

MICROSCOPIC MODELING OF CROWDS INVOLVING INDIVIDUALS WITH  
PHYSICAL DISABILITY: EXPLORING SOCIAL FORCE INTERACTION

by

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in

Electrical Engineering

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## Abstract

Microscopic Modeling of Crowds involving Individuals with Physical Disability: Exploring  
Social Force Interaction

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It has been shown that nearly one quarter of a population is affected by a disability which influences their interaction with the built environments, other individuals, and evacuation policies inhibiting their exit ability during an emergency evacuation. It is predicted that the number of individuals with a disability is on the rise. In the 21st century alone, there have been hundreds of events attributed to stampede or crowd crush, natural disaster, political revolt, terrorism, and other related emergencies. With an increase in the world's population, understanding emergency evacuations and how to best apply them is of growing importance. While research has investigated how crowds interact and evacuate, very little has been investigated in the impacts of how the disabled change an evacuation. While there are some beginnings to affect modeling with heterogeneous behaviors of disabled, little has been known in the analysis of crowds involving individuals with disabilities. There is a need to understand and model such interaction and how it impacts crowd movement. This dissertation implements and develops a novel video tracking system to study heterogeneous crowds with individuals with disabilities towards conducting a large-scale crowd experiment. A large-scale crowd experiment is conducted and the results are analyzed through a developed analysis graphical user interface for use with crowd dynamics experts. Preliminary results

of the large-scale crowd experiment demonstrate differences in the velocities and overtaking perception of various groups with disabilities composed of the visually impaired, individuals with motorized and non-motorized wheelchairs, individuals with roller walkers, and individuals with canes or other stamina impairments. This dissertation uses these results to present a hybrid Social Force model that can capture the overall overtake behavior of the empirical data from our crowd experiments. Finally, future research goals are discussed in the eventual development of a Mass Pedestrian Evacuation system for crowds with individuals with disabilities. Lessons from this dissertation are discussed towards goals of crowd control.

(138 pages)

## **Public Abstract**

Microscopic Modeling of Crowds involving Individuals with Physical Disability: Exploring  
Social Force Interaction

Daniel S. Stuart

Nearly one quarter of a population is affected by a disability which influences crowd evacuation. Emergencies such as stampede or crowd crush can occur during evacuations. While research has investigated crowd evacuation, little has been researched involving individuals with disabilities. There is a need to understand and model individuals with disabilities in their interaction and how it impacts crowd movement. This dissertation creates a video tracking system to study heterogeneous crowds with individuals with disabilities towards conducting crowd experiments. A large-scale crowd experiment is conducted and the results are analyzed through a developed analysis graphical user interface. Preliminary results of the experiment demonstrate differences in the velocities and overtaking perception of various groups with physical disabilities. This dissertation uses these results to present a hybrid Social Force model that can capture the overall overtake behavior of the empirical data. Finally, future research goals are discussed in the eventual development of a Mass Pedestrian Evacuation system for crowds with individuals with disabilities. Lessons from this dissertation are discussed towards goals of crowd control.

To the children of my youth.

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## Acronyms

ADAAG	Americans with Disabilities Act Accessibility Guidelines
ARTKP	ARtoolkit Plus
BCH	Bose, Ray-Chaudhuri, Hocquenghem Code
BUMMPEE	Bottom-Up Modeling of Mass Pedestrian Evacuation
CA	Cellular Automata
CPD	Center for Persons with Disabilities
CSOIS	Center for Self-Organizing Intelligent Systems
FOPF	Fractional Order Potential Fields
FPS	Frames per Second
F-P	Fokker-Planck
GUI	Graphical User Interface
H-J-B	Hamilton-Jacobi-Bellman
HPER	Health, Physical Education, and Recreation
MPE	Mass Pedestrian Evacuation
NSSR	Networked Segway Supported Responders
ODE	Ordinary Differential Equation
PDE	Partial Differential Equation
POE	Power over Ethernet
RFID	Radio Frequency Identification
R-L	Riemann-Liouville
USU	Utah State University
UTC	Utah Transportation Center
WHO	World Health Organization

# Chapter 1

## Introduction

In the current century, catastrophic events around the world have demonstrated the need for reanalysis and review of crowd evacuation policies and procedures as well as the built environments they occur in. Recently 12 school children were killed due to stampede during an evacuation of an earthquake in Afghanistan [1]. Both crowd crush and stampede are believed to be part of an estimated +2000 deaths in the Hajj pilgrimage [2]. During a 2013 New Year's firework show, 61 people were killed in a stampede in the Ivory Coast city of Abidjan [3]. In a review of mass casualty incidents from 1982 to 2012, it was determined that 162 events were pedestrian injuries due to crowded environments [4]. A 2007 report by the University of Kansas showed that only 21 percent of emergency management individuals surveyed planned to implement policies for evacuation of disabled [5]. A White House report on the Hurricane Katrina response estimated that nearly 75 percent of fatalities were attributed to elderly or disabled individuals [6]. One study suggests that approximately 23 percent of the individuals evacuating the World Trade Center on September 11, 2001 were affected by a disabling condition impacting their ability to evacuate [7]. Most recently, during a trial over emergency response of Hurricane Sandy, emergency management testified that there are no specific policies in place for disabled individuals [8].

The World Health Organization (WHO) recently estimated that nearly 15 percent of earth's population is disabled in some manner or almost one billion people [9]. In some population mixes, the number can be even higher at a quarter or more of the individuals [10]. The dynamic and uncertain nature of disasters insures the need to understand how individuals with disabilities move, react, and interact in an emergency and how best to include policy and control in such events. The ratio of individuals with disabling conditions can further increase as true emergencies cause able individuals to fall into various levels of

injury sharing similar characteristics to those disabled. It is clear, that current evacuation policies need to account for the effects caused by individuals with disabilities and their impacts on crowd evacuation need to be understood [11–13].

## 1.1 Background

Recent studies have shown that current models simulating individuals with disabilities fall short of demonstrating the diverse characteristics of various physical disability groups including the visually impaired, those using motorized wheelchair, non-motorized wheelchair, and roller walkers, hearing impaired, and those with other stamina impairments [14]. Of a review of 25 studies, none looked at evacuation policy and the effects on individuals with disabilities in a crowd, only one looked at the behavior of those with disabilities in an evacuation environment. Current models of simulation have simulated individuals with disabilities by just changing their speed of evacuation, however this does not match with empirical data [14]. The needs of individuals with disabilities in an evacuation are diverse [11], there is a need for understanding and creating control for evacuations for those with disability.

The purpose of our current research is to study the impacts of individuals with disabilities on crowd behavior, and the effects of crowds on the movement of those with disabilities. Ultimately, this research aims to improve evacuation policies, procedures, and built environments that accommodate individuals with disabilities as well. Current research demonstrates that the effects caused by individuals with disabilities, and their impacts on crowd evacuation are not characterized well. To improve overall crowd evacuation, including varying physical disabilities, these interactions must be characterized [11–13]. The aim of our initial research and this dissertation is to understand influences of individuals with disabilities on a crowd in a built environment. With our eventual goal to study those same groups in actual crowd evacuations.

Due to the lack of understanding and analysis there is a lack of a modeling and management framework to study how crowds with individuals with disabilities, the built environment, contingent evacuation policies, and the proper placement of sensing and

actuation of the crowd can affect evacuation during an emergency. Additionally, in place contingency plans for evacuation, may not suffice for capable exit given the composition of individuals with disabilities in a mass pedestrian evacuation (MPE). There is also a lack of ability to identify the makeup of individuals with disabilities in a crowd, understand how best to execute egress plans for evacuation, and assist in ensuring safe evacuation of individuals with disabilities. While it is not the intent to find solutions to all of these issues within this dissertation, this dissertation will explore the basic analysis and interaction of individuals with disabilities within a crowd, then suggest ways to approach future answers to areas lacking thus far.

## 1.2 Motivation

The purpose of our current research is to study the impacts of individuals with disabilities on crowd behavior and also the impacts of the those without in a crowd on their movement. Our ultimate goal is to improve evacuation policies, procedures, and built environments to better accommodate different groups of physically disabled. Current research findings show that the impacts of individuals with disability on overall crowd movement is not understood well. To improve overall crowd evacuation, including varying disabilities, these interactions must be characterized [13–15]. Most models, simulating disability, do not include the diverse differences such as motorized wheelchair, non-motorized wheelchair, visually impaired, and mobility impaired. This is in part due to a lack of a modeling information on how crowds with different groups of disability interact and behave within built environments. Some initial models have started to include the heterogeneous nature of varying disability groups [12, 16], however without the input of detailed movement information. The aim of our initial research is to understand influences varying types of physical disability add to crowd movement in a built environment. With our eventual goal to study groups of individuals with disabilities composition in actual crowd evacuations. For this dissertation, non-panic interactions will be studied in a controlled experiment. The study Drury and Cocking [17] shows that a large portion of evacuations are actually non-panic situations, so such experiments are relevant for the foundation of study in crowds involving individuals

with disabilities.

Recently, there has been some preliminary work to simulate individuals with disabilities and their behavior in built environments under evacuation [14, 16]. The purpose of this research was to evaluate the effect of the Americans with Disabilities Act Accessibility Guidelines (ADAAG) through built environments during evacuation [18]. Simulations involving the Social Force Model and decision direction were also used to study emergency management practice of an international airport as well as other facilities common to evacuation [12, 19].

### **1.3 Contributions**

This dissertation continues this exploration in four parts. First to study the impacts of individuals with disabilities within a crowd, the crowd must be studied. To accomplish this goal, this dissertation presents a novel data collection framework designed to gather all levels of physical interaction between any and all individuals within a large scale crowd experiment. From that gathered data, this dissertation then implements a system to study that data and allow also for future studies of our large scale crowd experiment. This dissertation shows data analysis that suggests in initial findings the importance not only on understanding the varying speeds of individuals with disabilities, but also the more complex interactions between individuals and the crowd. From those initial findings, this dissertation then suggests a simulation model that can capture certain aspects of the empirical data. Finally, this dissertation takes lessons learned from research to discuss potential future elements of crowd control, crowd management, crowd sensing, and building evacuation plans that may lead to better evacuations of crowds involving individuals with disabilities.

#### **1.3.1 Automated Collection of Tracking Data in Heterogeneous Crowd Video**

For our research, there was a need to capture large scale crowd experiment data that captured the varying differences of a heterogeneous crowd involving individuals with disabilities. This would require the use of a system that can extract data from a crowd experiment in an automatic nature and provide varying analysis data on movement, speed,

flow, and density. Such a system needs to track each participant in a separable identifiable way. The common approach is to use cameras to capture the movement of a crowd through various building implements such as doorways, corners, and corridors and then use some method to extract that data. However, it was quickly discovered that there existed few methodologies that could automatically separate out the trajectory paths of any individual in a crowd and compare it with other individuals. Furthermore, walking gaits and movements of individuals with disabilities vary greatly and are different from those movements typically used to design tracking software for crowd detection.

This dissertation provides an approach that solved those problems and provides for a video-based tracking system that can separably identify trajectory data for experiment participants and do so from crowd experiment data in a semi-robust manner that takes into account the unpredictable nature of participants. This implementation used fiduciary markers on participants' heads that, unlike other methods, are independent of the height of a participant or their position. As individuals with disabilities will also occur at varying heights from the rest of the crowd, this allows for rapid experimentation without the need of relying on gathering very accurate height information from participants. In this dissertation, this system eventually provided valuable trajectory data from a series of large-scale crowd experiments held at Utah State University, the analysis of such to be discussed in a future section.

### **1.3.2 Crowd Experiment Heterogeneous Tracking Data Analysis**

In our research, we conducted a series of large-scale crowd experiments at Utah State University. The purpose of this experiment to study the interaction, and impact, of individuals with disabilities within a crowd in various built environments. In section 1.3.1, a system implementation to collect trajectory data on the large-scale crowd experiment was briefly discussed. From this trajectory data, an analysis program was created to study, manipulate, and analyze all the tremendous data collected from our experiments and will be presented in this dissertation. This system allows not only the author of this dissertation to study various variables and interactions within each experiment, but also other members

of our research group or other members from any civil engineering, environmental planning, or other crowd analysis field. From this analysis, this dissertation presents a brief study of velocity differences between both the crowd and individuals with disabilities. It will also be shown that other crowd interactions provide differences that may not be modeled presently. This is the case, in this dissertation, on the study of the overtaking interaction. Here, it will be shown that the perception to overtake or not overtake leads to large differences when crowds involving individuals with disabilities are studied. This dissertation will present those results in brief and provide for motivation to continue future studies in this field.

### **1.3.3 Crowd Modeling Including Overtaking Interaction**

In previous section 1.3.2, a system for analysis of the collected trajectory data of crowds involving individuals with disabilities is discussed. From this analysis, it is determined that there is an importance of study when it comes to individuals with disabilities. Two variables studied are the differences in velocity between various groups and also the perception of overtaking. The impact of overtakes in a crowd is more important when the velocity of certain groups provides that the crowd will start to slow down if not overtaken. Based on the analysis found, a model adaptation to the standard crowd Social Force Model, is created in an attempt to capture not only velocity difference, but also varying differences in overtake behavior between various groups of individuals with disabilities within a crowd. This dissertation presents some initial results from that model, and motivation for future exploration of both the model and this field.

In addition to providing a hybrid model that can model the perception of overtaking, this dissertation also uses the analysis results to suggest possible future rolls in crowd control, crowd management, crowd sensing, crowd evacuation, and evacuation contingencies. The goal of this final section is to present a road map of questions and possible solutions to future work.

## **1.4 Organization**

To gain an understanding of heterogeneous interactions, we conducted experiments to

study detailed movement and interaction in a crowd. This not only includes developing an understanding of velocities for each heterogeneous group of individuals with disability, but also things such as spacing in movement between interactions, density and flow information for different compositions of groups, how each group deals with varying changes in built environment, and also what happens as different groups of individuals encounter each other both in uni and bi directional movement. The rest of this dissertation is organized to demonstrate the work of each contribution, the results, and future exploration.

Chapter 2 starts by discussing the requirements set forth for capturing data during a large-scale crowd experiment. This also includes a discussion of current crowd data capture platforms and their deficiencies in respect to our goals. A creation of a data collection system is presented with a discussion over the hardware and software created and selected, steps taken to provide for calibration and setup for a future crowd experiment. The chapter wrapping up with the results of the creation of an automatic extraction of recorded video data into trajectory information. Finally, closing with problems and future improvements.

Chapter 3 starts with the setup and implementation of a set of large-scale crowd experiments and the implementation of a pilot study. A description of the need to study velocity and also study overtaking are described. A graphical user interface (GUI) is presented that allows civil engineers to study the data gathered from the experiments for various variables. Batch processing abilities are presented for saving time in data analysis. Finally, results found regarding velocity and also overtake information as well as problems and future improvements are presented.

Chapter 4 starts out with an overview of the various crowd modeling types within the field. From this, the motivation to create a model to describe overtake perception is offered. The Social Force Model is presented as a good choice to build upon and a form of potential fields called Fractional Order Potential Fields (FOPF) is offered. This hybrid model has the ability to change the order and shape of the field in increment to match varying behaviors. This Hybrid Social Force Model is used to describe the varying differences in overtake perception amongst the different disability groups. Results between

a simplified Social Force Model and the updated hybrid model are provided. The hybrid model allowing for the matching of overall overtake information similar to the large-scale experiments. Finally, problems and future inputs are suggested.

Chapter 5 explores larger reaching models of crowds with disabilities including concepts of sensing, actuation, control, and management. Thoughts on future crowd control are also shared based on the results found within the large scale crowd experiment. Finally, Chapter 6 concludes a summary of the contributions of this dissertation, future progress in the field of study, and ending remarks regarding this dissertation.

## Chapter 2

# Automated Collection of Tracking Data in Heterogeneous Crowd Video

### 2.1 Experimental Need and Setup

To gain an understanding of heterogeneous interactions, we desired to use video tracking through empirical experiments of various combinations and densities of crowds with and without individuals with disabilities. To gain understanding of differences caused by individuals with disabilities interaction with a crowd, these experiments occur in a built environment possessing common facility structures such as a doorway, bottleneck, corners, an oblique corner, and varying hallways widths.

In our proposed research, we want to investigate crowd dynamics such as speed, flow, density, and other interaction for groups containing individuals with disabilities. We also want to understand how each individual group of individuals with disabilities, separately and together change the standards of crowd movement through a varying degree of built environment features. To these ends, this author searched for tools to accurately track an individual within 0.3 meters or a foot step. Our goal is to understand how each disability group impacts the crowd movement, and how the crowd densities impact both groups together. A circuit would be built for our large-scale crowd experiment at a university gym. The circuit, Figure 2.1, covers a large area with various ADAAG compliant facility structures to analyze varying environment impacts. Due to the circuit size, each participant must be individually identifiable and tracked across multiple cameras covering the circuit. A large number of experiment participants, 60-100, would be required to fill the circuit to reasonable capacity levels. As such, the tracking software also needs to handle a large volume of separately tracked and identifiable markers.



would need to have several performance goals to work. As we would be paying our participants the system would need to be robust and also not take up a tremendous amount of time for pre-experiment and post-experiment while we have our participants. Also, as the experiments would cost both financial, time, volunteer, and participant resources, the results of the data extraction needed to be reliable, fast, and repeatable. For any form of crowd analysis from velocity to flow to density, information on trajectory of each crowd individual is needed. That is the Cartesian coordination of each pedestrian's movement over time. An additional element is needed in the case of our research which is in heterogeneous crowd analysis. For this, each pedestrian needs to be somehow identifiable from every other pedestrian. Moreover, since we would be doing this controlled experiment over a large area, this form of ID would need to be traceable between different sets of camera data. Camera based data collection was assumed from the very beginning of this experiment due to its low impact on participants and ability to capture both data as well as be reviewed visually after the fact. It is fairly standard to use camera collection or video to study crowd movement, and this will be discussed more in a future section. As the experiments would be run once, to remove another failure point, we would need to extract the data from recorded video so as to not rely on automatic processing while the experiment is taking place. To make the data useful, we determined that the data should be accurate in a 2-D plane with around 0.3 meters of accuracy or better. This value was determined as the foot path or foot step of an average individual. As we would be running a large number of participants through each experiment, 60-150, the system or software would also need to be able to separately identify and handle that large number of participants. There was also some grave concern about catching the data. Crowd pedestrians have unknown behavior and might act randomly and some of that could cause data to be missed. To ensure that enough data was captured, the system would need to be reliable to those changes and minimize both error in accuracy and loss of tracking. Finally, we desired to also study some movement and interaction of a crowd in a stairwell. This adds another element to the requirement that the vertical axis of tracking should not impact the 2-D data accuracy of the trajectory data extracted. Also, we would

be extracting trajectory data from non-standard crowd pedestrians including individuals with disabilities. That means that heights of pedestrians would have a greater range due to both wheelchair and roller walker individuals. They would also take up different spatial ranges due to the footprint of a wheelchair, individual with a cane, or roller walker taking up more space. Because we would be studying individuals with disabilities, the chances of greater height differences possibly occluding some data, the recording and trajectory extraction would have to take place from above to rule out as much occlusion as possible. A summary of some of the performance goals can be found in Table 2.1.

### 2.1.2 Resource Limitations

Although we had goals of collecting trajectory data from a crowd experiment, there were also limitations. The first limitation was to the financial means available to buy or put together a tracking system, including cameras, computers, resources, construction of circuits, etc. Also, our research had plans to conduct a large-scale evacuation study which would be part of our total financial means available. In this future experiment, a Radio Frequency Identification (RFID) system or other similar system would be required to study crowd movement, since cameras may not be able to be used due to both ceiling heights and building infrastructure. Many camera systems and RFID systems are immediately excluded from our use due to these financial means alone. Another research limitation

Table 2.1: Performance requirements for video tracking.

2-D Accuracy	0.3 meters or within foot path
Tracking	Individually identifiable over multiple cameras.
Capacity	60-150 participants possible in circuit, 30-60 in a frame.
Vertical Height	1.2 meters in height change for the circuit. 4.5 meters for the stairwell.
Reliability	Minimized error in accuracy and in loss of tracking.

was time. On our research time table, the large-scale experiment would occur a year after program start. So the research, development, and testing of a camera tracking system would need to fall within this timeline. Ultimately, it would be three months for research, one month for purchasing, four months for development, and another two months for testing and finalization. The additional resource limitation was personnel. For this project only the author would be available for most of the research and development. The personnel limitation means the system would need to be easy to assemble or put together and not require assembly of individual tracking circuitry or programming for each of the possible 100 pedestrians. The system goals and program resource limitations would be used to determine which visual tracking systems would work or if a system would need to be created. This will be discussed in the following section.

## **2.2 Data Collection Examples**

There has been a great deal of work into pedestrian tracking and identification. The research scope spreads from individual facial recognition to segmentation tracking of crowd movement. Much of the research surrounds large spatial area tracking of pedestrians across streets, campuses, and open areas [20, 21]. This research is useful for security and crowd analysis in a sparse scale, but suffers problems with severe occlusion caused by large scale crowds. Occlusion makes it more difficult to track individual crowd members accurately, a suffering of oblique camera placement. To track individuals within a denser crowd many techniques have been devised [22–24]. However, these approaches cannot track non-standard individuals such as users of walkers and wheelchairs. There has been some work to track items such as bicycles, as in Cho et al. [25], and even the beginnings of recognizing wheelchair individuals, as in Huang and Chen [26]. However, these approaches are not always desired for empirical experiments, because they often lack the accuracy and reliability needed to gain detailed information on crowd flow, density, speed, and change. Many other approaches exist to gather general movement of a homogenous crowd. These approaches rely on background deletion and optical flow recognition of crowd movement to determine directions of the crowd. However, all of these approaches are ruled out of discussion for this dissertation

since they simply lack the ability to cover heterogeneous crowd experiments.

Recent research focuses on controlled experiments, where the goals of reliability and accuracy are more important. In the paper Hoogendoorn et al. [27], researchers were able to use colored hats on opposing shirt backgrounds to track pedestrian trajectories accurately while gaining information on such things as uni-directional, bi-directional, crossing, and bottleneck flows. Figure 2.3 shows an implementation of this system. Their research is not only able to track separate groups in a crowd, but also separately identifies pedestrians on the camera frame being tracked. However, this system lacks the ability to separably identify more individuals than just those colors used and also identify those differences between different cameras. Similarly, the paper Boltes et al. [28], uses paper markers worn on participant heads in Figure 2.2 Each paper marker is the same, but each marker has an orientation to recognize pedestrian head movement and direction. The markers also include color information to indicate height range of each individual. This collected height information is used to improve accuracy of the 2-D positions of each pedestrian trajectory through corridors such as a bottleneck. This approach also suffers from the tracking ability over multiple cameras as pedestrians are only separably identifiable within the camera frame. Also, two dimensional accuracy is highly dependent on the measurement of pedestrian heights, but still puts them into height ranges limiting overall accuracy. While both these approaches provide great resources for crowd dynamic evaluation in an experiment form, they lack the ability to separate out individuals with different disabilities or groups of a disability from the other participants.

Given the lack of an affordable off the shelf option and the lack of available heterogeneous tracking options, the final determination is that a new approach would be required to facilitate all of the difficult performance goals and restrictions set forth for our large-scale experiments. The rest of this chapter will focus on that development and implementation.

### **2.3 System Design**

As research into possible crowd trajectory extraction possibilities fell short, a new system would need to be created. While many of the methods could fit most of our

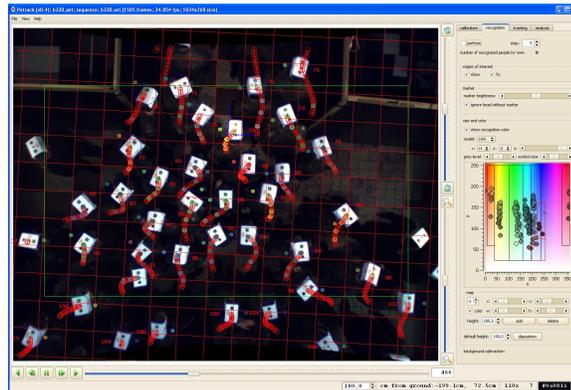


Fig. 2.2: PEtrack: automatic extraction of pedestrian trajectories from video recordings.



Fig. 2.3: Extracting microscopic pedestrian characteristics from video data.

performance goals, two goals could not. The first issue was to finding a tracking method independent of height. That is, a method that could be tracked accurately in a 2-D plane without knowledge of what the height, or distance from the camera, was. This leads naturally in the camera tracking realm to pattern tracking. While there is work out there for using pattern recognition to track individuals, using predetermined patterns would remove possible chances of error from the tracking. The second goal is also to separably identify each tracking point across cameras. This goal also lends itself to the need to use a pattern. For these reasons, this author determined that the best approach would be to use fiduciary markers of some sort to track each pedestrian as their known size and shape make them both in height independent and also separably identifiable. One source of fiduciary markers is in the field of Augmented Reality. This author has some experience in that field and the use of those markers in tracking mobile ground robots. A discussion of these markers and the development of a tracking system is discussed throughout the remainder of this section.

### 2.3.1 Augmented Reality Software

Augmented Reality is the technology of injecting virtual objects into the reality of an individual's vision through video goggles and a camera. The technology allows for them to view their normal environment with 'augmented' forms of reality such as virtual characters, virtual manipulation of the environment, or change. One such developed technology is ARToolKit [29, 30]. This series of libraries and functions allow for the use of identifiable fiduciary markers of known shape and pattern. Using knowledge of pattern size and a shape internally, the pattern can be recognized, identified, then tracked in location to the camera. That is, the perspective, orientation, and x,y,z location of the pattern can be located in relation to the camera. For Augmented Reality, this means that a virtual object can be placed onto any marker found within the camera scope and adjusted for perspective and location constantly. Thus the object appears at perspective, such as any real world object. The ability to track identification, orientation, and position of the pattern has spawned research into using such patterns to track a mobile robot's position. The package has also been utilized as a pseudo GPS for localization of formations of robots [31]. A great element of this library is that the axial distance from the camera does not affect the 2-D tracking of the pattern. Therefore, solving our ability to track individuals of great varying height and in the stairwell. While ARToolKit serves well for localization and tracking of objects, there are still some issues of importance in meeting our performance goals. In ARToolKit, each pattern must be individually created to be separable from every other. While this is fine for small groups of participants, this presents a time resource problem in creating patterns for large scale, 60-100, tracking of patterns. ARToolKit is also very inefficient in tracking large numbers of patterns at once, thus failing our capacity needs. Finally, ARToolKit is very sensitive to lighting conditions. While not a great issue for Augmented Reality, light change is important for patterns that will be worn on unpredictable and dynamic individuals.

