Shared Connectivity for Safer Shared Space Facilities: Improving mobility for non-motorized and vulnerable Road

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UNIVERSITY TRANSPORTATION CENTER

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16. Abstract

The proposal investigates the challenges of urbanization and studies the concept of "shared space," a holistic redesign of the existing micro-mobility infrastructure. To understand non-motorized agents' mobility and safety, we focus our research on developing a framework that simulates shared space active mobility scenarios. This framework will aid in studying the performance of established MANETs and engineer the formation of a stable and connected ad-hoc network for active urban mobility in shared space. We have developed a simulation framework based on convex optimization and utilizes pedestrian behavioral rules to imitate the realistic pedestrian movement in each scenario. The generated trajectories will aid in the development of a routing protocol that establishes and maintains a stable MANET for a dynamic network. Once stable network connectivity is achieved, the network will be capable enough for information dissemination between any nodes and at any time. Such a stable active agents traffic network can be used in shared space traffic scenarios and emergencies such as evacuation and disaster, and assisting the researchers and engineers from transportation agencies in assessing pedestrians' safety conditions in urban transportation and shared space.

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August 27, 2021

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ABSTRACT

The proposal investigates the challenges of urbanization and studies the concept of "shared space," a holistic redesign of the existing micro-mobility infrastructure. Shared space is a new urban design concept to alleviate congestion, maximize safety, and optimize available resources. Understanding the challenges, we focus our research on developing a framework capable of simulating active mobility scenarios in shared space. This framework will aid in studying the performance of established MANETs and engineer the formation of a stable and connected ad-hoc network for urban active mobility in a shared space.

The idea is to implement a robust and connected MANET in a highly dynamic active mobility traffic. We have developed a simulation framework that generates trajectories for active agents. The generated trajectories are used in developing a routing protocol that establishes and maintains a stable MANET for a dynamic network. The simulation model is based on convex optimization and utilizes pedestrian behavioral rules to imitate the realistic movement in each scenario. These realistic trajectories help analyze the performance of ad-hoc networks and aids in improving a MANET routing protocol. Once stable network connectivity is achieved, the network will be capable enough for information dissemination between any nodes and at any time. Such a stable traffic network can be used in shared space traffic scenarios and emergencies such as evacuation and disaster and assist researchers and engineers from transportation agencies in assessing pedestrians'safety conditions in urban transportation and shared spaces.

Keywords: Active mobility in shared space, trajectory planning algorithms, behavior-aware planning, pedestrian walking modeling, MANET routing protocols, convex optimization.

CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

The UN estimates that by 2050, 70% of the world's population will be living in urban areas. This urbanization will throw enormous challenges in housing, sanitation, pollution, and mobility [3]. Also, environmental issues and deteriorating people's health are on the rise. Moreover, about 3.2 million deaths per year worldwide are due to physical inactivity. The rapidly evolving urban mobility in the form of connected and autonomous vehicles (CAVs), active mobility modes (running, walking, cycling) [4], micro-mobility modes (e.g., electric scooters) has the potential to change the transportation and travel behavior of humans fundamentally. Research suggests that a holistic redesign of existing mobility infrastructure might be needed — one such concept being urban shared spaces which blurs the segregation between modes of road user [5]. Such new urban design concepts aim to alleviate congestion, maximize safety, and optimize available resources from roadways to energy. As a part of the operation of active transportation networks, share facilities encourage interactions between the commuters, the local population, and the built environment. In those facilities, mobility models of MANETs [6], [7] must account for the connectivity and communication patterns between pedestrians and other road-users like Micro-mobility, to maintain the safety of pedestrians and to study the pedestrians' influence on the shares-space traffic flow (mainly at controlled intersections) [8]. Failure to account for travel mode heterogeneity in shared-space challenges fine-tuning the communication parameters for effective network protocols connectivity. The research agenda of the Safer-Sim project includes addressing various challenges in urban mobility by creating a stable MANET communication platform [9] for connected, multi-modal shared space [5].

1.2 Objectives

Our research aims to design a stable communication channel in a MANET comprising active mobile traffic agents (i.e., pedestrians). This goal will be achieved through the following objectives:

- Developing a convex-optimization trajectory planning algorithm for pedestrians based onwalking behavior.

- Improving the communication routing protocol to ensure there is always exist a stable MANETamong walking agents.

- Applying the developed framework for studying various shared space scenarios to address safety and infrastructure design challenges.

1.3 Research Tasks

To meet the desired objectives, we plan the following research phases. Figure 1.1 shows the outline of our research plan:

- **Phase-I** is to develop a model generating realistic agents' trajectories. We will deploy convex optimization with a receding horizon control method to generate a realistic pedestrian trajectory. The objective function will capture the behavioral nature of the agent mobility and the kinematic motion of pedestrians in 2D dimensions. In this setting, assignment and obstacle avoidance requirements will be formulated at constraints.
- While framing the convex optimization problem, various behavioral case studies will calibrate and validate the model. For example, the behavioral movement of a small group of two to three agents will be considered; another case study will include the agents'movement when confronted with the stationary obstacle.
- **Phase-II** is about exploring various MANET protocols, testing them for the real pedestrian mobility scenarios. Based on the thorough understanding of MANET routing protocol, we propose to develop an adaptive mobility-aware MANET routing algorithm that ensures connectivity in the MANET of traffic agents in shared space scenarios. The idea is to modify an existing protocol such that it always maintains a path between the nodes, and therefore there exists a continuous communication between the nodes in a network.
- **Phase-III** of the research will integrate the generated trajectories from Phase-I to analyze the developed protocol (Phase II) to improve pedestrian MANETs for urban traffic scenarios.

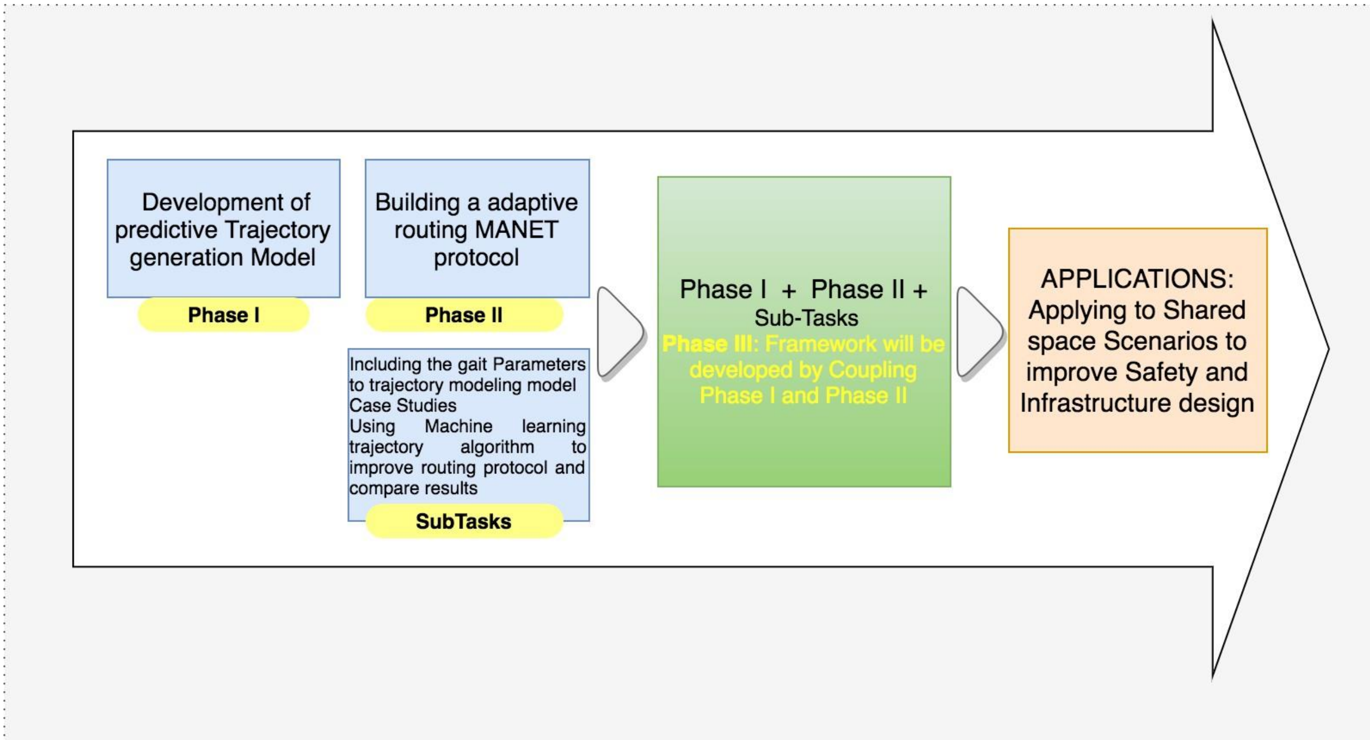


Figure 1.1: Planning of the research

1.4 Scope of the research

Our research focuses on developing a pedestrian trajectory planning algorithm for shared spaces scenarios based on pedestrian behavior during group, unidirectional, and fixed obstacle interactions. We developed the convex optimization-based trajectory planning model to simulate shared space scenarios and produce realistic trajectories for agents. Also, gait parameters (step length and step frequency) were extracted from the agent's speed profile, further validating the model's capability to generate high accuracy trajectories.

The generated trajectories, which imitates agents' natural walking behavior, then aids in achieving the goal of establishing a stable MANET in shared space to enhance the connectivity among them. The communication challenges in highly dynamic networks such as pedestrian networks will be addressed through this research.

1.5 Research Impact

This research addresses the transportation challenges that are emerging in smart cities. A framework that can allow testing the urban mobility scenarios provides a proactive approach in handling the challenges and allows the government to have a holistic redesign of existing mobility infrastructure that provides better traffic safety. Specific impacts are:

- The research has two independent contributions: developing an optimization-based trajectory planning for pedestrians and developing a routing protocol that ensures stableMANET for a highly dynamic pedestrian network.
- The developed framework aids in investigating urban mobility and peer to peer communication scenarios which will foster next generations shared transportation systems.
- A robust communication network can share information reliably with all the participating nodesin a network and, therefore, can be used to address challenging times of disaster evacuation, emergency evacuation, and occasional times of limited connectivity and break-ins.
- Better communication will help maintain the safety of non-motorized traffic agents and micro-mobility agents against motorized traffic in shared space. Also, there can be a better share of traffic updates when non-motorized agents regularly transfer traffic information. The simulated active mobility in shared space will help maintain and establish a stable communicating network among non-motorized traffic agents.

1.6 Current Existing Work: Brief Notes

- Many pedestrian trajectory planning algorithms address pedestrian mobility in various scenarios such as emergency evacuation, disaster evacuation, organizing large events, and at airports and railway stations. The existing models have performed well in such scenarios. However, the existing models based on social force and Cellular Automata modeling approaches neglect the fact that pedestrians are rational beings and takedecisions based on their experience and characteristics, and there is much heterogeneityin the pedestrian population.
- When we focus on maintaining a stable path between the nodes from source to destination, we usually focus on the link stability. The need is of the protocols which provide the Quality of Service (QoS) as well as maintain the stability and the durability of paths. The current protocols, such as OLSR, maintain link stability but are not so successful for highly dynamic MANETs such as pedestrian MANETs

CHAPTER 2 PROPOSED FRAMEWORK

2.1 Framework Outline

The proposed work aims to develop an agent-based trajectory planning simulation algorithm that simulates various connected urban shared space scenarios and helps us visualize the challenges in ad-hoc communication in active mobility. The generated trajectories then aid in engineering the formation of adapting routing protocol which ensures stable and connected ad-hocnetwork for an urban active mobility in shared space. Figure 2.1 shows the main components of our research.

- We aim to achieve our proposed research through the series of tasks:
- We propose developing a convex optimization-based method with an embedded model predictive control (MPC) trajectory planning algorithm that acknowledges the walking behavior of road users in shared space and generates agents' trajectories that mimic the real trajectories for a given scenario.
- The generated trajectories will help understand the various pedestrian traffic scenarios and challenges in forming MANETs in pedestrians.
- The understanding of challenges will aid in improving a routing technique that establishesand maintains a robust and stable pedestrian MANET.
- We aim to develop a new adaptive MANET routing algorithm that ensures connectivity always exists in a Pedestrian MANET, taking their natural walking behavior into account.

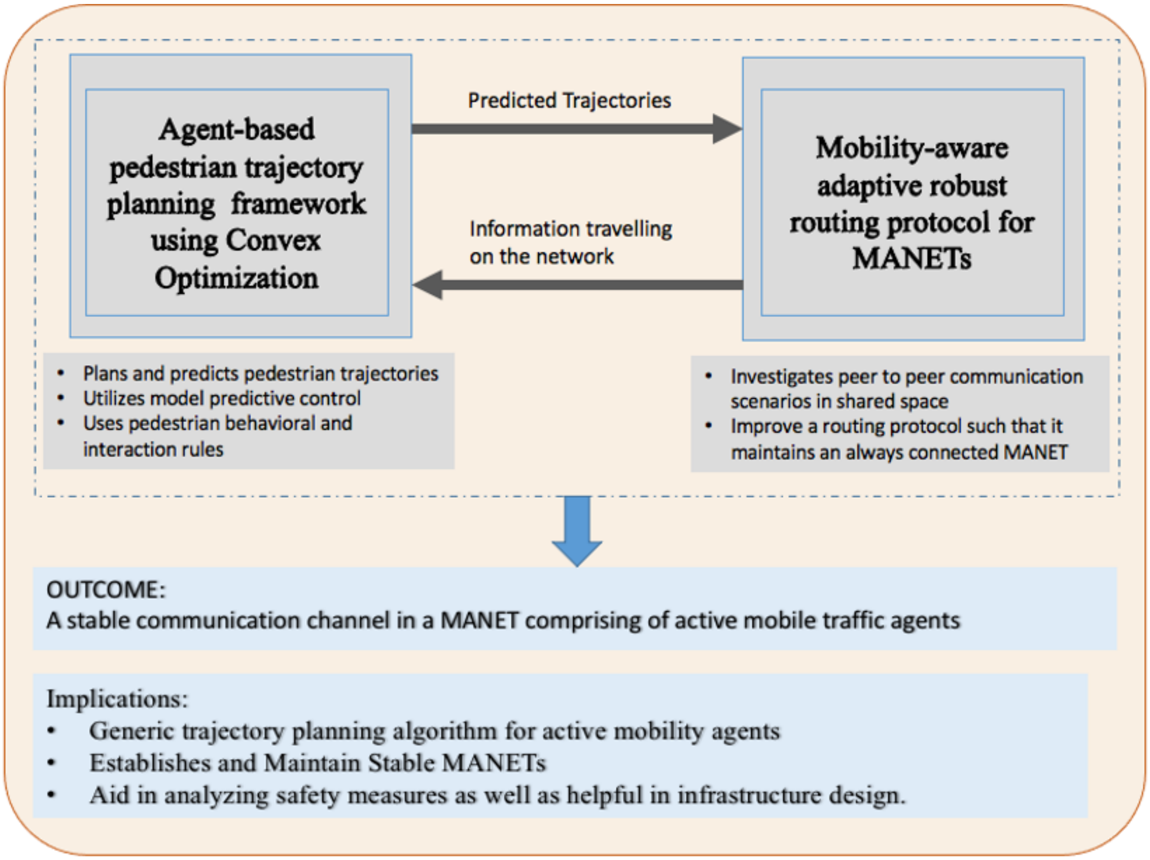


Figure 2.1: Main components of the Proposed Research

We emphasize active mobility - pedestrians, cyclists, and micro-mobility modes -and how their participation will be crucial for traffic mobility and safety in the urban, connected autonomous traffic scenarios. MANETs and VANETs will play a significant role in maintaining safety and achieving efficient and rapid traffic flow in urban transportation. MANETs will form in non-motorized traffic agents such as pedestrians, cyclists, micro-mobility vehicles.

