision to implement a conceptual model into a) current evacuation modeling tools and b) future evacuation modeling tools?
- How might the implementation of a conceptual model be tested/verified?

3.4. Conceptual Model Usage

After development and implementation, the next question that arises is when and where a conceptual model of HBiF is needed. Evacuation model users would benefit from guidance on its usage for different types of projects and project objectives. It is likely that the development of this conceptual model will be expensive, and therefore, the use of such a model may be expensive as well. There are certain instances (e.g., scenarios, projects, purposes, etc.) where the inclusion of a conceptual behavioral submodel within an evacuation computer model would be more beneficial than others.

First, there are certain types of fire evacuation scenarios where the use of a conceptual model matters. A conceptual model of HBiF would be most useful in scenarios where most or all of the evacuation timing can be spent in the decision-making process. The domestic setting is a prime example of this phenomenon. In domestic settings, the time to movement from "Point A" to safety (i.e., outside of the residence in the case of a building fire) can be insignificant, especially when compared to the time often spent seeking information, deciding to evacuate, and preparing. Therefore, a conceptual model would be crucial when modeling evacuation from domestic fires, and even larger-community scale fire events, like wildfires or wildland-urban interface fire events, where people are required to decide whether to leave their homes and evacuate their neighborhoods (often in vehicles). In changing scales, however, from building to community, it will be important to understand the additional factors that can influence household decision-making processes and subsequent evacuation behavior in community-wide disasters. Community-wide evacuation is often complicated by existing household vulnerabilities, e.g., financial constraints, access to a vehicle, age, disabilities, etc. (Lindell 2011; Cutter, Boruff, & Shirley 2003) and/or potentially aided by existing social ties and relationships within the community (also known as social capital) (Aldrich & Meyer 2014).

With that said, a conceptual model may be beneficial even in scenarios that are dominated by people movement and flow, e.g., stadia evacuations. That is, <u>if</u> the user wishes to explore more than just the evacuation timing of the fire event. Without a conceptual model, the user may superficially treat the evacuation as laminar flow. By doing so, he/she is potentially ignoring the impact of social clusters and group dynamics on evacuation performance. In other words, if a user wishes to study individual experiences of groups/evacuees (at lower levels) during the stadium evacuation, in order to better understand locations of 'turbulent' flow throughout the building or structure, the use of conceptual model is essential.

Second, there may be certain types of project objectives (over others) that require the use of a conceptual model. In projects where the evacuation model is being used to simulate agents strictly adhering to a specific procedure, the benefits of a conceptual model are limited. An example of this is exploring the results of a procedure whereby the building population evacuates immediately and uses the main exit. This is a legitimate use of current modeling tools, given that the evacuation model used is capable of capturing the outcomes of the agents. In this project, the benefits of a conceptual model are limited because the "behavior of the occupants" in the modeling scenario can be sufficiently pre-defined by the user. Projects where a conceptual model is of most benefit are those where the user is required to answer "what could happen if…." questions. Essentially, these projects require the model to explore what agents would do, given only a series of initial conditions. In these projects, a model's ability to simulate emergent behaviors and outcomes (i.e., those not completely pre-defined by the user) is crucial, and only possible through the inclusion of a refined and comprehensive conceptual model of HBiF.

At the moment, it is up to the model user to decide, based upon project requirements, the capabilities of the evacuation modeling tool(s) required for the job, and in turn, select the correct/appropriate tool to use. The same would be true when/if a conceptual model was available. Currently, we do not have the capabilities of a conceptual model of HBiF in any of the current evacuation modeling tools. In the future, if these capabilities are made available to model users (either within certain modeling tools or as a sub-model to accompany current tools), users would benefit from a guide that would help them decide when, and for which projects/scenarios, a conceptual model would be most beneficial.

4. Conclusion

This article provides ideas/suggestions for improvement to current and future evacuation modeling tools. Discussions are provided on the current techniques used by evacuation models to simulate HBiF; namely, user-defined techniques and the use of component theories. However, since there are gaps in our current representation of human behavior, this paper advocates for the development of a conceptual model of HBiF that can be implemented into current or future evacuation modeling tools. Examples of conceptual models of human behavior are then provided to identify different methods by which such a model can be developed. The paper ends with discussions on research and data required to develop a comprehensive model of HBiF (including theory development), validation efforts, model implementation into current evacuation modeling tools, and the benefits of its usage.

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Questions and Answers

Following the presentation, a set of comments and questions were asked to the speaker. A summary of these questions along with the answers are provided below.

(Max Kinateder): A general question can be asked concerning the exact meaning of validation in the context of evacuation modelling. Does it relate to the outcome or the behaviour itself?

(Peter Thompson): Validation should be intended as the validation of each component of behaviours. It is important to have a common set of references in order to have agreement among the evacuation modelling community on validation.

(Ed Galea): An overarching concept of behaviour needs to be defined in the community. Engineers may consider the Required Safe Egress time (RSET) and (ASET) separately. Few models indeed allow the coupling of fire and evacuation. Many models are simply movement models which do not take into consideration the impact of fire on behaviours.

(Enrico Ronchi): A comprehensive conceptual model would increase the credibility of the field and the use of models. Nevertheless, it is important to identify solutions given the current state of the art in which such comprehensive model does not exist.

(Ed Galea): An example that can be taken into consideration is the fire in the Kiss nightclub. In such type of scenarios it is of fundamental importance to consider the coupling between fire and evacuation since models may be able to predict how people use walls to aid way-finding.

(Erica Kuligowski): Initial efforts have been made given the current state of the art to provide guidance on the development and use of models. Two papers have been published on this issue (Gwynne et al., 2015; Kuligowski et al., 2017). It is important to learn how to use different types of models given their limitations rather than ignoring some of them.

(Enrico Ronchi): It might be interesting to understand what could be borrowed from the area of community evacuation in this sense, i.e. how the coupling is represented.

(Adam Pel): Evacuation is generally performed in communities before the disaster happens, thus risk perception is a quite important aspect rather than the coupling with the disaster itself

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Overhead pedestrian tracking for large scale real-life crowd dynamics analyses

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ABSTRACT

Accurate measurements of pedestrian dynamics, in form of individual trajectories, are paramount to investigate the complex motion of walking individuals and to produce reliable crowd simulation models for ordinary and evacuation conditions. This paper reviews one pedestrian trajectory collection technique, recently employed by the same authors for acquiring crowd dynamics data in real-life conditions. Operating unsupervised, the technique has enabled unprecedented, 24/7, months-long, pedestrian measurement campaigns that provided millions of individual trajectories, allowing novel statistical insights. The tracking technique leverages overhead depth-sensors, such as Microsoft Kinects, arranged in grids, and ad hoc pedestrian localization algorithms. Here we review its relevant technological aspects in view of statistical crowd dynamics analyses.

KEYWORDS: pedestrian dynamics, real-life pedestrian tracking, overhead Kinect sensors

1. Introduction

Experimental measurements of the dynamics of pedestrian crowds have grown rapidly in quantity and accuracy during the last decade sustained by a two-fold purpose. On one side, it stands the scientific challenge of unveiling the complex interactions and stochastic mechanisms at the basis of the crowd motion. This involved, among others, physicists, applied mathematicians, fire safety engineers and social scientists (Cristiani et al., 2014; Helbing and Molnar, 1995). On the other side, the societal need of safe and comfortable civil infrastructures calls for predictive models of pedestrian traffic. In fact, quantitative models have countless engineering uses, including designing of walkways, streamlining exhibition paths and maximizing the efficiency of evacuation routes (Schadschneider et al., 2008; Venuti et al., 2016).

Regardless the context, scientific or technological, accurate pedestrian dynamics measurements are paramount for hypotheses validation or model calibration. Over time measurement techniques evolved: manual measurements for flux-density relation estimates (the so called "fundamental diagrams", e.g. (Seyfried et al., 2005)) has been replaced by increasingly automatized individual(-head) tracking ((Boltes and Seyfried, 2013; Seer et al., 2014a; Zanlungo et al., 2014)). Simultaneously, pedestrian models operating at different scales, from lumped to particle-based, have been proposed and calibrated (cf. reviews in (Cristiani et al., 2014; Schadschneider et al., 2008)).

Since recently, crowd dynamics experiments in real-life conditions are receiving increasing attention (e.g. (Helbing et al., 2007; Seer et al., 2014b; Zanlungo et al., 2014)). They come as alternatives of established laboratory-based, "in vitro", pedestrian data acquisition campaigns, in which experimenters involve groups of voluntaries, that possibly wearing special clothing to aid tracking, take part to crowd flows scenarios (such as a queuing, bottleneck, or counter-flow dynamics. See, e.g. (Liao et al., 2016; Zhang et al., 2011)). Real-life measurements present two main advantages over laboratory approach: first, they involve pedestrians unaware of being part of a scientific experiment. While in laboratory the measured dynamics is orchestrated, thus unavoidably more or less biased by the experimenter instructions, in real-life pedestrian flows respond to the free will of the randomly involved individuals, allowing to truly expose the stochasticity of pedestrian motion. Secondly, real-life pedestrian measurement campaigns can span over potentially limitless time intervals; therefore, they can collect thousands or millions of trajectories. Such a large amount of unbiased data, impossible to collect in a laboratory framework, enables to measure the motion beyond its average quantities and estimate its fluctuations and its characteristic rare events. Questions such as “what is the probability distribution of the walking speed of individuals moving alone?” “How does it change as the traffic increases?” “How often does an extreme event of the dynamics, possibly having dangerous consequences such as a person stumbling or reverting their trajectory, occur?” can be addressed safely away from potential influences of experimenters’ instructions (Corbetta et al., 2017a).

On the opposite, real-life measurements, when targeting the acquisition of thousands of trajectories, must occur in an unsupervised manner, demanding a strong technological effort for robustness and accuracy. For instance, unaware participants can wear any sort of clothing or headgear, that the tracking algorithmic must be able to deal with. Also, in laboratory, the experimenter can fully define “control parameters” for their experiment (e.g. number of individuals involved, crowd density, directionality), while in real-life they are subjected to the randomness of the crowd flow (Corbetta et al., 2017b). In real-life conditions, privacy of the involved crowd is also a crucial issue, as individuals must consent to participate to experiments, especially if not anonymous (e.g. in case tracked individuals remain recognizable in the recorded data).

In this article, we first describe a pedestrian tracking approach able to operate unsupervised in real-life conditions that we employed for months-long, 24/7, real-life measurement campaigns. This approach is distinguished by measurement accuracy, speed, and the need for simple, geometric-based, signal processing.

Our campaigns, held respectively in a building of Eindhoven University of Technology (years 2013-2014, about 200.000 trajectories collected, see e.g. (Corbetta et al., 2014)) and at Eindhoven train station (years 2014-2015, about 5 millions trajectories collected, see (Corbetta et al., 2016a), cf. Fig. 1), analyzed the pedestrian dynamics with high statistic resolution, targeting motion fluctuations and rare events (e.g. (Corbetta et al., 2017a)). A brief overview of the analyses outcomes is the topic of the second part of this work.

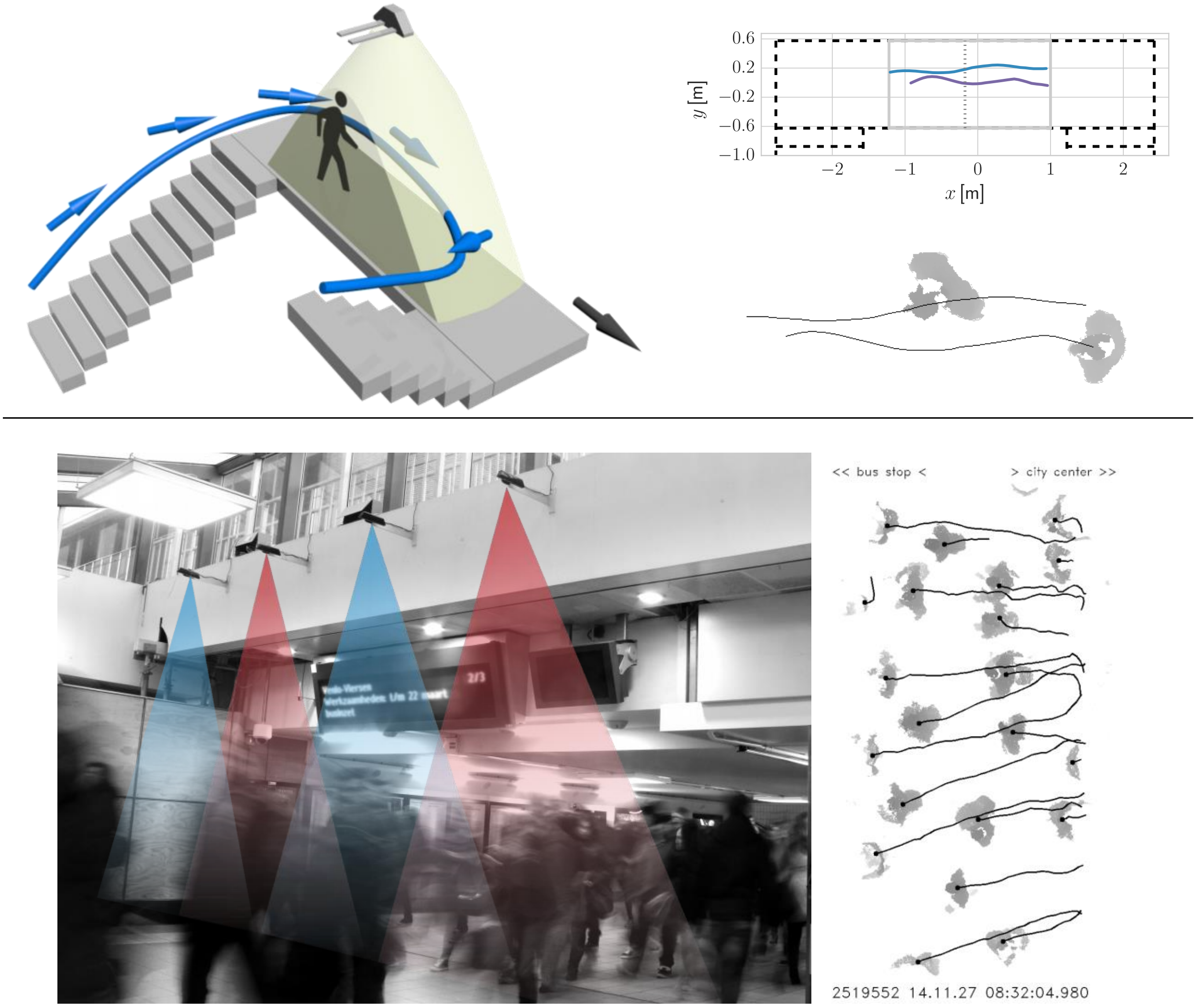


Figure 2. (top) Crowd tracking experiment at the Metaforum Building, Eindhoven University of Technology; setup sketch, example of collected trajectories and related depth maps (figure from (Corbetta et al., 2017b)). (bottom) Crowd tracking experiment at Eindhoven train station with four Kinect sensors: snapshot and sample depth map with trajectories. In both cases depth maps have grayscale colorization (figure from (Corbetta et al., 2016b)).