For the preceding reasons, a different package, similar to ARToolKit, called ARToolKitPlus (ARTKP), is used instead [32, 33]. The first improvement of this library package is the ability to track up to 512 different markers at once. This meets our capacity performance

requirements. Additionally, ARTKP has added luminance correction code and robust positioning code to improve overall pattern accuracy. The library also allows for the automatic tracking of patterns that can be automatically created. The software presents for up to 4096 BCH encoded ID patterns such as that found in Figure 2.4 . Finally, ARTKP still maintains all the features of the original ARToolKit package. With ability to track large numbers of different patterns, we can assign pattern IDs to individuals with different disabilities and then identify and separate them out of the video data after the experiment. Thus, we can provide for customizable analysis of heterogeneous crowd movement based on the group or interaction we want to analyze.

### 2.3.2 Camera Selection

With the proper tracking software libraries selected, the next requirement is hardware to support recording experiments in the circuit. Since occlusion is a problem, tracking would need to be of people’s heads from above. Therefore, each camera needs to be suspended above participants to record the patterns attached to their heads. The circuit chosen for this research covers the outside of an area of  $19 \times 12$  meters. Due to camera coverage and suspension requirements, the camera must be light in weight and able to use a wide angle lens. A wide angle lens can capture a large area for tracking at a given suspended height, reducing the needed number of cameras. A final requirement on the camera is frame rate. As our experiments deal with many participants in a large scale, there is to be expected a



Fig. 2.4: ARToolKitPlus BCH-ID encoded pattern.

great deal of boredom or unpredictability in the recordings. For this reason, we aimed to raise the frame rate from standard of 25 fps to double that at 50 fps. If participants look down at times, or do anything else to remove the pattern from tracking, the sampling rate of data is high enough to maintain tracking accuracy. Table 2.2 summarizes these goals.

Wireless cameras were considered for use, but we chose wired cameras over concerns of reliably capturing all needed data in an experiment. Wireless cameras have the risk of power failure and also require a separate network, both points possible fail points in a cost sensitive experiment. With a required frame load of 50 fps, our best option is gigE cameras which are capable of transmitting at such speeds. To reduce hung cabling, we went with Power-over-Ethernet (POE) cameras which only need one cable. The IDS Imaging camera 5240CP, provides for all these abilities [34]. This camera is compact at  $29 \times 29 \times 41$  mm, but still affords a high resolution of 1280x1024 pixels at a maximum frame rate of 50 fps. For a lens, we went with a c-mount 3.5mm focal length lens that gives a large area of coverage per camera [35]. A color camera is selected to allow for flexibility in future unknown experiments. The camera and lens combination can be found in Figure 2.5.

### 2.3.3 Software Design

The standard libraries for ARTKP, only work for tracking markers on a picture or from a live web camera. While real-time processing may be possible, it is too risky for reliability performance requirements. Therefore, the pedestrians are recorded the day of

Table 2.2: Performance requirements for camera hardware.

Weight	Light enough to be safely suspended above participants
Coverage	Cover as much of an area as possible while still tracking well
Speed	50 fps to reduce abrupt actions interfering with tracking



Fig. 2.5: Ueye 5240CP with 3.5mm lens.

the experiment, and then tracking data is post processed from the recorded videos. To do this efficiently, and allow for varying video requirements, the open source software libraries called Cinder are used [36]. Cinder contains libraries and example code for many different artistic, graphical, and 3D rendering toolboxes. ARToolKitPlus has also been integrated into the library setup for easy use [32]. The software has been modified to replace camera streaming portions with functions to access video and analyze it with ARTKP one frame at a time. Also added functionality to move forwards and backwards through the video for portions of tracking data as required. On each successive video frame, all BCH ID markers found are recorded, in the form (ID, X, Y, Z, time), to a text file. The Cartesian coordinates are off the camera lens center. For the data to be correct, it needs to be inverted and subtracted from the height of the camera to the floor. While currently not in use, the orientation of each pattern, and thus the turn of a participant's head, can also be observed and tracked. At the end of processing a video file, all trajectories for each ID at each time step are recorded to one camera text file.

### Camera Calibration

One general problem with the ARTKP platform was camera calibration. The wide angle lenses chosen for coverage, have a radial curve of a parabolic lens. The traditional calibration sequence used for ARTKP is the Matlab Camera Calibration Toolbox [37,38]. Several attempts were taken at trying to obtain good calibration data using this platform

and a standard calibration chessboard. Calibration appeared to straighten out curvature of standard chessboard images, but at farther distances distortion was still apparent. Viewing tracking data horizontally, camera lens curvature is severe. To solve this problem, the calibration software called Omni Camera Calibration Toolbox for Matlab is used [37,39,40]. Greater distortion and aberration correction are possible with this program and it derives much more accurate tracking data. This calibration approach, and most approaches, require the subsequent taking of photos of some known pattern to determine how camera aberration occurs throughout the camera and the lens. In the case of this calibration software, a checkerboard pattern is taken at various heights and positions to gain an overall calibration file for the camera. This pattern can be seen in Figure 2.6. After calibration, a static fiducial marker position can be found reliably in a 2-D plane from five to fifteen cm, depending on distance from the camera.

### **Vision Tracking**

With the software calibrated to a camera/lens combination, the next step is to determine the accuracy region and coverage of the camera. The goal is to determine how many cameras to cover the entire circuit for complete tracking ability. To do this, tests of the camera horizontally to a wall simulates a suspended camera as in Figure 2.7. These tests showed



Fig. 2.6: Lens calibration chess board for Omni Camera Calibration Toolbox for Matlab.

that the most accurate distance of the camera to the ground should be at four meters. This distance was obtained by observing the ratio of failed to tracked data at varying distances to an object, realizing that the camera needs to detect people up to two meters tall and yet still detect wheelchair members. At four meters, there is a maximization of detected data of the patterns for this particular camera/lens setup. Increasing the size of the pattern would increase the distance the camera could be away from the pattern. However, the size of the pattern is 30 cm squared, about as large as to be manageable when worn on a participant's head, the only place best visible from above. At this distance, the radius of coverage is roughly 2.5 meters of detection. The shorter the pattern to the ground the more the coverage due to the extended spread of the lens aperture. With a coarse idea of the suspended height distance and coverage of the camera, a short camera suspension test was conducted to verify and fine tune in on a proper height.

This suspended distance was confirmed by temporarily suspending a camera overhead at several heights and confirming the pattern detection radius. With the camera region of detection known, camera quantity, and placement in the circuit, is easily determined. Overlap between consecutive cameras, is included in this determination to provide maximal tracking coverage in the circuit. Pieces of tape were marked out in a grid on the floor of the test area and patterns were statically placed on the ground as well. Test participants wore hats and walked around within the room, including tracing out their paths on the grid

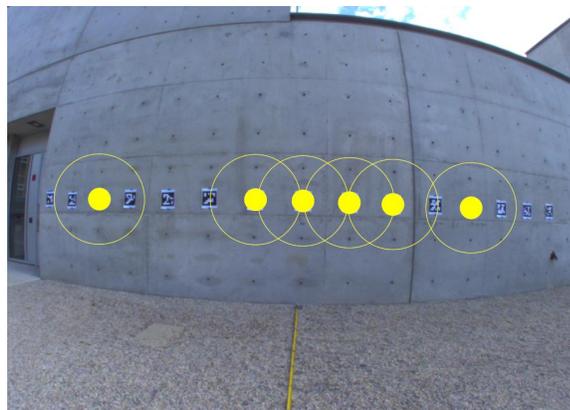


Fig. 2.7: Testing fiducial pattern recognition at various distances.

in both directions. Figure 2.8 shows the testing of participants. To simulate wheelchair heights, participants on office chairs were used to ensure a full height coverage at each camera height distance as shown in Figure 2.9. Various heights around the four meter offset from pedestrian's heads were tried at 0.3 meter increments.

Many accuracy tests were performed to gain a sense of the overall error for the patterns in all three dimensions. This data was compared with the known distances with the walking grid to determine a ground truth. In the most important two dimensions, data are accurate to a region cloud of seven to seventeen cm. This accuracy depends also on pedestrian speed as it is captured through the 50 fps shutter of the camera. The accuracy also trails off the farther the pattern is from the camera and the camera pattern. This meets our basic need to track each pattern, within foot step as long as pedestrians do not waiver too far



Fig. 2.8: Preliminary ground truth testing of camera at various heights above the ground.



Fig. 2.9: Preliminary ground truth testing, simulation of wheelchair heights.

out of the specified regions. The best accuracy was obtained at a height of 4.2 meters with a radius of 2.1 meters around the center of the camera. The third dimension, on the camera axis, is not as accurate due to perspective. The error there is 0.3-0.5 meters. However, for the circuit, this error in data does not impact accuracy. Two dimensional trajectories remain accurate, regardless of the height, as long as the height is within the previously determined range. As a precaution, participant heights are recorded with their ID in case they are later needed as a backup only. Their known heights are more important in the stairwell, where vertical accuracy will impact the results due to vertical movement. Varying light conditions can change the accuracy of the pattern occasionally. They either cause sporadic error outside the circuit or extreme difference between time steps. However, this noise is usually separable to the actual participant trajectories. Using this information and the floor plan of the proposed circuit, it was determined that 14 cameras would be required. Twelve cameras would be used to cover the circuit outline and two for covering two proposed stairwells for study. A map of camera accurate tracking range coverage over the circuit can be found in Figure 2.10. The positions and identification of each camera are found in Figure 2.11. An attempt was made to uniformly distribute the cameras over the circuit based on the radius of best accuracy. However, the circuit lies on the edge of the gym and therefore requires camera spacing that allows for continuous coverage of the circuit path. Placement was adjusted to ensure that accurate camera centers were placed over the desired built environment sections such as the oblique corner, small and large 90 degree corners, small and large corridors, bottleneck, and doorway. The remaining cameras were spaced to ensure continual coverage over the rest of the circuit.

## 2.4 System Implementation

The circuit, in Figure 3.1, is built out of wood and set up in a local gym of our university. The university gym is spacious enough to account for the size of our circuit. Ceiling heights are at eight meters allowing for ample room for suspending cameras. The challenge in suspending cameras is to place them safely above participants' heads without adding to the weight above. Connections points amounted to steel building girders. To suspend the

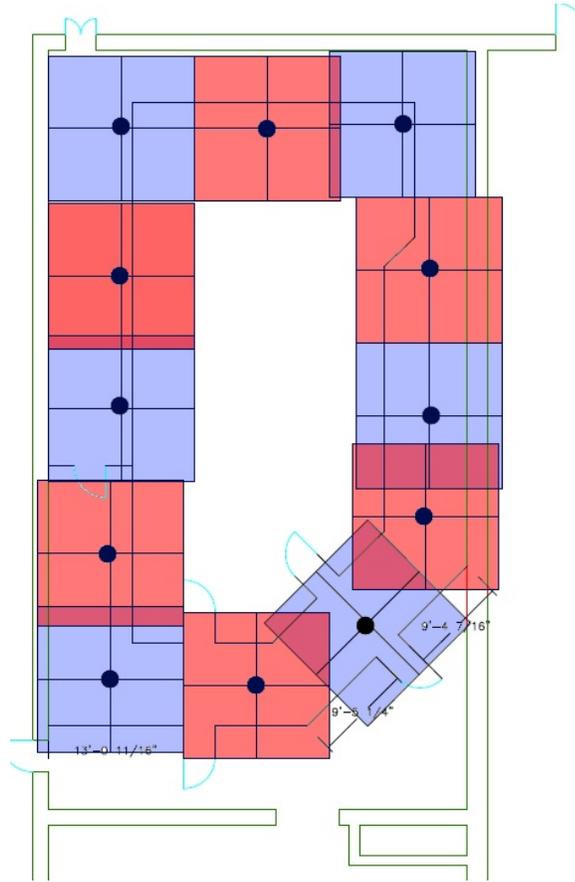


Fig. 2.10: Camera position layout given recognition region at proposed camera height.

cameras, we used a system of cord to hoist each camera, and supported Ethernet cable, into position. To account for inaccuracies in suspending them and allow for minute adjustments, each camera is placed on a gimbal as seen in Figure 2.12. The camera gimbal is simply a child's food bowl device offering a cheap, yet fairly effective, way to use the weight of the camera to remain roughly parallel to the ground [41]. The gimbal provides for some stability if camera position is changed. This approach was tedious, but it provides ability to adjust the camera's position if needed. One must, however, be careful about the attached cords, as bumping can jiggle the camera.

All twelve cameras are suspended over the circuit to provide full coverage with overlap. The Ethernet cables lead back to three 8-core 32Gb memory computers, each handling the data from four cameras. Power to each camera, as well as communication, is handled using

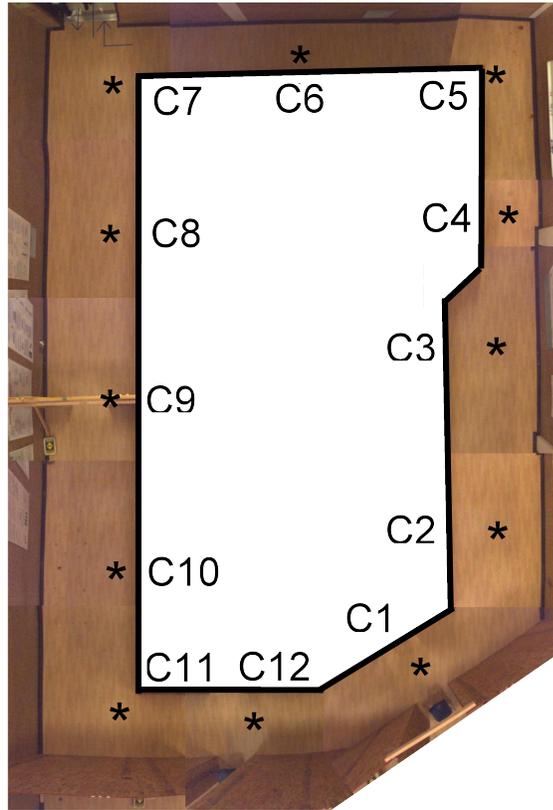


Fig. 2.11: Camera position and ID addresses overlaid over read circuit image.

Adlink GIE64+ POE PCIe cards [42]. The final portion to obtaining the data is recording software for handling the large amount of data coming in from each camera. Raw video data from each set of four camera arrives at 60Mb/s or 213Gb an hour. Our original goal was to be able to handle an eight-hour day of recording or two Tbs of data. As mechanical hard drives cannot download fast enough to handle the data throughput, solid state drives are used along with memory as a buffer. To reduce the load on each computer, which could affect reliability, recording software needs to handle both multiple cameras and high frame rates. The software Streampix 5 filled our need, and its proprietary sequence format reduces the data footprint by almost a factor of ten [43]. To further increase reliability, compression is reduced down to 60 percent Lossy JPEG. Although resolution is lost due to this action, tracking of the fiduciary patterns remains unaffected.

Each experiment day is divided into recording sessions of ten-minutes. Each session



Fig. 2.12: Gyro Bowl converted camera gimbal.

is crafted to analyze various densities, direction flows, crowd characteristics, and varying compositions of individuals with disabilities groups. A discussion of the actual experiment is given in Chapter 3. Streampix logs the start time of recording for each camera. All three computers are time synced over the internet with the National Institute of Standards and Technology time server shortly before the experiment. While there is no common clock during the experiment, an initial time sync allows the record times, between cameras, to be closer together. A few preliminary results, as well as how adjustments are made, are given in the following section.

After each experiment day, all session recordings are exported into .avi format that can be easily handled by the ARTKP/CINDER program. Each of the 12 cameras is processed for each ten-minute session time, leaving 12 text files of trajectory data for each session. An example shot of the tracking data processing can be seen in Figure 2.13. Yellow circles imply pattern recognition with the numbered ID. This feature was left in the processing to allow for catching problems in our procedure visually before obtaining tracking trajectories.

With twelve sets of data for each camera, it is then necessary to develop the means to combine data from each camera together and analyze trajectory information. Data from



Fig. 2.13: On the left bi-directional flow through a doorway, the right uni-directional.

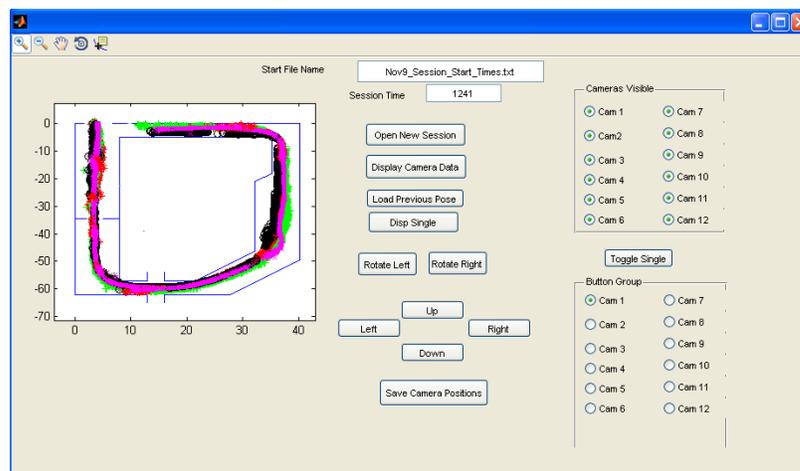


Fig. 2.14: Created Matlab GUI for managing and adjusting each camera position and orientation.

each camera is based on the camera's center and orientation. Globally converted data from each camera cannot occur until all camera tracking data is adjusted for varying differences in camera placement. For the sake of time, this was done using a Matlab [38] GUI that could load in all camera data from each session and visually manipulate the trajectories of one or all together. Patterns were placed in corners and other spots around the circuit to aid in aligning camera footage. These adjusted positions are then recorded and used to

convert each local pattern position into a global pattern position. The camera recordings from each video are also off slightly in time. An initial adjustment in time can be made by using the recorded start times of all cameras. However, record times and positions may still be off. An example of this current GUI can be found in Figure 2.14. To aid in understanding the relation of each trajectory to the map, `dx2coord` 1.1 created by Lukas Wischounig, is utilized to load a simple cad drawing of the map, or any map at dimension, into the same field as the data. The data from the cad drawing is also used in the aiding of basic data filtering on all trajectory data. Since any data found outside the bounds of the circuit cannot be tied to position they are dropped all together. A flowchart showing the overall process of movement of information from camera to output tracking data can be found in Figure 2.15. During each experiment day, the process to gather video data and record it was all that is accomplished. After the experiments are conducted, the data is moved from the Streampix sequence file format into a much larger video format to be processed by the ARTKP/CINDER built application. From here the files are gathered together and transformed into global coordinates for the circuit using cad model information and information from the circuit adjustment program. Then some basic filtering of the data alongside the floor plan is done before finally delivery of each camera trajectory file. Each trajectory file is identified by camera number and the session time of when it was recorded.

Some preliminary results for the circuit data can be found in Figure 2.16. Here ten IDs are plotted through the whole portion of several cameras in a particular session. Each ID goes through the circuit more than once. The resultant data shows formation consistent with the built environment and validates that trajectory data exists for each pattern. Three facility environments, a corner, bottleneck, and doorway, are shown here for example. Additionally, videos of singled out IDs through time show movement of logged markers consistent with the video data.

A stairwell experiment also took place. However, only two stairways are recorded and no corridors in between. Software tracking results of the data can be found in Figure 2.17. However, the trajectory data now moves in the vertical more, instead of the flat trajectories

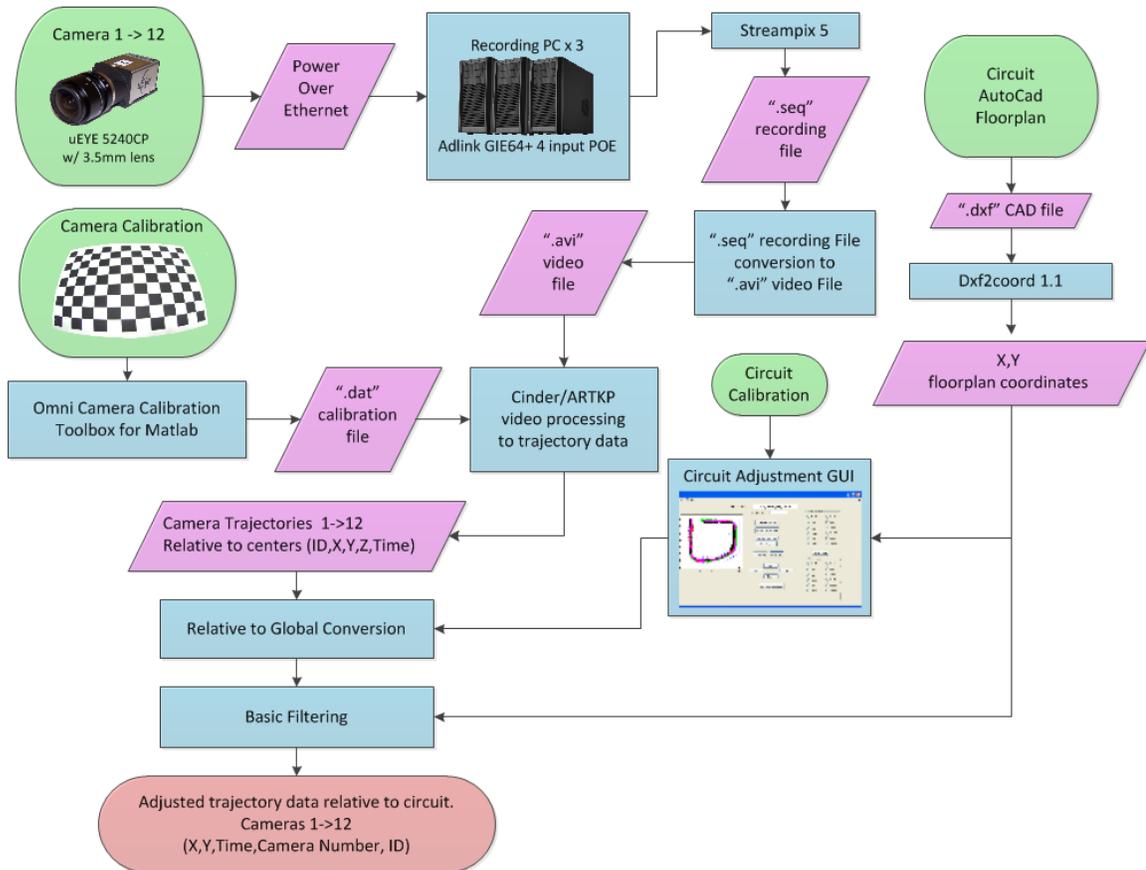


Fig. 2.15: Flowchart of camera data to crowd trajectory data results.

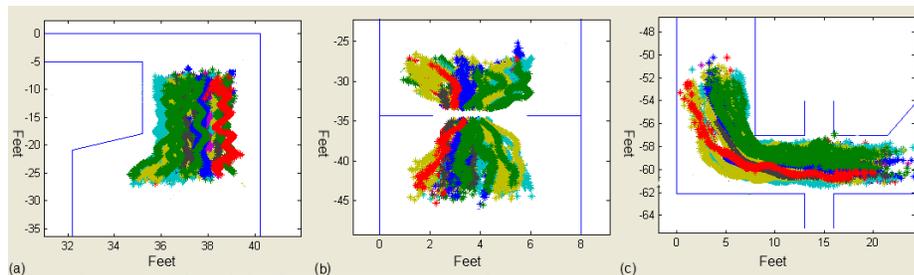


Fig. 2.16: Ten IDs through time, (a) bottleneck, (b) doorway, and (c) corner.

of the circuit. This presents more difficult issues, as the accuracy in the z-axis is not as accurate as the 2-D position within the stairs. For this reason, each experiment participant includes their height along with their ID. This way, correlations of ID and height can be used to reposition each ID trajectory based on position in the stairwell. A preliminary result

of the 3-D trajectories of ten IDs through time on one stairwell can be seen in Figure 2.18. Here the ID trajectories within the camera frame through the whole session are displayed, allowing for understanding of the trajectory formation on stairs and within the stairway environment. Overall this tracking system offered the ability to gather the data required. A further analysis of this data to be studied in Chapter 3. Discussion of the implementation and design of this tracking system can also be found in [44].



Fig. 2.17: bi-directional flow on a stairway with tracked data.

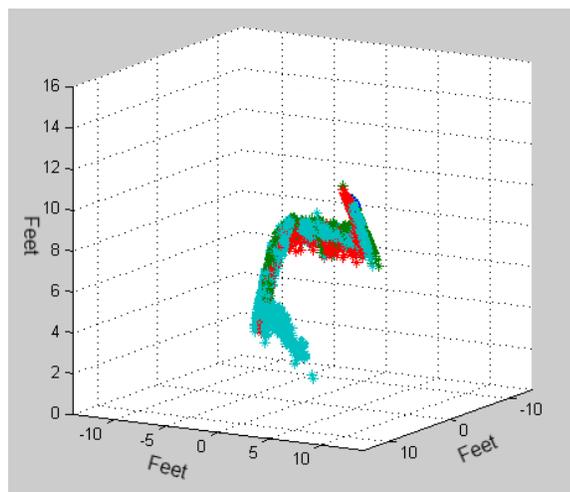


Fig. 2.18: Trajectory data of ten IDs through time on a stairway.