2.2 Experiment Plan

- To develop an Agent-based pedestrian trajectory generation simulation model using pedestrian mobility behavior. The experimentation steps are:

- Perform a literature review to extract pedestrian behavioral rules that can be used in themodel.
- Develop functionality for 'V' formation consisting of three pedestrians
- Develop functionality for 'U' formation consisting of three pedestrians
- Develop functionality for stationary obstacle (e.g., poles) avoidance
- Develop functionality for moving obstacle (e.g., other pedestrians, cars) avoidance
- Identify a suitable dataset for validation and testing
- Extracting scenarios and trajectories for validation and parameter estimation
- Scenario specific parameter estimation
- Scenario specific predicted trajectory validation

- To develop a routing protocol that utilizes the pedestrian trajectories generated by the developed trajectory planning model to maintain a stable MANET. The experimentation steps involve:
  - Perform literature review to understand existing routing protocols
  - Select a potential routing algorithm(s) as base protocols
  - Use the model generated trajectories to establish a MANET
  - Propose modifications in the routing protocol which maintains an always-connected MANET
  - Perform validation and testing using network software for different traffic scenarios in Shared space.

The research agenda includes addressing various challenges in urban mobility by creating a simulation framework [11], Figure 2.2, for a connected and multi-modal shared space [5]. It will focus on an essential and unique application of Mobile Ad-hoc Networks (MANETs) in transportation [10] to enable safer shared space by connecting the active road users. A stable communication between agents influences the shared-space traffic flow and promotes safety. A model is developed after utilizing the pedestrians' behavior understanding, MANET characteristics, thorough calibration and validation process, and performing many case studies.

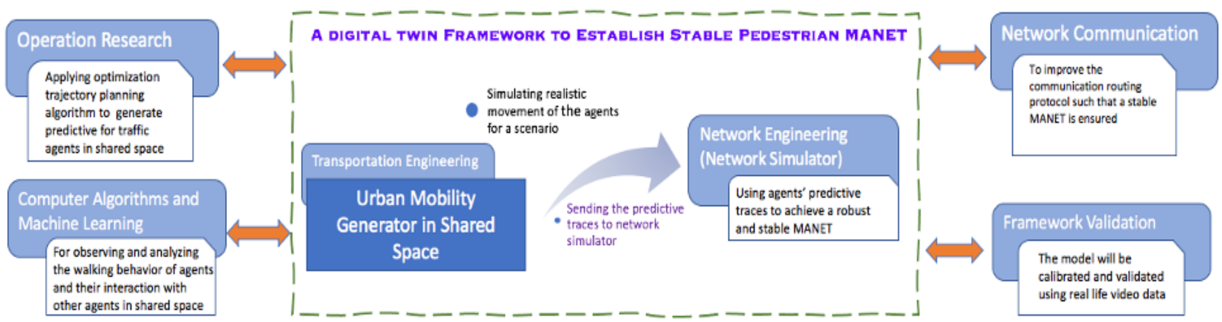


Figure 2.2: Overview of the Research Plan and Interdisciplinary Components

Part I

PEDESTRIAN TRAJECTORY MODELING

CHAPTER 3 METHODOLOGY OUTLINE

This chapter will describe the methodology for implementing the agent-based trajectory planning algorithm, which predicts and generates pedestrian trajectories that imitate the real pedestrian movement for a specific scenario. For instance, a scenario may be student movement from one building to another on a university campus. They might move individually or in a group of two, three, or more in such a case. On the other hand, there might be obstacles in the form of stationary obstacles (e.g., trees, landmarks, stalls) or moving obstacles (e.g., a walking pedestrian, a cyclist, a scooter). Therefore, focus questions are: how will the trajectories evolve, and which models are most suitable for capturing pedestrian trajectories in each context or scenario?

3.1 Approach

The pedestrian trajectory planning algorithm is based on a convex optimization technique to generate realistic pedestrian trajectories. The convex optimization problem is defined such that the objective function is based on the behavioral nature of the agent mobility and the constraints include kinematic in 2D dimensions and assignment and avoidance requirements of the problem. The concept of receding horizon control is also embedded in the problem to generate realistic trajectories, which will also aid in Objective-2. Several convex optimization problems are framed, mimicking pedestrian's individual and group behavioral scenarios. For example, the behavioral movement of a small group of three to five agents was considered. Another case study includes the movement when confronted with the stationary and moving obstacle.

The flowchart (Figure 3.1) explains the main components of Objective 1. This part ofthe research proposes an agent-based trajectory planning algorithm based on convex optimization. The trajectories generated replicate the realistic agents' trajectories as the proposed procedure assimilated the behavioral rules of mobility and incorporated the Receding Horizon control method.

3.2 Trajectory Planning Problem

The designed convex optimization problem is generating trajectories by calculating the objective function's cost/value. The objective function is a linear or non-linear function of decision variables.In an optimization problem, the objective function value must be minimized or maximized. We have designed a minimization problem, and the cost of the designed objective function is calculatedat each timestep to produce a required trajectory, and whatever configuration and corresponding paths produce the minimum cost is selected.

The optimization-based trajectory generation algorithm is designed such that the proposed model generates trajectories for heterogeneous agents such as pedestrians, cyclists, scooters, UAVs, etc. However, in the current research, we have developed the pedestrian trajectory generation model based on pedestrian behavioral rules and environment interaction rules.

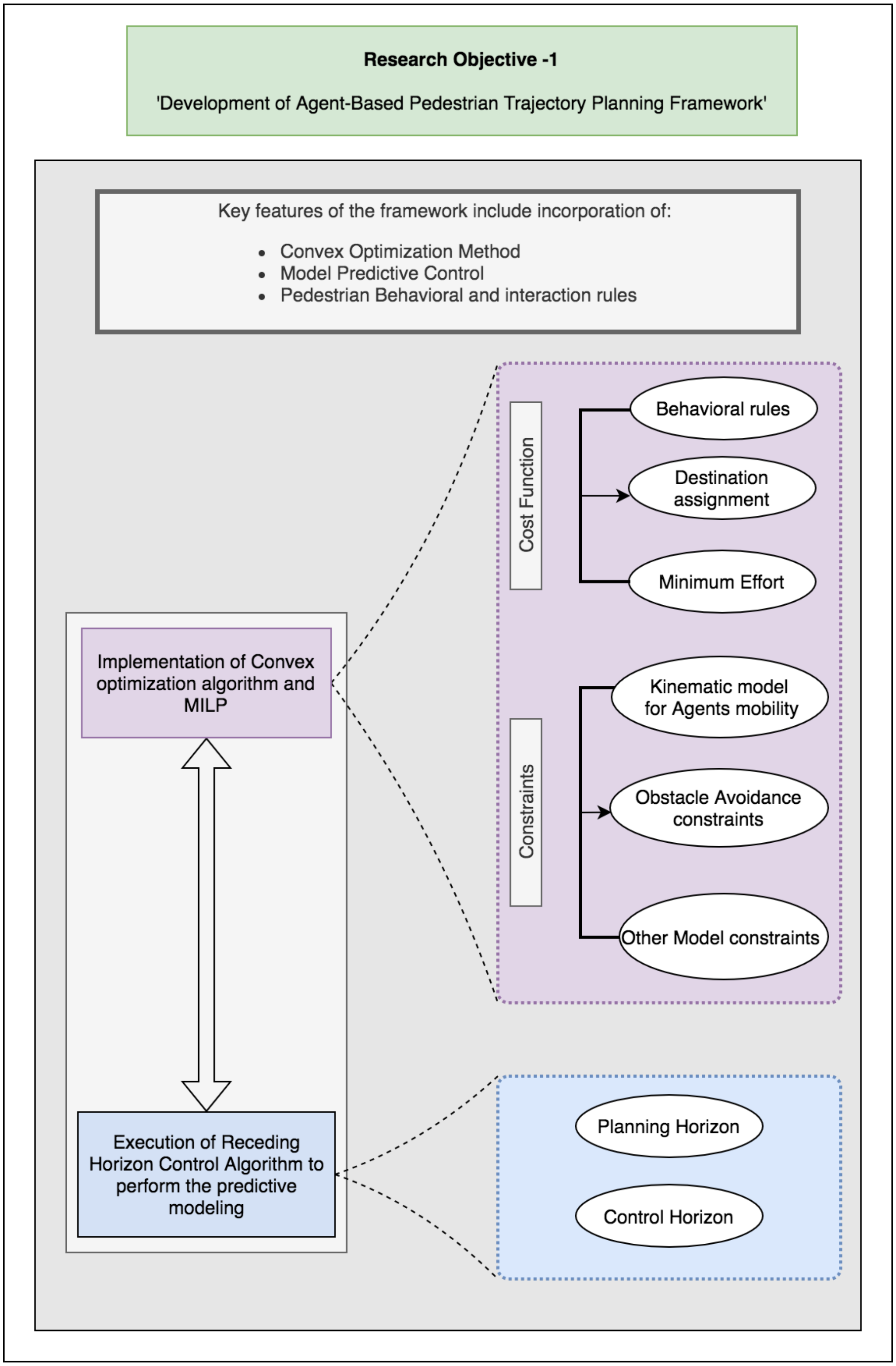


Figure 3.1: Research Objective -1 Methodology Outline

To the authors ' best knowledge, this is the first attempt to exploit the convex optimization method to simulate realistic pedestrian trajectories.

3.3 Avoidance and Assignment Problem

Pedestrian trajectories generation framework also incorporates *avoidance and assignment problems*. The avoidance problems deal with maneuvering around stationery and moving obstacle which comes in the path. The assignment problem formulates the boundary conditions (origin anddestination) for the maneuvers. We can either provide the terminal or initial points as constraints in the optimization problem or be placed in the cost function. Although there is an inherent couplingof the assignment and path-planning sub-problems, the MILP approach retains this property, and the problem is solved in a single, centralized optimization problem.

3.4 Trajectory Prediction Problem

We also incorporate Receding Horizon Control (RHC) as model predictive control (MPC). This is included to have a more realistic approach for trajectory generation. For example, when a pedestrian walks, they plan their trajectory certain timesteps ahead. RHC is an approach in which trajectory planning is performed at each timestep, optimizing the path at every current position to reach the destination.

3.5 Case Study Scenarios

The effectiveness of the proposed methodology is studied by considering case studies related to the walking behavior. We start with the research examining a small group of walking pedestrians - a group of two, three, and five pedestrians -. Prior research describes the walking behavior and small group and walking pattern formation. The existing research observed that when there is a group of three people, there is either a *V* formation or an inverted *V* formation. It means the center person will lead the group or stay behind. Similarly, if there is a group of five people, we usually observe the *U* formation [12]. Figures 3.2, 3.3, and 3.4 illustrate the formation of *V-pattern*, *U-pattern,* and a sample *obstacle avoidance* by walking pedestrians.

3.6 Tools and Software

We used MATLAB and a MATLAB-compatible tool for convex optimization - CVX- to implement the proposed framework. CVX is a MATLAB-compatible modeling system to formulate andsolve convex optimization problems. The unique feature of CVX is that it converts MATLAB into a modeling language, thereby allowing the specification of constraints and objectives using MATLAB syntax.