2. Measurements via overhead depth sensors

The grounds of the measurement technique that we employ have been firstly and independently posed in (Seer et al., 2014a) and in (Brscic et al., 2013), and leverage depth field signals, acquired via depth sensors such as Microsoft Kinect (Microsoft Corp., 2012), for pedestrian localization. Thanks to the usage of depth map signals pedestrians remain unrecognizable, thus fully preserving the individual privacy.

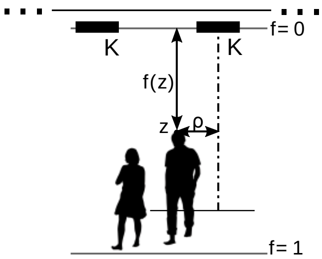


Figure 3. (left) Conceptual sketch of an overhead depth measurement system, with Kinect sensors denoted by the "K". Definition of the depth field f as the distance between each point z and the camera plane. To generate axonometric maps, we normalize the depth field to be in the $[0,1]$ range and consider cylindrical coordinates centered around each camera axis (cf. ρ).

Depth sensors return distance-field maps, or depth maps. While an ordinary digital image reports pixel-by-pixel a color information (RGB, i.e. three channels), a digital depth map reports the distance between each pixel and the camera plane. This is a single channel (scalar) information, usually encoded in grayscale images. We write a depth map in formulas as

$$f = f(z) = \text{distance}(\text{location } z, \text{camera plane}) \qquad \text{[Equation 1]}$$

where $z = (x, y)$ denotes a spatial location in the depth image (cf. Fig. 2).
A fairly extended selection of depth sensors is currently available on the market differing in resolution, depth reach, acquisition frequencies and prices (cf. (Brscic et al., 2013; Stoyanov, Todor and Louloudi, Athanasia and Andreasson, Henrik and Lilienthal, 2011)). Since the early 2010s, depth sensors entered the consumer market with devices as Microsoft Kinect, which has been conceived to enhance human-machine natural interactions, i.e. interactions based on physical motion rather than on keyboards, mice, or joysticks. The sensor has been sold for use with Microsoft Windows™ computers or Microsoft Xbox 360™ gaming consoles (Han et al., 2013) until 2015 (and is currently replaced by an updated version). On side of a standard color camera, the Kinect™ is equipped with an infrared structured-light sensor (Stoyanov, Todor and Louloudi, Athanasia and Andreasson, Henrik and Lilienthal, 2011) and, via an embedded system, it delivers an estimate of the depth map of the scene at VGA resolution (640x480 px) and at 30Hz refresh rate. Microsoft Kinect sensors provide the raw depth images of pedestrians at the basis of the tracking technique considered in this paper.

We place Kinect sensors overhead to observe the scene in a vertical, top-to-bottom, fashion. When it comes to measurements, overhead observations of crowds are generally favorable, in comparison e.g. with oblique views, typical of surveillance. In fact, from an overhead perspective, mutual occlusions hardly occur leaving individual heads visible at all times. This holds true regardless the specific imaging approach (color, depth).

The pedestrian localization approach we employ exploits one key empirical concept:

> *In an overhead depth field, the scene foreground, in which the pedestrian dynamics occurs, coincides with the region of lower depth (i.e. of smaller distance to the sensor, in opposition with the background). Furthermore, pedestrian bodies are expected as compact blobs in the foreground and their heads, as the uppermost parts of the body, measure the lowest depth.*

In the following, we detail our implementation of this concept.

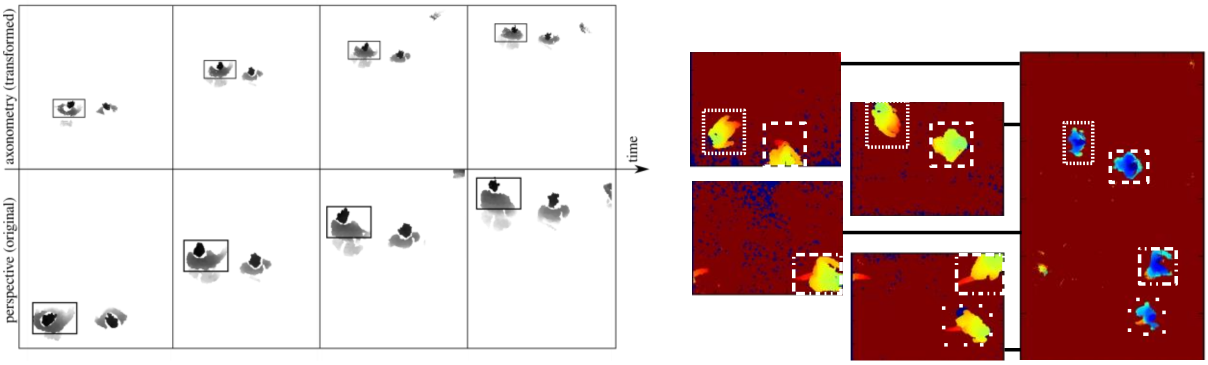


Figure 4. (left) four depth frames in axonometric view are compared with the original perspective view. After the transformation shapes are translationally invariant. (right) juxtaposition of four depth frames into a larger depth frame (depth maps colorized for visualization ease. Figure from (Corbetta et al., 2016b))

2.1. Localization and tracking principles

We split the trajectory extraction problem into two tasks: frame-by-frame pedestrian localization (T1) and multi-target point tracking (T2). In other words, first, we analyze singularly all the frames to extract the positions of each pedestrian (e.g. of their head or of the centroid of their body), second, we follow these positions over time obtaining the trajectories.

Task T1 is strictly context-specific and is the matter of the next sections. On the contrary, multi-point tracking is a general problem addressed in several fields. For instance, in experimental fluid mechanics and, in particular, in the particle tracking velocimetry (PTV) community, the statistical properties of turbulence are studied by tracking thousands of small polystyrene particles immersed in fluid flows (Willneff, 2003). Over the years, the community developed robust tracking algorithms including, for instance, multi-camera particle tracking and optical distortion corrections. Therefore, we deal with task T2 employing state-of-art PTV algorithms for multi-target point tracking and, specifically, we adopt the OpenPTV library (The OpenPTV Consortium; Willneff, 2003).

Also, it is worth remarking that the task split T1-T2 is not mandatory and techniques extracting trajectories in an end-to-end fashion exist for general target tracking problems.

2.2. Spatial coverage

We collect overhead depth maps, providing the raw input for localization, employing one or more Kinect sensors. Using multiple sensors allows to overcome the rather limited spatial coverage allowed by single units. However, frames captured simultaneously by multiple sensors need to be merged before the localization. In (Corbetta et al., 2016a) we proposed a two-steps merging algorithm based on simple geometric rules (see Fig. 3):

1. **Generation of aerial axonometric depth maps**. The overhead depth maps supplied by the Kinect come with the perspective view of the sensor. As per the conic view, true "vertical" aerial views are limited to pedestrians roughly aligned to the sensor axis (i.e., walking below the sensor location). Instead, pedestrians moving to the edges of the view cone get a skewed image. Depth maps can be processed to align points lying on the same vertical ray obtaining actual aerial views. In this way depth maps of shapes moving on the horizontal plane are translation invariant.

   Let (θ, ρ, f) be the cylindrical coordinates (in the angle θ) aligned with the camera axis ($\rho = 0$, cf. Fig. 2), normalized so that the view cone and the ground intersect at $\rho = 1$

and $0 \leq f \leq 1$ spans (vertically) the depth (distance) from the sensor ($f = 0$) to the ground ($f = 1$). The transformation

$$(\theta, \rho, f) \rightarrow (\theta, \rho f, f) \qquad \text{[Equation 2]}$$

displaces each point to its vertical line (note that $\rho f \leq \rho$ and $\rho f = \rho$ only at the ground level, i.e. the ground level is invariant under this transformation). Extracting the lowest depth value (top-most) for each vertical line yields the final aerial view.

2. **Juxtaposition of aerial depth maps and pixel size calibration.** We merge simultaneous aerial depth maps by juxtaposition/superposition according to the sensors sight overlap. We find superposition parameters via a manual calibration procedure involving sliding beams of known size under the cameras (beams are 1-2m long). Areal views are then combined to fit the original beam shape. Also in this case, the superposition procedure selects the lowest depth value for each vertical line. Furthermore, the length of the beams enables to find the pixel size in meters and the pixel-to-meter conversion for each point.

2.3. Pedestrian localization via agglomerative clustering

At each depth frame captured by the depth sensor $f = f(z)$ we perform pedestrian localization with the following steps:

1. **Background subtraction**. Depth maps collected at a given location typically share a common background that includes walls, parapets, decorative elements, etc. These elements are not to interfere in the pedestrian localization and can be subtracted. Let $B(z)$ a depth map of the background preliminarily collected. We isolate the foreground $F(z)$ of a depth map $f(z)$ by arithmetic subtraction:

$$F(z) \leftarrow \begin{cases} f(z) & \text{if} \quad f(z) < B(z) - \epsilon_B \\ & f_{\text{floor}} \end{cases} \qquad \text{[Equation 3]}$$

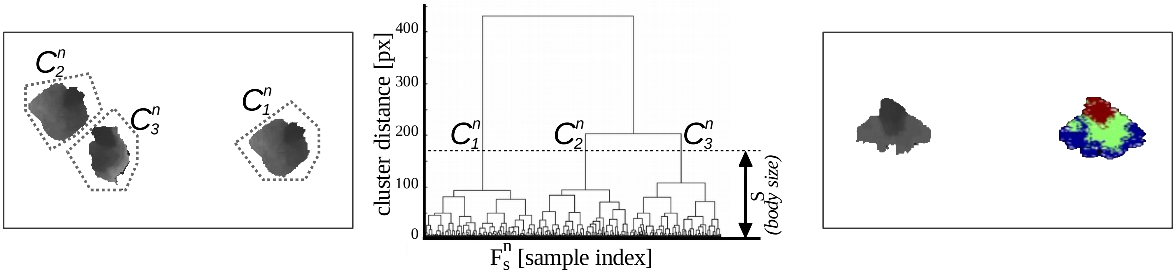
where ϵ_B is a (small) tolerance that reduces the depth of the background, to segment the foreground more robustly, and f_{floor} is the depth of the floor, i.e. the maximum measurable depth. In words, we are replacing background objects to appear as the floor.

2. **Height thresholding.** Only foreground elements that are taller enough can be candidate pedestrians, i.e. trolleys, carts, trays need to be removed. In the depth field, this translates in a second thresholding operation

$$F(z) \leftarrow \begin{cases} F(z) & \text{if} \quad B(z) < \mathrm{h} \\ & f_{\text{floor}} \end{cases} \qquad \text{[Equation 4]}$$

which removes, i.e. replaces with floor depth values, elements that are farther than the camera than a cutoff depth h.

3. **Foreground noise reduction.** The foreground so obtained can be noisy, containing depth artifacts in form of spots, that can result from depth reconstruction or foreground segmentation errors. We remove these by performing a morphologic closure of the



(a) (b) (c)

Figure 5. (a) Three pedestrians distinguished on the basis of the clustering tree in (b), cut at the body size S. (c) Localization of the pedestrian head (red) through as 5th percentile (or less) of the local depth distribution. Shoulders (green) are identified as the region between the 5th and the 20th depth percentiles (figure from (Corbetta et al., 2014)).

foreground mask ($\overline{\{z : F(z) < h\}}$, cf. (Serra, 1982) for a reference on binary mask closure operations) and we remove connected components of small area.

4. **Point cloud sampling.** We sample randomly the foreground component in F, generating a sparse depth map of N points

$$\mathrm{F_s} = \{(\mathrm{z_1}, \mathrm{F}(\mathrm{z_1})), (\mathrm{z_2}, \mathrm{F}(\mathrm{z_2})), \ldots, (\mathrm{z_N}, \mathrm{F}(\mathrm{z_N}))\}, \qquad \text{[Equation 5]}$$

where $F(z_i) \leq f_{\mathrm{floor}}$, for all $1 \leq i \leq N$ holds.
Note that $\mathrm{F_s}$ is a sparse set of points, a cloud. Each point it contains belongs to the foreground and likely to some pedestrian. We perform this "simplification" procedure for computational reasons: if N is large enough, the sparse depth map F_s provides a truthful approximation of the original point cloud that can be efficiently processed in the next step.

5. **Sparse samples clustering and pedestrian detection.** This is the crucial step for localization and aims at finding clusters, or "compact blobs" in $\mathrm{F_s}$ in 1:1 correspondence with the pedestrians. We perform this agglomeration procedure employing a hierarchical clustering algorithm and, in particular, a complete-linkage hierarchical clustering.
Hierarchical clustering aims at iteratively merge points in $\mathrm{F_s}$ merging them one at a time in larger and larger clusters until just one larger element, coinciding with $\mathrm{F_s}$, remains. At each iteration the two points, or clusters, that are closest are themselves clustered into one element.
Ideally, whenever a cluster C_j features a distance from all others clusters larger than the diameter S of the human body (say the shoulder size), then C_j corresponds to a single pedestrian. From a formal point of view, the length S is adopted as cutoff parameter of the clustering tree, and the clusters $C_1, C_2, \ldots, C_n$ returned by the tree cutoff correspond to the pedestrians, that are n in total (see pedestrians in Fig. 4(a) which are identified via the clustering tree in Fig. 4(b)).

6. **Head localization.** Given a pedestrian identified with the cluster C_j, we localize their head H_j as the region of minimum depth (i.e. top most in the scene and closest to the camera). Formally, we choose a depth percentile, usually the tenth, and we define

$$\mathrm{H_j} = \{\mathrm{z} \in \mathrm{C_j} : \mathrm{depth}(\mathrm{z}) \leq \mathrm{d_k}\}, \qquad \text{[Equation 6]}$$

where d_k is the k-th depth percentile in C_j. We finally estimate the head position as the centroid of H_j (cf. Fig. 4(c)). The head positions so obtained can then be tracked over time (task T2).