## 2.5 Problems Encountered and Future Improvements

There were many problems that suggest future improvements required of this system. The first is the alignment of different cameras within the circuit. The choice of lens for the camera was done conservatively to allow for maximal coverage. However, this lens choice made it difficult not only for calibration, but ultimately for stitching the data between cameras together. Originally, the data gathered in the circuit was to be continuous from the perspective of the end user. However, due to limitations of time, this concept had to be scrapped and all analysis would be performed through only the ranges of each camera detection field. A future implementation would allow camera stitching to occur and the data to appear more continuous without compromising the results of the trajectory data. There is also a slight difference in accuracy depending on the distance of the pattern from the camera, this causes the radius of accuracy to be different between a tall individual and a wheelchair member. While this difference was still negligible, it presents a source of error. Head patterns are tracked properly when not occluded in some way or too far from the camera. Patterns lower to the ground are impacted by shadows which lead to less pattern detection. Wheelchair level patterns are sufficiently high enough for good detection. As participants are unpredictable in their actions, there is a certain amount of error that will be caused that cannot be detected or tracked. Also, the alignment of suspended cameras is currently done manually, a more automatic form of alignment would be more helpful in improving accuracy of the data. Another place to improve is the time differences of the three recording computers. While those differences were not large, after learning to synchronize the time of each computer to a global clock before recording, the infrastructure of the facility and software did not allow for continuous time sync once the experiments start. Finally, within the circuit, the suspension of the cameras by rope offered a few problems. While the gimbal worked well to keep the cameras relative parallel to the ground, the suspension by string led to some problems. As the strings were tied off to the circuit structure, any bumping or intentional banging of the structure would translate potentially to the camera. As camera position determines pedestrian position, this is a problem that should be solved

in future experiments. Finally, in the stairway experiment, the ability to track patterns is much more difficult. For one reason, the patterns have a greater change in size vertically and patterns on the ground level are harder to detect. Also shadows that could not be removed, cause error with pattern detection. Mostly, participants must raise or lower their heads more than 45 degrees to view stairs, which removes the pattern from being tracked occasionally. Future improvements would suggest to use a stairwell that can be well lit to improve ability to track. Also, current stairwell results are in only the two dimensions. Inclusion of participant heights can be used to create 3-D trajectories accordingly.

## **2.6 Chapter Summary**

In this chapter, the goals for a tracking system to extract the trajectories out of a large-scale crowd experiment are described. Through initial research, it is determined that both the goals and limitations exclude any standard readily available method of tracking from being used. Using the abilities of fiduciary markers, a system is created to extract trajectories from a large-scale crowd experiment with a heterogeneous makeup of individuals. In this manner each pedestrian can be separably identifiable. The selection of cameras and hardware are described as well as the calibration process to get the best accuracy. A basic explanation of the setup for data collection of the experiment is shown. Some basic results and the problems that occur are also described. Future improvements are suggested for making this system work better and more efficiently. With the basic ability to take recorded video from experiments and process it to accurate trajectories leads to the next step which is analyzing those trajectories into meaningful crowd performance information. In the following chapter, the experiments and setup will be discussed and a program to analyze the data is described. Results from our crowd experiments are discussed in brief leading to motivation for the rest of the dissertation.

## Chapter 3

### Crowd Experiment Heterogeneous Tracking Data Analysis

In the previous chapter, a system to record and process a large-scale crowd experiment heterogeneous data into trajectories was discussed. The system was set up for a proposed experiment and design. This chapter will discuss the large-scale experiments we performed in 2012. The various variables to be possibly studied will be shown as well as the variables so far studied. To allow for not only this author but others to analyze the data found within our experiments a graphical user interface (GUI) was created. The outcome and use of this GUI is also explained in this chapter. For this dissertation, two variables of velocity and perception of overtaking are studied within our experiment results. The reasoning behind these variables and the results of velocity and overtake study in crowds with individuals with disabilities is presented in exploration. Finally, the challenges and problems faced for both the experiment and the data analysis are discussed. The end results of this chapter leading to the genesis of a need to create a model describing overtaking and further study of individuals with disabilities within a crowd.

#### 3.1 Experiment Design and Implementation

We conducted a series of large-scale crowd experiments in 2012, to study heterogeneous combinations of individuals with disabilities within a crowd. To track pedestrians, each individual wore a graduation cap with a marker affixed that can be tracked via a series of cameras.

The experiments took place in a gym at Utah State University, where a circuit was built containing a built environment possessing common, ADAAG compliant, facility structures. The circuit, shown in Figure 3.1, is shown in detail and size. Also shown, an overview of crowd movement in the circuit while wearing tracking markers.



Fig. 3.1: Crowd experiment circuit,  $12.2 \times 18.9$  meters.

For each experiment, individuals were injected at regular intervals to slowly increase the density of movement within the circuit. Included in that injection, a set of individuals with varying physical disabilities, to match a general composition realistic to the crowd. A large number of experiment participants, 60-100, are required to fill the circuit to reasonable capacity levels. Experiments dealt with uni-directional flow, bi-directional flow, as well of varying events in between. Each experiment going for ten-minutes to allow for participant rest and recording time of the system. A few captures from those experiments can be found in Figure 3.2.

From these experiments, data such as trajectory information, velocities, flow, density, and other interaction behavior has been collected for understanding, with a goal to created better models and better built environments. Pre and post surveys were also conducted to measure pedestrian perception and interaction. The need to link administered social

surveys, provided to all experiment participants, with data gathered in individual movement. Similar experiments were also conducted in a pair of stairwells, omitting groups of disability that cannot use stairs. A detailed description of the experiment, procedures, and detailed results pertaining to velocity can be found in [45,46].

### 3.1.1 Research Organization

To complete our large-scale crowd experiment studies, a research team was composed with a variable set of multidisciplinary members. The goal was to gather a team with knowledge in crowd dynamics, data analysis, data collection, crowd modeling, building

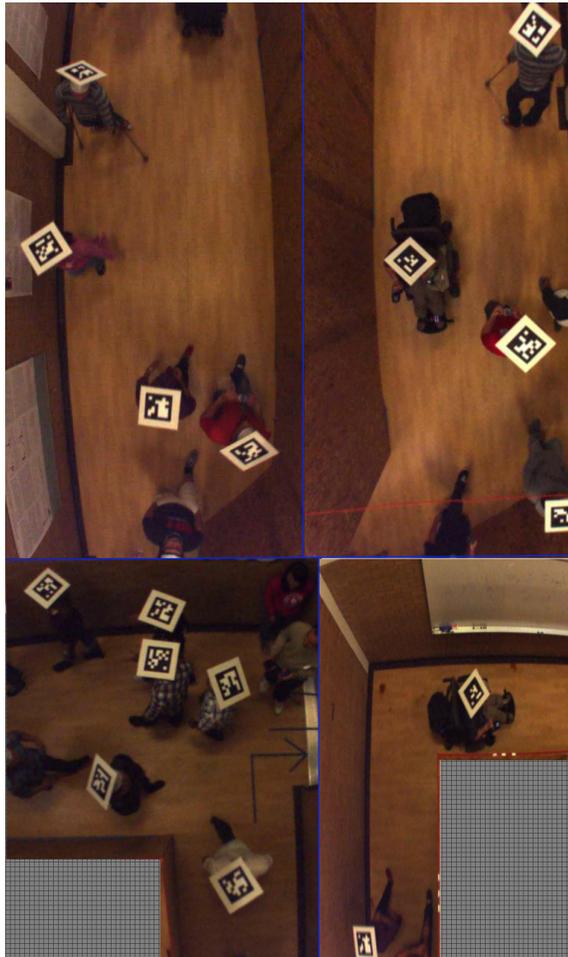


Fig. 3.2: Crowd experiment examples from CINDER/ARTKP program.

planning, crowd evacuation, and disability studies. This team was formed with five different disciplines of disability studies, transportation engineering, electrical engineering, management information systems, and environmental design. Each member or group delivered contributions and experience to the project surrounding automated extraction of trajectories from visual measurement, disability studies, built environment studies, individual-based modeling, and data mining. The research team was the collaboration of three centers at Utah State University: Center for Persons with Disabilities (CPD), Center for Self-Organizing and Intelligent Systems (CSOIS), and the Utah Transportation Center (UTC). This diverse collaboration allowed for the unique experiences needed to quickly develop and run several large-scale crowd experiments.

### **3.1.2 Experimental Variables**

With a research team capable of covering all aspects of the experiment, the variables to study needed to be found to shape how the experiment should be conducted. Experiment variables would form in the need of walkways, which are composed of level passageways, right angle corners, oblique angle corners, bottlenecks, doorways, and stairs. The common aspects of an indoor built environment encountered by a pedestrian. Also part of this composition are directions such as uni-directional flow, bi-directional flow, or some combination of both. Finally, the capacity and density level are of importance to study. After that the context variables such as the physical disabilities, sensory disabilities, individuals without disabilities, age, and gender. Those two sets of variables prescribe what is needed to setup the experiment, then it must be known what variables are desired as outcomes. Among those common and important to most crowd studies are walking speed, walking trajectory, longitudinal spacing, latitudinal spacing, speed/density, flow/density, speed/flow. A few examples of such studies can be found in [47, 48]. This author's contribution to the actual running of the experiment is minimal, however a detailed discussion and overview of the experiment can be found in [45, 49, 50].

### 3.1.3 Experimental Environment

The location to do the experiment in needed to be a controlled environment large enough for a solid construction circuit to be built within. The environment also must be able to facilitate the needs of the data gathering equipment and to be left there securely for the time required to setup the experiments, conduct the experiments, and take down the experiments. For the crowd experiments, the USU Motion Analysis Lab, a former gym, in the Health, Physical Education and Recreation Building (HPER) was chosen. A wooden circuit was constructed within the gym designed to allow participants to be injected from an outside doorway, while leaving the center for data capture gear. The circuit was built with six foot tall wood walls attached together and supported with half A-frame trusses supported by bags of concrete. The circuit, Figure 3.1, is shown in detail and size with the different built environment features. Two stairwells found in the racquetball court of the HPER building were also used due to their ability to be controlled for smaller periods of experimentation.

### 3.1.4 Participant Recruitment

Experiment study participants would be chosen in two forms, individuals without disabilities and individuals with disabilities. The plan to get a mixture of individuals with mobility-related physical, sensory, and other types of disabilities, including hearing and other impairments related to what is defined as ‘Go-Outside-Home’ disability. The criteria set forth in mobility-related disability is based on definitions found in the U.S Census Bureau’s American Community Survey (ACS) [51]. This survey separates mobility-related disability into Sensory, Physical, and ‘Go-Outside-Home’. Sensory disabled are defined as individuals with blindness, deafness, or a severe vision or hearing impairment. Physically disabled are defined as a condition that limits basic activities such as walking, climbing stairs, standing, etc. Finally, ‘Go-Outside-Home’ is a condition that creates difficulty in going outside the home to shop or visit a doctor’s office. Disability is also defined in the Federal Americans with Disabilities Act (ADA) as a physical impairment that substantially limits one or more of the major life activities of the individual [52]. Participants with

disabilities were recruited through the help of the Center for Persons with Disabilities (CPD) at USU. Those participants without disabilities were recruited from USU students, faculty, and staff. All participants were paid a 50 dollar stipend for their help each experiment day.

### **3.1.5 Recording System Implementation**

An overview for the recording system implementation can be found in Chapter 2. Each recording session was limited to ten-minutes to allow for participants to rest as well as allow the recording buffer to catch up. Given the tremendous amount of data being recorded, two individuals were used through each session to both start the recording and monitor the memory and solid state drives to ensure recordings were obtained. Recording start and stop times were coordinating through radio communications given the inability to see what was going on within the circuit.

### **3.1.6 Additional Survey Study**

A set of written surveys were given to the participants before and after each experiment to gather demographic data, walking habits, crowd perception and other pertinent information that cannot be understood through the data collection. This author was not part of this portion of the experiment, but it is mentioned due to its importance. A further explanation of those surveys can be found in Christensen et al. [49], Sharifi et al. [50], and Sharifi et al. [45]. Before each participant was sent into the circuit, they were assigned a hat and their height was measured. The hat identification number was written on the pre-survey along with the height so that their survey demographic information could be linked up with the trajectory data later. The height information was recorded for backup in case of failure in post processing or for three dimensional trajectory information in the case of the stairwell experiments.

### **3.1.7 Pilot Test Experiment**

Before we ran the official experiments, a pilot test experiment was conducted in the circuit. This test was performed only with individuals without disabilities. This allowed

for the testing of the camera tracking software, getting volunteers figured out for helping participants within each experiment, and resolving any potential congestion issues, etc. From this experiment, it was found that the tracking software works well, but a large amount of participants used their cellphones while walking the circuit. Other participants often removed their hats and others banged on the circuit walls often. It was also discovered that the recording computers would need to be synchronized in time before the experiment to ensure that recording video stamps were accurate. This pilot study also became the source of data on individuals without disabilities.

### **3.1.8 Experiment Study**

The large-scale experiment studies were conducted over two days (November 9th, and 15th, 2012). The stairwell experiment was conducted on another day (November 22nd). The experiments each day were composed of both uni-directional and bi-directional studies and compositions in between with a mix of 90/10, 80/20, 70/30, 60/40, and 50/50 percent bi-directional flow proportions. Finally, there would be a uni-directional study session of only the individuals with disabilities for each set. Each day consisted of 12-13 ten-minute sessions followed before and after with surveys. The group composition for each session varied from 64-84 participants without disabilities and 7-14 participants with disabilities. Each session was controlled by an individual with a radio who communicated the session start to those controlling the recording computers. Each participant was injected at roughly five second intervals with a goal to ramp up the density and congestion of the circuit. Individuals with disabilities were composed of vision impaired, those using non-motorized wheelchairs, those using motorized wheelchairs, those using roller walkers, and those with other stamina related physical disabilities. Each day, and session, had different compositions of disabilities based on participant availability, but all disability groups discussed in this dissertation were covered.

### 3.2 Data Analysis Examples

With the experiments conducted, the data was processed into the form of crowd trajectories as described in Chapter 2. To analyze this data, a graphical user interface would need to be created to study various variables of crowd interaction and to separate out the particular camera and individuals or lists of individuals to study. Then a list of variables to study were needed. The crowd analysis team came up with a list of the following variables that would be useful for study in our large-scale crowd experiment. These variables are incorporated into the GUI described in the following sections.

- ID number
- start and end times
- walking speed
- walking acceleration
- walking orientation
- numbers and identification of leaders and colliders
- mean and standard deviation of speed and acceleration of leaders and colliders
- mean longitudinal and lateral spacing
- mean time headway
- mean longitudinal and lateral spacing from inner and outer walls
- number and identification of overtaking individuals
- local speed
- local flow
- local density

Each one of the above items would be in relation to a single selected ID of study. For this dissertation, only a few of the above variables will be discussed in detail. A detailed discussion of the rest is described within the appendix.

### **3.2.1 Concerning Velocity**

One variable to be studied is walking speed of participants. As discussed earlier, common current models of individuals with disability assume the walking speed at half or set to only some slower value. Only more recently has it been determined that models should incorporate the heterogeneous differences that may exist between varying groups. In the aspect of evacuations, this variable would be useful to know how different individuals move as their evacuation time and impact interaction with the crowd can be dependent if they move slower than the crowd moves. Velocity is a common variable used as found in Helbing et al. [47] and Helbing et al. [48]. The further use, study, and definition are described later in this chapter.

### **3.2.2 The Importance of Overtaking**

During the large-scale crowd experiments it was visually noticed that the crowds slowed down significantly with the injection of some individuals with disabilities. As some individuals with disabilities are far slower than those without disabilities, there has to be a reason for why the crowd slows down. This can be for two reasons. One reason is if there physically is not enough space to pass the slower individual. This would be the case in an extremely tight corridor or doorway. The second reason would be that they do not pass the individual, even when there is space to do so. While this perception and reasoning for why they may or may not overtake for other non-physical reasons will not be studied in this dissertation, the concept of whether they overtake or not and how that occurs will. If a following individual does not overtake a slower moving individual, then they are forced to go at the same pace and speed as the slower individual. In an environment, this can dictate crowd movements and cause congestion upstream from where the decision was made. There are several studies currently looking at concepts of overtaking [53–55], as well as a study that

focuses on controlled experiments on the overtaking of individuals using wheelchairs [56]. This variable will be explained in definition and usage farther within this chapter.

### **3.3 Heterogeneous Crowd Data Analysis Graphical User Interface**

After conducting the large-scale crowd experiments, we ended up with a tremendous amount of data that will take a long time to analyze. To do this, there needed to be a way to collate, separate, and study various aspects of each experiment session, camera section, and groups or individuals within the experiment. To do this for both the author's research and the research groups analysis, a graphical user interface (GUI) was created that can allow any user to load up data files from a particular session and camera and study any and all variables previously described. The following subsections will go through a description of the GUI and some of its capabilities.

#### **3.3.1 Data Graphical User Interface**

To facilitate analyzing the various aspects of our crowd experiment, a GUI was created using Matlab [38]. While there are other forms of programming that can be used, Matlab was initially used due to its ability to be easily coded by several different programmers and also its ability to display graphs and manipulate data quickly. As time limited getting research data out, doing so in this platform allowed for fast prototyping and implementation of analysis in a graphical environment. The completed GUI can be found in Figure 3.3. A look at what the program looks like after a data file is opened can be found in Figure 3.4.

The operation and processes available within the GUI are as follows. First the session time and camera number of a particular file are entered in. Data files are text files labeled by session time and camera number. Once a new session is opened, the user can set up different groups to be studied, the identification numbers of each individual are entered into a group data file corresponding to that group number. The user can use a slide bar to look at different times in the experiment and the corresponding identification numbers for those individuals will show up on the screen as they were in the experiment. Finally, a time range of overall study can be set. Once the appropriate selections are made, the data can

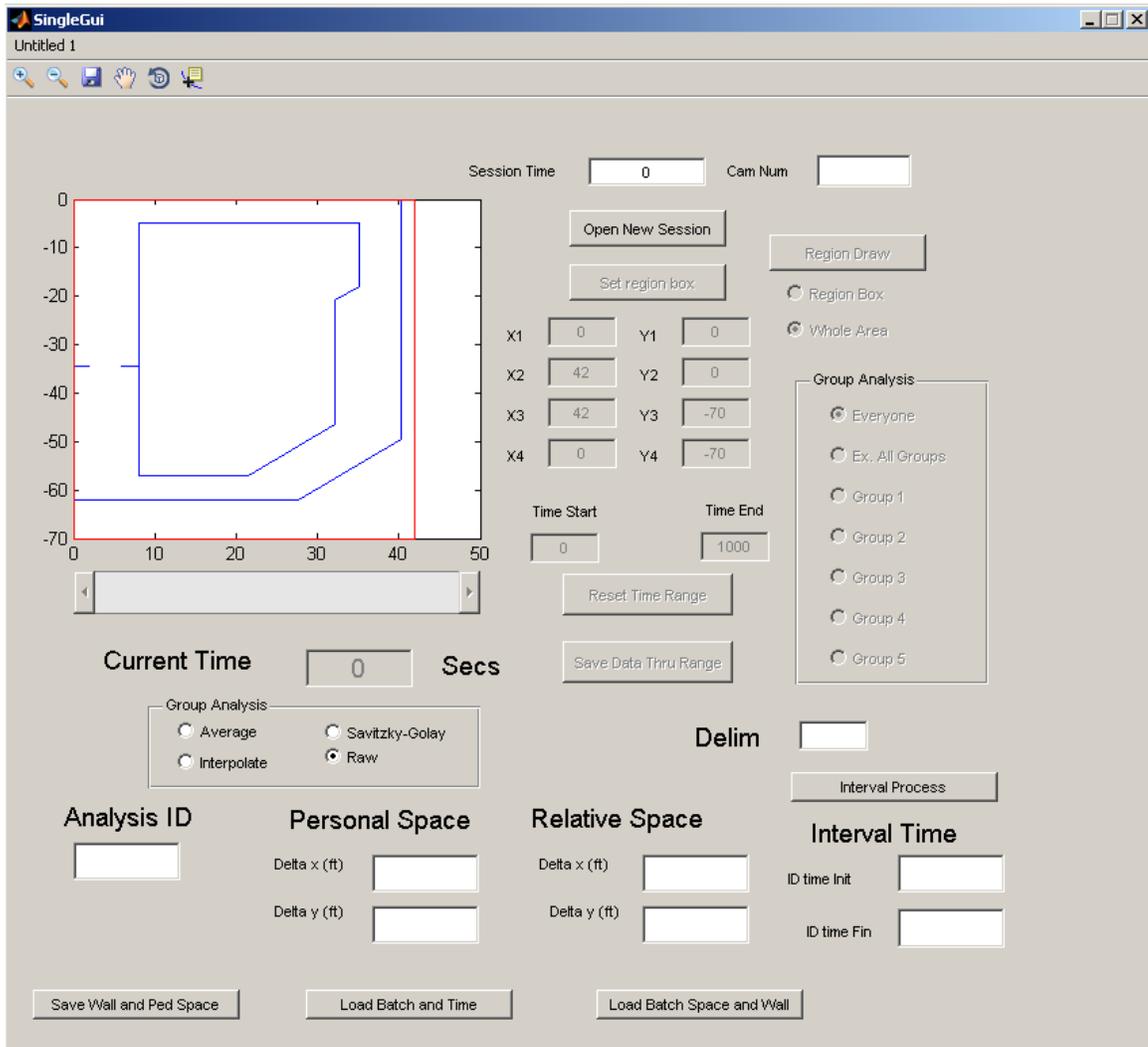


Fig. 3.3: Data analysis graphical user interface.

be processed to provide overall trajectory, velocity, acceleration, orientation, and direction information. After this process is performed, the user can now study variables specific to a particular individual. To do this, they enter in the specific identification number, variables of personal space and relative space, and a time interval range. These variables will be discussed in detail in a later section. From this analysis, they can then process to obtain variables regarding relative velocity, space and acceleration, overtaking, time headway, or a short form that includes a large selection of the mean results of variables discussed in section 3.2. They can also process values involving leader and collider spacing or wall spacing. A

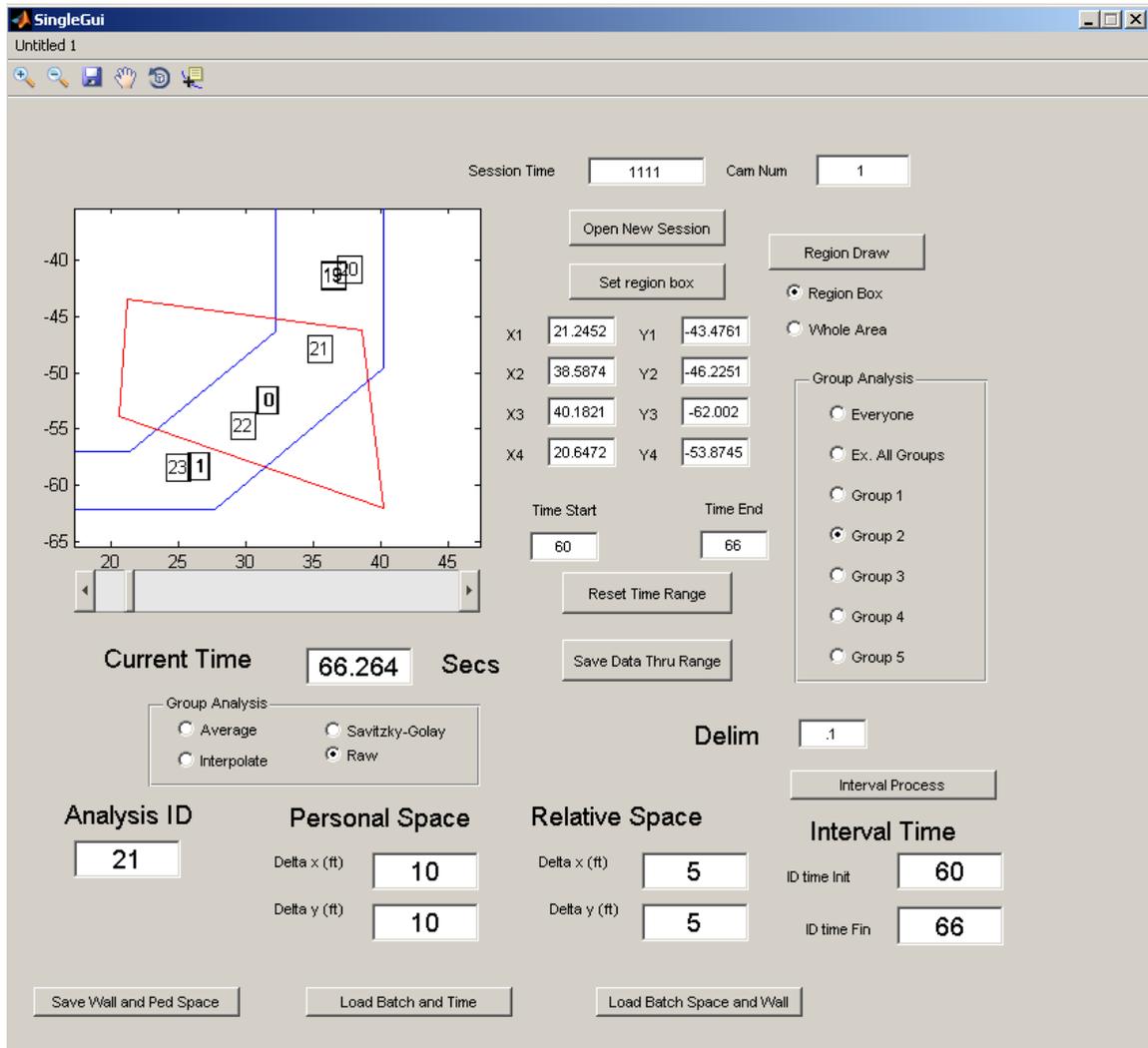


Fig. 3.4: Data analysis GUI with opened camera file.

description of the operation flow of the GUI and data files can be found in Figure 3.5.