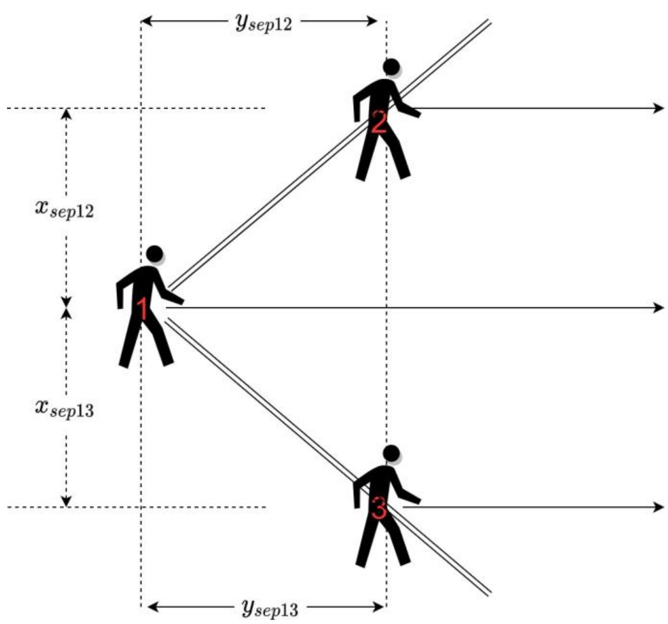


Figure 3.2: V Formation

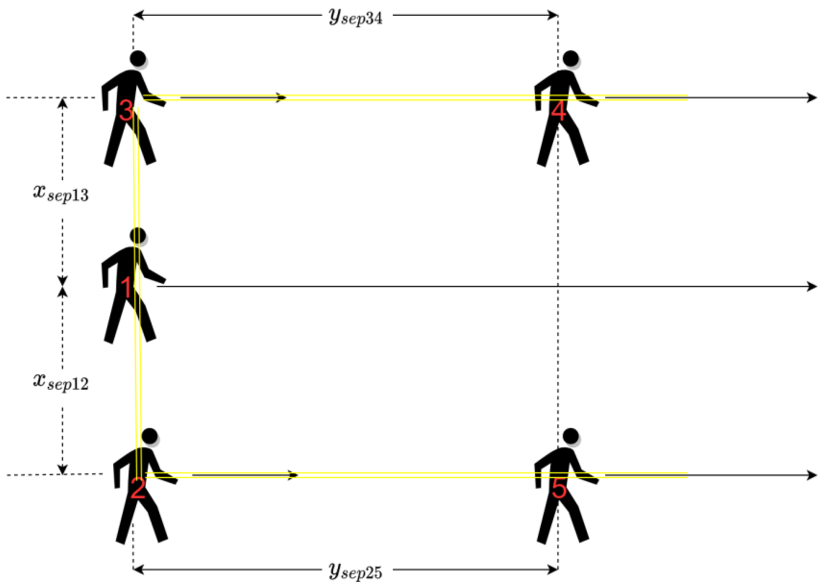


Figure 3.3: U Formation

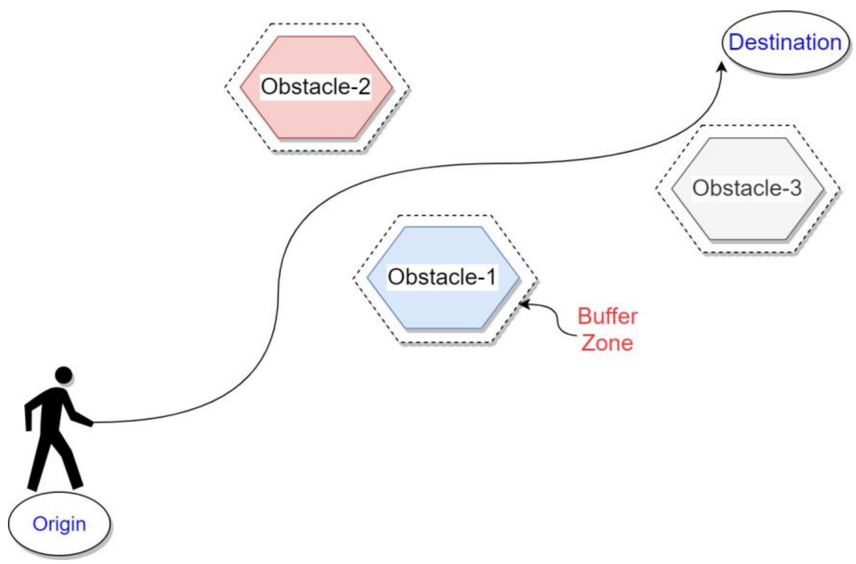


Figure 3.4: Obstacle Avoidance

CVX solves convex optimization problems using disciplined convex programming methodology proposed by Michael Grant, Stephen Boyd, and Yinyu Ye. Convex problems to be solved must adhere to the DCP ruleset. CVX allows the constraints and objective functions to be expressed using standard MATLAB expression syntax [13].

We also used Python to extract the trajectories from ground truth video data and model calibration and parameter estimation.

The MATLAB-CVX-based simulation framework generates trajectories of the given scenarios. The generated trajectories are considered realistic as they incorporate actual pedestrian walking behavioral rules and use parameters calibrated from the real-world data [14].

3.7 Salient Features of the developed Trajectory Planning Model

- The advantage of the proposed approach is the generality of the developed convex optimization cost function to produce predictive trajectories for wider range of scenarios.
- The developed methodology involves a low number of parameters as calibrating many model parameters can be cost prohibitive as it may require many observational data.
- Currently, we have used the pedestrian group walking behavioral rules to develop the algorithm. However, the algorithm design can be expanded to generate trajectories for heterogeneous agents such as pedestrians, cyclists, scooters, UAVs, etc., in a way that the agent's specific behavioral rules and scenario parameters are applied.
- The developed model is also able to examine how commonalities between agents affect mobility.
- State-of-the-art agent-based modeling approaches that consider the interaction rules

have the shortcoming of facing the computational complexity, especially at high-density levels, due to many behavioral and interaction rules.

- Our developed model has continuous-space representation, which allows agents to walk at any desired direction with any walking speed, and all the elements present in the environment are considered as independent agents or objects. This kind of space representation provides a flexibility that mimics a real walking environment.

CHAPTER 4 PRELIMINARIES

4.1 Convex Optimization

Convex optimization is an optimization problem that includes least-squares and linear programming problems and spans beyond them. It also covers a new class of problems such as semi-definite programs and second-order cone programs. The mathematics of such problems is already established. From 1947, the vigorous development of algorithms for solving linear programming began. In 1947, Dantzig developed the algorithm for the solution of linear programming known as the Simplex Method. Until the late 1980s, algorithmic development focused mainly on solving Linear problems. Then, researchers realized that interior-point methods (developed in the 1980s to solve linear programming problems) could also solve convex optimization problems efficiently.

Convex optimization has multiple applications such as automatic control systems, communications and networks, electronic circuit design, data analysis and modeling, and global optimization. Embedded (convex) optimization is also used for the model predictive control technique, whichrequires the solution of a quadratic convex program at each time step. Therefore, recognizing or formulatinga problem as a convex optimization has many attractive - theoretical or conceptual advantages. Furthermore, a problem can be solved very reliably and efficiently using convexoptimization problems. Therefore, these reliable solutions are used in various applications.

The optimization problem involves making the best possible choice among the set of candidate (acceptable) choices. Thus, various real-life decision-making problems can be cast in the form of mathematical optimization problems. This has applications in engineering, control systems, electronic design, and many other fields.

A convex optimization problem can be formulated as:

$$\begin{cases} \text{minimize } f_0(x) \\ \text{subject to } f_i(x) \le b_i, \; i = 1,2,3,\ldots,m, \end{cases} \qquad (4.1)$$

where the vector $x = (x_1, x_2, \ldots, x_n)$ is the optimization variable, function $f_0 : R^n \to R$ is called the objective function (or cost function), functions $f_1, f_2, \ldots, f_m : R^n \to R$ are called constraints, and the constants $b_1, b_2, \ldots, b_m$ are the bounds of the constraints. Convex optimization refers to

a subclass of optimization problems, and linear programming problem refers to a subset of convexoptimization problems as all linear functions are convex. In a convex optimization problem, boththe objective functions and constraint functions are convex. That means they satisfy:

$$f_i(\alpha x + \beta y) \le \alpha f_i(x) + \beta f_i(y) \qquad (4.2)$$

$\forall\, x,\ y \in \mathbb{R}^n$ and $\forall \alpha,\ \beta \in \mathbb{R}$, with $\alpha + \beta = 1$, and $\alpha \ge 0, \beta \ge 0$.

A vector x^* is an optimal solution of the problem formulated in (4.1), if x^* results in the smallest objective value among the set of all acceptable vectors (i.e., all vectors that satisfy constraints). Inother words, for any x satisfying $f_1(x) \le b_1, \ldots, f_2(x) \le b_m$, we have $f_0(x^*) \le f_0(x)$.

The problem formulated in (4.1) is a mathematical abstraction of the optimization problem of making the best choice of a vector x in R^n from a set of possible choices. The optimization variable x represents the choice made, the constraint functions $f_i(x) \le b_i$ limit the choice set of variable x and represent the firm specifications that must not be violated, the objective function $f_0(x)$ represents the 'cost' associated by choosing x. $f_0(x)$ is also referred to as cost function or fitness function. The function $f_0(x)$ may be considered a value function or utility function for choosing x.

4.2 Integer Programming

In real-world walking scenarios, mobility takes place in inhabited areas. Hence the Agent has many interactions, and their environment influences their walking behavior.

A convex optimization-based model is developed to generate trajectories as realis-tic as possible to the real walking behavior of the agents for a given scenario. The model or frameworkis developed by including all the variables and parameters required to navigate to a realistic moving scenario. Introducing these features in a simulation framework leads to the development of Avoidance and Assignment problems. Avoidance problem is about the approach to avoid the stationery and moving obstacle as well as other agents. The assignment problem defines the trajectory planning approach by assigning the initial and final position as a boundary condition tothe generated trajectory. The *avoidance and assignment* problems inclusion lead to non-convex constraints leading to challenges in performing optimization. For convex optimization, the cost functions and constraints must be convex. Therefore, we solve problems with non- convex constraints by formulating them as mixed-integer linear programs (MILP). MILP simplifies the non-convex constraints to a linearized form.

For instance, to implement obstacle avoidance, an agent must either be "left" or "right" of an obstacle, each leading to a convex sub-problem. Avoidance problems, as well as assignment problems, can be expressed as a discrete choice of destination. Therefore, using MILP, the problem is formulated as such in which some variables are constrained to take only integer values. Applying constraints on some variables (such as these variables can take only binary values 0 or 1) allows toinclude discrete decisions in the optimization, which helps to encode the non-convexity of avoidance problem [15].

An optimization problem is called an Integer Program (IP) if all decision variables are positive integers. However, if the decision variables are a mix of (non-negative) integers and real values, teoptimization problem is a mixed-integer program (MIP).

A MIP is called a mixed-integer linear program (MILP) if the objective functions and all the constraints are linear and if some but not all decision variables are integer.

The convex optimization problem formulated in (4.1) will become a mixed-integer program (MILP) if all the optimization (decision) variables can take a non-negative number, and some will take integer values (in particular, we use binary variables, taking only the values 0 or 1) , i.e., $x \geq 0$and $x_i \in Z\ \forall i \in I$.

MILP formulation can be given as:

$$\begin{cases} \min\ c^T x + d^T y \\ s.t.\ Ax + By \leq b \\ x \geq 0,\ x\ \varepsilon\ X \subseteq R^n \\ y\ \varepsilon\ \{0,1\}^q \end{cases} \tag{4.3}$$

- where x is a vector of n real variables
- y is a vector of q 0-1 variables
- c,d are $(nX1)$ and $(qX1)$ vectors of parameters
- A,B are matrices of appropriate dimension
- b is a vector of p inequalities

4.3 Receding Horizon Control

The main idea of Receding Horizon Control (RHC), also referred to as Model Predictive Control (MPC), is to use the model of the plant to predict the future evolution of the system [16]. A basicstructure of RHC is explained in Algorithm 1. Based on this prediction, at each time step *at* a specific performance index is optimized under operating constraints with respect to a sequence of future input moves. The first of such optimal moves is the control action applied to the plant at time t. At time $t+1$, a new optimization is solved over a shifted prediction horizon.

Algorithm 1 RHC Algorithm - A Basic RHC Understanding

1: T: Time horizon

2: w: Planning/Prediction horizon

3: dt: Control horizon

4: x: Current state

5: x_f: Final desired state

6: t: Current time

7: > RHC code in general is written as such a trajectory is predicted for dt period and during iteration process every time initial position is updated to dt+1. Also, w is decided as such, when an iteration is running then an agent can reach the destination

while $t < T - dt$ **do**

$\triangleright$ The loop has started to execute RHC, the loop runs for T-dt times

Solve trajectory optimization starting at current time t and current state x, and finishing at final desired state x_f at time $t + w$.

Implement the first dt steps of the control sequence found by the optimization.

Repeat.

end while

CHAPTER 5 PROBLEM FORMULATION

In this chapter, we mathematically formulate the convex optimization in conjunction with the receding horizon problem.

5.1 Nomenclature

Table 5.1 provide details of the variable used to formulate the problem.

Table 5.1: Variables used for describing Dynamics

Symbol	Meaning
G	number of agents
X_i	Agent *i*
n	number of pedestrian dynamical states
A_c	state matrix for continuous system
B_c	control matrix for continuous system
A	state matrix for discrete system
B	control matrix for discrete system
$x_i y_i$	*x* position for Agent i
$\dot{x}_i \dot{y}_i$	*y* position for Agent i
u_i	x velocity for Agent iy
T	velocity for Agent i
	control input for Agent i
	Number of time-steps

5.2 Pedestrian Dynamical Model

We consider the 2D kinematic model to define the pedestrian motion in a 2-D plane. This model serves as a relationship between position, velocity, and time. It is a linear time-invariant (LTI) model to represent the approximate pedestrian dynamics. There are four state variables, position in x and y axis (x_i, y_i) and velocity in x and y axis ($\dot{x}_i$, $\dot{y}_i$) and two control variables, acceleration in $x$and y axis (u_{xi}, u_{yi}).

The corresponding state and input vectors are:

$$X_i = \begin{bmatrix} x_i \\ y_i \\ \dot{x}_i \\ \dot{y}_i \end{bmatrix} \quad \text{and} \quad u_i = \begin{bmatrix} u_{xi} \\ u_{yi} \end{bmatrix}$$

$$\forall i \in [1 \ldots G]$$

$$\forall t \in [0 \ldots T].$$

X_i is the state vector for Agent i representing the four state variables - position and velocity in x and y direction. u_i is the control vector for Agent i representing the two control inputs in x and y direction. Note that these control inputs are in the form of acceleration in x and y direction. We assume that the acceleration of a pedestrian can be directly controlled.

The continuous system dynamics are given by:

$$\begin{cases} \dot{x}_i = x_i \\ \dot{y}_i = y_i \\ \ddot{x}_i = u_{xi} \\ \ddot{y}_i = u_{yi} \end{cases} \tag{5.1}$$

These dynamics can be represented in a more compact form using the following matrix

$$\dot{X}_i(t) = A_c X_i(t) + B_c u_i(t)$$

$$\text{where} \quad A_c = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{and} \quad B_c = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{5.2}$$

The dynamics in (5.2) can be discretized as follows:

$$X_i(t+1) = AX_i(t) + Bu_i(t) \tag{5.3}$$

where A and B are defined as follows:

$$\begin{cases} A = e^{A_c T_s} \\ B = \int_0^{T_s} e^{A_c \tau} B_c d\tau \end{cases} \quad (5.4)$$

and where T_s is the sampling period. The above equation (5.3) represents the discretized form of the continuous system dynamics.

5.3 Objective Functions

The cost (objective) function is optimized by the algorithm based on the variable, parameters, dynamics, and constraints. The cost function is a criterion for the performance measure, and the objective can be the minimization of cost or the maximization of profit or output of a process.

Therefore, identifying a suitable cost function is one of the fundamental goals and contributions of this research problem. To achieve the desired goal, selecting the appropriate cost function is veryimportant for any optimization formulation.