7. **Post-tracking filtering.** Head positions obtained can be affected by measurements errors, e.g. for noisy fluctuations in the depth map reconstruction, or can even be false positive. To make the localization more robust we can use the tracking output in two ways: first, smoothing filters help to reduce measurement noise: we apply a smoothing filter to the trajectory. Specifically, we employ a Savitsky-Golay smoothing (Savitzky and Golay, 1964), common in Particle Tracking Velocimetry (e.g. (Gülan et al., 2012)). As far as the parameters of the filter are concerned, we adopt a local quadratic approximation evaluated on observation windows of total size 7. This avoids non-physical accelerations due to noise in the detection, while preserving small fluctuations due, e.g., to oscillations of the head (contrarily, for instance, to a spline-based smoothing). Second, we expect trajectories to have certain physical properties, such as length: trajectories which are too short in time or space are most likely results of false positives in localization.

2.4. Accuracy and parameter selection

In the campaigns discussed in (Corbetta et al., 2014) and in (Corbetta et al., 2016a), we employed either one or four sensors that we place roughly at 4m meters above the ground. The effective spatial coverage provided by a single sensor is about 2m x 2.2m, i.e. within this area heads of subjects 1.8m tall are observable without cuts. Sensors are juxtaposed in a way that a continuous coverage of such effective area is provided. We adopt a 15 Hz time sampling, i.e. half of the maximum sampling rate allowed by Kinect™. At this sampling rate, a pedestrian walking with a constant speed of 1 m/s is sampled approximately every 6.6 cm, circa 18 px. We deem this sampling rate a good compromise between measurement accuracy and computational and hardware resources.

Notably, Kinects' frame acquisition cannot be manually triggered or multiple sensors cannot be synchronized to acquire at the same instant. Accepting a maximum error of half the acquisition period (i.e. 1/30 s), we treat frames closely acquired by the different sensors as simultaneous.

We run our analysis considering a background threshold $\epsilon_B \approx 30$cm, a height threshold $h \approx 1.25$m (measurements were based in the Netherlands, one of the tallest populations worldwide (Wighton, 2016)) and clustering cut-off $S \approx 50$cm. In similar conditions, (Seer et al., 2014a) report a fairy high detection rate of 95%. Generally, the detection rate remains high for pedestrian densities below 1.5ped/m2, to drop for higher crowding. This relates to the inability of the clustering algorithms to segment the different individuals as they get densely packed.

2.5. Scalability, performance and real-time analyses

This tracking procedure is quite computationally intensive as well as space and bandwidth demanding. Our train station campaign collected about 25GB of data per sensor per day (i.e. 100GB of daily) data that we could process for tracking in about 20minutes, employing 300 processors (in fact, localization admits a trivial parallelization, while tracking can be parallelized by artificially breaking the observation time in sub-intervals to address independently).

The clustering algorithm is the slowest component as the execution time scales as $N^2 logN$ (Duda et al., 2012). Therefore, the choice of N is crucial. In general, the algorithm accuracy grows with

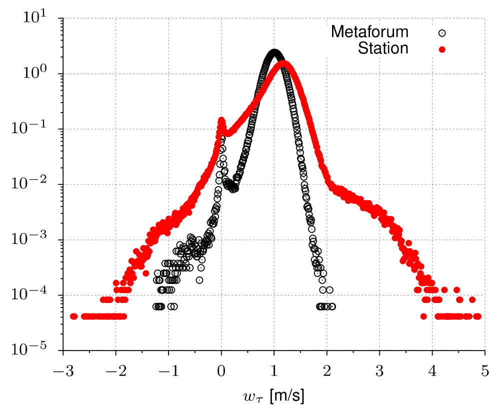


Figure 6. Probability distribution function of walking velocity w_τ measured through our measurement campaign at Eindhoven University (Metaforum) and at Eindhoven station. The distributions, in log scale, show a heavily non-symmetric shape, with negative velocity events following the rare trajectory inversions.

N, as F_s approximates F better, at the cost of the execution time. As the number of subjects in the scene (n) scales with the number of pixels occupied in the foreground ($p_f = \#\{z : F(z) < h\}$), we recommend to choose N proportionally to p_f and not larger than few thousands.

N should further grow proportionally to the number of sensors to conserve the sampling quality. This is a scalability limit for the localization system.

Real-time executions are also possible and, in our case, have been achieved with a prior severe down-sampling of the depth maps, a parallelization of the perspective correction steps, and a halved time sampling frequency of 7.5 Hz.

3. High statistics measurements of pedestrian dynamics

Throughout our real-life experimental campaigns, we collected hundreds of thousands of pedestrian trajectories aiming at unveiling statistic signatures of the pedestrian motion. The analysis of real-life measurements comes with an intrinsic complexity, determined by the randomness with which different crowding conditions follow one another. In a train station, a diluted flow composed of one or few people can, in a matter of seconds, turn into a dense crowd, e.g. after the arrival of a commuter train. In this sense, data acquired in real-life campaigns come from a (random) sequence of experiments (e.g., now related to the diluted flow, now related to the dense flow) and should undergo an aggregation phase preliminary to the analyses. For instance, all the measurements with comparable pedestrian density, flow conditions (e.g. uni-, bi-, multi-directional) are to be aggregated first. The statistics from each of these groups can be compared. The identification of similar flow conditions is a challenging problem per se, of which we propose a graph-based solution in (Corbetta et al., 2017b).

A first outcome of our analysis is the study of the stochastic fluctuations characteristic of diluted pedestrian flows. Our extensive tracking of about 100.000 pedestrians walking free of peer interactions (thus at minimum pedestrian density) in the Metaforum landing at Eindhoven University (Fig. 1(top)), reveals that the walking speed distribution deviates significantly from a Gaussian distribution. The ensemble of pedestrians entering from one side of the landing features two typical fluctuations around the average walking speed of circa 1.1m/s. First, we observe a frequent and small fluctuation due to inter- and intra-subject variability of walking individuals. Moreover, rarely but reproducibly, pedestrians show larger deviations that culminate in trajectory

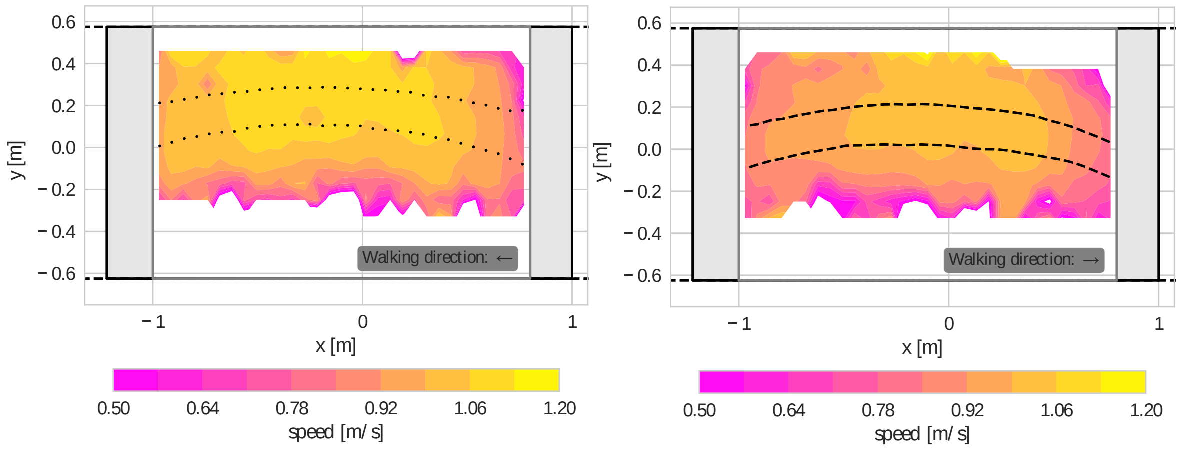


Figure 7. Walking speed distribution and band of preferred positions for pedestrians walking in the landing in Fig. 1(top), respectively to the left (left panel, descending direction) and to the right (right panel, ascending direction). (Figure from (Corbetta et al., 2016a))

inversion events. These occur with a Poisson statistics and, on average, once every five hundred facility crossings. Similar statistical signatures can be observed in our train station measurement campaign (cf. Fig. 5). In (Corbetta et al., 2017a), along with the statistical analysis of this fluctuating phenomena, we propose an active particle model (Romanczuk et al., 2012) that quantitatively reproduces this fluctuation structure. In particular, our model is social force-like (cf. (Helbing and Molnar, 1995)) and leverages a bi-stable velocity potential (that extends the desired velocity relaxation term typical of social forces models) to capture both small and large fluctuations.

High statistics measurements enable also unprecedented insights in usage patterns (cf. (Corbetta et al., 2016b, 2017b)). For instance, in the landing in Fig. 1(top), that is walked in clockwise direction to ascend in the building, pedestrians ascending and descending exhibit different positions and velocity dynamics (see Fig. 6). Individuals tend to walk on the relative right-hand side of the facility, despite the absence of handrails (cf. Ronchi et al., 2015). With a probability of about 70% (Corbetta et al., 2016a), they remain confined in the 20 cm thick bands reported. These bands are themselves shifted on the relative right of the facility. Furthermore, pedestrian descending walk slightly faster and with a more uniform velocity profile than pedestrian ascending.

4. Discussion and outlook

In this work, we discussed a pedestrian tracking algorithm based on overhead depth imaging data. The algorithm enables real-life data collection of pedestrian trajectories with high accuracy. As it requires no supervision from the experimenter, we could perform months-long data collection campaigns to reach resolved statistics of pedestrian dynamics, e.g. of walking velocities or positions, in dependence on the flow conditions.

Resolved statistical descriptions of the dynamics allow new insights in pedestrian motion. These are relevant toward the comprehension and the quantitative modeling of the complex motion of crowds. Individual pedestrians, for instance, show a non-Gaussian velocity distribution connected to the rare trajectory inversions. Inversion events, occurring with reproducible statistics, can be the beginning of unsafe traffic conditions in crowded scenarios as it may be followed by collisions and tumbles.

Finally, we remark that the localization algorithm exploits simple geometric concepts identifying pedestrians as cluster within the foreground of an overhead depth cloud. The geometric simplicity of this algorithm is the key for its execution speed and the high localization accuracy in moderately dense conditions (up to 1.5ped/m2). The algorithm performance, in fact, decreases as soon as the correspondence between point clusters and pedestrian vanishes. This occurs at high densities or in presence of foreground elements which are not pedestrians (strollers, bikes, removable obstacles and so on), that are unavoidably marked as walking individuals. To address such richer scenarios, more complex localization algorithms are necessary, which effectively analyze the frames and classify each element for type. Only for the element classified as pedestrians they further estimate the locations. Recent advancements in machine intelligence and, in particular, in deep learning (LeCun et al., 2015), showed impressive performance at such recognition and localization tasks, making excellent candidates for algorithmic improvements.

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Disclaimer
Different figures contained in this manuscript have been previously published by the same authors. Fig. 2 is partly published in (Corbetta et al., 2017b) and partly in (Corbetta et al., 2016a). Fig. 3 is partly published in (Corbetta et al., 2016a), Fig. 4 is published in (Corbetta et al., 2014), Fig. 6 is published in (Corbetta et al., 2016a).

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Questions and Answers

Following the presentation, a set of comments and questions were made to the speaker. A summary of these questions along with the answers are provided below.

(Enrico Ronchi): It is important to assess for what types of applications the methodology presented can be applied. For instance, this could be very useful for structures such as stadia where massive numbers of people are present.

(Alessandro Corbetta): Real world data are extremely important to draw statistics. Having big data as the basis for the development and evaluation of evacuation models is potentially significantly better than relying on experiments with a limited number of participants. In laboratory settings conditions are artificial and it is hard to capture rare events. This means that it is hard to incorporate fluctuations in the models. For example, somebody falling down during an evacuation in a train station might be rare but at the same time have a significant impact on the whole evacuation process. The study of big data allow understanding how frequent such type of events are.

(Ed Galea): It would be interesting to assess to which extent it is possible to understand the characteristics of the observed population (e.g. age, crowd densities, if people carried luggage, etc.) and the details of the pedestrian interactions. This is of particular interest for agent-based modelling applications.

(Alessandro Corbetta): In many cases, the pedestrian observations refer to one person walking at the time, but this is not the only case. The final goal would be to draw crowd speed/density relationship which take into consideration also the individual differences of pedestrians. This would mean to generate relationship which are full probability distributions rather than just regression lines. This would mean considering individual variation based on big data observations. This would include a wide variety of scenarios, e.g., unimpeded and impeded speeds, uni-directional and bi-directional flows (counterflows), etc. The hardest challenge remains the identification and clustering of homogenous situations. Different classes have to be identified and studied separately.

(Arturo Cuesta): it would be interesting to assess from big data on pedestrian movement what are the most important variables affecting the movement (including rare events). For instance, this could inform evacuation modelling analysis. An example could be the identifications of the factors affecting the people negotiation of an exit (people waiting, merging, individual characteristics, etc.).

(Alessandro Corbetta): Significant rare events are generally not included in the models since they cannot be observed in laboratory settings, while this can be done with big data observations.

(Enrico Ronchi): An example of the importance of big data is their use of the concept of effective width (Gwynne and Rosenbaum, 2016) in building egress design. The definition of the effective width could be re-evaluated with the use of big data, i.e. the design could be based on thousands of observations. This can have a great impact on decreasing uncertainty (Eriksson Lantz, 2015).

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Evacuation Modelling in the field of Transport

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ABSTRACT

Evacuation transport models predict the travel behaviour and traffic conditions associated with an evacuation, accounting for disaster dynamics and evacuation control strategies. In the paper, we introduce and review various modelling aspects, starting with a generic framework of a typical evacuation transport model and its various sub-models, followed by a discussion on each of these sub-models and the modelling methods that are being applied. We discuss issues with respect to model applications, and conclude with identifying main research challenges that are ongoing issues in this field of evacuation transport modelling, and that are relevant in the context of this workshop paper.

KEYWORDS: evacuation; travel choice behaviour; traffic flows; transportation modelling.

1. Introduction

The threat or immanency of a disaster - such as a wildfire, flood, terrorist attack - may warrant the evacuation of a populated region. Hazard prone regions may therefore invest in efficient evacuation strategies. Such strategies can consider avoidance, where precautionary measures reduce the probability of such disasters (e.g. clearing fire control lines, and reinforcing flood barriers), as well as mitigation, where responsive measures reduce the impact of such disasters (e.g. evacuation). Focussing on the latter, the success of an evacuation strong depends on many factors, including warning time, response time, information and instructions dissemination procedure, evacuation routes, and traffic control measures. Given the complexity of the underlying processes and the multitude of factors influencing these processes, we often use evacuation simulation models as these are helpful or perhaps even indispensable for the analysis and planning of emergency evacuations.