### Explanation of Variables

While there are many variables listed in 3.2, only a few are studied in this dissertation. The first variable needed is direction. As the experiment performed both uni-directional and bi-directional flows this is crucial to understanding which individuals are leaders versus followers. Also, the circuit is in a circle, so the direction of movement will change in relation to an overall coordinate system. Finally, to determine overtaking, there must be

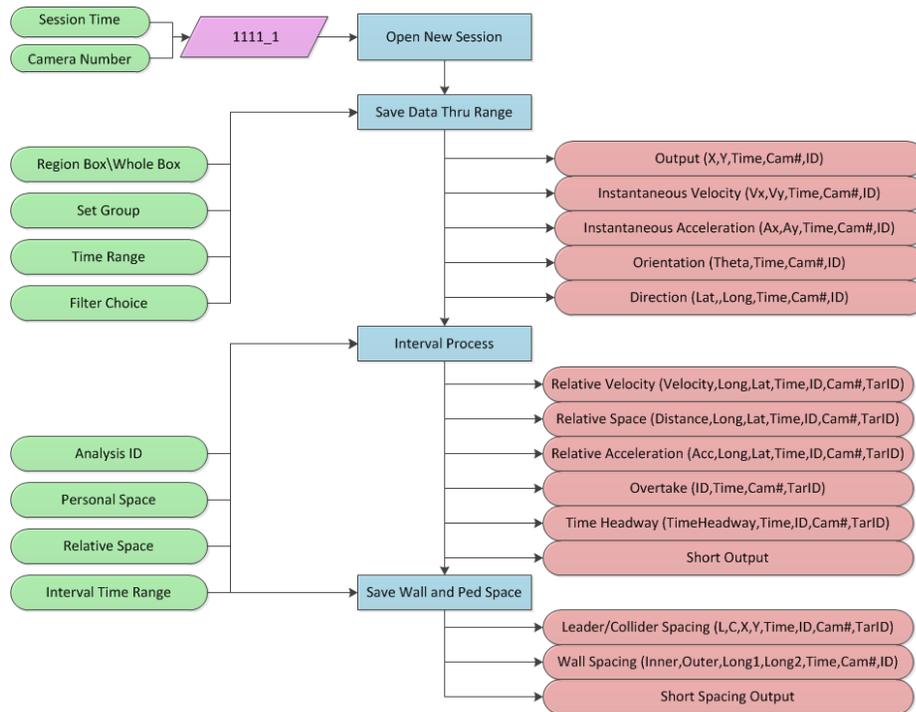


Fig. 3.5: Graphical user interface program flowchart.

an understanding of when a following individual becomes a leading individual. Figure 3.6 describes an individual at position  $r$  who has two values of direction, a longitudinal direction and latitudinal direction. These directions are universal and in respect to the circuit walls. To determine direction then falls down to the movement in the longitudinal vector over time as this is the direction of flow parallel to the walls. One direction value positive is then the direction clockwise in movement in the circuit and negative is counter clockwise.

One problem that exists is how to determine what is consider longitudinal when in corners and other aspects of the circuit. To do this, a direction test set out areas of longitudinal direction through the whole circuit and a test is performed to determine longitudinal movement for each section. This is not most likely the best way to calculate movement, but is the way chosen given time restrictions. Figure 3.7 describes those regions of longitudinal movement.

Analysis of pedestrian trajectory and velocity information are common forms of crowd analysis such as in Helbing et al. [47] and Helbing et al. [48]. Using these definitions walking

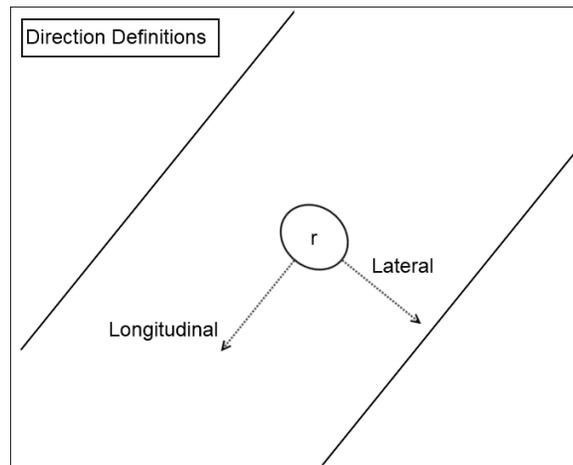


Fig. 3.6: How direction is determined relative to circuit walls.

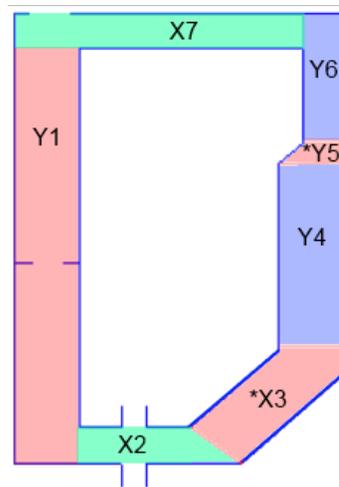


Fig. 3.7: Specified longitudinal versus lateral regions.

velocity over a given time range is given by

$$V_i(t) = \frac{\delta r_i(t)}{\delta \Delta T} \quad (3.1)$$

and

$$V_i(t) = \frac{\sqrt{(x_{t2} - x_{t1})^2 + (y_{t2} - y_{t1})^2}}{\Delta T}. \quad (3.2)$$

Here  $V_i(t)$  is the velocity of pedestrian  $i$  at time  $t$ . The position of the pedestrian  $i$  then  $r_i(t)$  at time  $t$ .  $\Delta T = t_2 - t_1$  is an interval of time between  $t_2$  and  $t_1$ .

Next is the study of overtaking. For this dissertation, an overtake is considered when a following individual overtakes the individual of study and remains a leader to that individual over the period of time remaining in the interval of study. A visual definition of what is considered an overtake is found in Figure 3.8.

Finally, variables used within this dissertation surround the analysis of what happens in the immediate region around the individual of study. These include local flow, velocity, and density. The generalized forms of common local calculations of flow, velocity, and density are called the Edie Definitions [57]. Density is commonly used for analysis of capacity and level of service study within crowd analysis [58]. These studies require the definition of a space called Relative Space, that surrounds the individual to be studied. Figure 3.9 describes Relative Space.

To study levels of service, which will be discussed later density must be obtained. This can be found by looking at the local speed and flow. The density variable used for all calculations is local density  $Density_{ave}$ , is

$$Density_{ave} = \frac{Q_{ave}}{V_{ave}}. \quad (3.3)$$

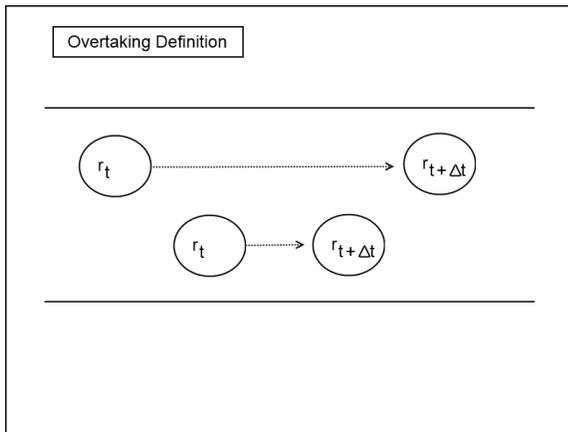


Fig. 3.8: How overtaking is determined in a following pedestrian.

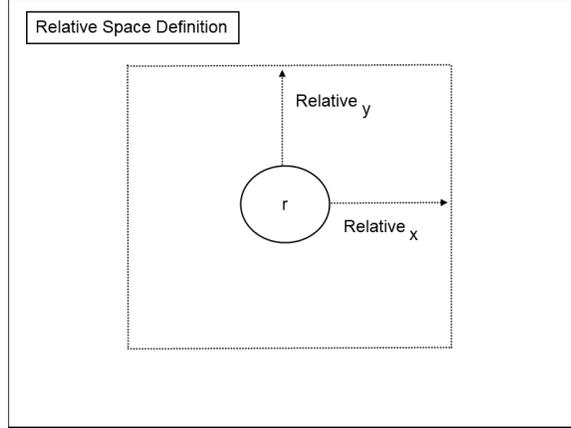


Fig. 3.9: How relative space for local variables is defined.

This is calculated using local flow  $Q_{ave}$ ,

$$Q_{ave} = \frac{\sum_i d_i}{A \cdot \Delta T} \quad (3.4)$$

and local velocity  $V_{ave}$ ,

$$V_{ave} = \frac{\sum_i d_i}{\sum_i \tau_i}. \quad (3.5)$$

All local variables are calculations of the pedestrians within an agent's relative space in a certain time interval. In the above equations,  $d_i$  is the distance traveled by pedestrian  $i$ ,  $A$  is the area of the relative space, and  $\tau_i$  is the time pedestrian  $i$  spent in the relative space.

### Batch Processing

As the crowd interaction with up to 14 individuals with disabilities needs to be studied per session, hand entering in every calculation became an impossible task. So a bulk processing capability was added to the analysis GUI. This allowed for an index file to be given to the GUI. Inside this index file is the session time and camera number followed by every ID to be studied and the start times of each ID to be studied. Since an individual may spend up to 20 or 25 seconds under each camera, the period of study interval is added

on to the start time of each camera or until the ID is no longer visible under the camera. Using this index, multiple sessions and multiple cameras can be entered under multiple IDs to be studied. The batch program will then process all of the possible GUI information variables and place the results in corresponding folders for session time, camera number, ID, and start time. A flowchart explanation of the batch tools added to the GUI can be found in Figure 3.10.

### Final Data Processing

Once batch files were composed for a set of individuals for a particular session, this information can then be processed and looked at for things such as velocity or overtake. This requires the analysis of various densities where these speeds or overtakes may occur. A set of density ranges are commonly used and called the Level of Service (LOS). Level of service ranges from A, where the individual has a very low density of individuals around and is able to walk at their desired speed of travel. At the other range, F, the individual is in a high to extremely congested density and is impacted in movement. The LOS values used for this dissertation, in Table 3.1, can be found in the 2000 Highway Capacity Manual [59].

### 3.4 Experiment Results

For this dissertation and due to the enormity of information collected from the crowd experiments studies of individuals with disabilities and their interaction in a crowd were limited to only the uni-directional sessions of which there were three each experiment day. As there was a limitation of time for analysis, only nine of the possible twelve camera data

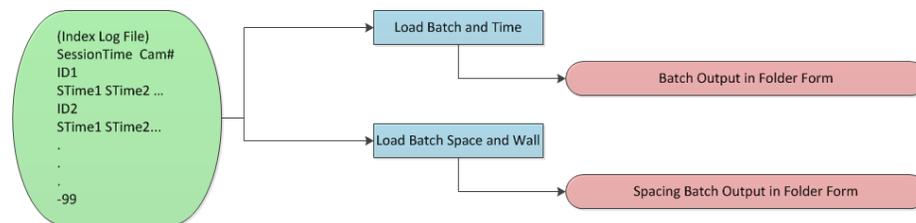


Fig. 3.10: Graphical user interface batch process flowchart.

Table 3.1: Level of Service densities.

	Density ( $P/m^2$ )
A	0 to 0.178
B	0.178 to 0.27
C	0.27 to 0.454
D	0.454 to 0.714
E	0.714 to 1.33
F	> 1.33

points were analyzed for this dissertation. All results are based on those nine cameras only in analysis. The areas of study can be found in Figure 3.11 with an emphasis on particular built environment features.

An initial analysis of pedestrian speeds versus level of service for all uni-directional sessions shows a distinct difference between the session with individuals without disabilities and those gathered with individuals with disabilities, and can be found in Figure 3.12. This provides strong motivation that speeds and the varying differences in speeds of different groups of disability need to be studied

While this dissertation is focused on only the variables needed for basic understanding and for motivation of a model, further and far more in depth crowd analysis, as well as a

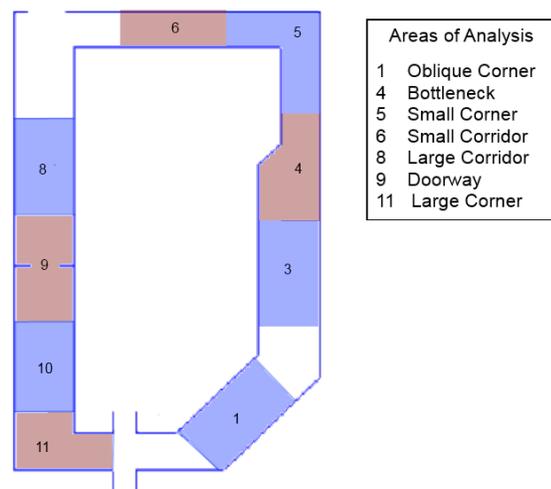


Fig. 3.11: Sections of circuit studied for analysis.

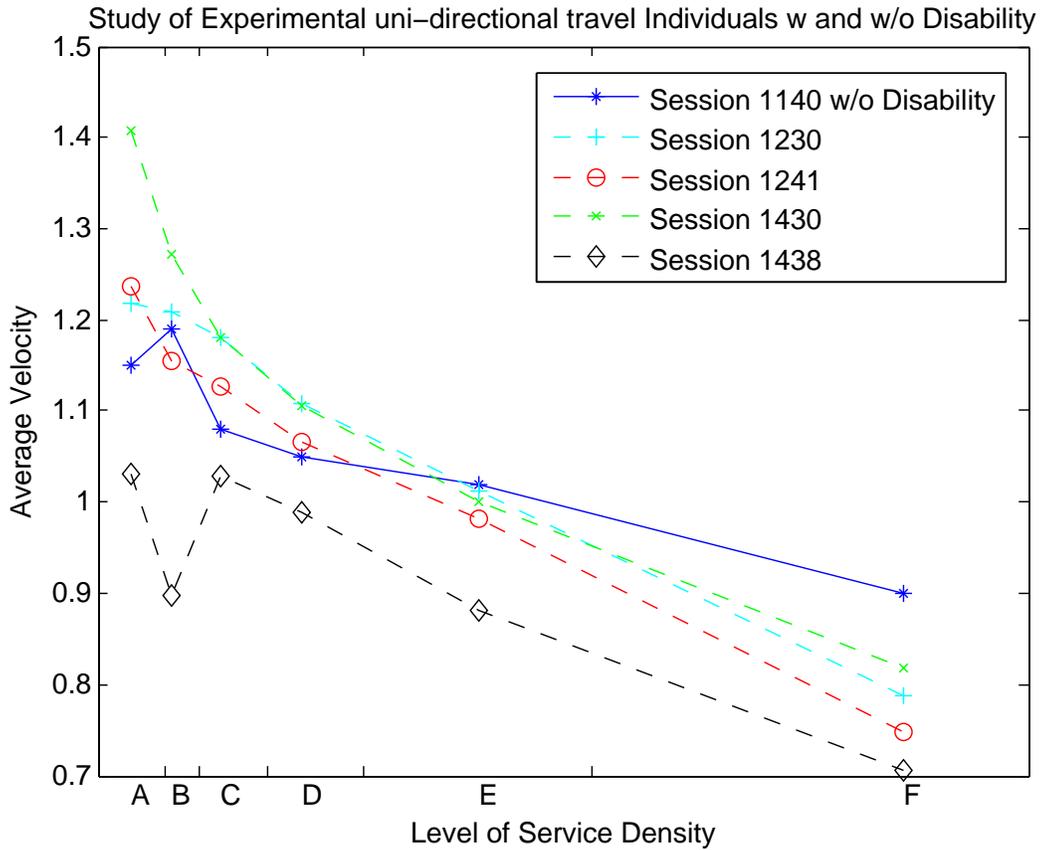


Fig. 3.12: Results of uni-directional experiments with and without disability.

discussion of data gathered, was published [45, 49, 50, 60–63].

### 3.4.1 Analysis of Velocity Information

Walking speeds were gathered out and separated out for each group with disabilities. As there were not enough non-motorized participants, their velocities were combined with those of roller walkers and served as the group of individuals using non-motorized ambulatory devices. Our paper Sharifi et al. [45], presents an in-depth study of velocity difference between vision impaired, motorized wheelchair, and individuals using non-motorized ambulatory devices. Its conclusion is that including individuals with disability in a crowd has a considerable reduction in the mean speed of the crowd through all types of built environments.

The mean travel speed for each group, over various parts of the circuit, can be found in Table 3.2. In this study, vision impaired and individuals using non-motorized ambulatory devices composed a 12% difference from individuals with no disability. The slowest group, motorized wheelchairs, had a 26% difference in speed.

For the purposes of future modeling, the desired speed for each group of individuals with disabilities was also gathered. This is defined as mean speed found when the individual speed was gathered when there was zero local density. That meaning the comfort speed that the individual travels when no impacted by those around them. This data was gathered through the sessions involving only individuals with disabilities. A table of those values can be found in Table 3.3. The desired velocities will be used to describe basic variation in future models found in Chapter 4. Here it is shown that those using non-motorized wheelchair and those using roller walkers travel at the same mean speed from our gathered experiments. All individuals with disabilities travel at slower rates than those without disabilities.

### 3.4.2 Analysis of Overtake Information

Given the differences in speed, individuals without disability will move faster than those with a disability. In Miyazaki et al. [56], the impact of the behavior of individuals overtaking those in wheelchairs was studied. As such, overtaking behavior dictates flow of a crowd as individuals decide to move past or stay behind a slower moving individual with disability. To study other potential differences between groups with physical disability, the

Table 3.2: Mean velocity of each crowd type through the whole circuit.

Vision impaired	0.7375 m/s
Indiv. using non-motorized ambulatory devices	0.7325 m/s
Motorized wheelchair	0.6425 m/s
Individuals without disability	0.81 m/s

Table 3.3: Mean desired velocity of each crowd type.

Vision impaired	1.19 m/s
Non-motorized wheelchairs and roller walkers	1.14 m/s
Motorized wheelchair	1.11 m/s
Cane and stamina impaired	0.9 m/s
Individuals without disability	1.3 m/s

average pedestrian overtake per person is looked at. An overtake can be described as an event where agent  $j$  is following agent  $i$ , both in the same direction, and agent  $j$  moves to a leader position in front of  $i$ . For the purposes of ruling out possible proxemic issues where people may travel in groups, an overtake for analysis only occurs when agent  $j$  remains a leader for a significant time within each study. Proxemics is the study of the space around pedestrians and the impacts of crowd density on social interaction.

In our experiment, we looked at sessions with combinations of disability and sessions without. The expectation should be that there are more overtakes experienced by the slower individuals with disability than those without. In analysis, individuals without disability experience on average of 6 overtakes in a ten-minute session, while individuals with disability experience an average per pedestrian of 25 overtakes under similar conditions. In Sharifi et al. [45], the groups of disability are separated into vision impaired, motorized wheelchair, and individuals with non-motorized ambulatory devices. For the purposes of this section, the non-motorized group is further separated into individuals with non-motorized wheelchairs, roller walkers, and canes/stamina. The results found in Table 3.4, show the mean overtakes per individual in each type group.

As shown, the mean number of overtakes found per pedestrian during a ten-minute session varied greatly per disability group. This is due not only to physical means but also some form a perception not to be studied within this dissertation. The data of overtakes

Table 3.4: Mean overtakes per pedestrian of each disability type.

Vision impaired	26.92 overtakes/ped
Motorized wheelchair	20.7 overtakes/ped
Non-motorized wheelchair	19.5 overtakes/ped
Roller Walkers	14.83 overtakes/ped
Canes/Stamina	44.4 overtakes/ped

is also studied for various portions of the circuit representing different built environments commonly found. Figures 3.13, 3.14, and 3.15 show the results for oblique, small, and large corners. Figures 3.18 and 3.19 describe small and large corners. Finally, Figures 3.16 and 3.17 describe the doorway and bottleneck portions. All Figures show the differences in overtakes found for various groups of disability. Of particular interest, the doorway, small corner, and small corridor saw far fewer overtakes.

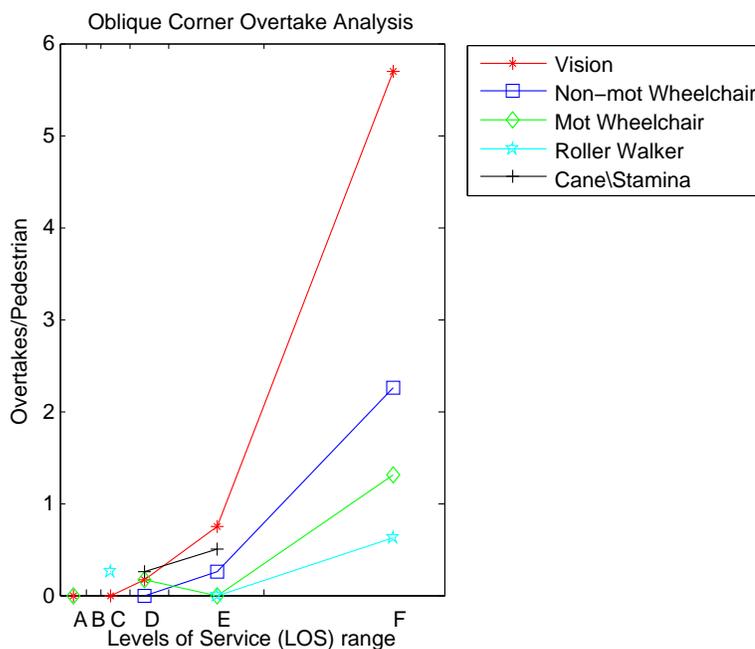


Fig. 3.13: Oblique corner overtake analysis, 2.44 m wide.

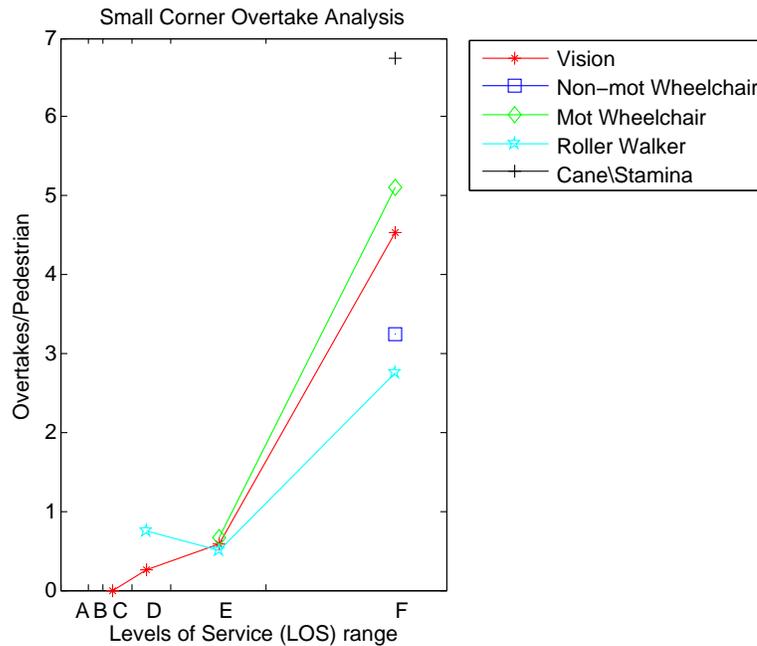


Fig. 3.14: Small corner overtake analysis, 1.52 m wide.

### 3.5 Problems Encountered and Future Improvements

During the pilot study, various additional problems were discovered regarding the tracking system. Short development time led to the lack of synchronous recording. This required two people to press record at the same time to start. This feature is an easy one to fix in future applications. Additionally, some patterns were taped onto with clear plastic tape over the top due to participants having extreme gait movement. However, the shining light occluded enough of the patterns that automatic detection was impossible. Overall it was discovered that participants were not focused often within the pilot study. While this was good from an experimental point of view, leading to hopefully more natural behavior, they would often look at their phones or even take their hats off. While the tracking system can handle fairly steep angles of hat deflection and still be detected, signs were placed throughout the circuit to remind participants to center their hats flat on their head so that they can be detected even if participants look down at their phones or up at the cameras while walking. Figure 3.20 shows the participant instructions chart. These

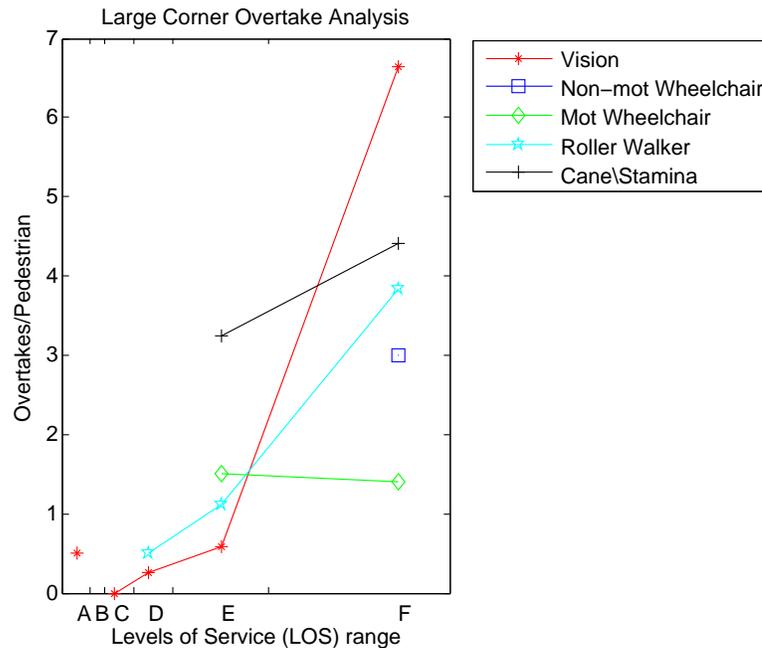


Fig. 3.15: Large corner overtake analysis, 2.44 m wide.

instructions alone eliminated most of the tracking problems outside of a few individuals running and jumping and providing unnatural crowd movement for the study. The final problem was a lack of study in individuals without disabilities to compare to our data. Only during the pilot study was any data gathered. And although a uni-directional session and three bi-directional sessions (90/10, 70/30,50/50) were gathered, they were gathered while problems in the tracking system existed so the data is poor and not completely representative. More analysis similar to the studies with individuals with disabilities would have been helpful for comparative reasons.

There were many problems encountered in the processing of data from our experiments. As markers were placed on the heads of pedestrians, their head sway motion can add artificially higher speeds to the mean speed averages calculated. While no attempt to find a way to filter this data out was done for this dissertation, this presents an effort that should be done to properly understand the data. Only basic sliding filters and mean filters were used to get rid of major differences in velocity between each instant of time.

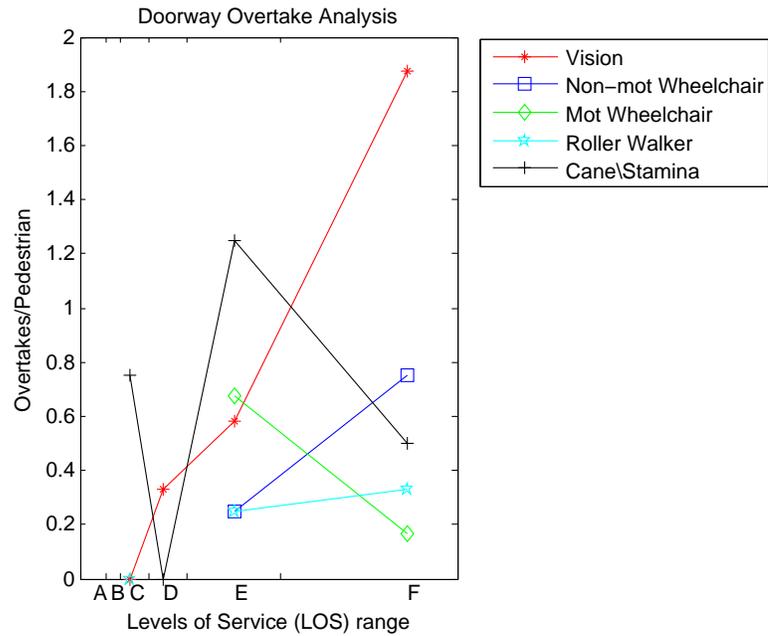


Fig. 3.16: Doorway overtake analysis.