Agents pursue personal objectives (e.g., minimization of individual effort, reaching the desired individual destination) and global objectives shared with other agents (e.g., maintaining desired x-y distances for close formation). We have formulated three different cost functions for the following case studies:

- Case Study 1: Two agents are walking together
- Case Study 2: Three agents are walking together in *V-formation*
- Case study 3: Obstacle avoidance by an agent

5.3.1 Case Study 1:

When two agents walk together, they will maintain a certain distance as a close group formation. Thedesigned cost function will incorporate the close formation distance criterion, minimum efforts foreach Agent, and the final destination. The objective function is given as:

$$J = \sum_{k=1}^{T} \sum_{i=1}^{2} u_{x_{ki}}^2 + u_{y_{ki}}^2 + (\Delta x_{12} - x_{des})_k^2 + (\Delta y_{12} - y_{des})_k^2 + (x_i(T) - x_i(T)_{des})^2 + (y_i(T) - y_i(T)_{des})^2 \tag{5.5}$$

5.3.2 Case Study 2:

When three agents walk together, they will maintain a certain distance as a close group *V-formation*.The designed cost function will incorporate the close formation distance criterion, minimum effortsfor each Agent, and the final destination. The objective function is given as:

$$J = \sum_{k=1}^{T} \sum_{i=1}^{3} \sum_{n=1}^{2} u_{kin}^2 + (\Delta d_{ij} - d_{ij}^{des})_{kn}^2 + (d - d^{des})_{Tin}^2 \tag{5.6}$$

5.3.3 Case Study 3:

When an agent walks avoiding an obstacle, the designed cost function will incorporate the mini- mum effort and the final desired destination for the Agent. The obstacle avoidance criterion will be embedded in the constraints. The objective function is given as:

$$J = \sum_{k=1}^{T} \sum_{i=1}^{G} \sum_{n=1}^{2} u_{kin}^2 + (d - d^{des})_{Tin}^2 \tag{5.7}$$

5.4 Constraints

The convex problem is set up to optimize the objective function while following certain constraints.We next list the constraints followed by the optimization problem.

5.4.1 Pedestrian Dynamics

- Pedestrians initial starting point

$$X_i(:,1) == X^{ini}_{\ i}$$

(The $X_i ini$ value will be input to OPT function)

- Defining the final assignment problem constraints for all the agents. Explained in detail in equation 5.10.

- Input vectors are confined to lie within specified limits

$$-u_{max} <= u_i <= u_{max}$$

- Velocity of all agents are constrained with

$$-v_{max} <= X_i(3,:) <= v_{max}$$

- Constraints for Obstacle avoidance. Explained in detail in equation 5.9.

5.4.2 Avoidance Problem Constraints

To produce pedestrian trajectories close to real walking patterns, we will introduce stationary and moving obstacles; the agents must avoid these elements while waking. Also, the trajectory will be assigned to locations (initial and terminal) as boundary conditions. These Avoidance and Assignment problems inclusion leads to non-convex constraints and, therefore, a challenging optimization. For convex optimization, the cost functions and constraints must remain convex. Therefore, solving problems with non-convex constraints are formulated as mixed-integer linear programs (MILP), representing the non-convex constraints as integer programs.

The location of the rectangular obstacle is defined by its lower left-hand corner (Z_1, Z_3) and its upper right-hand corner (Z_2,Z_4). The point (x, y) must lie in the area outside of the obstacle. This requirement can be formulated as the set of conditions:

$$\begin{cases} x \leq Z_1 \\ x \geq Z_2 \\ y \leq Z_3 \\ y \geq Z_4 \end{cases} \tag{5.8}$$

These constraints can be transformed into a mixed-integer form by introducing binary variables a_n. Let M be an arbitrary positive number, some significant number like 10^5 (larger than any other distance in the problem). The constraints in 5.8 are represented by the following mixed-integer constraints:

$$\begin{cases} x_{it} \leq Z_1 + Ma_1 \\ -x_{it} \leq -Z_2 + Ma_2 \\ y_{it} \leq Z_3 + Ma_3 \\ -y_{it} \leq -Z_4 + Ma_4 \\ 2 \leq \sum_{n=1,t=0}^{4,t=T} a_n \leq 3 \end{cases} \tag{5.9}$$

5.4.3 Assignment Problem Constraints

Assigning the Final destination Positions:

This section explains the procedure of implementing the assignment problem using MILP.

Let us consider, the agent X_i is required to reach the destination (x_{if} , y_{if}) at some timestep before the maximum T. The binary variable m_{it} are introduced, with a value of 1 if the i^{th} vehicle reaches its destination at the t^{th} timestep, and 0 otherwise. The necessary MILP constraints are:

$$\begin{cases} x_{it} - x_{if} \leq R(1 - m_{it}) \\ x_{it} - x_{if} \geq -R(1 - m_{it}) \\ y_{it} - y_{if} \leq R(1 - m_{it}) \\ y_{it} - y_{if} \geq -R(1 - m_{it}) \\ \sum_{t=1}^{T} m_{it} = 1 \end{cases} \tag{5.10}$$

$\forall i \in [1...G]$ and $\forall t \in [0...T]$. Where R is the very large, positive number. From the above equation, it can be understood of $m_{it} = 1$, the destination algorithm forces the agent position to equal the destination position at timestep t.

Each component of the proposed framework is described in detail below:

- The function OPT : Build to implement the convex optimization and MILP
- The function RHC: Build to perform the execution of Receding Horizon Control to performthe predictive modeling.

5.5 Implementation Details

The framework in MATLAB is implemented using the following two main functions: OPT and RHCwithdt.Figure 5.1 illustrates the loop between Receding horizon control and convex optimization via the two MATLAB functions. At any time, instant t, OPT function performs convex optimization for the given next w time window (planning horizon) and outputs planned trajectories from the time $t+1$ to time $t+w$. These planned trajectories are input to the RHCwithdt function, which performs the receding horizon control and executes the planned trajectories for dt time (control horizon). It then loops back the updated state matrix at the time $t+dt$ to the OPT function.

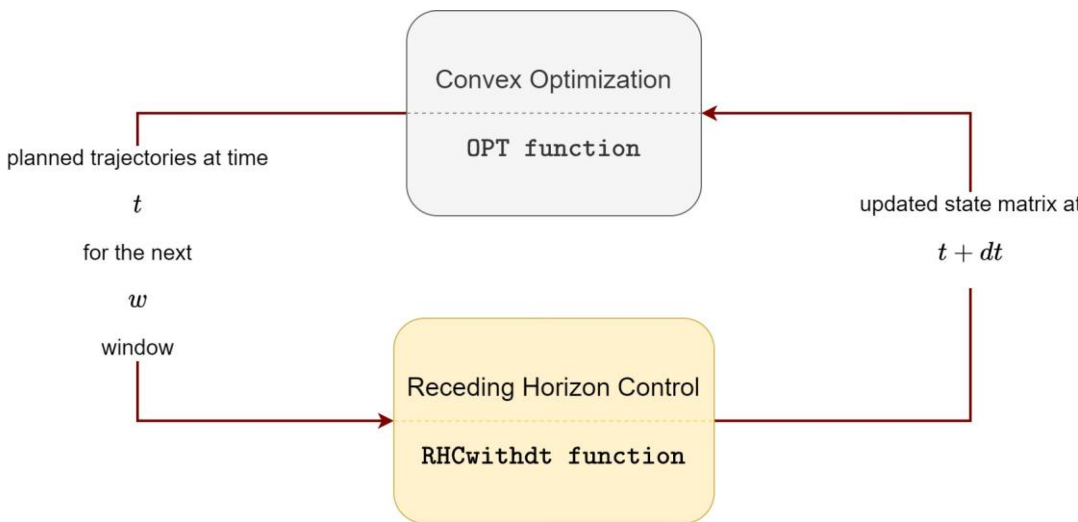


Figure 5.1: Flow of the implemented algorithm

5.5.1 Function OPT

Recall that we aim to develop a convex optimization mathematical framework to generate pedestrian trajectories based on a behavior rules analogy. Research studies have analyzed pedestrian walking behavior for various scenarios such as group walking behaviour, obstacles avoiding behavior, behavior based on commonalities, etc. Thus, the optimization framework will use those behavior rules to generate the trajectories that mimic the real walking behavior of pedestrians. We are defining a kinematic 2D model for the agent's mobility, certain fixed obstacles, certain moving obstacles as a setup. This framework will have system variables, parameters, constraints, mathematical relationships (such as dynamic of agents), and cost function.

Algorithm 2 provides a brief description of the developed OPT *function* to perform convex optimization. The OPT *f unction* works together with RHCwithdt *function* to generate pedestrian trajectories. Algorithm 3 explains the working of RHCwithdt *function* implementing Receding horizon control (RHC). The two functions are nested to perform trajectory optimization at each time step, allowing it to adapt the system in real-time for uncertainties such as disturbances and noise.

The OPT *function* is about arranging the whole systematic execution of the convex optimization problem to generate trajectories. We started with pedestrian motion, and to definetheir motion, we have considered the kinematic 2D model. The model has state variables, control variables, state matrix, and control matrix. All are declared and defined in the OPT *f unction*at line 2. The most integral part of OPT *f unction* is the objective function, declared at line 9 in Algorithm 2, designed to generate trajectories that can imitate the real trajectories for a given scenario. Depending on the scenarios and requirements, the objective functionmust be changed. In addition, there are constraints applied, declared at line 10 in Algorithm 2, which are the critical part of any optimization problem.

Algorithm 2 Function OPT

```
procedure OPT(Agents Initial and final values, w,T)
    Declaring Pedestrian Dynamics Model matrices
    Declaring the obstacle's x and y axis coordinates
    Declaring pedestrian behavior parameters to be used in objective function
    Calling cvx-solver Mosek
    procedure CVX-BEGIN
        Declare decision variables used in optimization
                (these are variables which are updated and optimized at every t time)
        Define Objective function
        Define constraints - [Kinematic 2D Model Dynamics, constraints on decision variables, obstacle
avoidance constraints and assignment constraints]
    end procedure
    Return the optimized matrices values by OPT function to RHCwithdt function
end procedure
```

5.5.2 Function RHCwithdt

Algorithm 3 explains the working of RHCwithdt *f unction* implementing Receding horizon control (RHC). As explained in the previous section, the OPT *f unction* and RHCwithdt *f unction* coordinate and work together. The OPT *f unction* is called from RHCwithdt *f unction* asshown at line 10 and optimal values calculated are sent back to RHCwithdt *f unction* shown at line13 in Algorithm 3. The final state matrices are the output of RHCwithdt *f unction*.

Algorithm 3 MATLAB code Algorithm for Receding Horizon Control

procedure RHCWITHDT($XX1, XX2, XX3$)

$XX1$: The matrix for agent 1 state variables

$XX2$: The matrix for agent 2 state variables

$XX3$: The matrix for agent 3 state variables

$X1_0, X2_0, X3_0$: State values for each agent at the first time point

$X1_f, X2_f, X3_f$: State values for each agent at the final time point

T: Time Horizon

w: planning horizon

dt: control horizon

procedure CALLING THE FUNCTION OPT

for each j $\in [1 : dt : T - dt]$ **do** ▷

OPT(Agents Initial and final values, w,T)

procedure INITIALIZATION USING THE RETURNED VALUES OF FUNCTION OPT

[Assigning the state values returned by function into new matrix for each Agent]

$XX1, XX2, XX3 \leftarrow$ OPT function returned matrices

[Assigning the Agents new initial position so to pass in the function OPT again]

$X1_{new}, X2_{new}, X3_{new} \leftarrow$ OPT function returned new matrices

end procedure

end for

end procedure

end procedure

CHAPTER 6 CALIBRATION AND VALIDATION

6.1 Key Model Parameters

The key parameters of the developed pedestrian trajectory planning model are:

- Sampling time (T): This is the total time in seconds to run a simulation
- x-axis separation between two agents (x_{sep}): This is the distance between two agents inx-axis direction in meters
- y-axis separation between two agents (y_{sep}): This is the distance between two agents iny-axis direction in meters
- Maximum and Minimum mean velocity
- Maximum and Minimum acceleration
- Receding Horizon control Value (*dt*): This is the time window in secondsfor actual motion
- Receding Horizon control Horizon Planning Value (*w*): This is the time window in seconds when the model plans the motion.
- Commonalities weights: This value defines the closeness and tightness of thepeople in the group walking together.
- Buffer zone: The gap that the pedestrian tries to keep while passing the stationary obstacle

6.2 <u>Data Description</u>

We evaluated the generated trajectories of the developed trajectory planning model in various individual and group mobility scenarios. We considered data from the dataset of paper [17] collected at the campus of Dalian University of Technology (DUT) in China. The location includes an area of pedestrian crosswalks at an intersection without traffic signals. A *DJI Mavic Pro* Drone with a down-facing camera was used as the recording equipment. The video resolution was 1920×1080 with a *fps* of 23.98. Pedestrians in the data are mainly college students. In the paper, the authors have extracted the trajectories from the recorded data using video stabilization, Pedestrian Tracking, Coordinate Transformation, and Trajectory filtering using Kalman filter. Figure 6.2 is a sample from one of the dataset video files we are using for our research. It shows moving agents and their respective trajectories in white.

Figure 6.1: Location for Data Collection on a Crosswalk

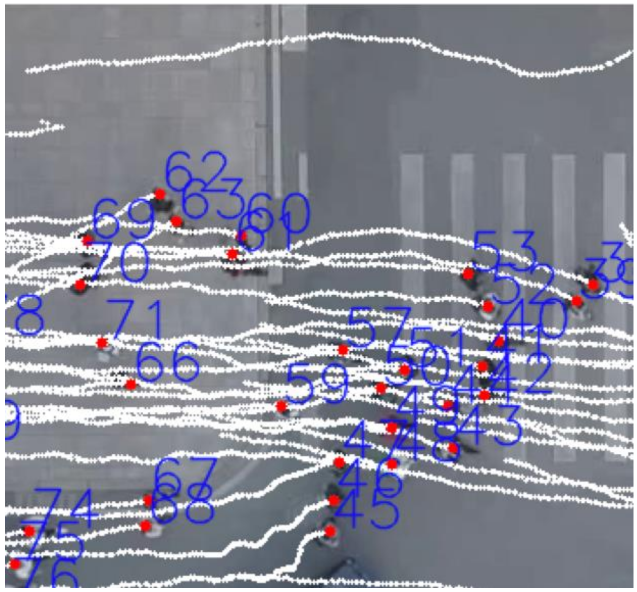


Figure 6.2: Sample Extracted Trajectories

6.3 <u>Model Calibration</u>

6.3.1 Calibration Methodology

The calibration process requires us to identify enough pedestrians moving as individuals, as a group of two agents, and as three agents from the video by using an image processing algorithm. Once the individual agents and small groups are identified, values are calculated and extracted automatically from the dataset and saved in an excel file - the values of maximum and minimum velocity, maximum and minimum acceleration, average *x sep* and average *y sep* values,sampling time, each Agent's initial and destination values. The excel file contains the valuesextracted and calculated from the dataset. We then use the values from the excel file in MATLABto calibrate our model's key parameters. Some values are used directly from the excel table, and some values are further calculated in MATLAB.