From a transport modelling perspective the subject of evacuation relates to the travel decisions and traffic flows associated with the evacuation process. Thus, evacuation modelling in the field of transport pertains to developing models that: (1) can predict the spatial-temporal traffic conditions in case of an evacuation, (2) conditional on situational factors such as disaster dynamics and human response behaviour, and (3) conditional on strategic factors such as the dissemination of evacuation information and instructions and the deployment of traffic control measures. Such transport models are then used, for example, to assess the evacuation capability of a region, to assess the strengths and weaknesses of an evacuation strategy, or to adopt a model-predictive framework in order to design optimal evacuation strategies. Furthermore, models can be used for theory testing; By developing a model based on a (behavioural) theory, the theory can be tested by verifying the model predictions against empirical data.

The transport models that are used to simulate evacuation traffic conditions and travel behaviour are in essence similar to the transport models that are used to simulate the effects of new transport policies, infrastructure, services, technologies, and control measures in everyday conditions.

Therefore, these models contain sub-models that describe individuals' travel choice decisions (i.e., activity-travel patterns, mode of transport, routing) based on characteristics of the individual and the available travel alternatives. While also, these models contain sub-models that describe the traffic flows in the transport system (i.e., traffic congestion, passenger flows in the public transport, travel times), based on the collective of travellers' decisions and the characteristics of the available transport infrastructure and services.

Although the evacuation transport models are in essence similar to transport models used in 'regular' studies, the context of evacuation requires certain adaptations to these models. For example: travellers are unfamiliar with the situation and hence rely differently on information and expectations based on past experience; driving behaviour changes due to stress, emotion, driving task attention loss, weather conditions, etc. causing large changes in road capacity; infrastructure may be affected substantially (e.g. flooded tunnels) or used differently (e.g. lane reversal); travel choice behaviour may be affected due to adaptation in decision-making under time pressure and uncertainty. Furthermore, a large role of heterogeneity in behaviour and high levels of uncertainty (in behaviour and in conditions) further complicate the modelling tasks.

This paper is written in preparation of the workshop New Approaches to Evacuation Modelling, organised in concurrence with the International Symposium on Fire Safety Science (IAFSS). The workshop addresses how evacuation modelling is pursued in various disciplines. With this audience and purpose in mind, the paper outline is as follows. First, a generic framework is presented of a typical evacuation transport model and its various sub-models. Second, each sub-model is discussed in turn elaborating on modelling methods that are found in the literature. Third, we discuss evacuation model applications in the field of transport. Fourth, we conclude by identifying current research directions and challenges in this field.

Due to the nature of this paper, providing a general overview of the field of evacuation transport modelling, literature references are omitted. However, good starting points for the interested reader are Pel et al. (2011) for a review on evacuation simulation models, Murray-Tuite and Wolshon (2013) for a review on evacuation studies, and Bayram (2016) for a review on evacuation optimisation models.

2. Transport modelling for evacuations

A transport model framework generally consists of five sub-models, where the first four sub-models describe the travel choice behaviour and the fifth sub-model describes the (resulting) traffic flows in the transport network. The travel choice behaviour sub-models have as purpose to predict the decisions that people make both prior to departure and during their trip, and what the collective of these individual decisions yields in terms of travel patterns. These sub-models thus relate to,

1. Trip generation: how many people will evacuate and at what time they will do so,
2. Trip distribution: where they will evacuate to,
3. Modal split: by what mode they will evacuate,
4. Traffic assignment: by what route they will evacuate.

These four sub-models are ordered in a way that roughly represents how they are interdependent. That is, the available choice alternatives in a later sub-model generally depends on the alternative that is chosen in an earlier sub-model (e.g. the route alternatives evidently depend on which destination is chosen), while at the same time the attractiveness of a specific alternative in a later sub-model generally depends on the attractiveness of alternatives at an earlier sub-model (e.g. the attractiveness of a specific destination evidently depends on the attractiveness of the routes towards this destination). Due to these interdependencies between these four sub-models, the model framework is solved either as a nested problem or as a fixed-point problem.

These four sub-models describe individual choice behaviour. Although some models may determine 'choice behaviour' by applying exogenous statistical distributions (e.g. response curves stating the percentage of evacuees over time), most simulation models use endogenous econometric choice models, such as regression models (for continuous variables like departure time) and discrete choice models (for discrete variables like to evacuate or not, destination choice, transport mode choice, and route choice). These choice models are calibrated using data from stated preference surveys (where respondents are asked to state their preferred decision given a number of hypothetical situations and choice alternatives) and data from post-disaster questionnaires (where respondent are asked about their travel activities preceding, during, or after the disaster event).

The fifth sub-model is the traffic flow model, which has as purpose to predict the traffic flow process. This sub-model thus relates to,

5. Traffic flow: for road traffic, it predicts the traffic flows at corridors and intersections, and determines the resulting congestion bottlenecks and travel times; and for public transport (and dedicated bus services), it predicts the passenger flows in vehicles and at stations, and determines the resulting levels of crowding and travel times.

This fifth sub-model is interdependent with the previous four sub-models, because on the one hand the traffic conditions in the transport network depend on the collective of all individuals' travel decisions, and on the other hand individuals' travel decisions depend on (their expectations of) the traffic conditions in the transport network. Due to the fact that individuals' travel decisions depend on expectations rather then actually experienced/revealed conditions, this interdependency is solved in an interleaving fashion. That is, these sub-models are simulated in parallel, where travellers may adapt their travel decisions (given by the travel choice sub-models) whenever going by the information available at that time another travel alternative appears more attractive (given by traffic flow sub-model). For example, travellers may decide to reroute based on the prevailing traffic conditions.

This fifth sub-model describes the traffic flows. Simulating the passenger flows in the public transport is reasonably straightforward, as we typically assume that public transport vehicles will operate according to a timetable and thus the traffic flow sub-model only requires to keep track of service lines and vehicle occupancies. Simulating the car traffic flows on the road however is more challenging, as it requires modelling the driving task and congestion dynamics. Car traffic flow sub-models can be formulated atomically, by representing individual vehicles and vehicle interactions by means of car-following and lane-changing models. These atomic models are used in studies that focus on the driving task (under evacuation conditions). Or alternatively, car traffic flow sub-models can be formulated aggregated, by representing aggregate flows of traffic by means of differential equations describing the relationships between average speed, average vehicle headway, and average flow (which is analogous to fluid-dynamics models). These aggregated models provide a more parsimonious approach that is used in studies that focus on the transport network conditions as a whole. These traffic flow models are calibrated using data from empirical traffic counts or driving simulator experiments.

3. Sub-models

Upon presenting the general framework of a transport model in the previous section, five sub-models where introduced. In this section, each of these sub-models is elaborated on in more detail, discussing the main modelling techniques that are used and their pros and cons.

3.1. Trip generation models (predicting the decision to evacuate)

Trip generation models predict the number of people who will evacuate and when these people will depart. Two approaches can be distinguished: two-step static models, and integrated recursive models.

In **two-step static models**, two separate models are estimated: the first model describes the evacuation participation (either the probability for an individual, or the percentage for a population), while the second model describes the evacuation departure time (either as most likely time window for an individual, or as response rate for a population). Then combining the models predictions yields the number of evacuees departing at any specific time. These models are static in the sense that the trip generation is predicted prior to simulating the evacuation, and hence any time-varying changes in the conditions that may influence the trip generation is not accounted for. Typically simplistic statistical distributions are used here, as opposed to explanatory econometric models. Evacuation participation is estimated through cross-classification or neural networks. And evacuation timing is estimated using a response curve following a Rayleigh distribution, Poisson distribution, Weibull distribution, or sigmoid curve.

This two-step model is commonly applied, likely due to the mathematical simplicity of the approach and the fact that relatively little situation-specific data is required. Model attributes and parameters are estimated based on expert judgment or past evacuation data. A main drawback of this two-step static modelling approach is the lack of a behavioural theory underlining the model. As a consequence, it is difficult, if not impossible, to incorporate any findings on (socio-psychological and circumstantial) factors determining individuals' evacuation decision. Furthermore, response curves are typically constructed for short-lasting evacuations (up till several hours, while many evacuations may last for several days), time-of-day variations are not included (the response curve does not allow incorporating the behavioural effect of day/night time on the departure times which are observed in real-life), hazard specific dynamics known to influence the travel demand are not included (e.g., the speed, intensity and track of a hurricane or wildfire inappropriately have no effect on travel demand), and the effect of an evacuation strategy cannot be realistically assessed (since the impact of the evacuation order is not addressed).

In **integrated recursive models**, integrating the evacuation participation and timing decisions relaxes many of these limitations. This is done by recursively (i.e. interleaving with the evacuation simulation model) predicting the evacuation departures for that specific time. Here typically an econometric model is repeatedly used, which predicts the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate. The econometric model models this binary decision based on the differential utility associated with evacuating (compared to not evacuating) as a function of the current or expected conditions. As these conditions change over time, so can the evacuation decision be predicted dynamically as the disaster evolves.

Using an econometric model allows accounting for any factors that may influence the decision to evacuate such as: spatial-temporal disaster characteristics (e.g. proximity, intensity), socio-demographic characteristics (e.g. age, gender, household composition), and circumstantial factors (e.g. issuance of evacuation warning or instructions, observing neighbours evacuating, opportunity to undertake property protection). These econometric models have been estimated for the case of wildfires and hurricanes, using both stated preference surveys and post-disaster revealed preference surveys.

Reviewing these two modelling approaches, both models are used. The two-step static models are commonly used in practice and in studies focusing on other aspects then evacuation timing behaviour (e.g., with a focus on traffic management), due to their simplicity. The integrated recursive models are generally used in studies focusing on predicting the dynamic evacuation trips under various conditions, due to the fact that it provides insight into the actual decisions of evacuees. For the latter type of model, a note can be made that currently most models are based on prevailing conditions, while there is good reason to believe that evacuees may base their decision on their expected future conditions as well (i.e. distinguish patterns in changing hazard conditions), and evacuees may distinguish steady conditions from temporary fluctuations.

3.2. Trip distribution models (predicting the evacuation destination)

Trip distribution models predict individuals' destination choice. This sub-model is only included in case of an evacuation with some minimal notice time, such that evacuees are actually capable of consciously deciding on their evacuation destination. In case of an evacuation with little to no notice (e.g. due to a terrorist threat) a common modelling assumption is that the evacuation destination is not actively chosen, but instead a mere result of the chosen (presumably fastest) evacuation route. That is, evacuees will choose the route that leads them out of the threatened region as soon as possible, and once safe may continue their trip to their final destination.

Trip distribution models are almost without an exception always an econometric discrete choice model comprising of two components. The first component estimates the type of location that an individual evacuates to, thereby distinguishing: family and friends, public accommodation (e.g. hotels), and dedicated evacuation shelter. This location-type decision is largely determined by socio-demographics of the household. The second component estimates the specific destination, conditional to the type of location. The destination decision depends on characteristics of the available alternatives (e.g. costs, capacity, perceived safety) and the travel resistance to reach the destination (e.g. travel distance, travel time).

Traditionally, the trip distribution models were applied to predict individuals' trip from their origin location (often home or work) to their destination (either network exit point or final refuge location). More recently this has been extended upon in two ways. First of all, many studies nowadays will model the normal daily travel behaviour up to the disaster warning, thus having a more realistic starting situation when the evacuation commences. Second of all, many studies will account for the fact that households tend to evacuate as a unit, and hence will explicitly include household interactions, such as how carless household members are picked up by the other household member(s) at their school, work or residential location to then continue their trip together. Both these model study extensions allow capturing otherwise unexplained evacuation travel patterns (such as longer trips and initially 'evacuating' towards the disaster area) and avoids too optimistic evacuation time predictions.

3.3. Modal split models (predicting the mode of transport for evacuation)

Modal split models predict the mode of transport that evacuees will use. Transport modelling tends to focus on evacuating suburbs and regions, where evacuation distances require some form of motorised transport. At the same time, many empirical examples (of evacuations due to wildfires, hurricanes, flooding, and storms) have shown that when a car is available, it is the preferred mode of transport for evacuation. This is ascribed to the fact that evacuating by car enables securing the safety of the car as asset while also it enables to bring along other personal items and assets (and makes it easier for a household to evacuate together). Therefore, it is seldom that a modal split model with be estimated. Instead, more commonly, census data and local expert knowledge/judgement is used to estimate the population share who have access to a car and the population share who will rely on public transport and dedicated evacuation (bus) services.

3.4. Traffic assignment models (predicting the evacuation route)

Traffic assignment models predict the route that evacuees will follow. Although the vast majority of evacuation models do explicitly include a traffic assignment sub-model, there are a number of studies that sidestep this sub-model. One way is to simply insert pre-defined evacuation routes, thus simulating mandatory prescribed routes to test various evacuation route strategies. This however does assume full compliance, which is most certainly too strict an assumption to make. Another way to sidestep this sub-model is to simply estimate the ratio between the total spatially distributed travel demand (i.e. number of travellers) and the capacity bottlenecks in the road network (i.e. number of travellers that can pass per unit of time), which then together with some correction terms give a 'first guess' on the minimum time required for the complete evacuation. Apart from the questionable validity of this approach, more importantly, this method does not provide insight into: the dynamic evacuation traffic conditions, the underlying (success and failure) factors that determine the evacuation process, and the benefits of deploying control measures.

Empirical analyses have shown that dominant factors influencing route choice decisions are: expected travel time, familiarity with the route, availability of fuel and shelter (in case of longer evacuation distances), and road type (with a bias towards motorways and main arterials). While the latter three factors are static, the first factor is time-varying. Thus, as opposed to the earlier sub-models, route decisions may occur both pre-trip (i.e. planned behaviour) and on-trip (i.e. adaptive behaviour). Similarly, traffic assignment models can be distinguished as to: pre-trip models, on-trip models, and hybrid models combining both behaviours.

In **pre-trip traffic assignment models**, evacuees are assumed to choose their route from origin to destination upon departure, and to not switch routes while travelling. Route choice behaviour is predicted using an econometric discrete choice model that is based on the currently prevailing or expected route conditions. Evidently, the chosen routes may prove to be not the most attractive routes when the resulting traffic conditions (derived when executing the traffic flow sub-model) deviate from the initially predicted traffic conditions on which the route choices were based.

The pre-trip route choice paradigm may appear inappropriate to model route decisions under evacuation conditions. This is because the sub-model is adopted from other transport models for long-term planning studies. There the pre-trip route choice model is embedded in an iterative procedure mimicking how travellers build up experiences (from one iteration to the next) leading to well-informed expectations about what traffic conditions to expect, thus iteratively updating their route choice until a steady (equilibrium) state has been reached. Such a day-to-day learning and habit formation evidently does not occur in evacuation conditions. On the other hand, the assumption that evacuees are inert towards changing traffic conditions also goes against empirical observations. This is hence resolved in the on-trip models.