Matlab was used for the creation of all tools to analyze data. However, much of the data requires order  $N$  type operations and therefore is very slow. While there was little time for implementing parallelism in the program code, unwrapping large loops and changing to a faster programming language would improve data analysis. Batch processing of a single ten-minute session for all nine cameras initially took 36 hours to process on one computer for a group of 12 individuals with disabilities. By creating separate parallel executions of the analysis for each camera, this time period was brought down to about eight-hours depending on the number of individuals analyzed for that session. However, this time can be reduced further. Another problem exists in the definition used in this dissertation to describe overtakes. The variable, overtakes per pedestrian, is composed as mean number of overtakes a particular group of individuals sees over a ten-minute period in this circuit only. While this variable is useful and demonstrates the differences between groups, it can only hold true for this circuit over that particular length of time. Therefore, another form of measure in overtaking should be explored and used in further research.

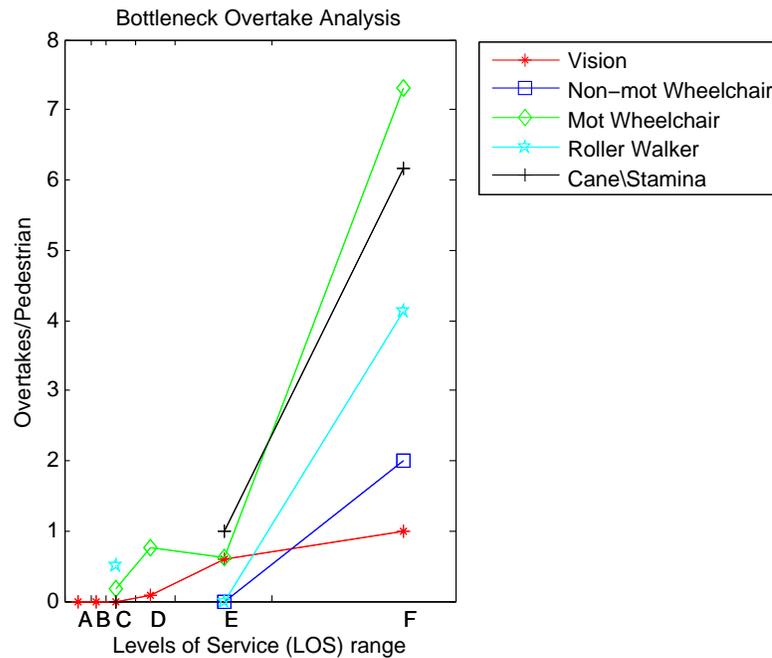


Fig. 3.17: Bottleneck overtake analysis, 2.44 m to 1.52 m wide.

### 3.6 Chapter Summary

In this chapter, the large-scale crowd experiments we performed are discussed in brief. The variables of study are presented and the particular variables of interest for this dissertation are described. A graphical user interface (GUI) is provided that can be used by crowd analysis individuals to study many different interactions and behaviors found within the data gathered from our experiments. From that GUI, the data of velocity and overtake is focused on. Data results show that there is a difference in the movement and interactions of groups of individuals without disabilities versus those groups with individuals with disabilities. Further those varying groups with disabilities have different velocities and also different overtake perceptions. Within the circuit, various built environments change those overtake amounts depending on the disability group looked at. Finally, problems and future elements not covered in this chapter are presented.

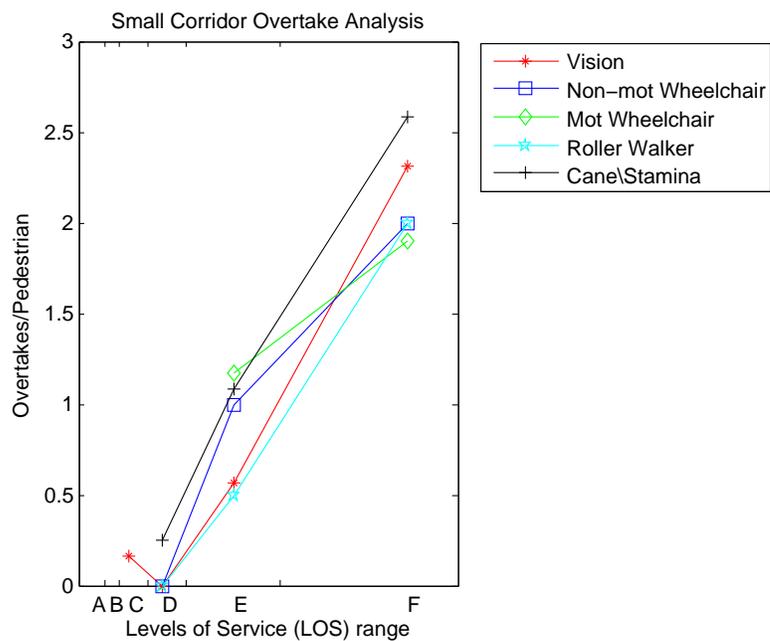


Fig. 3.18: Small corridor overtake analysis, 1.52 m wide.

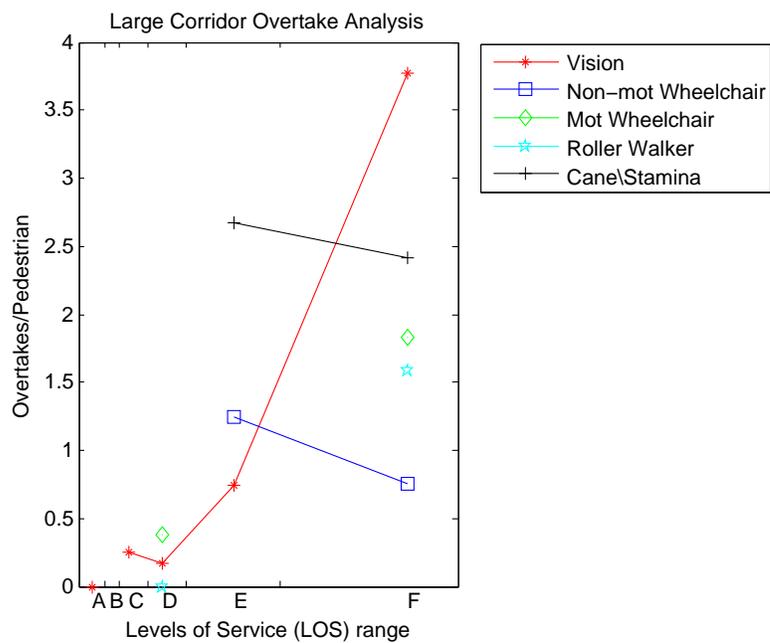


Fig. 3.19: Large corridor overtake analysis, 2.44 m wide.



Fig. 3.20: Instruction poster for participant hat placement.

## Chapter 4

### Crowd Modeling Including Overtaking Interaction

In the previous chapter, a GUI was created to analyze all the data gathered from our large-scale crowd experiments. Two variables in particular, velocity and overtaking, were analyzed. From these results, it was learned that individuals with disabilities shared varying and different walking speeds in crowds as well as in desired walking speeds. Also, it was shown that crowds overtake each group of individuals with disabilities differently. As pedestrians without disabilities move faster than pedestrians with disabilities their walking speed is only changed during congestion or when they do not move past the slower moving pedestrians. The reasons for why a faster moving individual may not move past a slower one can be broken down into physical congestion, or some form of perception that makes them decide not to move past. This chapter will explore the various forms of crowd modeling and then present an initial attempt at capturing the behavior of overtaking in its overall outcome to our circuit experiment. The model will be based on a common microscopic model call Social Force. This model will be modified to accept an additional overtaking component that can be varied to describe the varying differences of overtaking pedestrians found through the circuit experiments. This chapter will present some preliminary results to show what the hybrid model is capable of as well as problems and future improvements

#### 4.1 Forms of Modeling

There are three levels of modeling in crowd dynamics. The first and most accurate is microscopic, which intends to model the actions of every individual agent in the crowd, their interactions with each other, and their interactions with the environment. The next level is the mesoscopic. In the mesoscopic level, the agents are no longer looked at individually, but as classes or groups with their behaviors represented in distributions such as velocity

or flow. The final level is macroscopic. In the macroscopic level, all agents are treated homogeneously and concepts of movement are characterized in flow, density, and average velocities.

#### 4.1.1 Microscopic Modeling

Microscopic modeling works well for modeling heterogeneous behaviors as well as behaviors present in small interactions. However, this level usual requires a heavy computational burden, which until more recently, slowed down its approval. For this dissertation, the level of most interest is the microscopic modeling. Here individual behaviors and interactions can be modeled and implemented. One form of microscopic modeling is Cellular Automata (CA) [64]. In this form of modeling, everything is discrete in space, time and state variables. The design focuses on some form of a magnetic repulsion/attraction scheme. The dynamic interactions of individuals is based around a heuristic set of rules that determine agent interaction and movement at discrete intervals. The spatial area is discretized for a particular environment. At each iteration, all agent movements are considered based on rules for movement. The rules are developed in three categories exit path, interaction, and environment. The desired path to an exit can be developed based on a shortest path algorithm or some floor field. Rules involving the interactions with other agents, determine actions of attracting or repulsing from others. Finally, rules based around interactions, where agents are repulsed from colliding with the environment. A famous CA model is found in Blue and Adler [65,66]. Previous work has been done to study individuals with disabilities in a crowd environment using CA. This included the development of a system called BUMMPEE or Bottom-Up Modeling of Mass Pedestrian Evacuations [14, 16, 18]. This also included the study of individuals with disabilities in an evacuation of an airport and other facilities [12, 19].

The most interesting microscopic model, for the purposes of this dissertation, is the Social Force Model developed by Helbing and Molnar [67]. This technique was further proven and developed in Helbing et al. [68]. The social force or social behavior model was originally draw from a Boltzman-like gas kinetic model. Further developments lead to a

model that is based on the summation of three forces. All forces based on the idea that a pedestrian moves through an environment as if they are acted upon by three forces, a desired direction of movement, the pedestrian interactions around them, and the environmental reactions around them. A detailed discussion of the Social Force Model will be explained in a following section.

#### 4.1.2 Macroscopic Modeling

In the macroscopic level, crowds are described using some sort of fluid or gas theory, but with some constraints to semi-compressibility aligning more with human interaction. All agents in the fluid are therefore typically considered as homogeneous. Gas kinetic models make up some of the first macroscopic descriptions [69]. They describe large particle systems, with interactions between particles based on field interactions of the collective group. Here density and flow are parameters of analysis. Macroscopic examples of the kinetic model can be found as in Kachroo et al. [70] and Hoogendoorn et al. [27]. As gas models do not always work in more crowded environments, Dirk Helbing also created some of first modeling combining gas kinetics with fluid dynamics [71].

#### 4.1.3 Mesoscopic Modeling

In mesoscopic modeling, attempts are made to gain the behaviors and characteristics of the microscopic level with the simplicity and group behavior of the macroscopic level. Various examples of this can be found in Kachroo et al. [70] where a hybrid model is presented. Bellomo and Dogbe [72] explore the use of mean-field theory in crowd dynamics.

### 4.2 Social Force

The Social Force Model was first developed by Helbing and Molnar in [67]. This technique was further developed in Helbing and Molnar [73]. The model is originally developed from a Boltzman-like gas kinetic model. The model consists of a singular point  $\alpha$  with a point velocity that changes over time,  $\delta\alpha(t)/\delta t = v(\alpha)$ . That acceleration is impacted by a Social Force called  $F$ . The Social Force  $F$ , a representation of all the influences,

including other pedestrians and environment, that an individual would experience in a crowd. Those influences treated as an invisible Social Force. The force  $F$  on a particular agent  $i$ , is

$$F = F_i + F_{ij} + F_{iW}. \quad (4.1)$$

The self-driven force,  $F_i$  is a desired velocity to a goal, based on error of velocity to that desired goal.  $F_{ij}$  is the interaction of individual  $i$  with  $j$ . The social interaction, due to the perceived “personal space” and other physical interactions, described as a repulsive force decreasing over distance.  $F_{iW}$  represents interactions of agent  $i$ , with a wall  $W$ . The presented model developing the idea that pedestrians move with a set of strategies based on interaction and experience. The best route, which is efficient to the individual, becomes the route they take and it can be modeled. The first force  $F_i$ , is the desired force to a goal position  $p$ . This is based on the position of the agent  $r_i(t)$  and its current velocity described as  $\frac{\delta r_i^z(t)}{\delta t} = \vec{v}_i(t)$ . Assuming an individual starts out with the initial goal in mind, the desired velocity direction  $\vec{v}_i^0$  can be found in equation (4.2). This equation is the combination of the desired velocity  $v_i^0(t)$ ,

$$\vec{v}_i^0(t) = v_i^0(t)\vec{e}_i(t) \quad (4.2)$$

and the desired direction of motion  $\vec{e}_i$ ,

$$\vec{e}_i(t) = \frac{\vec{p} - \vec{r}_i}{\|\vec{p} - \vec{r}_i\|}. \quad (4.3)$$

All forces on a pedestrian are considered to be in the form of acceleration forces. There is also consideration of a relaxation time,  $\tau_\alpha$ , or the time it takes for a pedestrian to return to its desired velocity. The desired force  $F_i$  is then described as

$$F_i = \frac{1}{\tau_\alpha} \left( v_i^0(t)\vec{e}_i(t) - \vec{v}_i(t) \right). \quad (4.4)$$

The interaction between a pedestrian  $i$  and  $j$ , is a complex combination of personal space objectives and physical friction force. In the original introduction, this force was left

as a repulsive exponential potential field, for the purposes of simulation [67]. That means that any interaction between pedestrians takes into account forces from every agent within a prescribed region, regardless of being in front of or behind pedestrian  $i$  and its motion of travel. In Helbing et al. [68], options to introduce line of sight, angle of vision, and other concepts making the force more realistic were presented. For the purposes of this paper, pedestrian interactions will remain basic, with a note that more complex interaction forces will be introduced in the future. The basic interaction force is based on the direction difference between agent  $i$  and  $j$  as  $r_{ij}^{\vec{}}$ . The potential field  $U_{rep}$  is

$$U_{rep} = \exp(-\|r_{ij}^{\vec{}}\|), \quad (4.5)$$

and the subsequent force  $F_{ij}$  is

$$F_{ij} = \frac{r_{ij}^{\vec{}}}{\|r_{ij}^{\vec{}}\| \exp(\|r_{ij}^{\vec{}}\|)}. \quad (4.6)$$

The final force between agent  $i$  and a wall object  $W$  is the force found by the direction difference  $r_{iW}^{\vec{}}$ . The force  $F_{iW}$  is also presented as an exponential potential force as

$$F_{iW} = \frac{r_{iW}^{\vec{}}}{\|r_{iW}^{\vec{}}\| \exp(\|r_{iW}^{\vec{}}\|)}. \quad (4.7)$$

Summed together, the forces represent the Social Force acting on an agent as found in equation (4.1).

With the basics of the Social Force Model understood, a method needs to be added to describe the interaction force that is in addition for describing the perception of overtaking that exists in crowds. This particularly true when describing the interaction of crowds with individuals with disabilities. The following section will describe Fractional Order Potential Fields which will be the basis for this addition to the standard Social Force Model.

### 4.3 Fractional Order Potential Fields

Potential fields, [74], are often used in the path planning of robots as found in Ge and

Cui [75]. Such fields are used as with attraction fields to drive an agent towards something or repulsive fields as to drive an agent away from something. By assigning repulsive potential fields to objects or other robots and attraction fields to desired goals, a 'safe' path can be calculated for a robot to travel. An example of an attractive potential field between points  $i$  and  $j$  with a gain  $k$  is

$$U(x) = \frac{1}{2}k(x_i - x_j)^2, \quad (4.8)$$

where the force applied to the agent is considered the negative gradient of the potential field as

$$F(x) = -\nabla U(x). \quad (4.9)$$

In this manner, as the distance between  $i$  and  $j$  increases, the value of the potential field is greater, drawing the agent  $i$  to point  $j$ . The exact opposite is true for a repulsive potential field where the potential field value increases as the distance is decreased. The shape of the potential can be varied based on the potential field equation. One way to vary the shape of the potential field is through the use of Fractional Order Potential Fields (FOPF) [76]. Using a FOPF allows for a large variety of potential shapes that can be customized to fit a modeling situation. FOPF have been used to describe aerial robotic path planning in Jensen and Chen [77]. For our research, the varying shape will be used to describe how pedestrians interact with a disabled pedestrian. In some circumstances, a following or passing individual may have reason to pass a disabled individual, perhaps to differences in velocity. In other circumstances, an individual may not pass an individual with a disability, or have some hesitation in doing so, due the size, motion, or something else. Through FOPFs, both these extremes and everywhere in between, can be described.

A repulsive FOPF starts from the definition of the Coulombian electric field  $E(r)$  is

$$E(r) = \frac{q}{4\pi\epsilon_0 r^2}. \quad (4.10)$$

Integrating this field once produces a punctual charge  $V_1(r)$ ,

$$V_1(r) = \frac{q}{4\pi\epsilon_0 r}, \quad (4.11)$$

twice produces the Coulombian potential field  $V_2(r)$ ,

$$V_2(r) = \frac{q \ln r}{4\pi\epsilon_0}. \quad (4.12)$$

This is a potential field generated by the uniformly distributed charge along a straight line. In analyzing the normalized potential fields of both equation (4.11) and (4.12), there is a difference in field strength between the two when distance is varied. In fact,  $V_2(r)$  has a stronger force at a larger distance than  $V_1(r)$ . With successive integrations of equation (4.10), the force increases at larger distances. Using fractional calculus any  $n$ th iteration can be found including fractional order integrals. To do this, the Weyl fractional integral, [78], is of the form:

$$V_n(r) = W^r E(r) = \frac{q}{4\pi\epsilon_0 \Gamma(n)} \int_r^\infty \frac{(\theta - r)^{n-1}}{r^2} d\theta, \quad (4.13)$$

where  $V_n(r)$  is the  $n$ th integral of  $E(r)$ . In equation (4.13),  $n$  must be greater than 0 and  $\Gamma(n)$  is the gamma function,

$$\Gamma(n) = \int_0^1 \left[ \ln \left( \frac{1}{t} \right) \right]^{n-1} dt. \quad (4.14)$$

After manipulation, equation (4.14) can be written as

$$V_n(r) = \frac{q}{4\pi\epsilon_0} \frac{\Gamma(2-n)}{r^{2-n}} \quad \forall n \in (0, 2)(2, \infty). \quad (4.15)$$

Normalized between 0 to 1, over a distance range  $(r_{min}, r_{max})$ , the potential field is 1 at  $r_{min}$  and 0 at  $r_{max}$ . The simplification leads to the form

$$U_{drep}(r) = \frac{V_n(r) - V_n(r_{max})}{V_n(r_{min}) - V_n(r_{max})} = \frac{r^{n-2} - r_{max}^{n-2}}{r_{min}^{n-2} - r_{max}^{n-2}}. \quad (4.16)$$

Placing the minimum distance  $r_{min}$  at 1 and a maximum distance of  $r_{max}$  at 10, and  $1 \leq n \leq 5$ , the result of equation (4.16) is shown in Figure 4.1.

Equation (4.16) allows for large heavy strong fields at higher  $n$  and smaller fields with minimum impact at small  $n$ . This means the force at varying distances can be changed by varying the order  $n$  and also by modifying the minimum and maximum impact distances of  $r_{min}$  and  $r_{max}$ . This is beneficial in creating maximum force output, as if its a physical object, and different radii of distance representing perhaps the size of the object at the minimum distance. Also, allowing for the lack of potential field impact beyond a certain maximum distance. One problem with equation (4.16) is when  $n = 2$ , as the equation

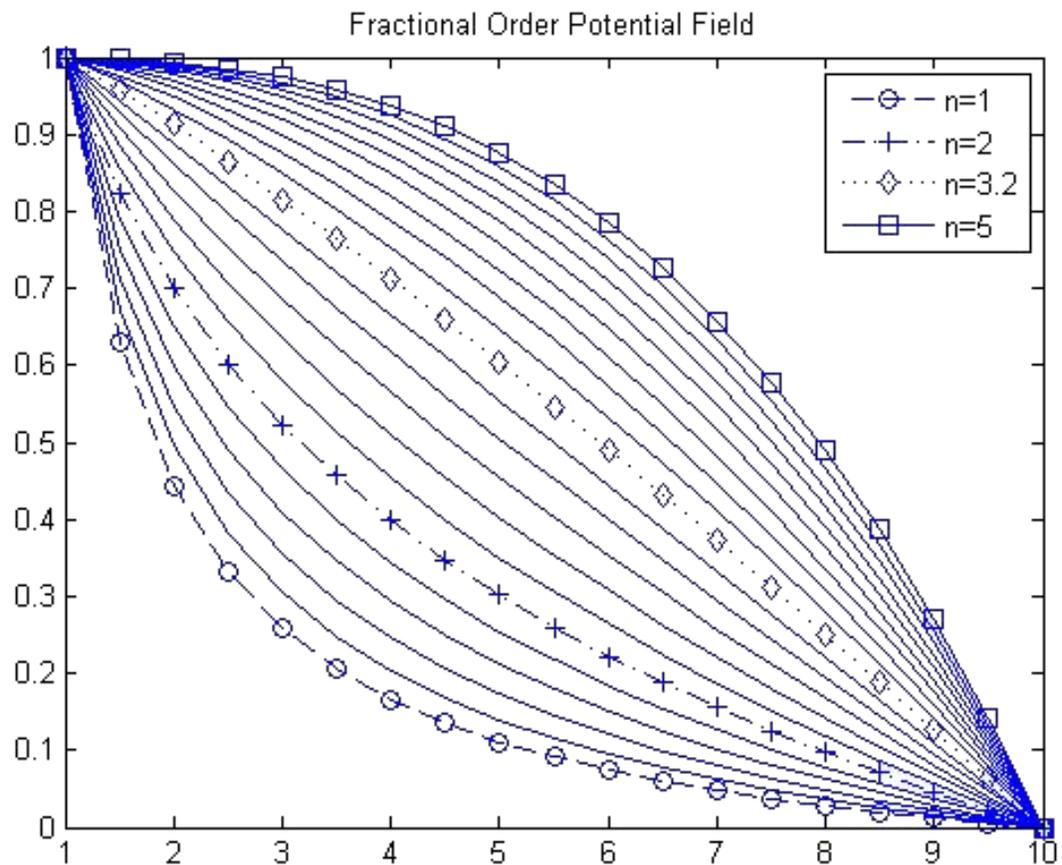


Fig. 4.1: Repulsive Fractional Order Potential Field,  $1 \leq n \leq 5$ .

becomes a singularity. For that reason, the normalized version of  $V_2(r)$ , (4.12), is used in its place. The normalized field in that case is

$$U_{drep(n=2)} = \frac{\ln(r/r_{max})}{\ln(r_{min}/r_{max})}. \quad (4.17)$$

#### 4.4 Social Force Simulation

In Chapter 3, it was shown that individuals with disability have slower velocities to those without disability. It was also shown that the number of overtakes each group experience vary. Social behavior can be described in three aspects of psychosis, physical attributes, and knowledge-base

To simulate Social Force, various libraries and programs were examined. The goal is to find a library which can simulate Social Force, within an environment under similar circumstances as the experiments, and with the ability to handle similar number of agent interactions. The library PEDSIM, by Christian Gloor provided for the best framework for testing pedestrian models [79]. The PEDSIM library allows for the simulation of a large number of agents, far over that of the experiment, in real-time conditions with very little lag. The library was combined into a graphical user interface. The circuit was coded to the same dimensions as the pedestrian experiment. To facilitate a heterogeneous crowd mixture, an additional agent type was added that can be changed in velocity and would include the FOPF as part of its model. Figure 4.2 shows the PEDSIM framework integrated into a graphical user interface.

Section 4.3 showed the versatility of Fractional Order Potential Fields in changing the shape of a potential field around an agent. In this manner the order  $n$  can be increased to change the number of pedestrians that can overtake an individual. The minimum size  $r_{min}$  can also be changed to meet the spacing difference that may be present between the different disability groups. Taking the negative gradient of (4.16), the force  $F_{d_{ij}}$  represents the interaction between a pedestrian  $j$  and agent  $i$  with a disability as

$$F_{d_{ij}} = -\frac{r_{ij}^{\vec{}}(n-2) \|r_{ij}^{\vec{}}\|^{n-3}}{r_{ij}^{\vec{}}(r_{max}^{n-2} - r_{min}^{n-2})}. \quad (4.18)$$

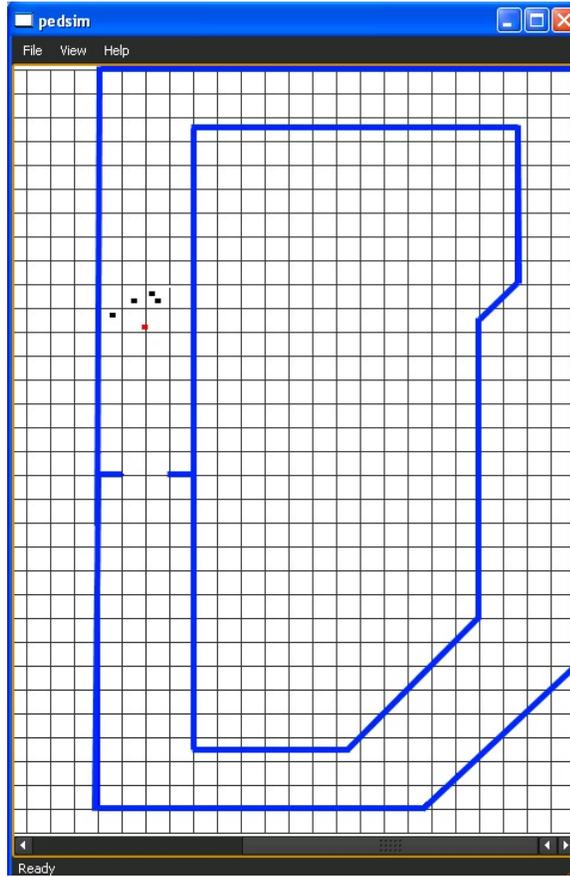


Fig. 4.2: PEDSIM library by Christian Gloor.