We have extracted about forty samples for two agents' group, thirty samplesfor three agents' group, and around twenty samples for individuals avoiding the obstacles. Considering the case study of two agents' group, we divided the forty collected samples into thirty samplesfor training the model and ten samples for testing the developed model. We have used the normal distribution method to dynamically calibrated the *x sep* and *y sep* values. The initial location values of the Agent are updated at every control horizon (dt) time based on receding horizon control.

6.3.2 Calibrated Model Parameters

To perform the calibration, we must configure the model as case studies. Presently, we have performed three case studies-

- Case Study 1: When two agents are walking together
- Case Study 2: When three agents are walking together
- Case study 3: Agent's stationery obstacle avoidance

Table 6.1 shows the calibrated values of key parameters for Case Study 1- When two agents walk together. We have extracted the $\bar{x}$ *sep* and average $\bar{y}$ *sep* values for all the samples for this case study. We then performed the normal distribution on the extracted values. The values perfectly fit the normal distribution, further verified by the chi-square test (h=0). The planning horizon (w) was considered 2 sec, and the control horizon (dt) was considered 1 sec.

6.4 Results

The developed MATLAB simulation based on behavior parameters produces smooth trajectoriesof a small group of two or three pedestrians walking together. Paper [12] explains that people walkingin smaller groups of two, three, or four tend to walk side by side. Smaller the density, the more perpendicular the group walking formation line to the walking direction. As the density increases, the group walking formation line starts bending; for example, three people form a V-like pattern, and four people form a U-like pattern. Understanding the behavior and interaction rules from existing pedestrian behavior studies, we developed a simulation generating trajectories, following the convex optimization algorithm, and utilizing the behavioral and interaction rules close to realistic mobility.

Table 6.1: Model Calibration for Case Study 1

Parameters	Calibrated Values
x_sep	dynamically update using Normal distribution $\mu = 0.097, \sigma = 0.046$
y_sep	dynamically update using Normal distribution $\mu = 0.52, \sigma = 0.15$
T	(Number of Frames)/23.98
Average min x-axis velocity	0.97 m/sec
Average max x-axis velocity	1.70 m/sec
Average min y-axis velocity	-0.32 m/sec
Average max y-axis velocity	0.64 m/sec
Average min x-axis acceleration	-0.3 m/sec^2
Average max x-axis acceleration	0.3 m/sec^2
Average min y-axis acceleration	-0.4 m/sec^2
Average max y-axis acceleration	0.4 m/sec^2

Table 6.2: Model Calibration for Case Study 2

Parameters	Calibrated Values
$\bar{x}$_sep between agent 1 and agent 2	dynamically update using Normal distribution $\mu = 0.294, \sigma = 0.237$
$\bar{y}$_sep between agent 1 and agent 2	dynamically update using Normal distribution $\mu = 0.612, \sigma = 0.194$
$\bar{x}$_sep between agent 2 and agent 3	dynamically update using Normal distribution $\mu = 0.719, \sigma = 0.221$
$\bar{y}$_sep between agent 2 and agent 3	dynamically update using Normal distribution $\mu = 0.241, \sigma = 0.178$
T	(Number of Frames)/23.98
Average min x-axis velocity	0.97 m/sec
Average max x-axis velocity	1.48 m/sec
Average min y-axis velocity	-0.20 m/sec
Average max y-axis velocity	0.33 m/sec
Average min x-axis acceleration	-0.3 m/sec^2
Average max x-axis acceleration	0.3 m/sec^2
Average min y-axis acceleration	-0.4 m/sec^2
Average max y-axis acceleration	0.4 m/sec^2

Table 6.3: Model Calibration for Case Study 3

Parameters	Calibrated Values
T	Number of Frame/23.98
Average min x-axis velocity	0.82 m/sec
Average max x-axis velocity	1.75 m/sec
Average min y-axis velocity	-0.32 m/sec
Average min y-axis velocity	0.64 m/sec
Average min x-axis acceleration	-0.3 m/sec^2
Average max x-axis acceleration	0.4 m/sec^2
Average min y-axis acceleration	-0.3 m/sec^2
Average max y-axis acceleration	0.4 m/sec^2
Gap between the agent and stationery obstacle	0.55 m

The trajectory planning is formulated as a convex optimization problem by linearizing the pedestrian dynamics and constraints. The behavioral rules are encoded in the cost function, the convexoptimization method will find the path or trajectory of the lowest cost, and at the same time, the motion also needs to be satisfied. In the following sections, we describe the details for each case study. To evaluate the results, we use the following performance metrics. Also, refer to table 6.4 :

- Mean Euclidean Distance (MED): Also known as average displacement error (ADE). The average Euclidean distance between the actual coordinates and the predicted coordinates ofthe pedestrian at every instant.
- Final Displacement Error (FDE): The Euclidean distance between the predicted final destination and the actual destination at the corresponding time point.
- Root Mean Square Error – rmse_xsep : The Average value for root mean square error (rmse)for the x-axis coordinated between the two agents' generated coordinates and ground truth coordinates at every instant.
- Root Mean Square Error – rmse_ysep : The Average value for root mean square error (rmse) for the y-axis coordinated between the two agents' generated coordinates and ground truth coordinates at every instant.
- Gait parameters: Analysis of basic gait parameters, i.e., step length and step frequency, helps understand a person's walking style. The step length and step frequency are affected by gender, age, group size, commonalities between agents [18] [19].To further validate our research work, we compared the gait parameters estimated in the case studies with those mentioned in [20].

6.5 Case Study-1: Two Agents walking together

6.5.1 Scenario Description

We are considering the scenario where two agents are walking together. The sample figuresin figure 6.3 are from actual video data. To perform the calibration and validation of the case study of two agents' group mobility behavior, we divided the forty collected samples into thirty samples for training the model and ten samples for testing the developed model.

Table 6.4: The performance metrics

Metrics	**Description**
MED_agent1	Average Euclidean distance Error of Agent 1
MED_agent2	Average Euclidean distance Error of Agent 2
FDE_agent1	Final position Euclidean distance error of Agent 1
FDE_agent2	Final position Euclidean distance error of Agent 2
MED_1	Average MED value for all the case study samples of Agent1
FDE_1	Average FDE value for all the case study samples of Agent 1
rmse_xsep	Average value of rmse between two agents predicted and actual values of x-axis coordinates
rmse ysep	Average value of rmse between two agents predicted and actual values of y-axis coordinates
step length	Distance covered when a person takes one step.
step frequency	The number of steps in a unit of time

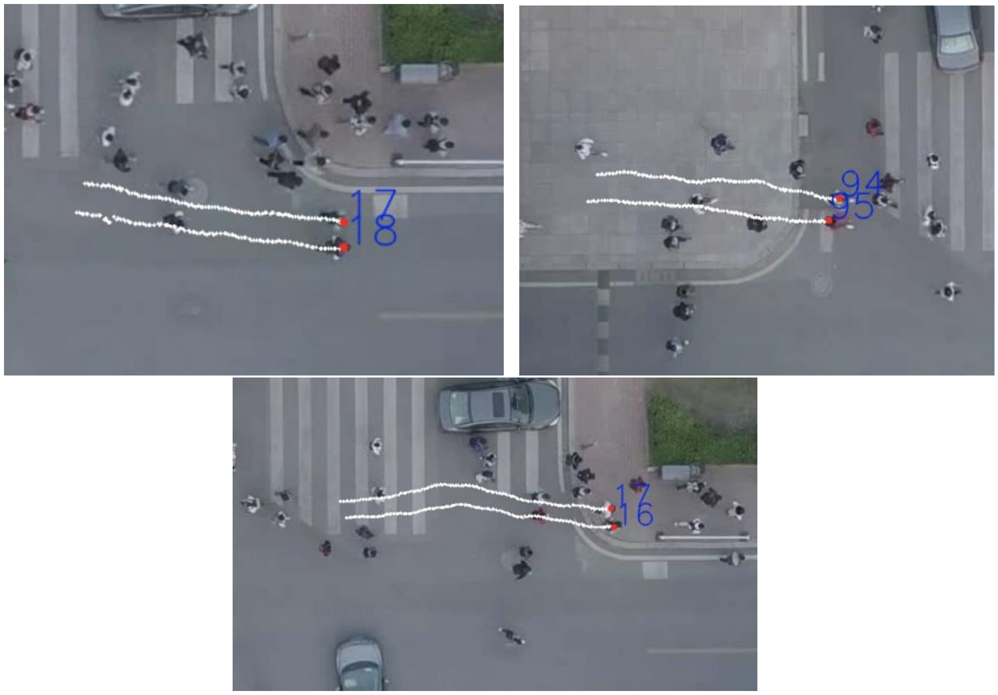
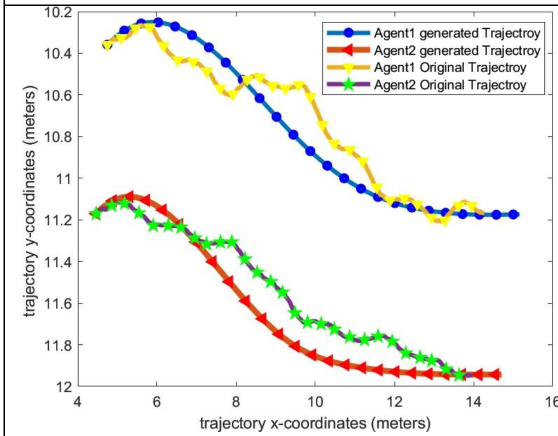
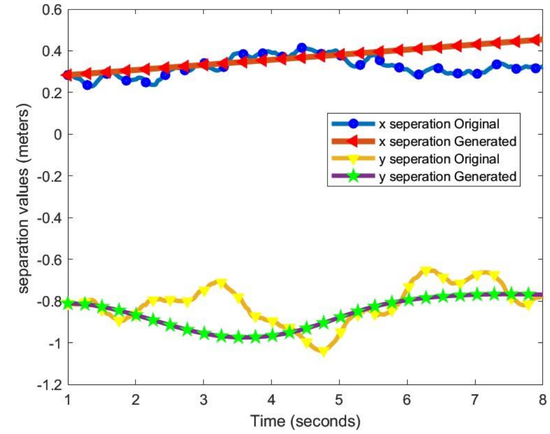


Figure 6.3: Sample figures of two agents walking together

6.5.2 Results

Once the model was calibrated, we have performed the validation on testing data. The results are shown in table 6.5, 6.6, 6.7. There are two columns in each table. The first column showsthe graph which is comparing the actual and predicted trajectories. The second column shows the plot for x-separation and y-separation.

Table 6.8 provides the average values of the performance metrics MED and FDE. The calculated values show good results. In general, a zero value would indicate that the predicted and actual data are almost the same. However, a value of zero is almost not possible practically. Therefore the closer the average values are to zero, the better fit the data has achieved.

<table>
<tr><th>Generated Trajectory</th><th>X and Y separation</th></tr>
<tr><td>
</td><td>
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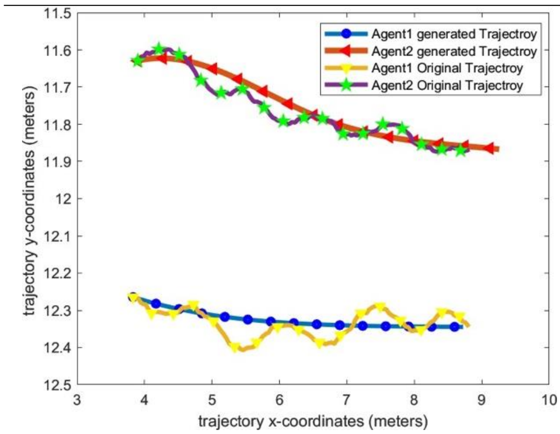
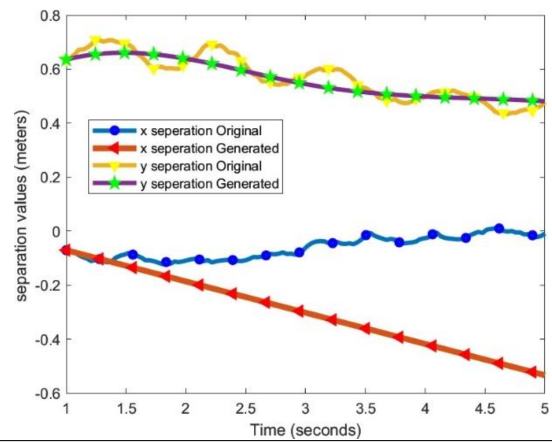
<tr><td>
</td><td>
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Table 6.5: Case Study-1 Result Table-1

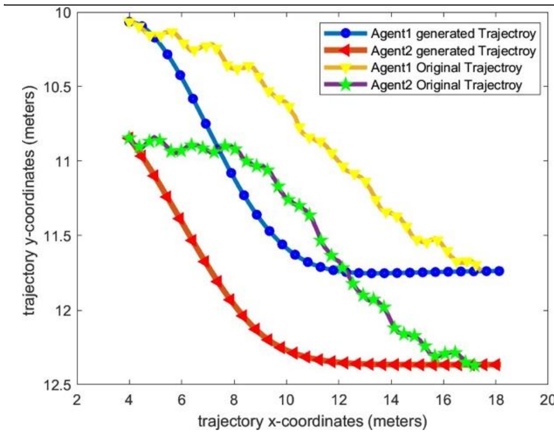
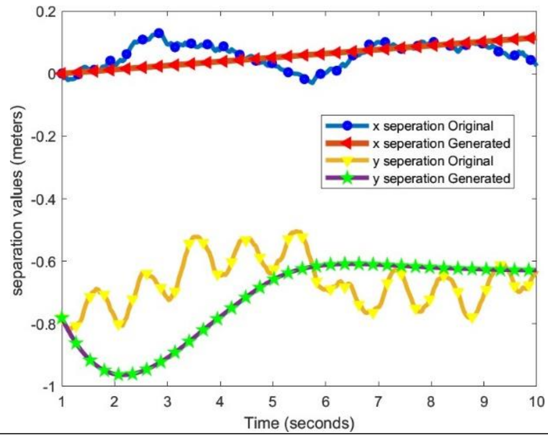
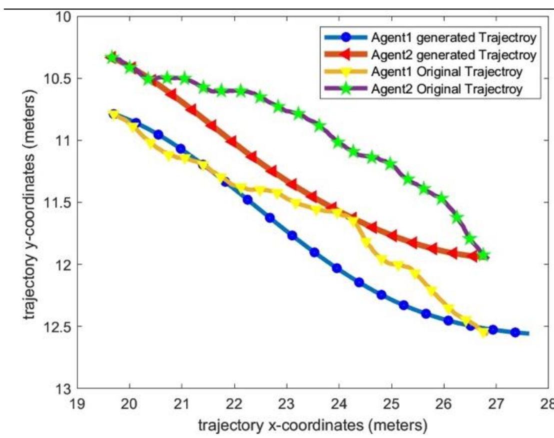
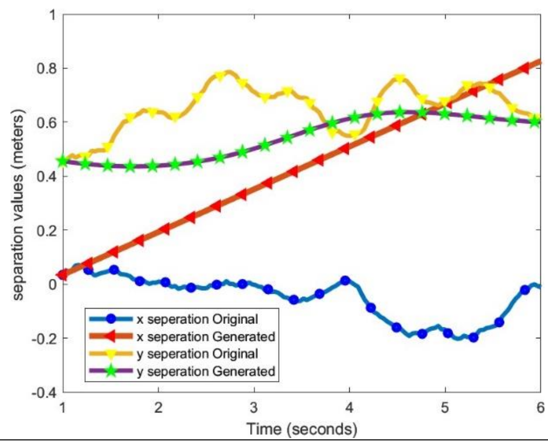
Generated Trajectory	X and Y separation
	