In **on-trip traffic assignment models**, the assumption that evacuees cannot deviate from their (pre-trip) chosen route is relaxed. Here, evacuees observe the prevailing conditions and make route choice decisions accordingly. Thus, where pre-trip models are applied at the origins to predict route fractions (per destination), on-trip models are applied at road intersections to predict split fractions towards downstream directions (per destination).

In **hybrid traffic assignment models**, both pre-trip and on-trip decisions are modelled. This way, evacuees are assumed to choose an initial route upon departure, after which they may adapt their route during their trip. They might do so when prevailing traffic conditions are such that they are better off (or have the feeling of being better off) by deviating to another route. In most such hybrid models, a model parameter will impose a minimum improvement threshold in order for evacuees to switch routes. This is in line with empirical evidence, and interpreted as either an indifference bandwidth or bounded rationality (and is generally found to be around 10-20% relative, or a few minutes absolute).

Reviewing this various traffic assignment models, pre-trip models are still often used in evacuation studies that focus on other aspects, although on-trip and hybrid models provide more insights into the conditions resulting in the observed route decisions of evacuees as well as are more in line with empirical observations (where 40-70% of evacuees is inclined to switch routes based on up-to-date traffic information). Furthermore, the latter models that include on-trip rerouting due to time-varying conditions have as advantage that they can adequately be used to evaluate the effects of the hazard's evolution in space and time (e.g., road sections becoming inaccessible due to flooding) and dynamic traffic regulations and control measures (e.g., contraflow operations to increase outbound capacity).

3.5. Traffic flow models (predicting the traffic flows)

Traffic flow models predict how vehicles drive through the infrastructure network and interact with other traffic, thereby computing travel times and congestion dynamics. They can also be referred to as network loading models. While static traffic flow models exist, which approximate the average steady state conditions, the majority of traffic flow models are dynamic, in the sense that they use simulation to compute the time-varying traffic conditions. Due to this simulation approach, with typical time-steps of a few seconds up to half a minute, this sub-model is by far the most time-consuming model component. Traffic flow models are best categorised along two axes; the first being the aggregation level for traffic representation and propagation; the second being whether flows are based on queueing theory or kinematic wave theory.

Traffic flow models can be microscopic, macroscopic, or mesoscopic depending on the combination of traffic representation and propagation. **Microscopic models** represent traffic as individual vehicles, and propagate traffic according to vehicle interactions. These models are built around drivers' speed choice models (including car-following behaviour) and lane choice models (including merging and overtaking behaviour). **Macroscopic models** represent traffic as continuous flows, and propagate traffic according to flow-density-speed relationships. These models are built around (steady state) relationships between an average traffic speed, a space-average traffic density, and a time-average traffic flow, and are analogous to differential equations describing fluid dynamics. Finally, **mesoscopic models** represent traffic as individual vehicles (similar to microscopic models), and propagate traffic according to flow-density-speed relationships (similar to macroscopic models). That is, vehicles are individually tracked while their speeds and acceleration decisions are based on aggregated conditions.

These modelling paradigms each have their merits. The level of detail in the microscopic models is ideal for studying driving behaviour under evacuation conditions. These models are used, for example, to translate findings from driving simulator studies to what this means for (reduced) road capacities. However, as the unit of computation is vehicle interactions, these microscopic models are less well equipped for large-scale model applications. Here computing traffic propagation by aggregated flows is more scalable. Hence for sake of computation time and model complexity, macroscopic and mesoscopic models are preferred in evacuation studies for larger regions, or when a model-predictive optimisation framework is used that needs to be solved iteratively or recursively. In the past, macroscopic models may have been preferred over mesoscopic models, due to memory usage, as the former scales with the number of roads and the latter scales with the number of vehicles; but this is nowadays no longer a strong factor in choosing the appropriate model. In the end, the sub-model should match the empirical data that is available and provide model results with the intended level of precision.

Macroscopic and mesoscopic models can be further differentiated according to their underlying theory being queueing theory or kinematic wave theory. In these traffic flow models, infrastructure networks are represented as a directional graph, constituting of links and nodes. Using **queueing theory** is a simpler approach as traffic flows are assumed to either be free flowing (when unconstrained) or be queueing (when constrained by insufficient downstream flow capacity). Here the traffic flow on a link can have a restricted outflow due to a downstream capacity bottleneck or the presence of a traffic queue; while it can have a restricted inflow once the link itself is fully congested. This way, congestion dynamics with respect to flow metering and spill back effects are incorporated in queueing models. Using **kinematic wave theory**, more advanced traffic flow dynamics are incorporated, additional to the basic flow metering and spill back phenomena. Here the traffic flows along the link follow from shockwaves, which in short account for bounded acceleration and bounded reaction times; thereby kinematic wave models model the time it takes for changes in traffic conditions further downstream (e.g. accelerating vehicles) to affect conditions upstream, and explicitly model the traffic conditions within a queue (where e.g. the queue density depends on the average speed).

In review of these traffic flow models, the appropriate model very much depends on the purpose of the evacuation study. For example, a macroscopic queueing model is a parsimonious approach that provides good estimates on evacuation travel times (e.g. for studying evacuation route strategies and network clearance times); A mesoscopic kinematic wave model allows good estimates on the traffic flow dynamics (e.g. for studying road network bottlenecks and dynamic traffic control); A microscopic model allows explicitly analysing the impact of driving behaviour (e.g. for studying driver adaptations and traffic safety).

4. Model applications

In evacuation modelling in the field of transport, models are used (1) to assess the evacuation capability of a region, (2) to assess the strengths and weaknesses of an evacuation strategy, or (3) to adopt a model-predictive framework in order to design optimal evacuation strategies. What is typically taken as starting point is the spatial-temporal threat or impact of the disaster, possibly including the consequential degradation of part of the transport network. From there, evacuation transport models are used to look into aspects of transport system performance. This field of research thus deals with evacuation choice and response behaviour, travel and driving behaviour under such conditions, transport/evacuation planning, traffic flows and traffic management measures, network connectivity and integrity, etc. Model studies tend to focus on behavioural, planning and control aspects from a transport system perspective; In other words, what are the effects of evacuee behaviour, infrastructure failure, and control measures, in terms of network performance indicators, such as evacuation clearance times and congestion levels?

The essence of a speedy and smooth evacuation lies in the balance between the travel demand (i.e. number of evacuees) and the network capacity (i.e. sustainable exit flow). Hence, likewise models are used to investigate demand and capacity strategies that aim to facilitate the evacuation. **Demand-side evacuation strategies** include,

- Phased evacuation; this is to execute the evacuation sequentially, usually by neighbourhood, in order to reduce evacuation time, risk, or the time for those in the highest risk areas to reach safety. A phased-evacuation strategy is straightforward to model, as it (partially) replaces the trip generation sub-model. Optimising a phased-evacuation strategy is usually done by using a bi-level formulation, where the evacuation model constitutes the lower level and the upper level is an algorithm that determines the time-dependent staging plan for each origin. This is sometimes extended to also optimise evacuees' destinations.
- Sheltering-in-place or close by; this is to shorten the evacuation distance and hence reduce the

amount of evacuation traffic on the road. This is typically not explicitly modelled, but would be straightforward to incorporate as additional trips on the road network.

- Reducing shadow evacuation and background traffic; this is to reduce the amount of unnecessary traffic on the road, focusing on unwarranted evacuation traffic from areas that are not under threat and traffic in the area that is not related to the evacuation. This is typically not explicitly modelled, and otherwise would be exogenously determined.
- Prescribed evacuation routes; this is to prescribe dedicated routes to evacuees, either via static or dynamic road signs (or perhaps in the near future via in-car navigation). Across all the traffic assignment models mentioned earlier, evacuees' compliance with prescribed dedicated evacuation routes can be incorporated either exogenously or endogenously. Exogenously means that the compliance rate is a model parameter, that determines the share of evacuees following the prescribed routes and the share of evacuees for whose route is predicted by the traffic assignment model. Endogenously means that the traffic assignment model predicts the way in which evacuees may respond to the prescribed routes, which is typically done by incorporating a maximum gain (e.g. expressed as travel time) that an evacuee is willing to forego in order to comply. Optimising prescribed evacuation routes is usually done by using a bi-level formulation, where the evacuation model constitutes the lower level and the upper level is an algorithm that determines the time-dependent evacuation routes either at each origin or at each intersection.

Capacity-side evacuation strategies include,

- Contraflow; this is when one or more road lanes are used for traffic flowing in the opposing direction, thereby increasing the directional (typically outbound) capacity. While the control measure itself is relatively straightforward to model, the effectiveness of it is significantly determined by the traffic flows at the starting and terminating points where traffic flows over into the other lanes, which are more difficult to model (in detail). Optimising the deployment of contraflow constitutes a network design problem.
- Crossing elimination; this is the prohibition of certain turning and crossing movements at intersections in order to avoid conflicting traffic stream interruptions that would slow down the otherwise continuous flow in the primary (outbound) direction. Modelling crossing elimination measures is straightforward. Optimising this control measure again constitutes a network design problem.
- Special signal timings; this is adapting traffic signals to operate in order to favour specific (outbound) directions or corridors (part of dedicated evacuation routes). Modelling this control measure requires a bit more effort as it entails running the signal control algorithm (or perhaps coordinated network control algorithm) in parallel to the evacuation model.
- Dedicated public transport services; this is to plan mass transport services (often busses) to serve mobility-limited populations during the evacuation. While incorporating the modal split effect is relatively easy, modelling the additional transport services on the road network (and interacting with the other traffic) requires a multi-modal traffic flow model.
- Use of hard shoulders; this is when the hard shoulder (i.e. emergency lanes) of the motorway is opened for evacuation traffic, thereby increasing the directional (outbound) capacity. This is perhaps the easiest control measure to model, while optimising this measure again constitutes a network design problem.

Next to evaluating the expected effects of evacuation strategies, the sensitivity of these strategies is tested using model **sensitivity analyses**. Such sensitivity analyses are conducted by a controlled varying of a part of the model (scenario input, model assumptions/sub-models, or model parameters) to test how this leads to changes in model output. Common analyses are to test the impact of,

- Spatial-temporal disaster dynamics; if the risk/disaster exposure concurs with the evacuation, the uncertainty in the predicted disaster impact can be used to vary the scenario input. In this regard, evacuation modelling studies typically aim to design strategies that are either robust, in that they perform well under probabilistic conditions, or resilient, in that they allow for adaptation during execution to ensure performance.

- Failure of transport network components; related to the previous item, the uncertainty in the integrity of the transport network (w.r.t. availability, capacity, and speeds, or the occurrence of traffic accidents) can be used to vary the scenario input, and similarly to design adequate strategies.
- Population characteristics and behaviour; various explicit and implicit assumptions are made regarding population characteristics and behaviour, in both the model input (e.g. population characteristics, car availability) and the sub-models (e.g. network familiarity, compliance with route guidance). Regardless of the modelling effort, these assumptions are likely to be a main source of uncertainty in the model. Hence, sensitivity analyses can investigate the effects of plausible deviations in these assumptions, both unilaterally and in conjunction.
- Failure to deploy control measures; the evacuation strategy may be designed to be effective as a whole, including combinatorial effects (such as dedicated evacuation routes which are then given traffic signal priority). In this regard, the loss of performance can be tested in case any of the control measures cannot be deployed as intended for whatever reason. This also allows ranking control measures with respect to their contribution (and hence importance).
- Modelling simplifications; in case of rather drastic model simplifications, that may be justified from the perspective of trade-off between model accuracy/precision and model complexity, these can be tested as to how they affect model output in comparison to a more sophisticated model (e.g. by using the reference scenario).

A remark on **evacuation models used in practice** is that, such planning studies would typically also include special considerations, such as dealing with hospitals and special facilities, scheduling services to provide on-route supplies to evacuees (fuel, water, food, etc.), and being resilient for traffic incidents during evacuation. These considerations do not pose significant modelling challenges from a methodological perspective, but rather require specific knowledge, expert judgement and input data on the (local) study context.

Finally, **model calibration** of these evacuation transport models remains an issue. As mentioned earlier, the various choice models are calibrated using data from stated preference surveys and post-disaster questionnaires, while the traffic flow models are calibrated using data from empirical traffic counts and driving simulator experiments. This amount of empirical data is growing, giving insight into evacuees' activity-travel patterns, the information that they had at hand at the time, and the resulting traffic flows in the region; Examples where data is more and more available are large-scale hurricane evacuations in the United States, wildfire and flooding evacuations in Australia, and tsunami evacuations in Japan. This data has been used to calibrate several regional evacuation models and sub-models (in particular trip generation models and traffic flow models). However, there are very few modelling studies that investigate in what way these calibrated (sub-)models can be applied to other regions, in a different cultural context, and possibly other disaster dynamics.

5. Current research directions and challenges

The previous sections presented an overview of the framework of an evacuation transport model, the various sub-models and modelling methods that are being applied, and issues with respect to model applications. Here we conclude with identifying three research directions/challenges that are ongoing issues in this field of evacuation transport modelling, and that are relevant in the context of this workshop paper.

The first research challenge is to build a clear and valid **theoretical foundation** for evacuation transport models. Current modelling methods, as discussed in this paper, are either adopted from models describing regular day-to-day (choice behaviour and traffic) conditions or have been derived from (and calibrated on) a specific data set. What is currently lacking is a valid theory on evacuees' travel choice behaviour, including their response to disaster and traffic conditions and information and control measures. This impedes evacuation transport modelling research in two ways. Firstly, it complicates developing a new model for a region with no past evacuation data. Secondly, it obstructs undertaking comparative (meta-)analyses on the growing amount of empirical data of evacuations worldwide.

The second research challenge is to embed evacuation traffic models into **decision support tools** used in disaster management. The information needed to be resilient towards various types of disasters is:

- knowledge on disaster probabilities and scenarios,
- knowledge on human response (of both citizens and authorities) to threats and disasters,
- knowledge on structural failure probabilities (and mechanisms) of transport network components due to disaster impacts,
- knowledge on deploy-ability and effects of information and control measures for intervention in evacuation process,
- on all prior aspects, knowledge on the dynamic evolution in space and time,
- on all prior aspects, knowledge on the uncertainties: inherent to the system, in measurements, and in models,
- knowledge on possible cascading effects: within the disaster impacts, the evacuation process, and the interactions between these two,
- within the context of the previous three aspects, knowledge on efficient and effective multi-layer safety principles.

Evidently, this requires an interdisciplinary approach with social scientists, structural engineers, transport engineers, and researchers from fields specifically related to the disaster type; Possibly also incorporating the fields of humanitarian logistics and disaster relief operations. Besides the practical relevance of disaster management decision support tools, such an interdisciplinary approach can lead to greater holistic understanding of evacuations, and aid in refining our evacuation (transport) models.