In the simulation, only the disabled type will have this interaction added to its total forces since it represents the forces imparted on all other individuals within the crowd.

Combining this new additional fractional order potential force with the Social Force Model in (4.16), the new hybrid model for a disabled agent is

$$F = A_{Fi}F_i + B_{Fij}F_{ij} + C_{FiW}F_{iW} + D_{dij}F_{dij}. \quad (4.19)$$

In this equation  $A_{Fi}$ ,  $B_{Fij}$ ,  $C_{FiW}$ , and  $D_{dij}$  represent gains that can be used to further adjust the overall strength of each force within the combined forces of agent  $i$ .

This new model now allows for the same standard interactions and properties found in Social Force, but with the additional ability to vary the shape of an additional potential

field to modify the way the crowd interacts with the agent. A published discussion of this model can be found in Stuart et al. [80].

#### 4.5 Simulation Results

To aid in comparison and understanding of the impacts of the hybrid addition to the Social Force Model, the Social Model used for simulation was reduced to its simplest form only accounting for desired velocity and using a basic form for the interaction force and environment force, where the gains are adjusted only. For simplicity, the initial results are created just to demonstrate the benefits and potential capabilities of the FOPF addition. Simulations were run on the PEDSIM library with one agent containing the disability model, and another agent, released a few seconds later, traveling in the same direction. To create similar velocity conditions between an individual with disability vs. one without, the velocity of the disabled individual was set to one m/s while the overtaking individual was set at two m/s. In this scenario, the faster agent should overtake the slower agent, unless prevented by the FOPF potential field. As stated previously, the initial models for both Social Force and FOPF do not include any limiting factors such as direction of travel and angle of vision. The first result, shown in Figure 4.3, demonstrates a disabled agent traveling on the dotted line and an overtaking individual without disability on the dashed line. The minimum and maximum field distance are set to one and ten respectively. The order  $n$  is varied from one to five, with several results included. A time snapshot of position is shown at every three seconds through a 21 second period. With a relatively small  $n$ , a passing individual has no problem overtaking. With increase of  $n$  the overtaking distance goes out to two feet and then to three feet in distance within the circuit. At an order  $n = 4$  the force is so great as to keep the faster agent from almost overtaking completely. If the corridor was any smaller, the agent would be forced to follow. In Figure 4.4, the order of  $n$  is fixed and the minimal distance is change from one to five. This change demonstrates a change in when the fractional field is at its maximum to the overtaking agent. Although caution must be taken as this also changes the field shape, and may require a change in the maximum distance and order to reach similar field shape results as a different order. As

the model is fractional, any order of  $n$  can be used, therefore allowing for a custom match of interaction to each individual disability type.

Next an input file was setup for the simulation to match the circumstances found similar to the crowd experiments. A model of the circuit used in our experiments is placed in the simulation and pedestrians are injected every five seconds into the circuit to represent the ramp up of density as done within our crowd experiment. For the simulations, the composition is composed of the average found in our experiments which is 71 individuals without disabilities and nine individuals with disabilities. The agents without disabilities can take in variables of desired velocity and entrance time. The agents with disability use the hybrid model addition and can take in variables of desired velocity, entrance time,  $r_{min}$ ,  $r_{max}$ , and  $n$ . For the purposes of all simulations within this simulation only  $n$  was focused on and  $r_{min}$  was left at one meter and  $r_{max}$  set to ten meters. Figure 4.5, shows the simulation with at low traffic density and the agents spread throughout the circuit. Figure 4.6 the simulation at medium traffic levels and Figure 4.7 at heavy traffic densities.

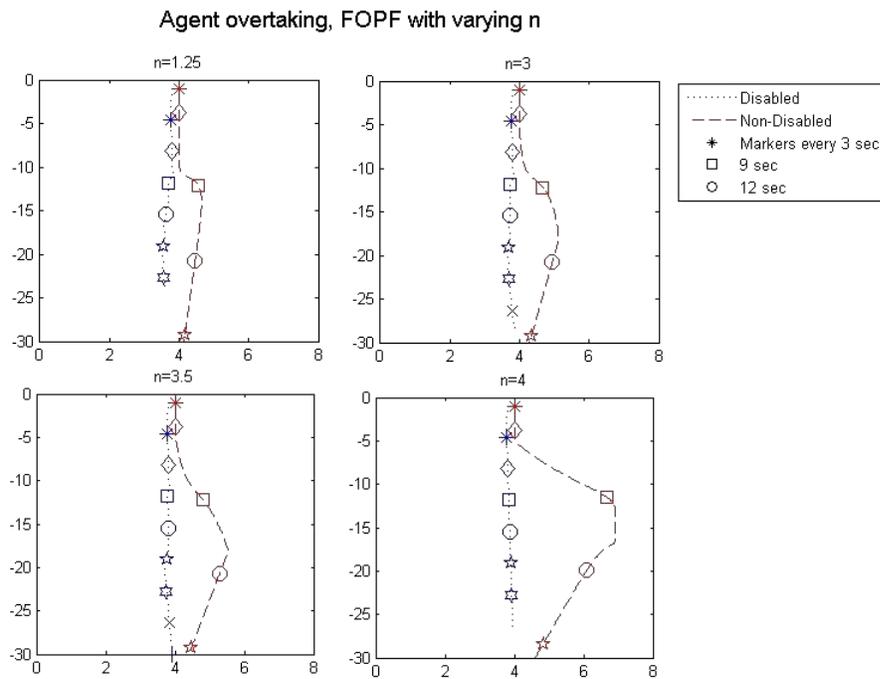


Fig. 4.3: Varying order  $n$  one to five gives different overtaking behavior.

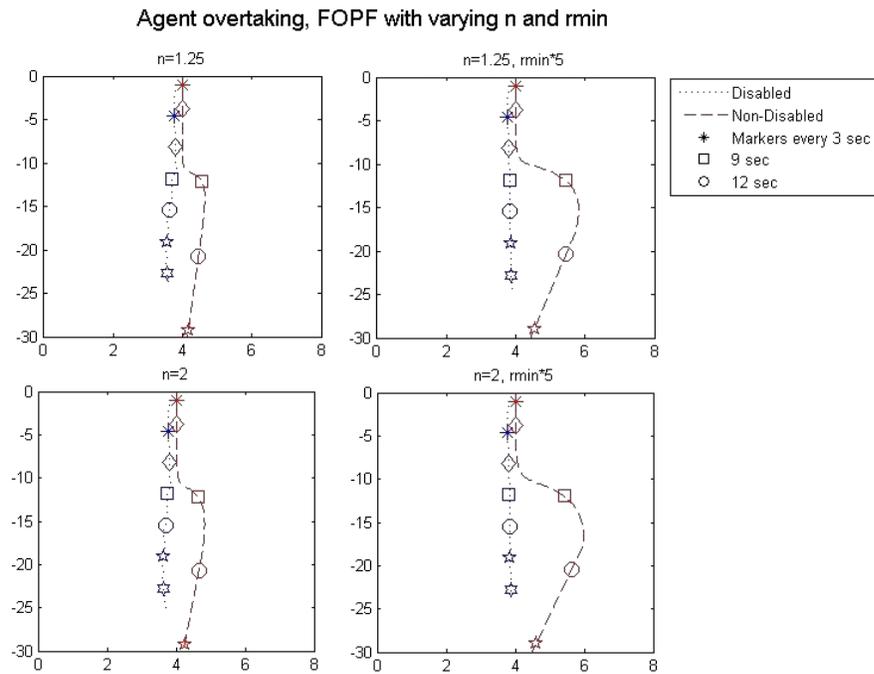


Fig. 4.4: Varying minimum distance  $r_{min}$  gives perception of spacing and change in overtake behavior.

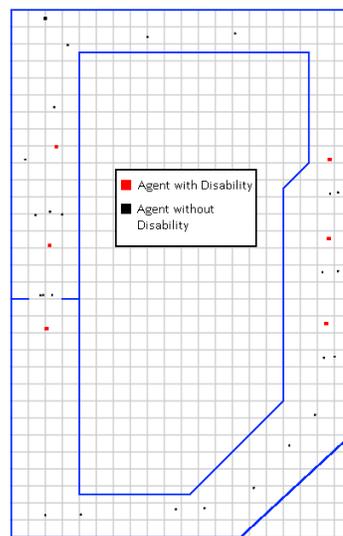


Fig. 4.5: PEDSIM hybrid model low traffic flow.

#### 4.5.1 Standard Model Results

For comparison, the simplified Social Force Model was first used to describe both

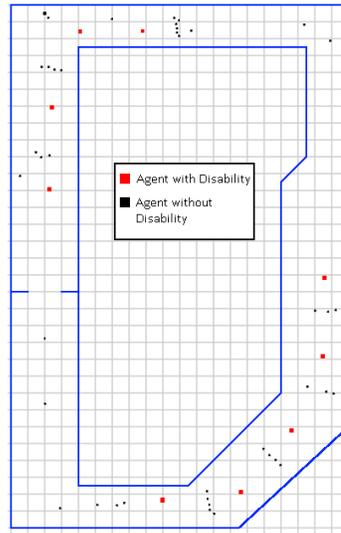


Fig. 4.6: PEDSIM hybrid model medium traffic flow.

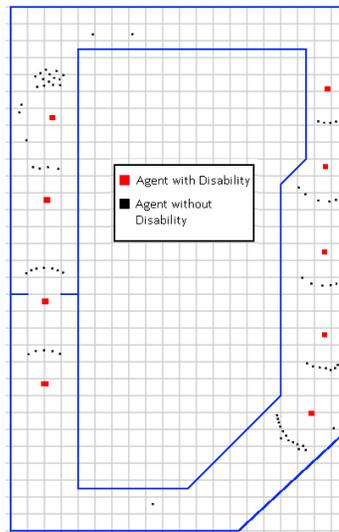


Fig. 4.7: PEDSIM hybrid model heavy traffic flow.

individuals without disabilities and those with disabilities. A simplified standard model of the Social Force Model is used for comparison because it offers the worst case model results with respect to overtaking. In a very simplified model, faster pedestrians will move past slower pedestrians unless physically blocked from doing so. The very simple standard Social Force Model includes no perception of overtaking that would limit faster

pedestrians overtaking slower ones. The individuals with disabilities were set from the hybrid model to the standard model that only relies on desired velocity. The results of these simulations will be unrealistic from the point of crowd overall interaction, but the focus of this dissertation is only in demonstrating the ability of the overtake portion of this model. But a standard simulation of all agents with only desired velocity, Table 3.3, as input is used as a baseline to compare overtake results to. Also unlike the experiments where the individuals with disabilities were composed of varying groups on each session, the simulations for this dissertation will be composed of only one disability group at a time. This will further remove the results from reality, but should serve as a baseline for what the model is capable of. Each simulation is run for an equivalent ten-minutes of circuit simulation time and then the resultant trajectories are translated into a form that can be analyzed by the already present analysis GUI described in Chapter 3. Processing all five groups for overall overtakes, it is shown in Table 4.2 that the amount of overtaking is far higher than what is experimentally found. This is no surprise since the simulated faster agents are just passing the slower agents as they move around the circuit. Next, the agents with disabilities will be changed to the hybrid model.

#### 4.5.2 Hybrid Model Exploration Results

For the rest of the simulations, the hybrid model is used for all nine individuals with disabilities that are simulated within the crowd. The range values of the FOPF remain fixed and  $n$  is varied each iteration and then processed to determine what the overall overtake value outcome is for the circuit. This process is done for each of the five disability groups over a range of  $n$  until the overtake outcome matches or gets close to the value determined

Table 4.1: Standard Social Force Model simulation overtake results.

Vision impaired	99.02 overtakes/ped
Motorized wheelchair	144.24 overtakes/ped
Non-motorized wheelchair and roller walkers	160.2 overtakes/ped
Canes/Stamina	226.5 overtakes/ped

from the experiment. The results found for the vision impaired simulation where the model is set to 1.19 m/s and the individuals without disability are set to 1.3 m/s is found in Figure 4.8. The result for individuals with motorized wheelchairs at 1.11 m/s is found in Figure 4.9. The results for individuals with canes or stamina impairments at using roller walkers at 0.9 m/s is found in Figure 4.10. As both individuals using non-motorized wheelchairs and individuals using roller walkers have the same desired velocity of 1.14 m/s, the initial results can be found together on Figure 4.11.

The first attempt to find an order value that would match experimentation lead to difficulty as found in Figure 4.11. It was discovered at this point that the specific time of when each agent with disability was injected into the circuit can matter in the case of simulation. At 1.14 m/s of movement, the agents would end up back at the injection point around the time another agent with disability is to be injected. This meant that the agents with disability are grouped closely together. The large shape created by the hybrid addition of the FOPF combined with the small required number of overtakes to match meant that the agents would occasionally reach jam conditions and get stuck in the circuit. These

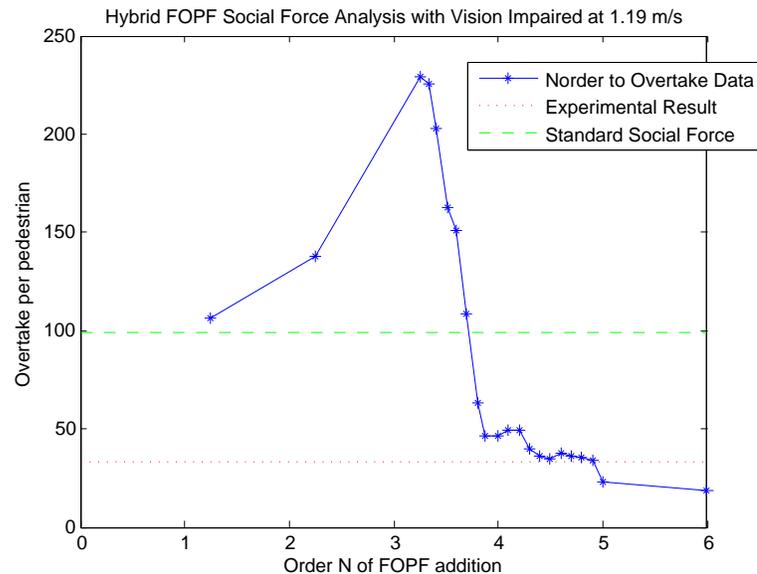


Fig. 4.8: Results of hybrid model of vision impaired while varying order.

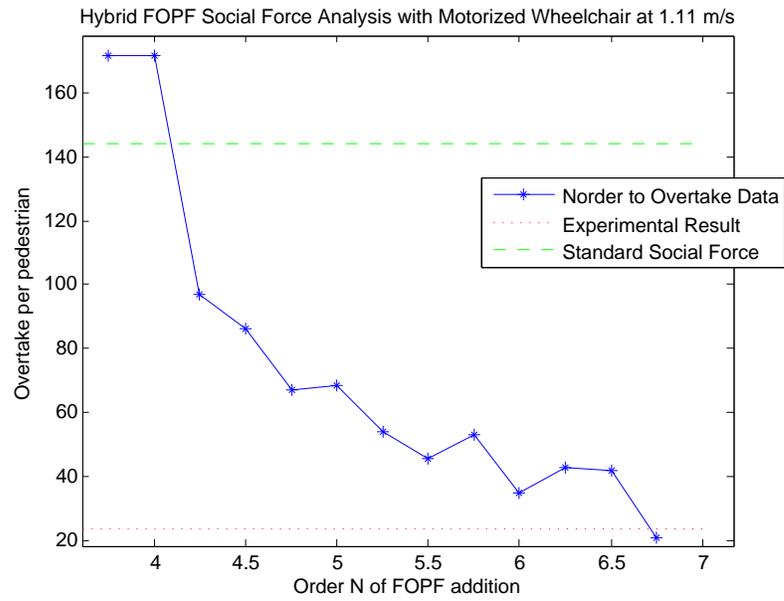


Fig. 4.9: Results of hybrid model of motorized wheelchair while varying order.

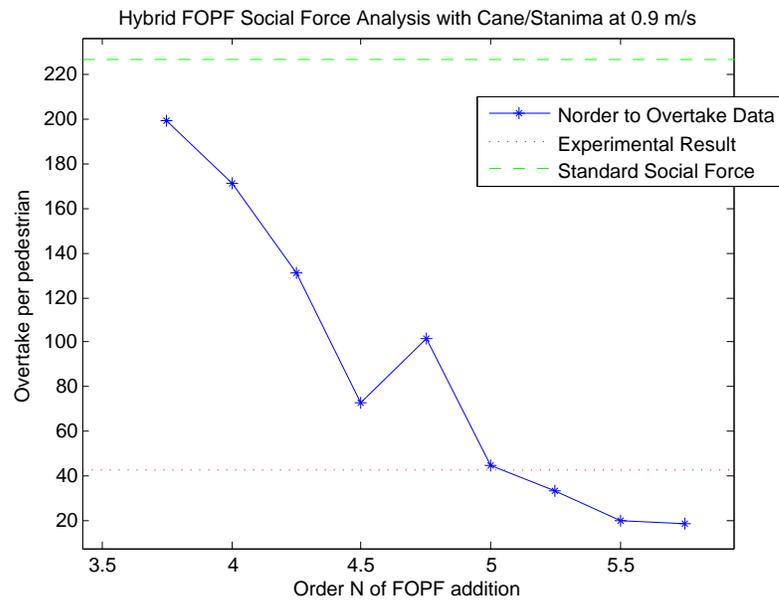


Fig. 4.10: Results of hybrid model of cane/stanima while varying order.

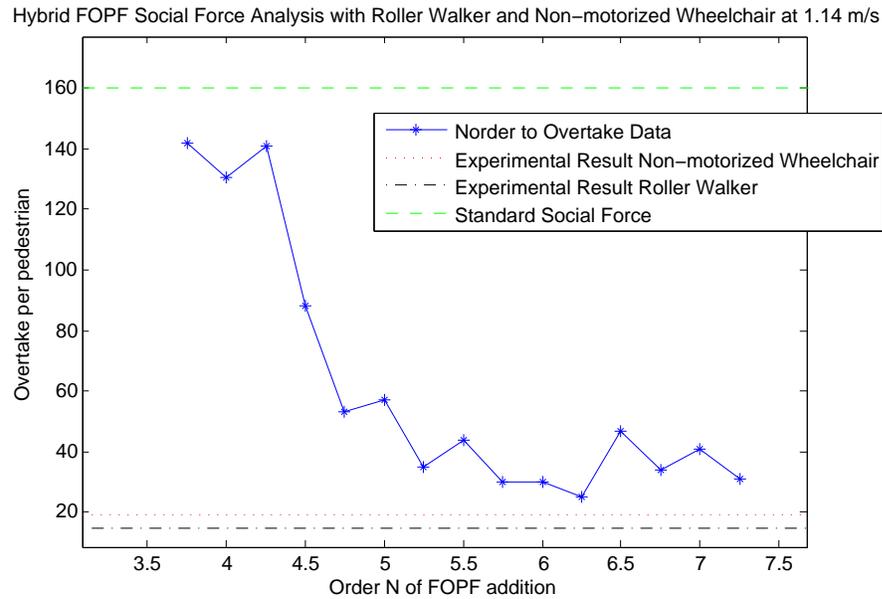


Fig. 4.11: Results of hybrid model non-motorized wheelchair and roller walker, first results while varying order.

jam conditions are unrealistic, but a phenomenon of the current design of the simulation. To fix this, the injection times of the simulated individuals with disabilities were changed slightly to allow for a more even spread of agents throughout the circuit. This resulted in the ability to achieve overtake numbers similar to the experiment for both groups with disabilities. The results of this modified simulation can be found in Figure 4.12.

The hybrid model appears to have the ability to match similar outcomes to those found within our empirical studies. A summary of the results can be found in Table 4.2 with the final orders  $n$  used for each model found in Table 4.3.

Finally, one uni-directional session was chosen from the crowd experiments and simulated. This session, named 1241 (for the time it occurred), is composed of 79 individuals without disabilities and seven individuals with disabilities. The group with disabilities is composed of five members with a visual impairment, one member with a roller walker, and one member with a motorized wheelchair. The results of the simulation were compared with the results of the experimental session for velocity over level of service ranges. Figure 4.13 shows those

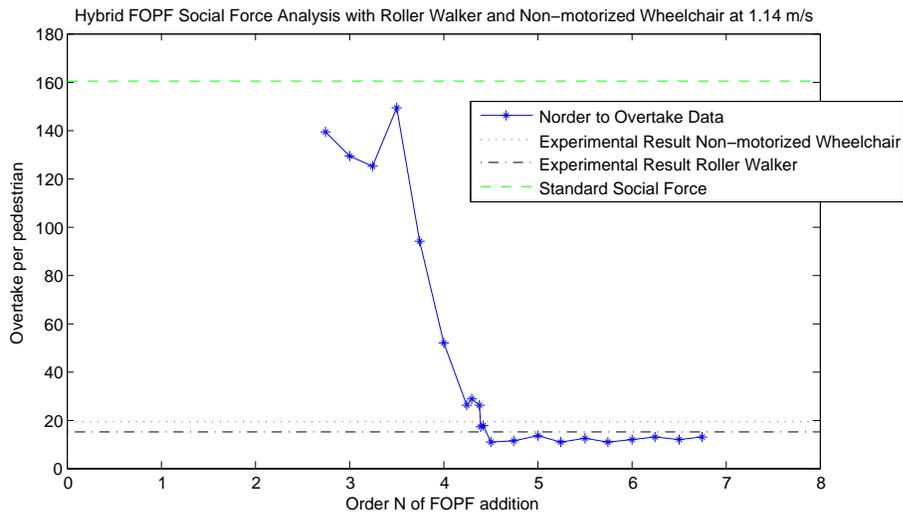


Fig. 4.12: Results of hybrid model non-motorized wheelchair and roller walker, adjusted simulation results while varying order.

Table 4.2: Hybrid Social Force Model simulation overtake results.

Type	Hybrid Results	Experiment Results
Vision impaired	33.68 overtakes/ped	33.45 overtakes/ped
Motorized wheelchair	20.84 overtakes/ped	23.54 overtakes/ped
Non-motorized wheelchair	17.75 overtakes/ped	19.00 overtakes/ped
Roller walkers	13.6 overtakes/ped	14.75 overtakes/ped
Canes/Stamina	45.14 overtakes/ped	42.5 overtakes/ped

Table 4.3: Hybrid Social Force Model simulation  $n$  values for overtake results.

Type	Order $n$
Vision impaired	4.9
Motorized wheelchair	6.75
Non-motorized wheelchair	4.42
Roller walkers	5
Canes/Stamina	5

results also in comparison with a simulation of all vision impaired and one of all stamina impaired. Although all three simulations reduce in velocity with increase in density, the

results are still not favorable to matching all aspects of a crowd with individuals with disabilities. However, the initial motivation is to present the hybrid model and do some initial matching to the overall overtake outcomes in separated form.

#### 4.6 Problems Encountered and Future Improvements

The addition of a FOPF to the Social Force Model only represents the beginnings of modeling the complex behavior of individuals with disability. Subsequently, more analysis of the crowd experiments will be required to continue. As mentioned before, this initial example does not have any features found in more updated representations of Social Force. In updated models, the forces within an individual's vision range have greater impact than those individuals following from behind. As such, future improvements of this model will include a more current Social Force Model as well as angle of sight modifications to the

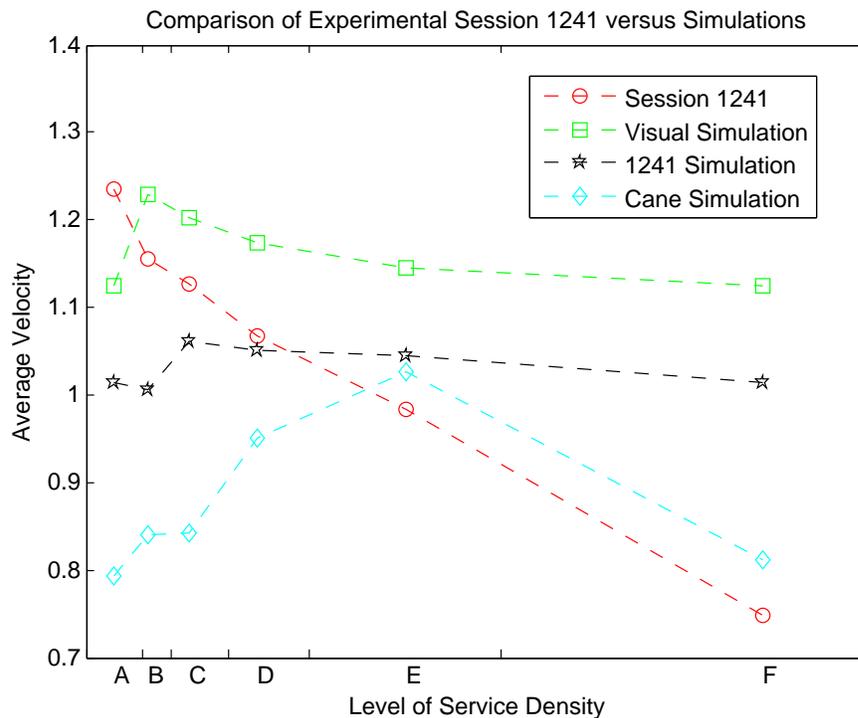


Fig. 4.13: Session 1241 experimental results versus various simulation results.

impact of the FOPF. Therefore, individuals with disability following other pedestrians will not have as great an impact due to varying shape of the field. As the order  $n$  can be any order or fractional order, future improvements would allow for optimizing a model's interactions to that as found from experimental analysis. The varying ability of  $n$  allowing for calibration of models to additional types of interaction as they are found and understood. As the initial simulations include a very simple Social Force Model, future research needs to occur to understand how the hybrid model works with a more complex form of the Social Force Model that can better capture impacts of velocity over density increase and the movement and flows through an environment. As can be seen from Figure 4.13, the velocity outcomes are still much higher than the experimentation results. This is also most likely due to both the simplification of the interaction behavior of the standard social force. This is also due to maybe the overtake orders being set to high thus not allowing enough agents to pass, etc. It may in fact be that although the overall overtake outcomes were matched, the actual overtake behavior is only partially matched. Further work to create a better way to study overtake should be created. This is only the beginning of exploration. A different way to analyze overtake behavior to speed up data collection and processing would also be of use. Currently it still takes eight-hours to determine the outcome of a simulation. Integrating the overtake analysis into the simulation so that it is done in situ would speed up the process. The original intent of this dissertation was to get to the calibration step where the models are automatically calibrated to the empirical data. However, this is determined to be much harder to do and time intensive. However, this is an important part of the model and the advantage of the 'fractional order' part of the FOPF addition to the hybrid Social Force Model. The simulation framework also needs improvement. Currently the desired force of each agent is to different waypoints that are placed around the circuit. As the agent arrives at a point, it then sets its force to another waypoint. The arrival at a waypoint is controlled by reaching within a determined radius. While this is not completely unrealistic, this may have consequences in overall behavior and interaction. Finally, specific jam conditions where the simulated hybrid model agents get stuck in the simulation still

exist. A description of these conditions is found in Figure 4.14. While a work around was determined, these conditions need to be resolved.