	

Table 6.6: Case Study-1 Result Table-2

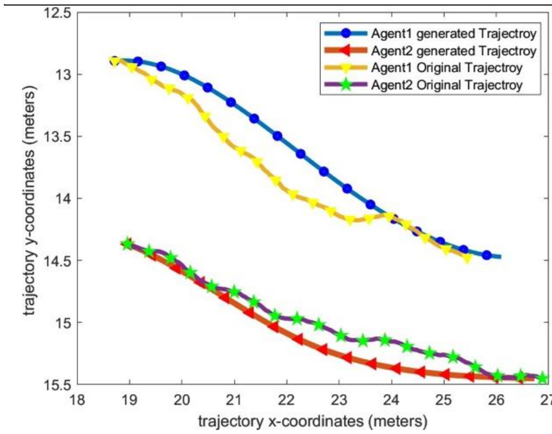
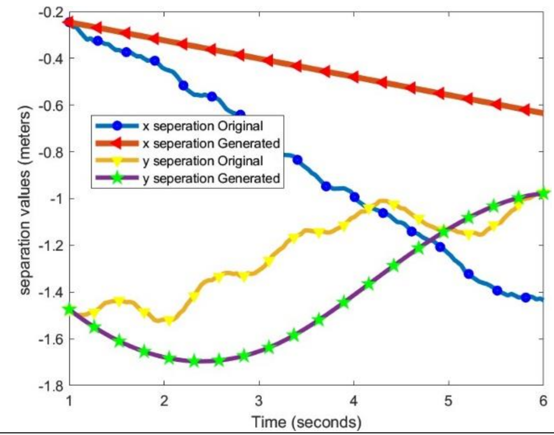
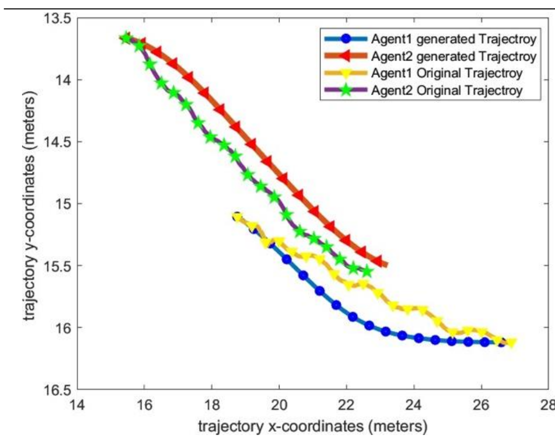
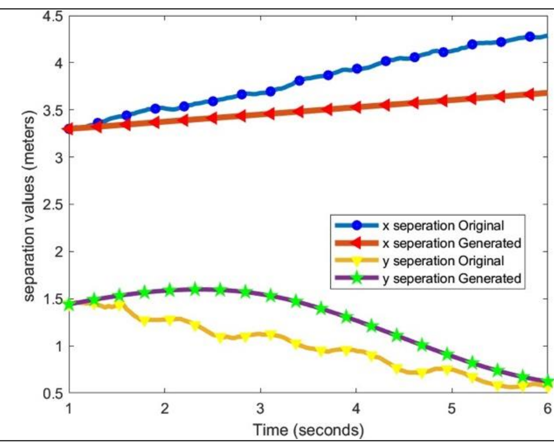
Generated Trajectory	X and Y separation
	
	

Table 6.7: Case Study-1 Result Table-3

Table 6.8: Case Study 1 Performance metrics average values

Performance metrics	Average values
MED_1	0.32
MED_2	0.24
FDE_1	0.54
FDE_2	0.45
rmse_xsep	0.36
rmse_ysep	0.007

Figures 6.4 and 6.5 illustrate the obtained gait parameters in case study 1. It can be noted that step length (shown in Figure 6.4) remains in the 0.6 to 0.7 meter range. On the other hand, pedestrians increase their step frequency to attain a higher speed to cross the pedestriancrossing in time (shown in Figure 6.5).

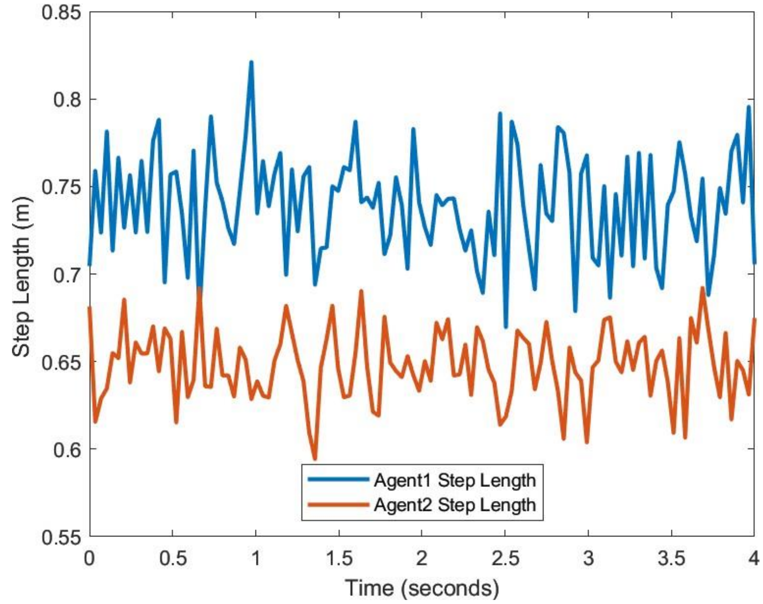


Figure 6.4: Step Length of Agents 101 and 102

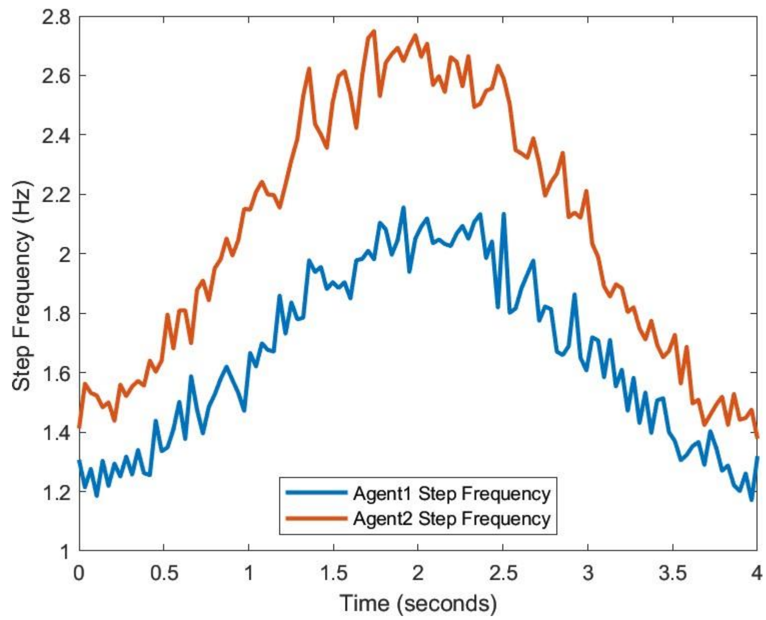


Figure 6.5: Step Frequency of Agents 101 and 102

6.6 Case Study-2: Three agents walking together

6.6.1 Scenario Description

We have studied the case scenarios where three pedestrian walks in a group. The model is calibrated, and parameters values are listed in table 6.2. The sample figures are from the actual data. To perform the calibration and validation of the case study of three agents group mobility behavior, we divided the thirty collected samples into twenty-three samples for training the model and seven samples for testing the developed model.

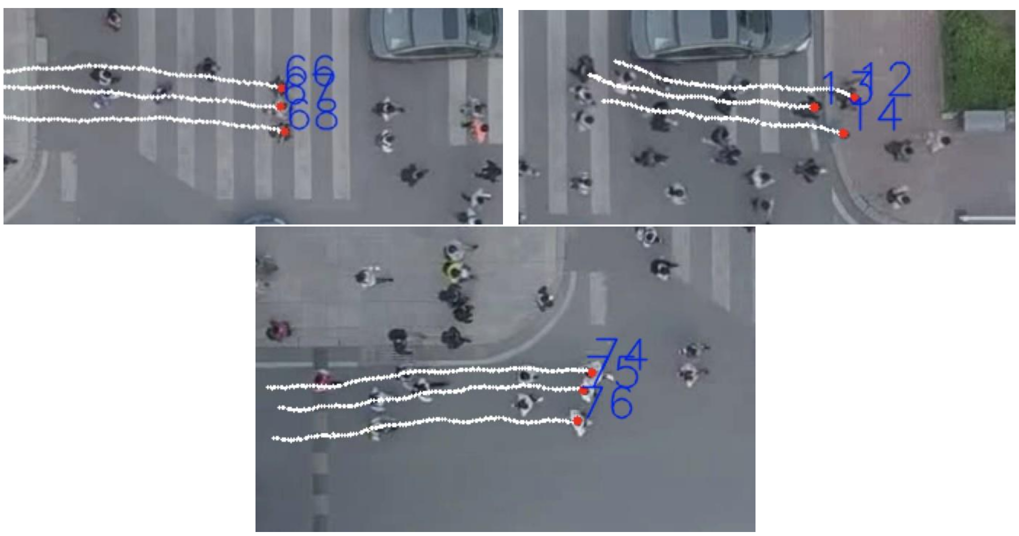


Figure 6.6: Sample figures of three agents walking together

6.6.2 Results

Once the model was calibrated, we have performed the validation on testing data. The results are shown in Table 6.10. The table shows the graph which is comparing the actual and predicted trajectories. The meaning of all the variables is described in table 6.4.

Table 6.9 shows the average Euclidean values and root mean square error values for the test samples. In general, a RMSE value of zero would indicate that the predicted and actual data are almost the same. However, the value of zero is practically almost not possible; therefore, the closer the RMSE values and Euclidean distance are to zero, the better fit the data has achieved. The average values are indicating good results as almost all values are under one, with MED_1 = 0.26 , MED_2 = 0.68 , MED_3 = 0.32 , FDE_1 = 0.00055 , FDE_2 = 0.32, FDE_3 = 0.00055

Figures 6.7 and 6.8 illustrate the obtained gait parameters in case study 2. It can be noted that step length (shown in Figure 6.7) remains in the 0.6 to 0.75 meter range. On the other hand, pedestrians increase their step frequency to attain a higher speed to cross the pedestrian crossing in time (shown in Figure 6.8).

Table 6.9: Case Study 2 Performance metrics average values

Performance metrics	Average values
MED_1	0.26
MED_2	0.68
MED_3	0.32
FDE_1	0.00055
FDE_2	0.54
FDE_3	0.00055
rmse_xsep12	1.36
rmse_ysep12	0.005
rmse_xsep23	0.32
rmse_ysep23	0.002