The third research challenge is to model how **new technologies** are utilised. This can pertain to information dissemination via social media, mobile devices and in-vehicle devices, with real-time information on disaster, infrastructure, and traffic conditions. It is currently insufficiently understood how this may affect evacuees' behaviour (across all sub-models) and how this can be incorporated in evacuation transport models. Furthermore, this is also relevant for data collection methods, for example, relying on GSM and GPS traces. How such data can be used real-time in evacuation management strategies, as well as used post-disaster in model development and calibration, is a challenge for future research.

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Questions and Answers

(Enrico Ronchi): It would be important to assess what can be learned from the traffic modelling world and what can be translated into building fire evacuation modelling. For instance, how to relate the different approaches (macroscopic, microscopic and mesoscopic modelling).

(Adam Pel): When the phenomenon of interest is at one level, then the measurement should be at a lower level. If for instance the high level phenomenon of interest in traffic modelling is the evacuation time, then macroscopic approaches can be used. Intermediate approaches can be used if the variable of interest is the driving speeds. Taking into considering the influencing behaviours at a lower level would require a more refined approach (i.e. microscopic or mesoscopic approaches). It is important to consider the trade-off between computational time and complexity when assessing which level should be assessed and the type of approach in use for its study.

(Ed Galea): The use of hybrid models can be a good solution to have the most suitable approach for different conditions, i.e. looking at multiple scales within the same model. Fine network modelling could be used for local issues, while coarser networks could be used for larger problems.

(Adam Pel): Given the application of the model, it may be important to change the balance of the model components in relation to space and time. Hybrid models may allow the representation of different portions of the regions adopting different assumptions.

(Ed Galea): There is a need to connect all modelling approaches, i.e. how the macro level affects the microscopic level. It is also important to assess all other behaviours which might affect the network (e.g. how response decision may congest the network). In this context, past experience with wildfires may significantly affect people response and this should be implemented within models.

(Adam Pel): In the application of traffic evacuation models, it is important indeed to consider not only the actual evacuation traffic but also the so-called background traffic, i.e. commuting traffic that might still be ongoing during an emergency. Other aspects are the impact of emergency services that can potentially go in counterflows. These behavioural patterns are examples of processes which may take place during the outbound evacuation and they can impact the process. Control measures for evacuation can fail if all other processes are not investigated in detail.

An analysis of human biomechanics and motor control during evacuation movement

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ABSTRACT

This paper focuses on two important, related fields of study - biomechanics and motor control - and aims to provoke thought around the many factors that influence movement when people are interacting with each other in a crowd. The collective movement of individuals is encapsulated (in fire and life safety) as crowd 'flow'. The 'flow' metric emerges from aggregating the sum movement of the escaping individuals expressed as people per-minute, or per-second. This 'flow' rate, as well as with walking speeds are common elements of current life safety engineering, and design. However the design guides, research and computer modelling for life and fire safety have largely ignored the key aspects of biomechanics and motor control. This paper briefly describes the existing approaches in the analysis of gait in these fields and examines some of the physiological and biomechanical factors that can affect gait such as ageing, physical conditioning, body sway and stride parameters. The current state-of-the-art in these fields focuses mainly on analysing individual gait. With the development of new technologies such as inertial sensors and depth sensors, the next frontier is understanding the fundamentals of gait when moving in relation to other human traffic. This would allow the fields of biomechanics and motor control to offer ecologically valid gait assessments to clinicians who need to assess a person's capability of carrying out their activities of daily living such as travel/transport, shopping etc. From the perspective of crowd flow research, knowledge of how the fundamental parameters of gait can change in relation to other pedestrians will lead to better crowd flow models and, ultimately, to safer building guides. It therefore makes sense for these fields to come together in an interdisciplinary space to advance this frontier.

KEYWORDS: biomechanics, motor control, locomotion, pedestrian movement, gait speed, evacuation

1. Introduction

The majority of crowd-related research to date has focused primarily on safety and security aspects. A recent study by Filingeri et al (2017) showed that that important aspects affecting people's experience are often not considered systematically in the planning of events or crowd situations. This qualitative and observational study identified crowd movement as an important factor in determining a person's experience of crowds. The data suggested that capacity should not only be calculated based on safety, but also on comfort levels that could alleviate unwanted encounters and frustrations, and allow for encumbrances and the respect of personal space. This echos Fruin's long-established level-of-service categorizations (1971), but those analyses took no specific account of population demographics. In order to truly understand and subsequently model human experiences and choices in a crowd and/or evacuation scenario, we need to understand what physical, cognitive, emotional and social factors are driving their movements. This paper focuses on two important, related fields of study - biomechanics and motor control - and aims to provoke thought around the many factors that influence movement when people are interacting with each other in a crowd.

'Biomechanics' and closely related fields can describe key elements of locomotion that are employed in the process of walking in congested space. In order to understand how these fields can interface with the discipline of crowd and evacuation modelling, we should consider the following areas of study:

a. The study of 'Biomechanics' evaluates the motion of a living organism and the effect of force on a living organism (Hamill and Knutzen, 1995). Nigg (1999) defined Biomechanics as the science that examines the forces acting upon and within a biological structure and effects produced by such forces
b. The study of Motor Control: an area of natural science exploring how the central nervous system (CNS) produces purposeful, coordinated movements in its interaction with the rest of the body and with the environment. Hence, the main goal of motor control research is to create a formal description, operating with exactly defined variables, of the physical and physiological processes that make such movements possible (Latash et al., 2010).

These fields of study are inextricably linked to the process of 'escape', particularly in terms of how humans move in relation to each other. The collective movement of individuals is encapsulated (in fire and life safety) as crowd 'flow'. The 'flow' metric emerges from aggregating the sum movement of the escaping individuals expressed as people per-minute, or per-second. This 'flow' rate, as well as with walking speeds are common elements of current life safety engineering, and design. However the design guides, research and computer modelling for life and fire safety have largely ignored the key aspects of biomechanics and motor control.

This paper is intended to illustrate why we really need to consider these additional aspects of scientific study, if we are to grow and expand the field of Fire Safety Engineering, potentially enabling new avenues of investigation and a much deeper understanding of the mechanisms at play. It would allow us to remove the need for 'rule of thumb' approximations of crowd flow and lead to much more rigorous assessments of safety; for older, younger, mixed-ability occupancy types, now and in the future. Population demographics have changed radically over the past 50 years (United and Nations, 2015), and originators of the simple flow aggregate values have called for them to be replaced.

2. Biomechanical processes

There are many aspects of locomotion biomechanics that *should* be considered by Fire Safety Engineers, such as:

1. Walking
2. Running
3. Assisting others
4. Reacting to stimuli
5. Accelerating, Decelerating, Turning
6. Passing through apertures
7. Adapting gait to confined space
8. Preserving one's own personal space/respecting others' personal space
9. Walking with encumbrances/disabilities
10. Transitioning between multiple phases of the above processes.

Many aspects of the above processes have been well studied in the biomechanics and motor control disciplines, particularly in the fields of sport and exercise science, sports medicine, health sciences and public health. How we measure, analyse, calculate or simulate these processes should all be of direct interest to Fire Safety Engineers. This section will describe the approaches that have already been used in these fields to improve our understanding of human movement. We will also explore the opportunities that exist for a more integrated approach across disciplines in advancing an important frontier in human movement analysis i.e. how interactive movement in a complex environment can be measured, understood and modelled.

2.1. Walking

2.1.1. Spatial and Temporal Gait Parameters

Gait analysis of walking is usually expressed in terms of spatial parameters e.g. step width, stride length or joint range of motion, and temporal parameters e.g. stride time, swing time, step time. The diagrams below demonstrate how one gait cycle - i.e. heel strike on one leg to the next heel strike on the same leg - can be broken down into discrete phases. The gait cycle, or gait stride, can be broken down in two broad phases: stance and swing, as shown in Figure 1, taken from the book Gait Analysis: Normal and Pathological Function by Perry and Burnfield (Perry and Burnfield, 2010). There are further classifications of events in the gait cycle also shown in that diagram and similar classifications in Figure 2. Figure 3 highlights the time dimensions of the walking cycle, including single and double support time, i.e. the time when only leg or two legs are touching the ground, respectively. These are important parameters as the time spent in double support changes with age and disability, giving an indication of the level of stability that is being exploited within a person. Spatial parameters such as stride length (illustrated in Figure 3) and step width also give an indication of the limits of stability in the anterior-posterior direction and lateral body sway.

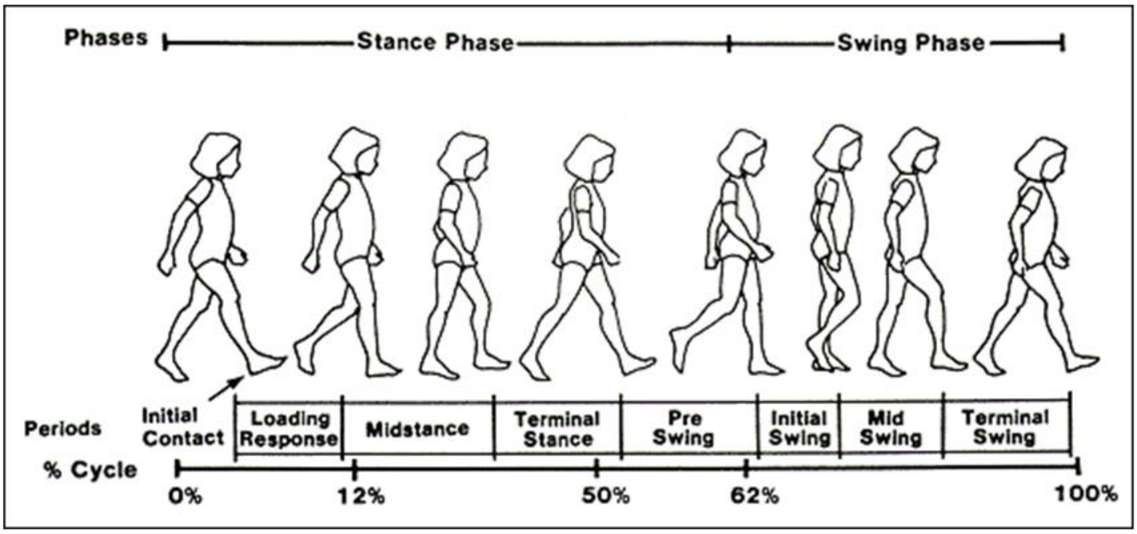


Figure 1: The Gait Cycle (taken from Perry and Burnfield, 2010)

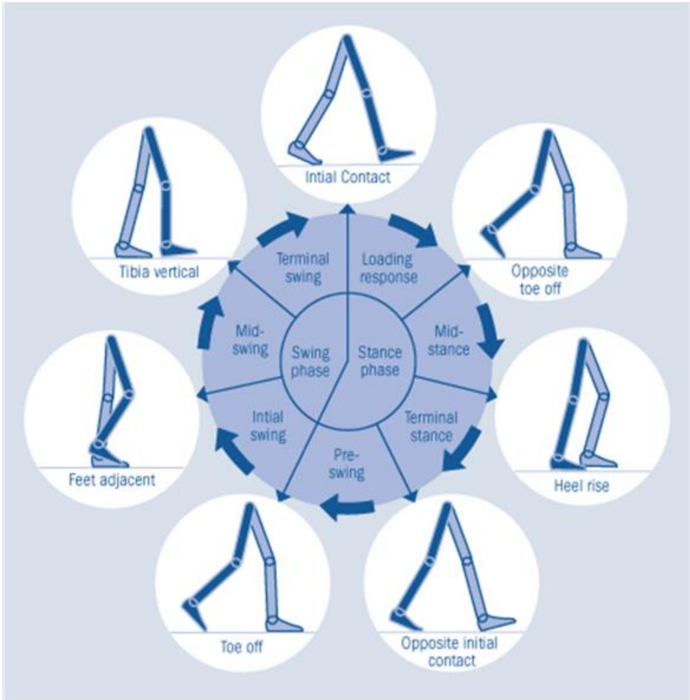


Figure 2: Events in the Gait Cycle

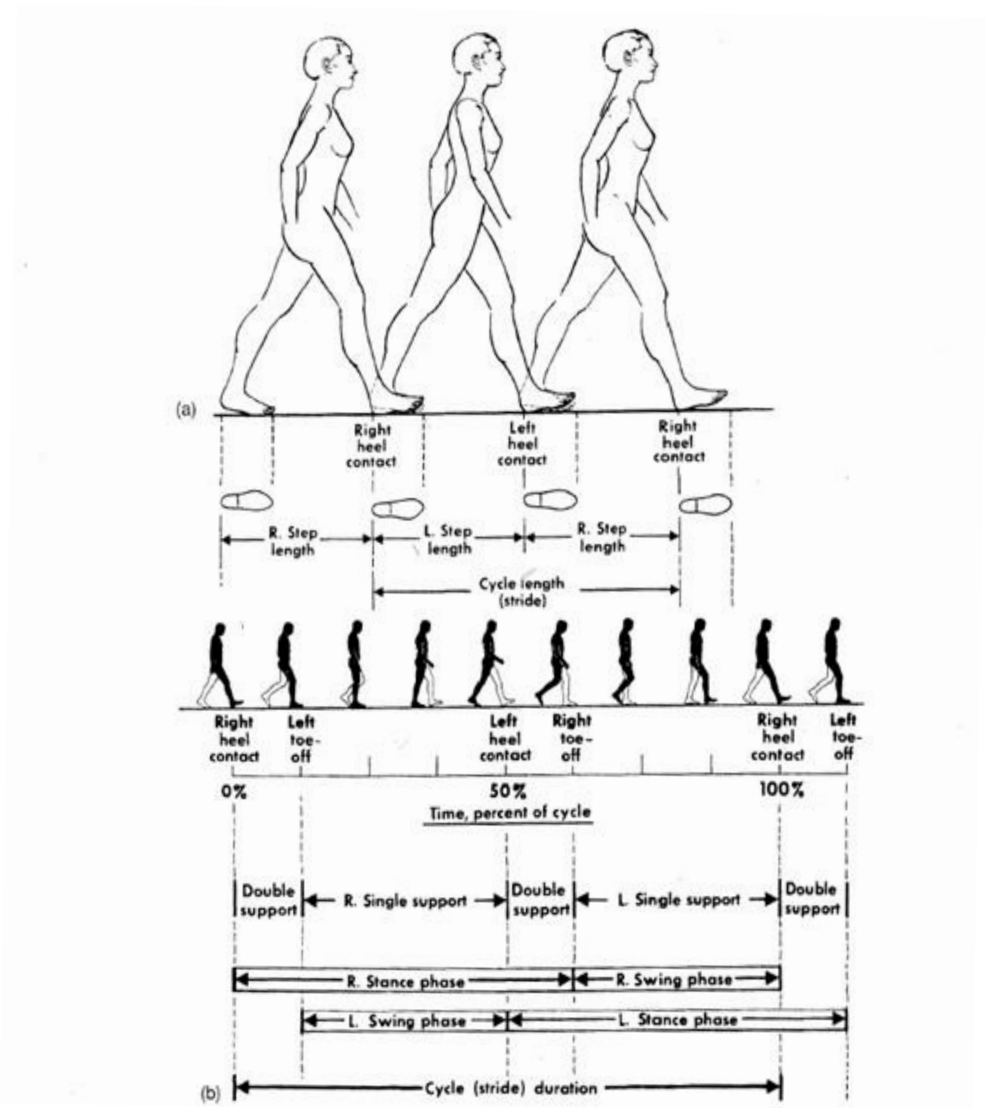


Figure 3: Time Dimensions of "Human Walking". Taken from Inman, Ralston and Todd (1981)

2.1.2. Gait Speed

Another commonly used variable in gait analysis is gait speed. A white paper entitled "Walking speed: the Sixth Vital Sign" (Fritz, 2009), suggests that walking speed, like blood pressure (a commonly used vital sign recorded as part of all health checks), may be a general indicator that can predict future events and reflect various underlying physiological processes. Fritz states that walking is a complex functional activity; influenced by many variables such as an individual's health status, motor control, muscle performance and musculoskeletal condition, sensory and perceptual function, endurance and habitual activity level, cognitive status, motivation and mental health, as well as the characteristics of the environment in which one walks. It is a reliable, valid, sensitive and specific measure that correlates with functional ability, and balance confidence and predicts future health status, functional decline, discharge location and mortality. The graph in Figure 4 is taken from Fritz's white paper and illustrates aggregated published norms for walking speeds across age and gender.