#### 4.7 Chapter Summary

In this chapter, crowd modeling is discussed and brief and motivation for the selection to use the Social Force Model is described. The Social Force Model is presented and the addition of a Fractional Order Potential Field is shown. This FOPF is used to explore the overtake behavior of individuals with disabilities. A simulation platform is presented and some initial exploration of the hybrid model in simulation is shown. The results provide for proof that the hybrid model can achieve the overall outcomes for overtaking found in our crowd experiments, however there still requires much work to meet the smaller interactions and other variable outcomes found in our empirical data. However, this chapter presents the hybrid model as a possible option in describing individuals with disabilities and offers a road map to follow for further study. The next chapter will present a review of larger discussions involving crowd involving individuals with disabilities and crowd evacuations.

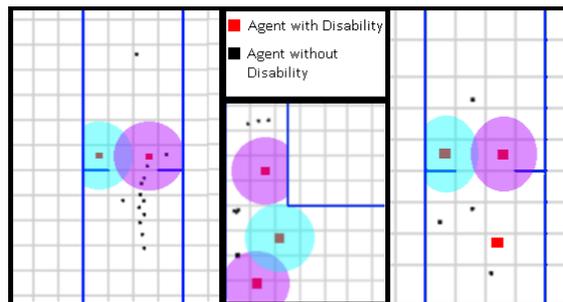


Fig. 4.14: Hybrid model jam conditions for doorway and corner.

## Chapter 5

### Future Work and Exploration in Crowd Modeling and Control

This chapter is composed of a discussion into other portions of research and review that this author has done in crowds with individuals with disabilities surrounding concepts of crowd modeling, actuation, sensing, and crowd evacuation. These concepts were composed into a proposed framework that might eventually be used during on-site crowd evacuations of crowds involving individuals with disabilities. The proposed research represents the coupling of the “physical”, Mass Pedestrian Evacuation (MPE) management of crowds with individuals with disabilities with the “cyber”, modeling and prediction of crowd evacuation with individuals with disabilities. The transfer of information between the two is implemented through the use of networked Segways, with on-board emergency response personnel, and facility sensing and actuation. The proposed research to create the development of a MPE management system , in the “cyber”, that can model crowd evacuation with individuals with disabilities makeup, develop tools to determine, through risk and mobility evaluation, which in place contingency plans to implement, and the creation of Networked Segway Supported Responders (NSSRs), to improve situational sensing and actuation of MPE involving individuals with disabilities, in the “physical”.

To accomplish such a crowd evacuation system requires the following:

- The development of a modeling framework that combines both macroscopic and microscopic models utilizing the computation efficiency of the macroscopic with microscopic interactions, based around a distributed parameter system approach and Fractional Calculus. The model describes crowd dynamics using a diffusion process, while placing individuals with disabilities, as spatial-temporal influences motivated by social-behavioral

interactions. Fractional Calculus is used to model the diverse characteristics of individuals with disabilities, and their crowd dynamic behavior.

- The development of a crowd management system combining modeling, sensing, and crowd actuation or management. The management system will use static sensors along with mobile sensors provided by NSSRs to measure crowd movement. Additional information about emergency and environmental change, and individuals with disabilities crowd composition can be fused into the “cyber” system through both NSSRs and command post authorities. The NSSRs provide a platform that operates both as actuation and sensing to the “physical” system, with information connections to the “cyber”. Using the modeling and spatial-temporal prediction of the diffusion process with understanding of individuals with disabilities and environment, information on destination is disseminated on-board to NSSR personnel to aid in improved MPE control. Crowd egress destination will be determined through the use of individuals with disabilities crowd composition, built environment, and emergency conditions; The author of this dissertation and collaborators recognize that one emergency and its environment is different from another and therefore varying solutions. For the purpose of this framework, we restrict to places of common congregation such as airports, college campuses, and convention centers where individuals with disabilities and crowds interact in evacuation. Larger scale emergencies and disasters are out of the scope of this research.
- A multidisciplinary model and control validation in different environments via comprehensive data collection of pedestrian evacuation behaviors of individuals with and without mobility-related disabilities using radio frequency tracking technologies, video tracking methods, and external experts (facilities managers, emergency management, and disability studies) to review simulations and the MPE management system, for validation of both the modeling platform and evacuation control of crowds with individuals with disabilities.

The following sections will present a view of work already accomplished towards these goals as well as future work that can be presented to accomplish such a crowd evacuation framework. A full discussion of the intended framework and a review of other portions that may belong in such a framework can be found in Stuart et al. [81], Cao et al. [82], and Cao et al. [83].

## 5.1 Preliminary Work

Towards a goal of creating a full MPE framework towards crowd modeling and control, some preliminary work has been achieved that can be utilized towards exploring and generating such a system. The following subsections layout the various efforts that may be applied towards future crowd modeling and control of crowds involving individuals with disabilities.

### MAS-Net

The Mobile Actuator and Sensor Network, (MAS-net), platform was previously created to study the effects and controls of fog diffusion processes [31, 84–87]. The physical setup combines the use of small ground robots, a fog diffusion chamber, and an overhead camera to track position information in great detail, Figure 5.1. This system was one of the inspirations for the system created to track heterogeneous crowds as discussed in chapter 2.

The system focuses on tracking a fog plume using moving sensor to make distributed measurements and characterize the diffusion process. The modeling of the process and its predicted outcome is used to disperse mobile robots with the goal to reduce or eliminate the fog. The MAS-net system employs the use of a temporal-spatial feedback control closed-loop system, where the networked sensors can be actuated for improved diffusion characterization, for goals of diffusion boundary determination and zone control. The process of a discrete parameter system control, Figure 5.1, shows the combination of the diffusion process with boundary conditions, sensing for modeling and spatial-temporal prediction, with understanding of built environment, and the control process to deliver actuators appropriately for the goals of fog elimination or diffusion reduction.

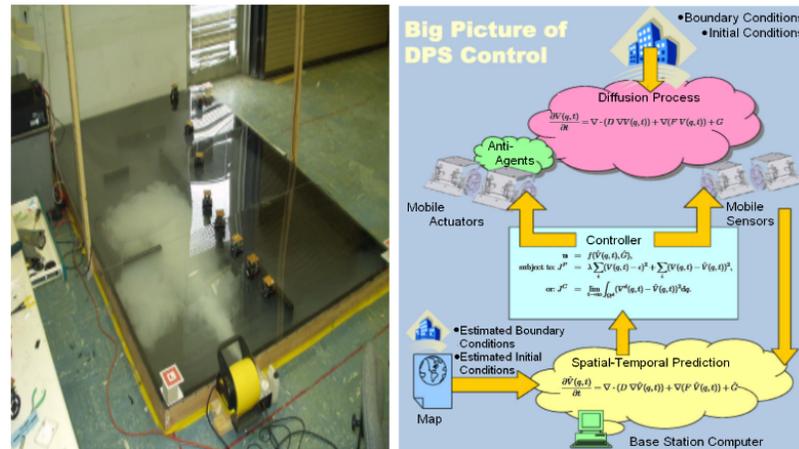


Fig. 5.1: MAS-net physical testbed system and program flowchart.

Previous research work surrounding MAS-net has been through the incorporation of optimal sensor and actuation deployment strategies for diffusion processes described by distributed parameter systems [88]. This previous work offers insight and steps ahead in understanding of how to control diffusion processes, as well as how to place sensors and actuators for effective sensing of the diffusion process. It offers for better model prediction, and also better placement of actuators to best effect change in the diffusion process. These previous efforts demonstrate a firm understanding of diffusion characterization as well as diffusion process control. Previous research has created frameworks for studying diffusion processes, optimal placements of sensors and actuators, and structures for understanding distributed networked actuation and sensing. Much like the fog, a crowd can be thought of and modeled as a diffusion process, and therefore many of the efforts shaped by the MAS-net platform may apply to crowd control on a macroscopic level. Much of this work can be leveraged towards efforts on the introduction of crowd sensing and actuation policies in a evacuation management system.

## BUMMPEE

In previous work of our research group a micro-simulation model called BUMMPEE (Bottom-Up Modeling of Mass Pedestrian flows —implications for the Effective Egress of

individuals with disabilities) was developed. The overall model architecture consists of four components: (1) environment, (2) population, (3) visualization, and (4) simulation, as seen in Figure 5.2. The environment component composes a discretized cellular grid virtual world using a Geographical Information Systems (GIS). The population component creates virtual evacuees distributed according to population of six distinct types of people: non-disabled, motorized wheelchair users, non-motorized wheelchair users, visually impaired, hearing impaired, and stamina impaired. The visualization component generates a graphical map and user interface. The simulation component demonstrates evacuation through evacuee movement at timed intervals.

The results of these prior studies using the BUMMPEE model, as shown in Figure 5.2, are comparable to a physical evacuation with a similar population and setting, suggesting that the BUMMPEE model is a reasonable approach for simulating evacuations representing the diversity and prevalence of disability in the population.

The platform offers a framework that already includes structures for describing built environment, visualizations of evacuations, and the beginnings to characterize six different groups of people including those with disabilities. The existing framework also has capability to accept control or actuation that can actuate or manage the crowd evacuation, therefore leading to a beginning set of capable software to build upon for visualization and study of crowd evacuations.

Utilizing the BUMMPEE platform may suffice for saving both time and money, as many of the preliminary steps to visualization, simulation, and facilities to characterize

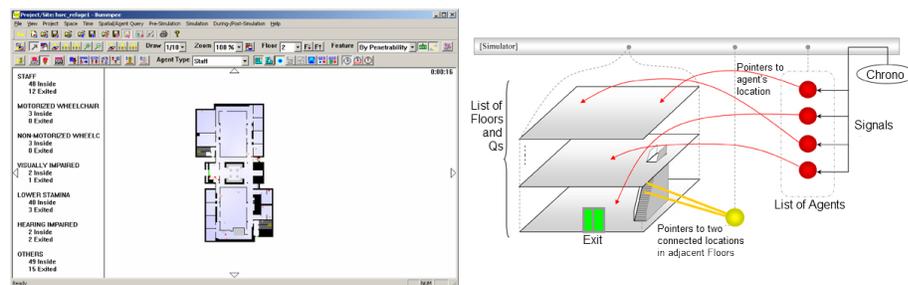


Fig. 5.2: BUMMPEE GUI simulations on a USU building and SLC airport.

disabilities have already been implemented. This platform can be coupled with developed control strategies from other preliminary work, along with preliminary work in fractional calculus, to create the beginnings of the “modeling evacuation” portion of the “cyber” part of a future MPE system framework.

### **Fractional Calculus**

The concepts of Fractional Order Control built on the field of Applied Fractional Calculus have been shown in their infancy to be applicable to crowd modeling and control [89]. Previous work in fractional order calculus has demonstrated the ability apply Fractional Calculus to complex systems and the control of complex systems [90–93]. Recently research has begun in the application of Fractional Calculus to understanding social behaviors. Social actions such as Internet traffic and financial trading can be shown to fit these qualities in Barabasi [94]. Further understanding of financial systems and human behavior can be found in Cui et al. [95]. In Song and Yang [96], Fractional Calculus is applied to the human model of Happiness. In this manner, the distribution, chaos, and variation of a social behavior can be modeled. The variation and distribution of Fractional Calculus has been used to characterize social behavior in the form of macroscopic movement in both Bogdan and Marculescu [97], where movement and dynamic games take on a fractional component for behavior. Also in Pires et al. [98], where fractional order is applied to the velocity movement of a swarm to optimize convergence. Of particular interest is the memory characteristic in Fractional Calculus. Fractional derivatives are non-local and therefore take on a memory of not only the current event, but also previous events. This component of memory is useful in social behavior, as individuals base their current actions on actions or experience they previously have had. In Kan et al. [99], this component is utilized in a leader-follower formation of social networking. The group is composed of several leaders with varying emotional states. The emotional states of the groups of followers is fractional order in nature, therefore their emotions change not only with the influence of leaders, but also their previous emotional states. The goal of this research, to find a convergence of all followers within a region presented by the emotional states of all leaders combined [99].

Much of the aspects being studied within Fractional Calculus application may eventually find their way into such a MPE system and therefore are presented here.

### **Heterogeneous Crowds with Individuals with Disabilities: Analysis and Modeling**

Finally, the efforts of this dissertation may play a role. While the tracking system would not, the data gathered and the tools built to analyze it will be required to determine a better understanding of who crowds involving individuals with disabilities behave. The results of study into the data gathered and future extensions of the hybrid Social Force Model provided may provide for possible aspects to a future microscopic model that is part of a MPE system.

#### **5.2 Framework for Modeling and Control of Crowd Dynamics with Individuals with Disabilities**

Although there is a lot of work in modeling of crowd pedestrians such as microscopic model [100–103], macroscopic model [71,101], and even mesoscopic model [72], there is little work that can achieve the scalability, heterogeneity and reconfigurability simultaneously. The modeling portion of a MPE system would need allow for the following:

- **Heterogeneity**

A microscopic model adopted for characterizing the heterogeneity of people such as the individuals with disabilities. Their presence analyzed in microscopic and macroscopic levels;

- **Scalability**

A macroscopic model employed to increase the computation efficiency and provide some useful information for controlling the whole group of pedestrians, making real-time prediction possible;

- **Control**

Control strategies can be derived using the framework in microscopic and macroscopic levels for route planning and crowd management to avoid disasters.

The combination of both microscopic and macroscopic models allows for the understanding of the heterogeneous aspects of the crowd involving individuals with disabilities that are cause for impact while leaving the macroscopic model to allow for real-time prediction and modeling of crowd movement. Thus covering the need to create for fast prediction, yet maintaining the heterogeneous behavior of the interactions of individuals with disabilities in a crowd, a mesoscopic model is desired. Recently in Bellomo and Dogbe [72] and also in Bogdan and Marculescu [97], dynamic games and specifically mean field games have been used to capture the microscopic behavior of heterogeneity along with the macroscopic behavior of the crowd. This is accomplished by the coupling of a ODE with a PDE, a forward fractional Fokker-Planck (F-P) equation as,

$$\frac{\partial m}{\partial t} + \nabla \cdot (mH'(\nabla u)) = \frac{\sigma^2}{2} \Delta m, \quad (5.1)$$

and a backward Hamilton-Jacobi-Bellman (H-J-B) equation,

$$\frac{\partial u}{\partial t} + \frac{\sigma^2}{2} \Delta u + H(\nabla u) - \rho u = -g(m). \quad (5.2)$$

Fractional Calculus can be added in here to allow for the variation of change and also social behavior. The forward F-P equation describes the dynamics of the pedestrians, while the H-J-B equations are calculated backwards to build up the expectations and decision-making towards exit. Information on crowd movement, facility issues, and emergency issues from both static sensors and dynamic sensors are used in the backward equations to create strategies of movement and desired expectations. Static indicators and mobile controllers such as mobile responders, police, and even office managers are then used in the forward equations to influence the evacuation process. Fractional dynamic game theory can approximate the decision making process under stochastic disturbance of crowd pedestrians.

A cyber-physical framework can then be created that both interacts and calibrates with this mesoscopic model, external sensors, external actuators, and decisions of emergency response personnel. As the crowd evacuates, the mesoscopic model and any management decisions can be used to best optimally evacuate the crowd given its individuals with disabilities composition and the building environment properties. A further in depth discussion of those portions of modeling and control in a mesoscopic model are discussed in Stuart et al. [81].

### **5.3 Additional Components to a Mass Pedestrian Evacuation Modeling and Management System**

Information on crowd composition is rarely looked at. This is especially true for individuals with disabilities. Future research poses questions of “How many individuals with disabilities are in the crowd?”, “What types of individuals with disabilities are in the crowd?”, and “How does this composition affect their exit ability and evacuation strategy?” Detecting individuals with disabilities within a crowd is difficult. This lends to the need of mobile sensors and technologies such as RFID to answer these questions.

In Drury and Cocking [17], it was shown that crowds develop a collective group behavior. Unfortunately, this may be in contrast with the overall goals or desires for evacuation. The best social influence on changing that group behavior is the use of emergency responders the crowd trusts. While crowd actuation could use robots, social “trust” leans towards humans over machines. However, with lack of information in a crowd evacuation, it is important that emergency responders deliver and receive up-to-date emergency information. Static sensors lack the ability to modify sensing given a dynamic and uncertain change in sensing environment. The need for mobile sensors is required to maintain situational awareness. For these reasons emergency personnel are an important portion to the above prediction and control framework as both actuators and sensors.

One proposed option is to combine emergency personnel with the “cyber” portion of an MPE system to create Networked Segway Supported Responders or NSSRs. These NSSRs will be discussed in detail in the next section. Along with static actuators and sensors, they

are the bridge between the “cyber” and “physical” portions.

As the ability to actuate the crowd to an exit is important, there are still concerns over whether the crowd can exit through a particular point. The individuals with disabilities group consists of varying mobility issues and needs. For example, a wheelchair individual cannot exit down stairwells, whereas individuals with stamina problems, may desire to take the shortest path to an exit, regardless of obstacles. It is then very important to recognize the varying needs of individuals with disabilities and to devise a system to best determine how to facilitate safe evacuation of crowds including individuals with disabilities. In the particular case of the above example, the whole crowd may be taken out the ramp exit, or if the ramp exit requires far travel, the group may be separated into two groups to facilitate the varying needs. Various sources for egress determination and assistance as in [104–106].

The goal of any future work is to create a framework that a facility can use in standard evacuations to best control a crowd, with the impacts and needs of individuals with disabilities taken in to account. The varying needs of these individuals will change how they evacuate and how the group in general evacuates.

### **5.3.1 Sensing for Mass Pedestrian Evacuation**

Arguably the first important part to understanding an emergency evacuation is the quality and quantity of measurement. This means understanding not only, “Where the crowds are?”, but also, “How big they are?” This information and information on the emergency and environment are then used to determine, “Where crowds need to go?” However, it is rarely the case that information on crowd composition is looked at, this is especially true for individuals with disabilities. If individuals with disabilities are considered, it is only as one complete group through slowness in speed, they are never considered in their diversity, capabilities of egress, and impact on the evacuation.

As stated previously, the sensing component of this MPE system would consist of both static and mobile sensing abilities. The static sensing is composed of information derived from facility security cameras, stationary sensors for crowd movement, and information that is aggregated from security personnel and fed to command post authorities. All sensing

data is networked to the command post, where the “cyber” portion of this project exists. Here control and evacuation contingency information is determined. To determine crowd dynamic information such as density, velocity, and flow, emerging video technology, such as segmentation tracking, optical flow, and histogram of gradient, will be used to analyze crowd dynamics off of facility security cameras. Stationary sensors that detect Radio Frequency Identification (RFID) markers, carried by individuals in the crowd, will be used to add additional verification of video-tracking technology, by tracking crowd movement through the built environment. The bulk of crowd movement is determined by both static camera and radio sensing devices, and can then be adjusted and improved by the mobile sensing devices discussed next. As RFID markers are individually addressable, information on disability can also be encoded to add a level of understanding to individuals with disabilities crowd composition, however additional information on composition will be determined via the NSSRs, or on-site entered data from responders. Current video technology to detect disabled individuals does not yet exist, and presents an open field of research outside current scope. As static sensor placement suffers from the lack of ability to modify sensing given a dynamic and uncertain change in sensing environment, the need for mobile sensors is required to maintain true situational awareness. This means the development of the NSSRs. The NSSRs are Segway vehicles, with on-board sensors and a display interface, that the emergency responders can ride on and interact with. The Segway is a self-balancing two-wheeled transportation vehicle [107]. The Segway platform was chosen due to its small spatial footprint and its ability to move responders quickly to proper actuation positions. The vehicle also carries all the sensing equipment and communication displays, relieving the responder to focus on their job. The on-board sensing equipment includes crowd-tracking video technology and RFID marker detection.

While static sensors detect crowd movement, the NSSR provides dynamic localized information, that could be missed. As the NSSRs have network communication ability, this additional information is sent to the command post, thus allowing for better real-time models and predictions of movement, and overall understanding for emergency managers.

The most important part of the NSSR sensing is in determination of individuals with disabilities crowd makeup. On-board emergency responders will be able to enter, through a display, individuals with disabilities characteristics or changes within the crowd. Additionally, RFID receivers can detect any individuals with disabilities carrying markers nearby, that may have been missed. As emergency responders are only human and may miss signs of disability, the RFID offer additional redundancy and accuracy. The NSSRs are networked to the command post, offering localized individuals with disabilities composition and crowd information for feedback control and decision. This networked layer provides manual entry of other information on the evacuation or emergency, freeing up emergency management radio communication for high priority discussions only. Another potential feature of the NSSR sensor platform, is its ability to be upgraded with environment and emergency sensors for improved awareness.

### **5.3.2 Actuation of Mass Pedestrian Evacuation**

Traditionally, crowd evacuations are composed of static, signs, alarms, vocal commands, barriers and on-foot emergency personnel. Information, such as leaving the building, where to exit, and the current emergency can only be communicated through command post understanding and brief radio communications between ground personnel.

Although there has been some research into evacuation control through variable signs and even robots, history has shown that crowd evacuees seem to best respond to human authorities such as emergency responders in direction to their egress and exit [108, 109]. For this reason, already in place facility actuation will be supplemented with the NSSRs. The Segway-based responders afford the unique combination of experienced emergency responders, who the crowd trust. Information is delivered to the Segway to update responders on current situational conditions, but also on improved positions of authority and direction egress through model-prediction, chosen contingency plans, and command authorities. One could argue that such a system of sensing and actuation could also be carried on-person, but the Segway platform offers to carry the equipment instead. The Segway also provides for the responders to reach crowds and emergencies at a faster speed and places them

higher in the crowd for better perspective and also a social command authority. As control actuation and contingency develop, the information is transmitted to an on-board visual and auditory display that provides the responder with updated egress direction. Facility maps also integrated now with improved data. The tradeoff, however, in providing method for faster actuation, large point sensing, and communication, is that the NSSRs are constrained to similar mobility as wheelchairs. This is why our scope is limited to airports, convention centers, and other facilities where NSSRs have more influence on evacuation, but realize that information fusion and actuation cannot begin or end with just the NSSRs.

The NSSRs will maintain the capability of localization with their environment through the use of both RFID and internal navigation (IMUs, encoders, etc.). Therefore, navigation commands to direct emergency responders on where to be, can be similarly delivered in the same manner as modern GPS vehicle navigation devices. This display also services as a station for individuals with disabilities, emergency, and environment input from the responder as discussed previously, with the intent goal to overcome potential difficulties in unseen detections. The goal is to provide emergency responders with information on where to best effect change on a crowd. That is, to provide them with more tools at their disposal for understanding of crowd movement and need, and to give them a better

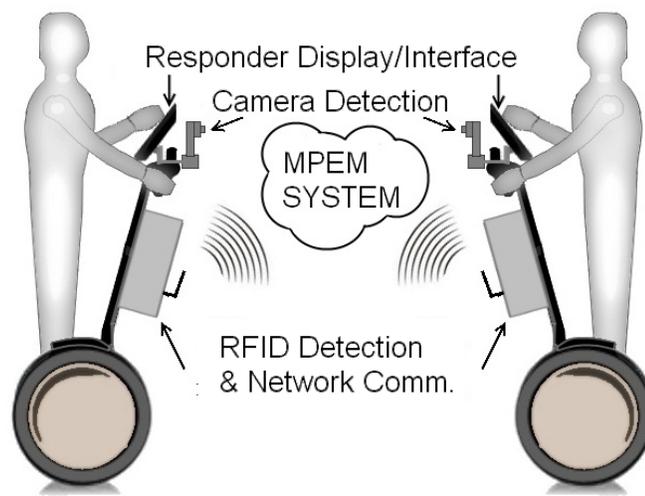


Fig. 5.3: Conceptual sketch of network Segway supported responders.

perspective, determined through a large networked sensing and control infrastructure, than can be feasible from their local perspectives.

### 5.3.3 Evacuation Egress Direction Control

With components in place for sensing and actuation for crowds with individuals with disabilities evacuation, the required components to control the egress of crowds will be discussed. One big concern during crowd evacuation is the “faster is slower” effect [110]. This discussion surrounds the concept that a crowd will tend to move faster as their environment allows it, increasing their flow, this flow is then subject to decrease as the crowd reaches parts of the environment, bottlenecks, that decrease their density. It is then, the goal to not only control the crowd to a certain exit point, but also ensure that the flow rate of the crowd is maintained at an eventual point where flow variance is kept at a minimum.

To provide for command feedback control to the NSSRs, the MPE system, located at the command post as part of the “cyber”, will use the previously detailed modeling system and expansions of previous research, to create a control strategy for proper boundary and zone control of the evacuating crowd [88]. This requires using all fused sensor information and the modeling to predict the future parameters of the crowd diffusion process. Using the modeling framework, this also includes the microscopic details of individuals with disabilities and their effect within the evacuating crowd. Through this determination, an improved placement of the NSSR group for both sensing and actuation can be determined. The goals of herding the crowd towards an exit point while maintaining minimized variation in flow, will be utilized through the understanding of crowd modeling prediction, built environments, individuals with disabilities composition, and emergency situations.