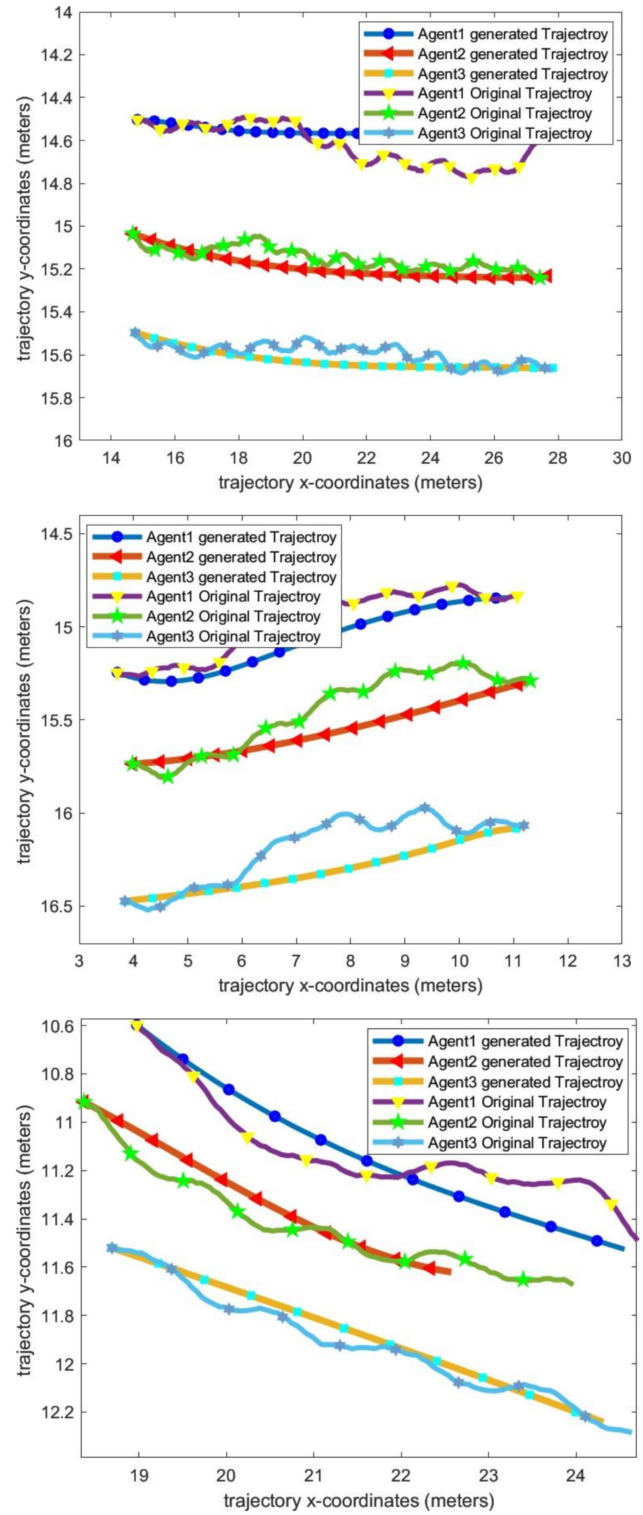


Table 6.10: Case Study-2: Sample Results

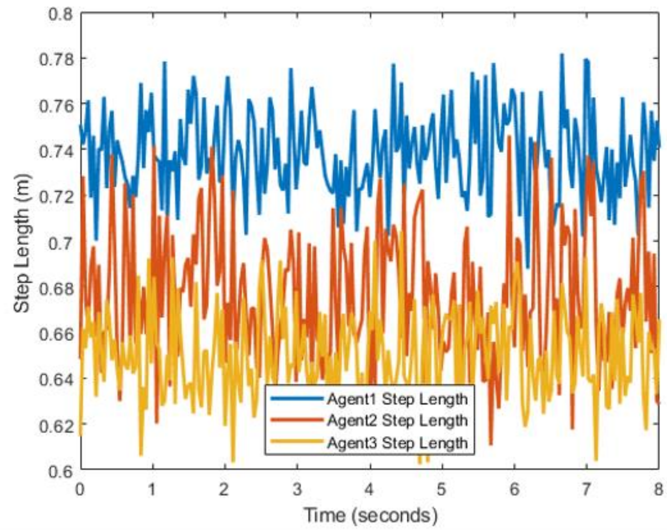


Figure 6.7: Step Length of Agents 22 and 23 and 24

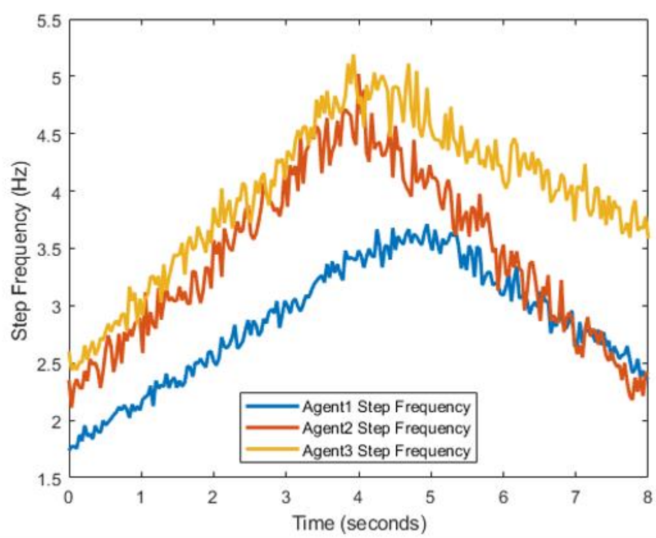


Figure 6.8: Step Frequency of Agents 22 and 23 and 24

6.7 Case Study-3: Agent's Obstacle Avoidance

6.7.1 Scenario Description

We have studied the scenarios where the pedestrian passes the stationery obstacle (in our case, it is a standing car). We calculated the average buffer zone that pedestrian keepshaving a safe pass. The calculated buffer zone is approximately 0.55 meters. The model is calibrated, and parameters values are listed in table 6.3. The sample figures in figure 6.9 are from actualvideo data. To perform the calibration and validation of the case study of one agent mobility avoiding the obstacle, we divided the twenty collected samples of an agent avoiding obstacleinto fifteen samples for training the model and five samples for testing the developed model.

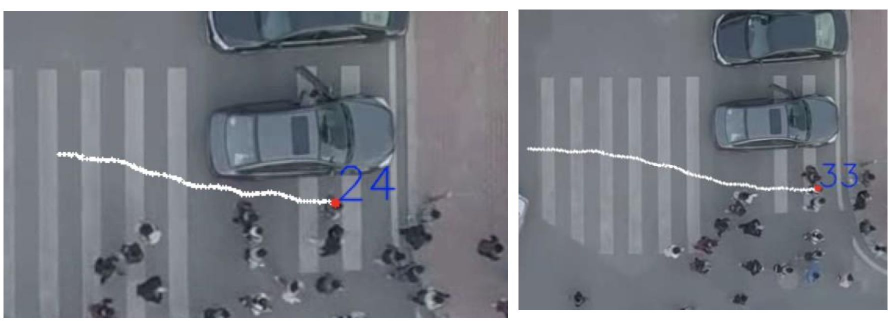


Figure 6.9: Sample figures of an agent and avoiding obstacle

6.7.2 Results

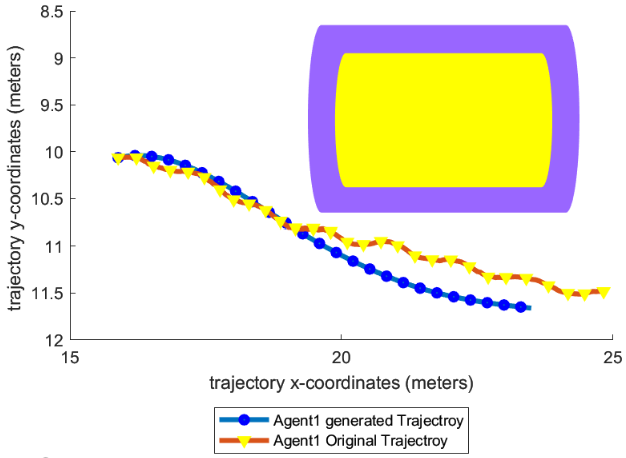
Once the model was calibrated, we have performed the validation on testing data. The results are shown in Table 6.12. The table shows the graph which is comparing the actual and predicted trajectories. The meaning of all the variables is described in table 6.4.

Table 6.11 shows the average Euclidean distance values. The closer the Euclidean distance values are to zero, the better fit the data has achieved. The average values are indicating good results as almost all values are under one, with MED_1 = 0.66, FDE_1 = 0.35.

Table 6.11: Case Study 3 Performance metrics average values

Performance metrics	Average values
MED_1	0.66
FDE_1	0.35

Figures 6.10 and 6.11 illustrate the obtained gait parameters in case study 3. It can be noted that step length (shown in Figure 6.10) remains in the 0.6 to 0.75 meter range. On the otherhand, pedestrians change their step frequency while encountering the obstacle (shown in Figure 6.11).



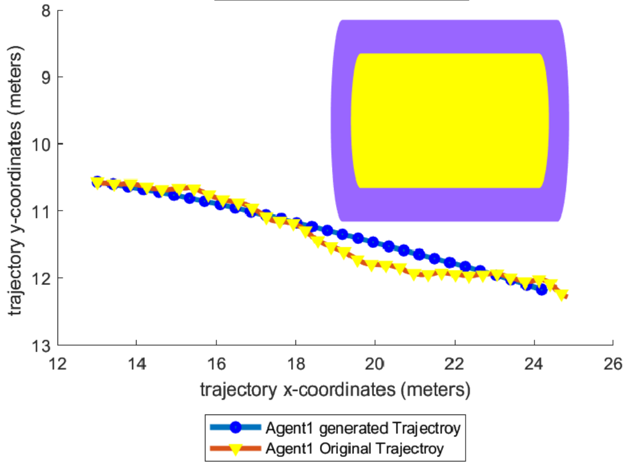


Table 6.12: Case Study-3: Sample Results

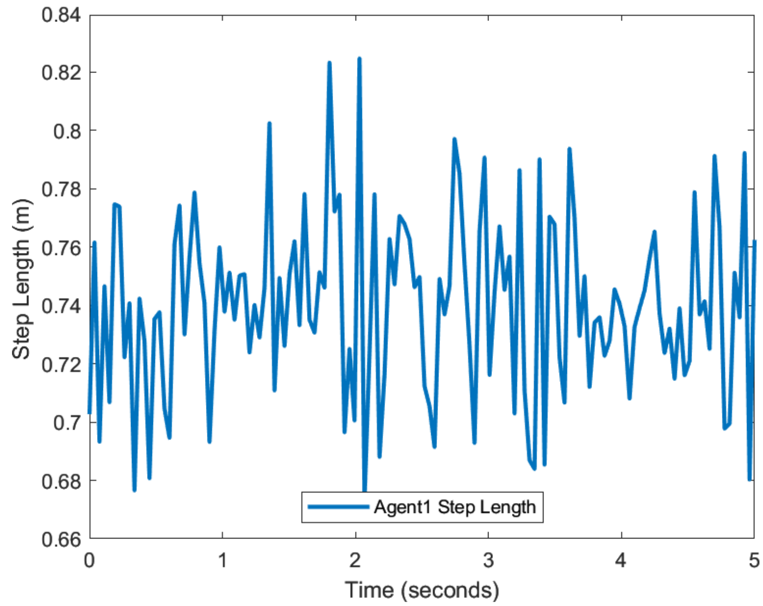


Figure 6.10: Step Length

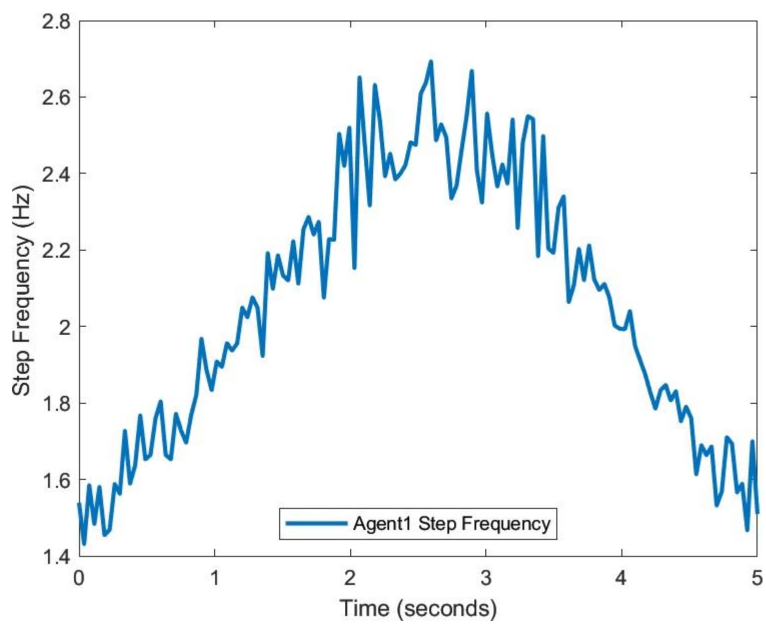


Figure 6.11: Step Frequency

Part II

MOBILITY AWARE ADAPTIVE ROUTING PROTOCOL

CHAPTER 7 PRELIMINARIES

Ad-hoc communication networks, namely MANETs and VANETs, will significantly maintain safety and achieve efficient and rapid traffic flow. In the urban traffic scenario, MANETs will form in non-motorized traffic agents such as pedestrians, cyclists, micromobility vehicles, and therefore these agents' participation will be crucial for traffic mobility and safety. Pedestrian walking behavior is very dynamic, they have their decision-making process, and therefore the walking behavior can sometimes be very ran-dom. An efficient ad-hoc routing protocol that can handle the randomness in pedestrian walking behavior and, at the same time, maintain a stable and connected network is a need for the shared space urban mobility scenario. The current research lacks utilizing real pedestrian walking behavior knowledge while evaluating and designing ad-hoc network protocols. Through the research work in part-II of this dissertation, we aim to develop a mobility-aware adaptive routing protocol that establishes and maintains a stable MANET for a pedestrian in shared space. A well-connected MANET would always ensure connectivity and therefore decreases the route failures.

7.1 MANETs

MANETs are mobile ad-hoc networks where every node is mobile and capable of communicating without any infrastructure. Mobile ad hoc networking aims to extend connectivity into the realm of autonomous, mobile, and wireless domains such as establishing communications for an emergency, disaster, safety, and rescue operations or other scenarios requiring rapidly deployable communications.

Communication in ad-hoc networking is also a multi-layer process as in conventional networking. [21] explains the role of each layer as follows- "The physical layer must adapt to rapid changes in link characteristics. The multiple access control (MAC) layer needs to minimize collisions, allow fair access, and semi-reliably transport data over the shared wireless links in the presence of rapid changes and hidden or exposed terminals. The network layer needs to determine and distribute information used to calculate paths in a way that maintains efficiency when links change often and bandwidth is at a premium. It also needs to integrate smoothly with traditional, non adhoc-aware internet, and perform functions such as auto-configuration in this changing environment. The transport layer must handle delay and packet loss statistics that are very different from wired networks. Finally, applications need to be designed to handle frequent disconnection and reconnection with peer applications as well as widely varying delay and packet loss characteristics."

Still, there are many aspects that make communication in MANETs different from conventional networks communication. These include - transmission in wireless medium, nodes

are mobile and therefore have dynamically changing network topology, the nodes energy constraints, the variations in link and node capabilities due to adjustment in transmission and reception parameters, and other factors [22].

In recent times, the ad-hoc networks have become more and more infrastructure-less, and therefore their role in the future transportation of connected, autonomous, urban, and shared space traffic scenarios can be seen as immensely significant. With the advent of 4G wireless evolution, an ad hoc mobile network is becoming both flexible and powerful and extending internet services to the non-infrastructure area. This motivates researchers to work on addressing the challenges in MANETs' communication continuously.

7.2 <u>Network Layer</u>

The network layer in ad-hoc communication is responsible for transmitting data packets from the sender to the receiver. Therefore, we can say that the network layer has two main functions

firstly, a routing algorithm determines the routing path from sender to receiver. Second, forwarding the packet is a router's local action, i.e., a router receives the packet at its input link interface and then transfers the packet to one of its appropriate output link interfaces. Therefore, determining the routing path and keeping the forwarding table up to date is a critical process and involves a powerful interplay between the route determination and maintaining the forwarding table at each router participating in the determined path between sender and receiver.

As a routing algorithm determines the path between the sender and receiver, it made it possible for routers to build and maintain a forwarding (routing) table. First, the routing algorithm determines the header value and output link values of the router's forwarding table. Then, with the help of the updated routing table, the routers successfully forward the data towards the path that will lead to the destination.

The developed trajectory planning model (Phase I) can predict the evolving trajectory, now once the future positions of nodes can be determined, utilizing the link stability protocol property to determine that if specific nodes are going to break away in the next few seconds, then a new path can be determined towards the breaking node, so it does not lose the communication, and also a new route is developed in place of prior existed path as a node exits, so that communication always continues in a network. A well-connected traffic MANET will play a significant role in maintaining safety and achieving efficient and rapid urban traffic flow.

7.3 Routing Protocols

The nodes in the MANET may move at any time or may even move continuously, MANETs routing protocols must learn new routes to maintain connectivity. Also, since sources of wireless interference and wireless transmission propagation conditions may change frequently, the routing protocol must react to these changes. Therefore, the routing protocols employ cross-layer optimization by supporting interactions across the protocol layers.