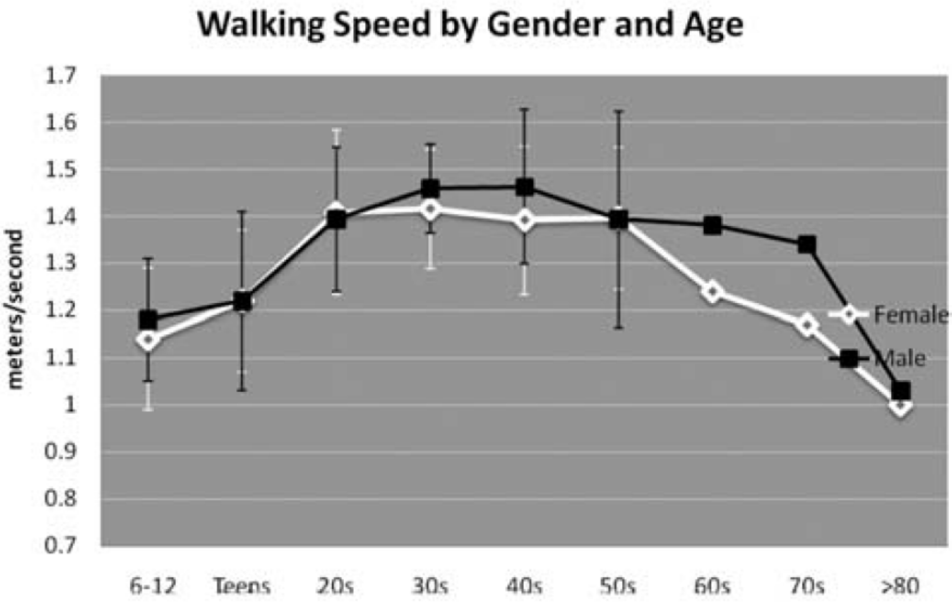


Figure 4:Self-selected walking speed categorised by gender and age (horizontal axis) (taken from Fritz and Lusardi, 2009)

2.2. Running

The biomechanical analysis of running has been a prominent topic of interest since the design of sports shoes became a huge commercial interest, back in the '70s. The 'deterministic model' is one approach that has been taken to understand the basic biomechanics of running. The deterministic model is a modelling paradigm that determines the relationships between a movement outcome measure and the biomechanical factors that produce such a measure (Hay & Reid, 1988). It is important to note here that this approach is completely distinct from mathematical modelling of dynamical systems. Dr. James G. Hay is the pioneer of deterministic model use in sports biomechanical analyses. According to Hay (1984), a deterministic model should have two distinguishing features. First, the model is made up of mechanical quantities or appropriate combinations of mechanical quantities. Secondly, all the factors included at one level of the model must completely determine the factors included at the next highest level, hence the term deterministic. Hay et al's studies (1976, 1978, 1981) were among the first to use partial correlation and multiple regression to account for intercorrelations between variables and identify biomechanical variables with unique associations with performance, particularly projectile motions in sport. In later years these association were verified through experimentation and simulation. The deterministic model approach, if done correctly, ensures that no major factor that determines the outcome is overlooked and redundancy is eliminated (Hay, 1984). Below is a deterministic model for running.

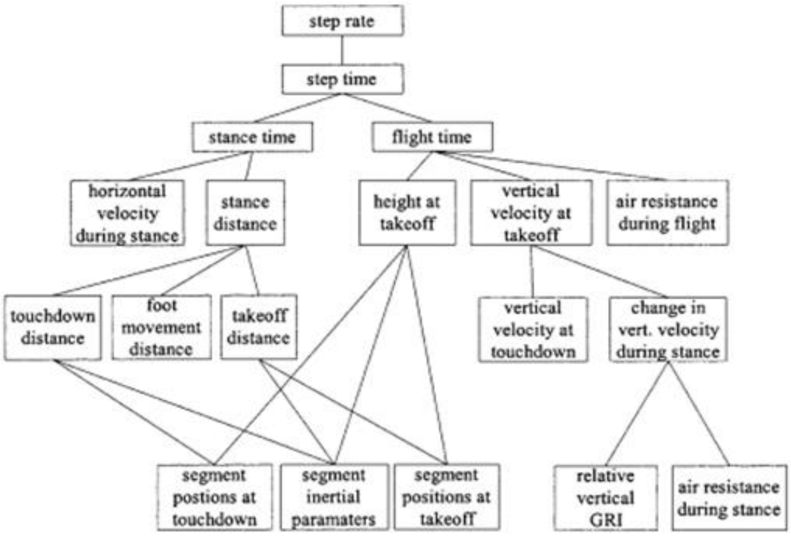


Figure 5: Determinants of step rate adapted from Hay (Hay, 1994)

This illustrates a potential approach that could be used to investigate the important factors that determine movement in a crowd. The first level of our model would start with "gait speed in a crowd", and the next level may include stride time/stride frequency and stride length. We would then begin to investigate and test the parameters that influence these, such as distance between people and anthropometric factors

2.3. Parameters which influence motion

2.3.1 Strength and Endurance

As described above, gait speed is influenced by many different factors, and Figure 4 in particular highlights how gait speed is influenced by age. Sarcopenia is the clinical term used for the decline of skeletal muscle tissue with age, characterised by a decrease in lean muscle mass and by a decrease in the quality of the muscle tissue. It is one of the most important causes of functional decline and loss of independence in older adults (Walston, 2012). Although no consensus diagnosis has been reached, sarcopenia is increasingly defined by both loss of muscle mass and loss of muscle function or strength. Its cause is widely regarded as multifactorial, with neurological decline, hormonal changes, inflammatory pathway activation, declines in activity, chronic illness, fatty infiltration, and poor nutrition, all shown to be contributing factors (Walston, 2012). Sarcopenia may therefore be an important factor that influences gait speed and walking cost in older adults. A recently published thesis (Valenti, 2016) showed that walking economy declines with increasing age and the decline is associated with the adoption of an increased gait rate (presumably due to reduction in propulsive force that affects stride length) and with irregular body acceleration in the horizontal plane. Given the start-stop nature of movement in crowd, this reduced economy may be magnified in this environment, creating a potential endurance challenge for older adults. The more physically fit a person is, the more economical their movements.

2.3.2 Balance

Decreased balance function due to injury, illness/disability, ageing or obesity has been shown to increase step width and/or double support time i.e. the time where both legs are in contact with the ground during walking. A recent study by Lee et al. (2014) reported norms for trunk sway in older adults and they concluded that the relationship between medio-lateral trunk sway and gait velocity was U-shaped for the overall sample. They reported that balance impairment is highly prevalent among older adults living in the community, with up to 30% of older men and 40% of older women reporting postural instability, and that the relationship between medio-lateral trunk sway and gait velocity differs depending on whether gait is clinically normal.

2.3.3 Perception-Action

In a proof of concept study carried out by our group (Thompson et al., 2017), we investigated whether or not a group of older adults would choose to leave a greater distance between them and a human-shaped fixed object while walking on a treadmill at slow, fast and normal speeds. Our data demonstrated that this indeed was the case, suggesting that older adults possibly require more time/distance to perceive and act upon stimuli in a dynamic environment. These findings are in line with existing studies that demonstrate changes in perception in older adults. Notwithstanding this, a systematic review published this year (van Andel, Cole, Pepping, 2017) has found that investigating perceptual-motor calibration in older cohorts should be a focus of future research because of the possible implications of impaired calibration in an ageing society. Crowd movement/evacuation is certainly one such area in which this needs to be explored.

3. Population Trends

The latest United Nations report on 'World Population Ageing', published in 2015, states that between 2015 and 2030, the number of people in the world aged 60 years or over is projected to grow by 56 per cent, from 901 million to 1.4 billion, and by 2050, the global population of older persons is projected to more than double its size in 2015, reaching nearly 2.1 billion. Preparing for the economic and social shifts associated with an ageing population is thus essential to ensure progress in development, including towards the achievement of the goals outlined in the 2030 Agenda for Sustainable Development. Population ageing is particularly relevant for the goals on poverty eradication, ensuring healthy lives and well-being at all ages, promoting gender equality and full and productive employment and decent work for all, reducing inequalities between and within countries, and making cities and human settlements inclusive, safe, resilient and sustainable. This trend in the ageing demographic is particularly important in the field of crowd movement. More and more older adults are staying in the workforce leading to a much more heterogenous crowd in the workplace, in transport systems and also in recreational areas.

The space surrounding the body has been termed the "peripersonal space" and its representation has been shown to be adapted during whole body motion. This suggest that this peripersonal space constitutes a dynamic sensory–motor interface between the individual and the environment (Noel et al., 2015). This peripersonal space is manipulated when crossing an aperture which then affects pedestrian flow through these openings (Imanishi et al., 2015). Peripersonal space has also been shown to be influenced by a number of different experimental conditions e.g. when passing through an aperture created by two humans versus created by two poles, individuals rotated their shoulders more frequently at larger apertures, initiated shoulder rotations earlier, rotated to a larger degree, left a wider clearance between their shoulders and the obstacles at the time of crossing, and walked slower when approaching and passing through the obstacles compared to when the obstacles were poles. Furthermore, correlation analyses revealed that the amount of change between an individual's critical point for the poles and the critical point for the human obstacles was related to social risk-taking and changes in walking speed (Hackney et al., 2015). In another study of obstacle avoidance (a moving and stationary mannequin) results showed that older adults increased their personal space more than younger adults while paying attention to messages and they made more mistakes when answering related questions (Gerin-Lajoie et al., 2006). Therefore, it appears that the increased information processing demanded by the environmental context affected both the motor and cognitive performance of older adults more than that of younger adults. Hackney and Cinelli (2013) found that older adults demonstrated age-related differences in dynamic perceptions during an aperture crossing task which were most likely the result of differences in dynamic balance control.

The reported effects of ageing on gait velocity, step width, step length and coefficient of friction, horizontal sway and perception of per personal space needs must logically impact on how heterogeneous crowds move in confined spaces, both in an emergency or normal situation. However the fundamentals of how - and the extent to which - this does impact the current understanding of crowd flow is currently a perilous ‘unknown’.

4. Walking in congested space

This discussion can begin with the assessment of the key elements of walking in congested space:

1. Gait - particularly step & stride length (Tanagotsuwan and Bobic)
2. Cadence - the frequency of a completed step cycle
3. Avoiding collision - factors include response time and anticipating the movement of others
4. ‘Comfort’ space where, in addition to space for leg-swing and avoiding a collision, we allow a buffer of space where we are comfortably allowing enough time and distance to avoid unexpected inter-person contact.

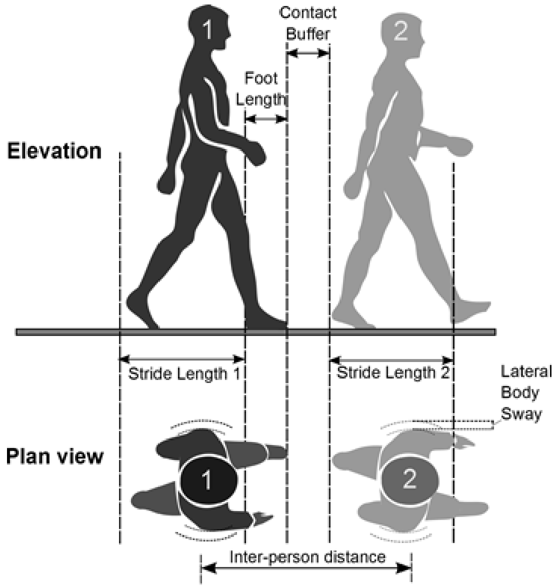


Figure 6. Elements of stride/distance in congested space

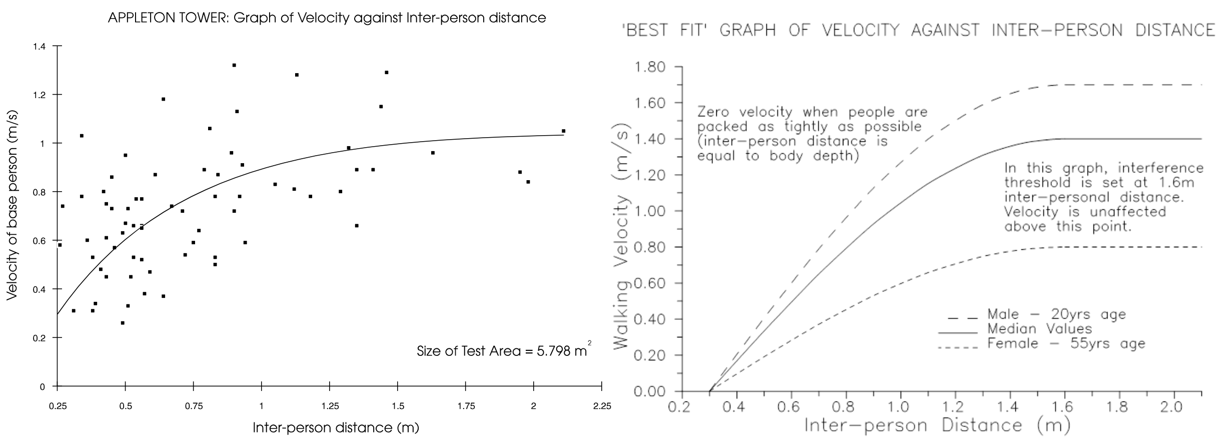


Figure 7. (a) Relationship between velocity and inter-person distance; (b) best fit of velocity against inter-person distance (taken from Thompson, 1995)

Early assessments of individual movements in congested space (Thompson 1995) have involved the assessment of inter-person distance and walking speed.[ref] In addition to the relationship between distance and speed, these early studies used the general approximation of acceleration and deceleration as 10% of unimpeded walking speed over 0.1 seconds, and also 10 degrees for rotational body 'twist' limitation over the same time period. When these parameters were implemented in the computer model 'Simulex'[ref] then it reproduced flow rates of 1.34 people/m/s for a nominal 'commuter' population type, using aggregating data from Fruin(1971), and Predtechenskii & Milinskii (1978)).