Additionally, to determine how many NSSRs may be needed for a particular crowd evacuation, and also ensure that the NSSRs are balanced out for all crowd issues, previous research and work, can be leveraged and expanded upon to determine the proper ratio to a given crowd event [88,111]. While these three component parts to the MPE system allow for crowd evacuation control, nothing has yet been mentioned over the use of individuals

with disabilities crowd composition and its effect on desired evacuation policies. The final component will use information on individuals with disabilities crowd composition, built environments, and emergency conditions to determine the best egress path for the abilities of the crowd.

#### **5.3.4 Evacuation Contingency Direction Determination**

As the ability to actuate the crowd to an exit in an improved manner has been discussed, there are still concerns over whether the crowd “can” exit through a particular point. The individuals with disabilities group consists of varying mobility issues and needs. For example, a wheelchair individual cannot exit down stairwells, whereas individuals with stamina problems, may desire to take the shortest path to an exit, regardless of obstacles such as stairs. Visually impaired individuals may be capable of exiting any condition, but need guidance from NSSRs or assignment of others to deliver aid. It is then very important to recognize the varying needs of individuals with disabilities and to devise a system to best determine how to facilitate safe evacuation of crowds including individuals with disabilities. In the particular case of the above example, the whole crowd may be taken out the ramp exit, or if the ramp exit requires far travel, the group may be separated into two groups to facilitate the varying needs.

The above issue requires a decision-making algorithm to choose an in place contingency plan that best suits each need. We stipulate only using in place plans, as these contingencies have been addressed for the facility and implemented in the training programs of facility based security and emergency personnel. The introduction of a new plan, may be even more effective to serving the individuals with disabilities needs, but it could cause confusion to emergency responders and would not have been studied for use in the particular facility. Given only in place contingencies, the system can be broken down into two parts.

- The first part consists of a rating system to prioritize the contingency plans based on individuals with disabilities capability, built environment zones, and emergency conditions. As only in place plans are used, it is important to know beforehand how

each plan is best suited to possible risks and situations of given emergency scenarios;

- The second part is the decision-making algorithm. This algorithm is based around decision tree concepts that integrated information of the varying individuals with disabilities compositions, environmental parameters, best practices in evacuation, and current emergencies to determine which plan maximizes the success and safety for a given group in evacuation egress.

Once such a plan is determined, it can be offered to the command post authorities as a unique tool to supplement their understanding of crowd needs and evacuation capabilities. While it will still be ultimately up to the emergency management on what to do, this system will quickly provide them with those solutions that best fit the situation as view by the overall system. Once policies are determined, the egress directions and commands can then be sent to the NSSRs for proper crowd evacuation based around that plan. The contingency determination and management is a complex part of a proposed framework, however it is included as it is a critical part in and overall MPE system.

#### **5.4 Experiment-Driven Thoughts on Crowd Control**

Given the observations determined through this dissertation and the initial results considering the impact of both velocity and overtaking in a crowd, there are several aspects of a crowd that would require control. The determining speed of each group of individuals with disabilities can impact their ability to evacuate and move in a crowd. However, these are factors that in their own sense cannot be changed, however making the right decisions to evacuate groups to the closest available exists or exits that are best suited for them would go a long way in improving evacuation by ensuring they can exit efficiently. The aspect variable that can be change partially is the perception of overtaking. Since the lack of overtaking causes following crowds to congest, following crowds need to overtake to maintain flow during an evacuation and also keep from impacting various groups of individuals with disabilities upstream. One proposed option is to create and assign travel lanes in corridors during evacuations, much like lanes on a highway. This can be done

by static signs and indicators, but ultimately may require the implementation of mobile actuation as well through emergency responders. If the elements of overtaking, outside of physical limitation, can be overcome then the overall flow of a crowd during evacuation can improve. Although such overtake behavior such as explored in this dissertation may not exist in panic evacuations, studies in evacuation have shown that a large portion of evacuations are considered non-panic and such behavior is more inclined to exist [17].

## 5.5 Chapter Summary

This chapter consists of elements proposed towards a future Mass Pedestrian Evacuation system. This system must cover all aspects of an evacuation from sensing the crowd, actuating the crowd, modeling and prediction of the crowd, control of egress direction, and contingency direction determination. Sensing and actuation can occur in such a system through static means and mobile means such as Networked Segway Supported Responders. Modeling of the crowd will require a mesoscopic model combination of microscopic means to capture the importance aspects of individuals with disabilities and a macroscopic means to predict crowd motion in real time. Evacuation egress direction control is employed to get each member of the crowd to the appropriate exits maintaining as much flow as possible. Finally, in a system a contingency direction determination component to determine what exits individuals with disabilities can use during an emergency while utilizing in place plans. In addition to the components of a MPE system, some additional thoughts to controlling crowds involving individuals with disabilities are looked at, with the concept of forming lanes to encourage more overtakes in instances where physical movement is possible reducing upstream congestion in an evacuation.

## Chapter 6

### Conclusion

#### 6.1 Summary of Results

In Chapter 2, the need for a system to track heterogeneous crowds involving individuals with disabilities and extract trajectory data is discussed. The video tracking system is researched and developed for the controlled experiment with goals matched to meet the demands and limitations of a controlled experiment. The video tracking system is implemented with problems and solutions laid out for the future. In Chapter 3 the development and goals of a large-scale crowd experiment are set forth. A pilot study is conducted to test and verify the capability of the video tracking system designed in Chapter 2. The experiments for both built circuit composed of ADAAG compliant environments were successfully performed. The built environment is made of various sized corners, oblique corners, bottlenecks, doorways, and various sized corridors. From these experiments, a video system is used to gather the trajectory data. A graphical user interface analysis program is then developed and implemented for analysis with potential use by other crowd dynamics researchers. Variables of this study are set forth for the GUI with particular emphasis on velocity and the perception of overtaking in this dissertation. Preliminary results for crowd velocity show that each group of disability, from visually impaired, individuals using non-motorized and motorized wheelchair, individuals using roller walkers, and individuals using canes or stamina impaired, shares different velocity values. All groups have velocity lower than that of individuals without disabilities. Analyzing overtakes per pedestrian of each ten-minute experiment session, the disability groups also share different values of overtake information. These overtake values are significantly higher than those of individuals without disabilities. This information shows the need to both study and modeling of individuals with disabilities when looking at overtake information. As those faster moving

individuals that do not pass slower moving individuals cause upstream congestion in crowd movement. In Chapter 4 the forms of crowd modeling are discussed. From the three forms, the Social Force Model is chosen. In efforts to describe a force that can model overtaking hesitancy, Fractional Order Potential Fields are presented for their ability to be varied based on fractional order and boundary conditions. A Hybrid Social Force Model is presented in simulation to capture the overall outcomes found in the empirical data. Results for the Hybrid Social Force Model are presented to show that the model can match overtake outcomes similar to those found in experiments. Problems and future work in the modeling are presented. Finally, Chapter 5 presents larger scope ideas in creating a Mass Pedestrian Evacuation system that can manage all aspects of an evacuation handling crowds involving individuals with disabilities. This includes static sensing and actuation, the creation of mobile Networked Segway Supported Responders for both sensing and actuation, a mesoscopic modeling framework, evacuation egress direction crowd control, and contingency evacuation exit control. Also discussed some initial thoughts on basic crowd control with individuals with disabilities based on the results found in this dissertation.

## 6.2 Future Work

A visual heterogeneous crowd tracking system is presented that can extract trajectory data on crowds involving individuals with disabilities. This system works well, but future implementations should handle more error, allow for stitching of trajectories between cameras, and be setup to handle automatic calibration and usage in universal controlled experiment environments. The application of this system to a large-scale crowd experiment was successful, but future experiments should also involve comparisons of environment with individuals without disability. As the aspect of overtake appears significant within interaction, future studies should also involve aspects study in the perception of overtaking. This includes the design of a better metric for studying how overtakes occur. A Hybrid Social Force Model was presented with some preliminary results that can match overall outcomes of overtaking in our crowd experiment. Future modeling should involve a more complex form of Social Force capable of matching other variable outcomes from the empirical data. Future models

should also form in situ processing of overtake goals to allow for calibration and faster model analysis. Finally, a broad set of components and goals for a Mass Pedestrian Evacuation system including individuals with disabilities is presented. The system has many goals and areas that are reviewed for potential. All aspects of the system should be explored in future research and developed towards the goal of implementation in built environments conducive to problems in evacuation.

### **6.3 Conclusions**

This dissertation takes the first steps in studying in depth crowds involving individuals with disabilities. Novel tools in both data collection and analysis of experiments involving heterogeneous crowds are presented. A large-scale set of experiments with crowds involving individual with disabilities are conducted, the preliminary results, using the tools, presented in this dissertation. The preliminary results show the importance of including and studying in detail velocity differences of the various groups with mobility-related disabilities. The concept of studying overtaking information amongst the same groups is also presented, with results showing potential impacts on crowd movement also discussed. Finally, a hybrid Social Force Model is developed with the ability to match overall outcomes of overtaking performance as found within our large-scale crowd experiments. To expand to a larger scope, the components of a Mass Pedestrian Evacuation system are presented for crowds with individuals with disabilities. Also, initial thoughts, based on lessons learned within this dissertation, are presented towards control of crowds with individuals with disabilities.

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## Appendices

## Appendix A

### Data Analysis Variables

#### A.1 Data Analysis Variables Overview

For the Data Analysis GUI created in Chapter 3, a list of crowd pedestrian variables was compiled by our crowd analysis team. These variables represent the bulk of characteristics that can be studied on crowd interaction and behavior. For this dissertation only the variables of velocity, overtaking, local flow, local speed, and local density are studied. However, the program GUI was designed to study a larger amount of variables which are itemized below. These variables to provide future analysis of our large-scale crowd experiment. This appendix will describe in brief the rest of the variable not used for analysis in this dissertation, but provided for study within the Data Analysis GUI.

- walking acceleration
- walking orientation
- numbers and identification of leaders and colliders
- mean and std. deviation of speed and acceleration of leaders and colliders
- mean longitudinal and lateral spacing
- mean time headway
- mean longitudinal and lateral spacing from inner and outer walls

#### A.2 Acceleration

The walking acceleration of a pedestrian  $i$  is useful in understanding movements in regards to changes in pedestrian load and environment. The acceleration is the derivation

of velocity equation (3.2). This is the calculation over change in time  $\Delta T$ . The formal definition of this variable  $a_i$  is

$$a_i = \frac{\delta v_i(t)}{\delta t} = \frac{\Delta v_i(t)}{\Delta T}. \quad (\text{A.1})$$

### A.3 Orientation

Walking orientation of a pedestrian  $i$  is based on the distance changes from time  $t$  to time  $t + \Delta T$  of that pedestrian. This variable is useful particularly in understanding the entry angle for built environment features such as corners and intersections. Figure A.1 describes the relationships of the variables through the initial and change in time instances of pedestrian  $i$ . The variable  $D$  is the Euclidean distance between both instances of the pedestrian  $r_i(t)$  and  $r_i(t + \Delta T)$  as,

$$D = \sqrt{(x_{t2} - x_{t1})^2 + (y_{t1} - y_{t2})^2}. \quad (\text{A.2})$$

The distances  $d_1$  and  $d_2$  are the distances perpendicular to the inner wall of the circuit. Combined, these result in the orientation angle  $\theta$  for a changed position of pedestrian  $i$  over a change of time  $\Delta T$  as,

$$\theta = \arccos \frac{|d_1 - d_2|}{D}. \quad (\text{A.3})$$

### A.4 Relative Spacing

The basis for studying interaction between pedestrians is to compare their relative distance, velocity, acceleration, etc. All of these variables require the understanding of position of the pedestrians to compare and therefore their relative spacing. In the Data Analysis GUI, the pedestrians to compare with pedestrian  $i$  of study, are all pedestrians within the relative space. The relative space was defined in Chapter 3 and found in Figure 3.9. As the circuit travels in multiple axes, the definitions of movement are composed of lateral and longitudinal movement. Both variables are in relation to the circuit. A summary of longitudinal distance and lateral distance, as well as direction of travel, can be found in

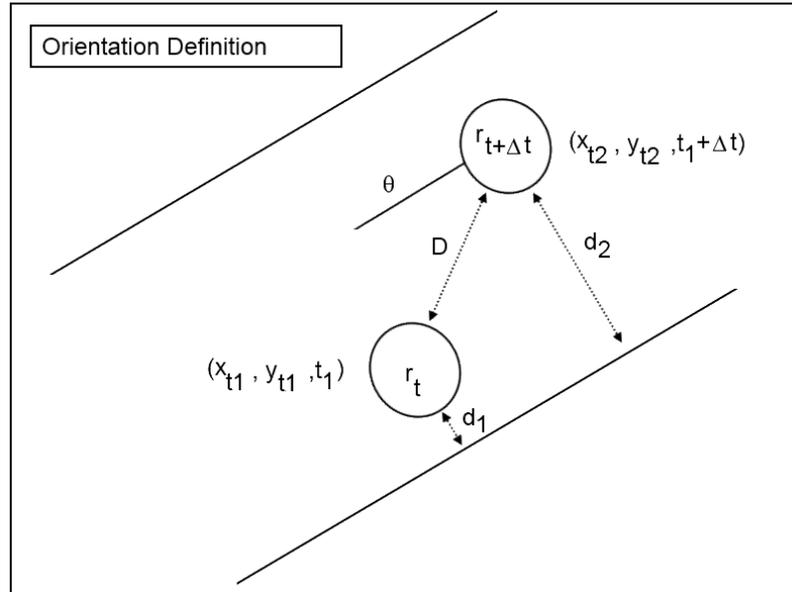


Fig. A.1: Pedestrian orientation.

Figures 3.7 and 3.6. Given these definitions, the relative spacing to each pedestrian  $i$  is broken down into the Euclidean distance, the lateral distance, and longitudinal distance. A description of relative spacing can be found in Figure A.2. As these calculations require far more comparisons, processing in the GUI for these variables are separated out into a function different from general analysis.

### A.5 Leader and Collider

With an understanding of relative spacing, the next step for understanding interaction is to separate out pedestrians in relation to pedestrian  $i$  into two groups. The leader group are the pedestrians who are traveling in the same direction as pedestrian  $i$ , but are leading ahead of the pedestrian of study. The collider group are the pedestrians who are leading the pedestrian  $i$ , but whose direction of travel is opposite of pedestrian  $i$ . These interactions are limited to a space defined as a personal space, or a square space in the leading direction of pedestrian  $i$ . This personal space is defined in Figure A.3.

Using this definition of personal space, the leader and collider pedestrians are then defined as in Figure A.4. The directions of each pedestrian group are composed of lateral

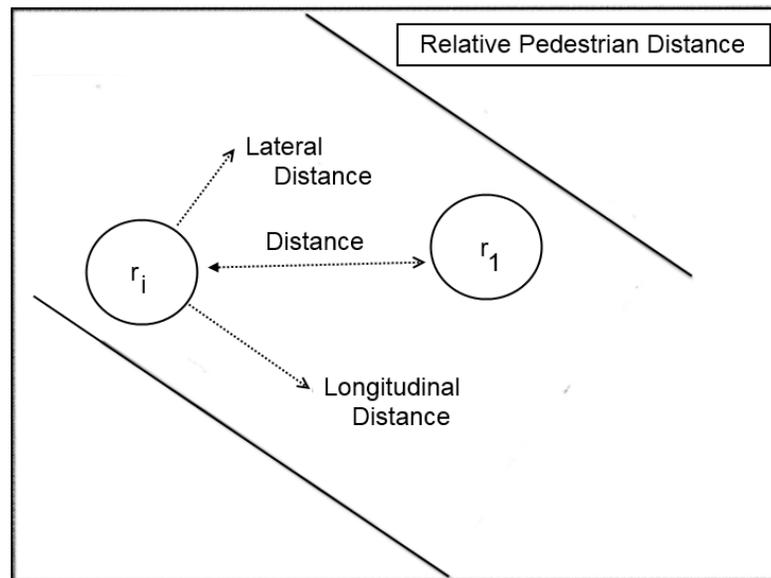


Fig. A.2: Relative pedestrian spacing.

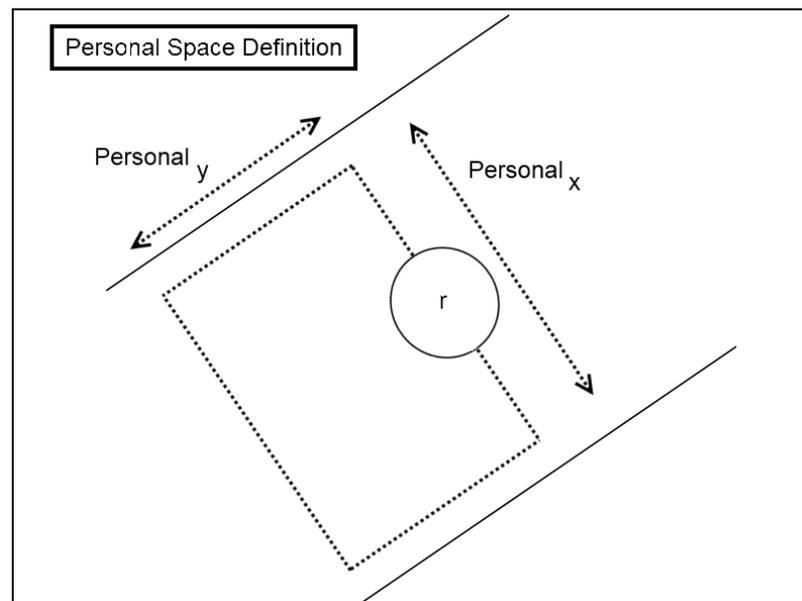


Fig. A.3: Personal space.

and longitudinal direction as defined by the circuit walls. These values were previously described in Figures 3.7 and 3.6. Once these groups are identified for a pedestrian of study, relative space can be determined between each. These values can then also be used to find

the first derivative, or velocity, or the second derivative which is acceleration. The Data Analysis GUI calculates all pedestrians found for the pedestrian of study, including relative spacing, velocity, accelerations, and standard deviations of each.

### A.6 Mean Time Headway

Time headway is the measure of time of two following or colliding pedestrians. That is the time it takes for one pedestrian to get to the other pedestrian's place at their current velocities. In traffic studies, this is another variable used to understand crowd pedestrian movement. The time headway variables for both the colliding pedestrian and leading pedestrian, in relation to pedestrian  $i$ , can be found in Figure A.5. For an instance of a leading pedestrian, the distance between the two is defined as  $d_1$ ,

$$d_1 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \quad (\text{A.4})$$

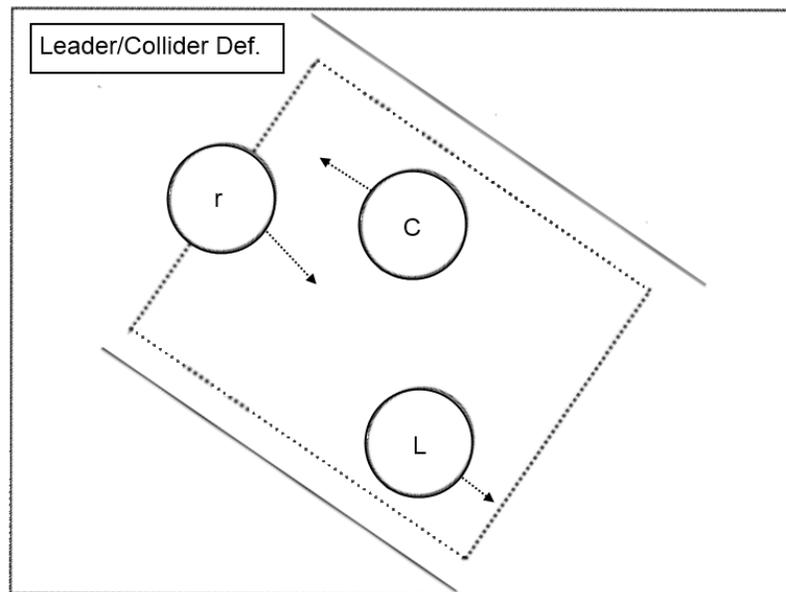


Fig. A.4: Circuit leader and collider.

This leads to the time headway calculation, based on velocities of the two pedestrians, as

$$T_{hl} = \frac{d_1}{v_i + v_l}. \quad (\text{A.5})$$

For an instance of a colliding pedestrian, the distance between the two is defined as  $d_1$ ,

$$d_2 = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}. \quad (\text{A.6})$$

This leads to the time headway calculation, based on velocities of the two pedestrians, as

$$T_{hc} = \frac{d_2}{v_i - v_c}. \quad (\text{A.7})$$

All pedestrians are limited to those found in the personal space as described in Figure A.3.

### A.7 Wall Spacing

A final important variable of study is the pedestrian  $i$  interaction with the built environment. This is helpful in knowing how close a pedestrian gets to certain aspects of a

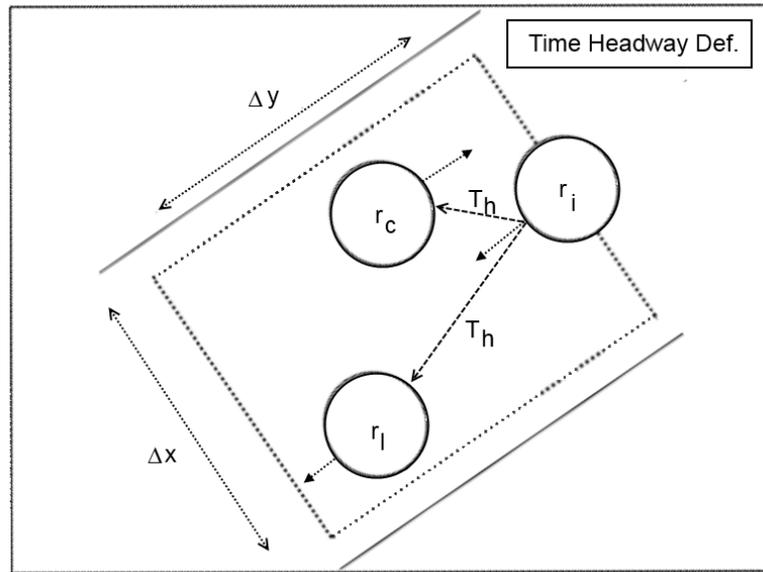


Fig. A.5: Mean time headway.

built environment and how those environment changes may impact pedestrian movement. These variables are based on the lateral and longitudinal directions as defined in Figures 3.7 and 3.6. There are four wall spacing's calculated over a time period for the pedestrian. These include a distance lateral to the inner wall, the outer wall and longitudinal distances to nearest wall behind the pedestrian and the nearest wall in front of the pedestrian. Values for wall spacing are defined as in Figure A.6. As these calculations require far more comparisons, processing in the GUI for these variables are separated out into a function different from general analysis.

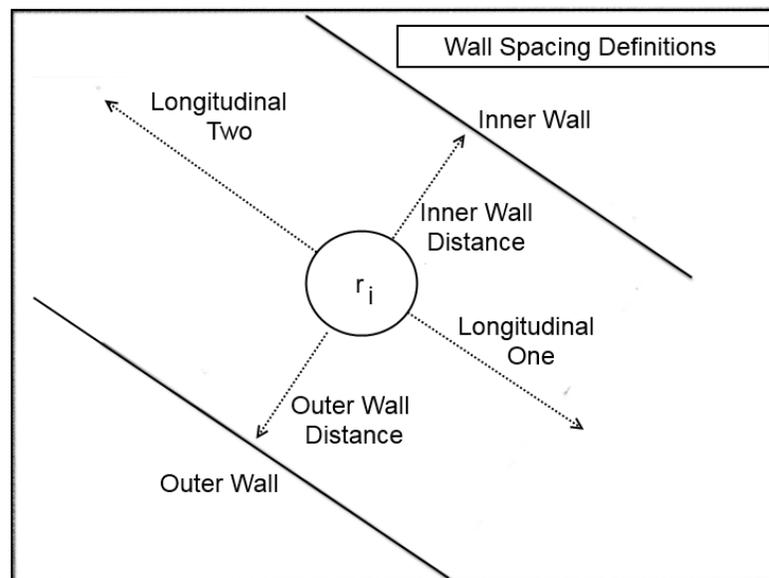


Fig. A.6: Wall spacing.

## Vita

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- To pursue a career in Electrical Engineering that enhances my expertise in the specialties of Controls and Robotics while complementing the knowledge I have gained through research, leadership, and project management to successfully turn theory into realistic, practical applications.

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#### Published Journal Articles

- “Traffic Flow Characteristics of Heterogeneous Pedestrian Stream involving Individuals with Disabilities”, Sharifi, M.S., Stuart, D., Christensen, K., Chen, A., *Transportation Research Record: Journal of the Transportation Research Board*, 2016. (*To Appear*)

- “A Fractional Micro-Macro Model for Crowds of Pedestrians based on Fractional Mean Field Games”, Cao, K., Chen, Y., Stuart, D., *IEEE/CAA Journal of Automatica Sinica*, 2015. [Online]. Available: <http://arxiv.org/abs/1602.01211> (*To Appear*)
- “Cyber-physical modeling and control of crowd of pedestrians: a review and new framework”, Cao, K., Chen, Y., Stuart, D., Yue, D., *IEEE/CAA Journal of Automatica Sinica*, 2(3): 334-344, 2015.
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- “Distributed Containment Control for Multiple Autonomous Vehicles with Double-Integrator Dynamics: Algorithms and Experiments”, Cao, Y., Stuart, D., Ren, W., Meng, Z., *IEEE Transactions on Control Systems Technology*, vol:19, Issue:4, pp. 929 - 938, 2011.
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- “Capacity Analysis of Pedestrian Queuing Facilities involving Individuals with Disabilities”, Sharifi, M.S, Christensen, K., Chen, A., Stuart, D., in *World Conference on Transport Research Society*, Shanghai, China, 2016. (*Submitted*)
- “Exploring Traffic Flow Characteristics and Walking Speeds of Heterogeneous Pedestrian Stream involving Individuals with Disabilities in Different Walking Environments”, Sharifi, M.S, Stuart, D., Christensen, K., Chen, A., in *Proceedings of the Annual Meeting of the Transportation Research Board*, Washington, DC, 2015.
- “Modeling Different Groups of Pedestrians with Physical Disability, using the Social Force Model & Fractional Order Potential Fields”, Stuart, D., Sharifi, M. S., Christensen, K., Chen, A., Kim, Y., Chen, Y., in *Proc. of the ASME 2015 International Design Engineering Technical Conference & Computers and Information in Engineering Conference (IDETC/CIE)*, August, 2015.
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