Most commonly encountered computer models use aggregated relationships for the speed and flow curves such as Predtechenskii & Milinskii(1978) , Fruin(1971) or other long-established references. Burghardt et al (2013) illustrated similar correlations for movement on staircases. However, these curves take no account of population demographic differences.

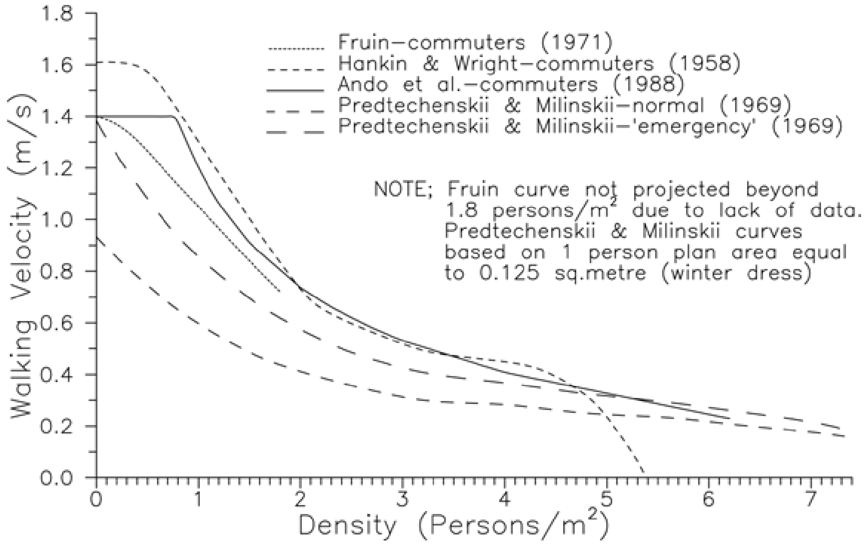
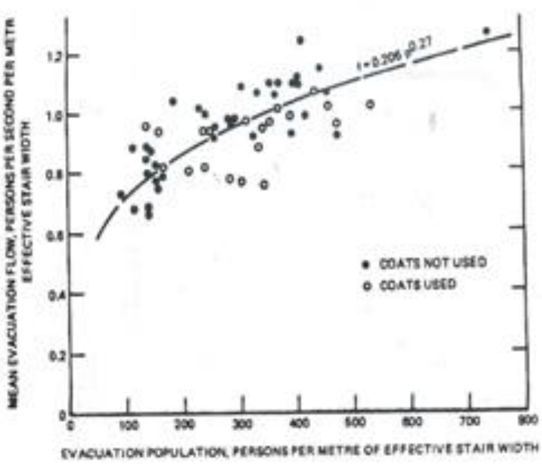


Figure 8: Some Walking Velocity vs Crowd Density relationships in horizontal surfaces (adults).

Some account is taken for wearing winter clothes in a few studies (Figure 9) but no account is taken of physical anthropology of the people, and these are rarely considered in the computer models.



(Pauls Fig 3-13.4, SFPE Handbook)

Figure 9. Data-set accounting for winter clothes.

5. Measurement

The biomechanics and motor control literature abounds with movement data that has been recorded using an array of technologies. The field of movement analysis originated with the advent of moving pictures, resulting in playback facilities that enabled the analysis of the quality of the movement. This type of approach is thus termed 'qualitative analysis'. The development of optical motion capture systems then gave rise to a more quantitative approach with high resolution, that moved from 2D to 3D analysis. The field continues to be dependent on technology development, and in the past decade there has been an explosion into the analysis of movement using wearable, wireless sensor technology. Depending on whether one is seeking to measure forces (kinetics) or kinematic parameters, different technologies can be used (Figure 10).

Despite the advances in technology, the area of movement analysis is still quite limited. The vast majority of quantitative analysis of kinematic data has been carried out on individual research subjects. Measuring inter-person distance with a high degree of accuracy, or measuring the kinematic parameters outlined above in a crowded situation is a significant technological challenge because the traditional 'line-of-sight' optical motion capture systems become obscured in crowds. Video technology is useful, but again lacks the degree of accuracy required to measure, for example, step length during walking. The potential of wearable inertial sensors is exciting but wifi or bluetooth technologies have not yet reached an acceptable level of accuracy for these kinds of measurements. The reality is that a number of approaches will have to be fused together to produce the best results. Development of techniques specifically for the accurate, high resolution analysis of movement of people in crowds is a frontier in the field of movement analysis that will very much impact a number of fields of study e.g. psychology, ageing, security and crowd flow in evacuation.

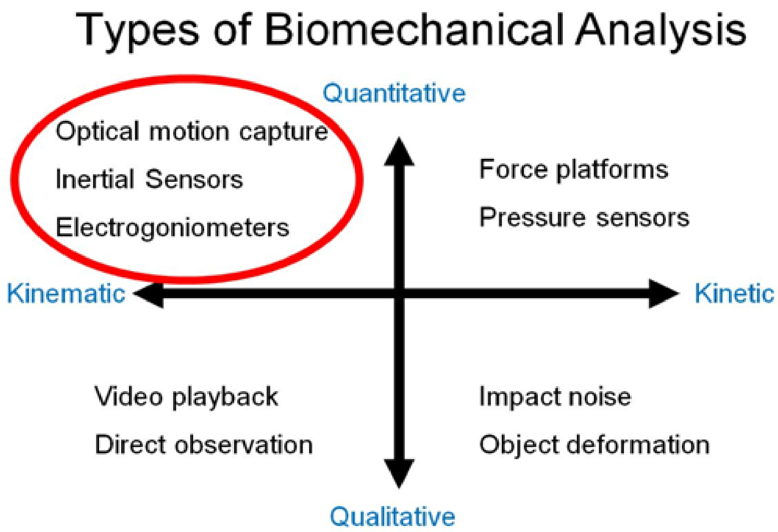


Figure 10: Approaches for analysing human movement

6. Simulation

For fire safety and crowd safety engineering, the models generally take 3 potential forms in terms of the representation of space:

1. Coarse network-node models where each room or space is a single 'node' with a network of connections representing the doorways. These were the earliest form of models, and have mostly been superseded in building fire evacuation applications, except for some very large-scale analyses or indicative use. Movement occurs by assessing:

   a. The maximum capacity of people at a node, related to the floor area
   b. The fixed maximum flow rate (usually 80 people/m/min or 1.33 p/m/s) for the connecting doorway or opening 'nodes'
   c. The walking speed along an indicative length for the node (usually fixed).
2. Fine 'mesh' network models where each floor (or staircase) of a building is represented by a fine 'mesh' (usually squares, often 0.5m x 0.5m) with connecting 'steps' between squares either orthogonally or diagonally, with 8 directions of movement (i.e., 'Moore Neighborhood'). Usually, these models use derivations of the standard curves relating walking speed to a quantified form of local density over the nearby cells, and additionally fix the standard maximum flow rate at doorways or openings.
3. 'Continuous' or vector-based models which use more precise definitions of the boundary of walls, doorways etc. People positions are stored as x, y positions on the plane of movement, and the movement is held as a vector with angle of movement and speed. Some models have different unimpeded walking speeds for different occupancy types, but the speeds are often generic. Most of these models use evolutions of the "social force model" which is derived from the same principles of magnetic repulsion forces, calibrated to represent people movements. One 'continuous model' which does not use the 'social force' approach is Simulex, which instead uses the relationship between inter-person distance and walking speed for individuals.
4. A combination of the first three methods, i.e., hybrid space discretization (Chooramun et al, 2011)

Few if any of these models implement any detailed approaches to biomechanics, but rather simple rule-of-thumb maths, and often no accommodation for mixed-ability populations.

7. Future Research in this Field

One human being is a very complex system. Numerous human beings moving together in one place is extremely complex. It is clear that research into this field has to have a strong interdisciplinary focus in order to understand all the elements of this complexity before attempting to model it and make accurate predictions. This field must be adaptive to take into account future societal trends such as an ageing population and increased levels of chronic disease and obesity. Our built environment has to accommodate the society that it serves; otherwise, we have failed and this failure will very likely lead to the loss of human life.

The next step in our interdisciplinary research is to develop a fundamental understanding of movement of mixed populations. We will do this by first determining the current 'state of the art' across multiple research disciplines related to societal change, public health, individual movement and pedestrian dynamics and motion capture techniques. We will identify potential biomechanical parameters that may influence individual movement and interaction in populated spaces in a deterministic approach similar to Hay's deterministic models that are described above. We will develop novel experimental approaches using technologies such a virtual reality, ambient and wearable sensors and biometric technologies to enable accurate analysis of movement in crowds. Finally, we will explore how physiological, social, psychological and environmental factors influence the fundamental biomechanical parameters that we identified, across a range of populations. It is our intention that the outcome will be in prototype analytical and numerical forms which could potentially be tested in mathematical and computer models of overall group movement.

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Questions and Answers

Following the presentation, a set of comments and questions were asked to the speaker. A summary of these questions along with the answers are provided below.

(Ed Galea): The work presented poses the question on the validity of some of the old data-sets which are still used in evacuation models (Fruin, 1987). Some of this data-set can still be considered relevant and should not be fully discarded. For example our WTC study (Galea, et al 2012) suggested that, when taking the significant levels of congestion experienced during the evacuation into consideration, the average stair descent speed found in the WTC evacuation was comparable to values suggested by Fruin. Furthermore, a recent study (Choi, et al 2014) suggested that horizontal walking speeds for the younger age demographic measured in trials were identical to the data collected by Fruin. Other studies have suggested that there was no evidence that women walk slower than males. An issue could be the footwear, women might be wearing flat shoes while women in the 60ies might be wearing heels. Preliminary analysis of a recent set of trials suggests that no significant trends can be found on the impact of fatigue on walking speeds (Vigili del Fuoco Comando Perugia and FSEG, 2016) for walking distances of around 2 Km.

(Enrico Ronchi): Other factors might have an impact on walking speed on stairs, such as motivation (i.e., how close they are to reaching their goal). This has been observed in experimental observations (Ronchi et al., 2015).

(**Peter Thompson)**: The presentation is not intended to recommend to discard the old data-sets but it suggested that they need to be reviewed in light of changes in demographics. The impact of demographics would potentially become greater in the future. It is also important to use the correct data for design, buildings designed for older people should be designed based on data of older people.

(Max Kinateder): It is important to look into people biomechanics and demographics. Elderly people might look further ahead if compared to younger people. It is important to evaluate at what density level people cannot see far enough ahead because this might influence the chance of tripping.

(Peter Thompson): Design guides have criteria for different buildings. Different flow rates should be applied for different demographics in relation to the expected population in the building.

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4. Discussion

The last part of the workshop consisted of an open discussion moderated by Enrico Ronchi and Ed Galea on all presentations. The whole audience and the panellists were invited to comment on all the presentations of the workshop. The discussion was initiated by a question:

(Enrico Ronchi): Having heard all these ideas, how do you see them being developed either as developers or users?

(Peter Thompson): There is a need for a common framework for components that modellers can include.

(Emanuele Gissi): As an end user and a regulator, it is important to bridge literature with day-to-day use. The design for fire safety is often done once in the life of the building. This means the designers have to take into consideration the potential uses of the buildings and people demographics in the future. Users may not be expert, thus it is important that models are easy to be understood and used.

(Ed Galea): It is difficult to have a comprehensive conceptual model in short time, thus it is important to not over-simplify models with the only scope to make them simple to use. All presentations demonstrated the richness with respect of the diversity of the field.

(Enrico Ronchi): It is important to take into account the trade-off between the complexity of the building under consideration and the evacuation modelling tool in use.

(Erica Kuligowski): Even if a model is relatively easy to use, the expertise of the user is needed for the definition of the appropriate evacuation scenarios. The user needs to understand evacuation theories.

(Enrico Ronchi): Given the variation in the level of expertise in the users, there might be the need for different combination of approaches for different users in relation to their skills.

(Rita Fahy): There is significant different between the approach employed in fire and evacuation simulations. In a fire modelling, many assumptions are made with the interest of evaluating the range of final outputs. In evacuation modelling, despite the complexity of the scenarios often the interest is mainly on evacuation times. It is still of fundamental important than the users understand the evacuation problem and are able to ask the right questions to the models and interpret the output correctly.

(Michael Spearpoint): In some instances, evacuation models may be under-estimated because they are deemed to be too simplistic, although they may be able to provide the needed results for certain scenarios.

(Ed Galea): This is in contrast with some instances where CFD modelling applications may be used badly but still being accepted given their graphic output.

(Enrico Ronchi): A good model does not necessarily provide good results if it is not used correctly. This means that the user judgement of the results is often of fundamental importance.

5. Conclusions

The workshop "New approaches to evacuation modelling" has been a great opportunity to gather experts outside of the field of fire safety engineering and evacuation modelling experts. The benefits of exchanging information between these two groups appeared evident during the workshop given the successful exchange of ideas. These are deemed to provide suggestions towards developments and improvements of evacuation models. The workshop created interest in the topic of evacuation modelling to the attendees of the symposium of the International Association for Fire Safety Science, leading the panellists to suggest that this could potentially become a recurring topic within the IAFSS symposium. This could be achieved by creating a new IAFSS working group which specifically focuses on evacuation. This should ideally include both the compilation and review of existing data on human behaviour in fire, issues associated with validation and the proper use of evacuation models as well as present and future modelling approaches.