The MANETs routing strategies can be classified as follows:

- The classical routing protocols - based on the paths search strategy-defines three classes: reactive, proactive, and hybrid protocols.
- QoS routing protocols - To guarantee the QoS requirements for multimedia

applications.

– QoS routing protocols based on link stability - to maintain the stability and the durability of paths.

7.3.1 Link Based

Routing protocol selects the best path between two nodes to relay the packet [1]. Establishing a stable path requires evaluation of the links that constitute that path.

We now discuss MANET routing protocols based on link stability. The link stability signifies the remaining lifetime of a network link. It can be expressed in terms of distance, probability, or other metrics [23]. The stability metric affects QoS metrics such as the end-to-end delay, packets loss, and bandwidth. In addition, the distance between nodes or the nodes' mobility can be considered a metric to assess the link stability between two nodes.

Figure 7.1 shows the classification of the MANETs routing protocols based on link stability [1].

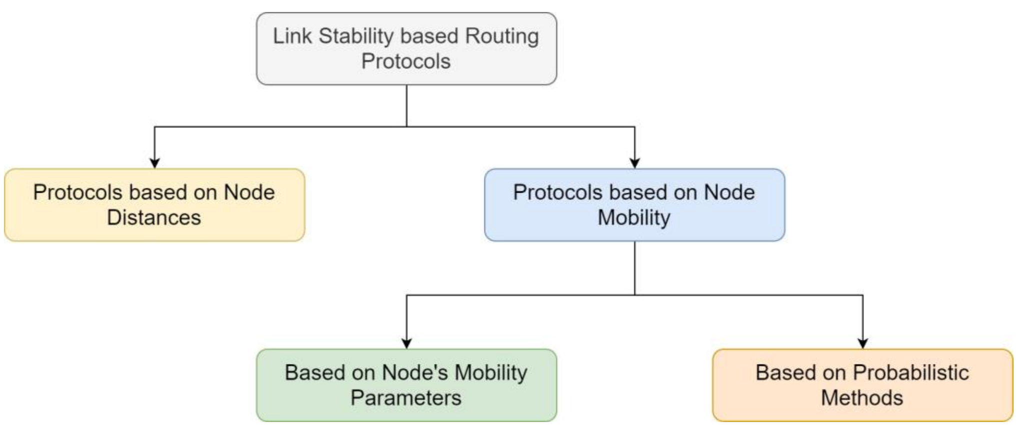


Figure 7.1: Classification of the MANETs routing protocols based on link stability

7.3.2 Distance-Based

The distance-based protocols are the ones that consider the distance between two nodes asa metric to elect stable paths. The distance between nodes is generally calculated using localization systems or based on the signal-power of messages exchanged between the nodes.

– TBP-SE protocol [24] (Zhu et al., 2006) establishes a stable path by selecting the more stable and sustainable among the feasible paths. This is performed by calculating the link stability distance metric of each node calculates for each of its neighbors. The principles for the stable link are that the more the distance between two neighbor nodes is small, the more these two nodes are still in the vicinity to each other for an extended period.

– Paper Triviño-Cabrera et al.,2006 [25] proposes improving reactive DSR protocol to establish a stable path. To evaluate the path stability, two criteria are used Maximum/minimum signal strength (MMSS) and a minimum number of hops.

– SSOD protocol [26] (Wang et al.,2005) - Reactive protocols that establish stable paths by generating RREQ packets. These packets transport two main fields, SL minet SL max. SSOD considers the path with the low value of SL min of the candidate paths as the most stable. The link stability value between two nodes in SSOD, is calculated by the signal quality of packets exchanged.

The Protocols based on the mobility of nodes can be further classified into Protocols basedon the parameters of nodes' mobility and Protocols based on probabilistic methods. The protocols based on the parameters of nodes' mobility use some criteria inherent in the nodes' mobility, such as their coordinates, their directions of movement, or their speeds, to calculate the metric stability values.

The Protocols based on probabilistic methods:

– They calculate the probability that the mobile nodes remain a neighbor of another node

– Mechanism of Qingyang Song [27]: Song et al. (2012): In this paper, the evaluation ofthe link stability is regarded as the probability that the link remains connected from thepresent time tp for the time ρ (called the remaining probability) The Authors also define the probability that a link recovers within a time ρ after a link failure (called the recovering probability)

– SDR protocol [28]: Liu and Kim (2013)- This paper proposed a stability-considered density-adaptive routing (SDR) protocol for the Ad hoc networks. SDR can perform different routing tactics according to the corresponding density of vicinity. Accordingto the density value calculated by each node for its vicinity, a node chooses the right tactic: D-mode or S-mode. If the density value is larger than a predefined threshold Pth, the D-mode is chosen as the routing tactic for the forwarding node. Otherwise, the S-mode will be chosen. These routing tactics reduce the overhead in a dense network, caused mainly by the control messages, and guarantee the routing quality in a sparse network.

– ST_OLSR Protocol [1] (Moussaoui et al. (2014)): Modification of proactive OLSR protocol [29], modify the mechanism to elect the most stable MPR (Mulitpoint relay) node set in the network. The link between node B and node A is considered stable ifthe signal power values are close to their expected value. The SND (Stability of NoDes) and the FND (Fidelity of NoDes) are used for electing the stable MPR nodes and the stable topology. (Figure 7.2 and 7.3)

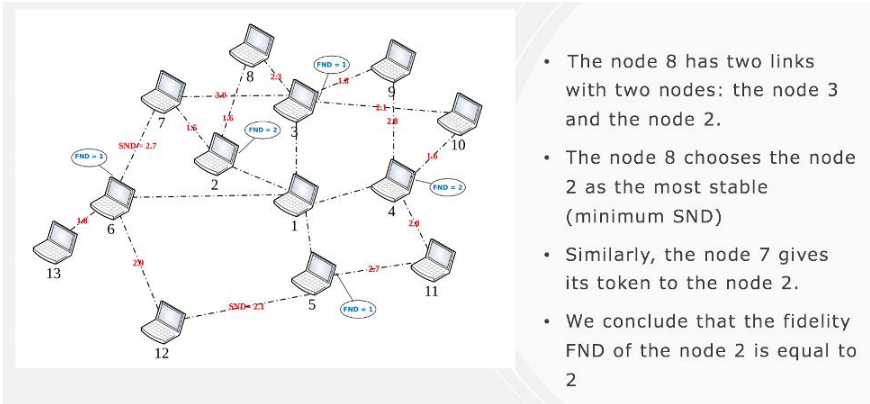


Figure 7.2: The concepts of SND and the FND in ST OLSR protocol (Picture taken from [1])

Figure 7.3: OLSR protocol (Picture Taken from [2])

7.4 Challenges in MANET

One of the significant challenges in MANET is how to minimize path disconnections? In [1], authors state that - "A routing protocol is required that elects among the candidate paths between two nodes, the more stable and the more sustainable one." Therefore, establishing a stable path requires evaluation of the links that constitute the path. Path disconnection minimization leads to reliable communication with less packet loss, less end-to-end delay, and high throughput.

Pedestrian walking behavior can sometimes be unpredictable and random. There are many studies investigating pedestrian walking behavior. Pedestrian mobility models help in simulating pedestrian motion to study various traffic scenarios. An efficient ad-hoc routing protocol that can handle the randomness in pedestrian walking behavior and, at the same time, maintain a stable and connected network is a need for the shared space urban mobility scenario.

Thus, the challenge is dual - a) simulating pedestrian trajectories realistically, b) using the realistic trajectories to improve the existing routing protocols. A well-connected stable pedestrian network can be used in emergencies such as evacuation, disaster; and assisting the researchers and engineers from transportation agencies in assessing pedestrians' safety conditions in urban transportation and shared space.

The random waypoint mobility model has dominated MANET research. While this model may provide valuable insights, it is far from realistic and will likely not give reasonable performance estimates of pedestrian MANETs. To best our knowledge, this will be the first research attempt to use the real walking behavior for establishing and maintain the stable pedestrian MANET.

CHAPTER 8 METHODOLOGY

8.1 Approach

The Phase II of our research aims at improving the routing protocol for establishing and maintaining stable MANET in shared space. The established stable communication can be utilized for testing communication scenarios to enable safer shared space traffic by prompt dissemination of useful real-time information to the end-users.

We are proposing one potential improvement technique which based on the hypothesis that if we have a good idea about future pedestrian mobility, if we can emulate the pedestrian mobility by understanding the real-time walking pedestrian behavior, then there will be a better understanding of how the topology will evolve in the future. Therefore, leveraging predictive mobility modeling benefits, the routing table can be updated based on the evolving topology. This will then help create the stable MANET connection, and then a seamless flow of information can be maintained all the time in MANET. Figure 8.1 illustrates a scenario where the source node transfers the information, and the objective to achieve is that all nodes remain connected for the most prolonged period, and there is a continuous transfer of information. Now, if we imagine a scenario, at a particular time at 3 sec, the link stability measurement indicates that node D link is about to break, and there is a requirement of particular arrangement such that node D remains in the network and receives continuous information. The arrangement is finding a new route or increasing the transmission range quickly without causing much delay and loss in transmission. If a routing algorithm keeps updating the routing table at each router based on how the nodes' location will evolve in the next few seconds in the future, route establishment tasks and maintenance tasks will always be preset, which saves the time overhead for route discovery.

8.2 Simulation Study

The paper [30] described OMNeT++ as a public-source, component-based, modular, and open-architecture simulation environment with strong GUI support and an embeddable simulation kernel. It is designed to simulate discrete event systems, but the primary application area is the simulation of communication networks. OMNeT++ is one of those many simulation tools available for simulating the communication network as close as a real communication network. OMNeT++ is open-source software with a robust library and a very intuitive simulation environment. OMNeT++ is based on Eclipse platform. OMNeT++ provides the functionality of developing and configuring models using NED (network development) and INI (initialization) files. In contrast, Eclipse provides the backbone with C++ files with network layer functionality, visualizations, and mobility features. OMNeT++ environment is a very successful open-source software for simulating communication networks. INET framework is

written for OMNeT++ simulator system. INET framework is an open-source communication network package allows for the simulation of the various wired and wireless network. INET framework has many modules supporting each layer of the communication model. It has a modular architecture supporting simulation of various features of communication networks, and as well as new protocols for wired and wireless networks can be developed and plugged in to evaluate their performance.

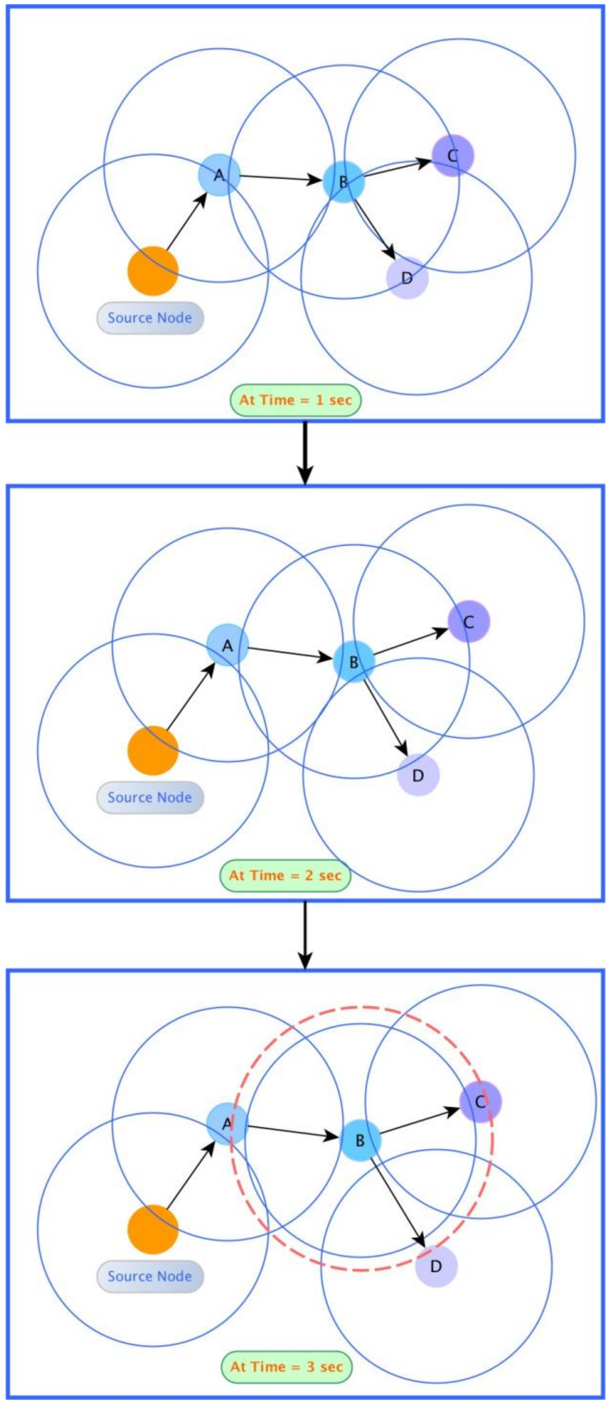


Figure 8.1: An Illustrative diagram explaining the proposed approach. ***Leveraging predictive mobility, it can be determined that Node D is going out of range at t = 3 sec; therefore, transmission range at Node B increases. (shown by a red dotted circle) to keep the continuous flow of information in all nodes***

This preliminary simulation study evaluates the existing MANET routing algorithms - AODV, DSDV, and OLSR. AODV (Ad hoc on-demand distance vector) is a reactive protocol where the route is created only when the source requests a route to a destination. Thus, it has the route discovery and route maintenance phases. DSDV(Destination Sequenced Distance Vector) and OLSR(Optimized link-state routing) protocols are proactive protocols in which routing tables are exchanged among neighboring nodes each time a change occurs in the network's topology. The simulation study focuses on the performance of the MANET routing protocol with a varying number of nodes. End to End Delay, throughput, and Packet delivery Ratio are considered the performance metrics that capture routing protocols' most basic overall performance.

We wanted to have trajectories closely related to real walking behavior; therefore, rather than using microscopic simulation, we used real trajectories as the primary sources of traces. We considered data from the dataset considered is the dataset of paper [17] collected at the Dalian University of Technology (DUT) campus in China. The location includes an area of pedestrian crosswalks at an intersection without traffic signals. The video resolution was 1920×1080 with a fps of 23.98. The paper authors have extracted the trajectories from the recorded data using video stabilization, Pedestrian Tracking, Coordinate Transformation, and Trajectory filtering using Kalman filter. The data files are extracted in csv format, then transformed using Python in a form readable by OMNeT++. Finally, the real trajectories are transferred to OMNeT++ using the BonnMotion mobility model. The BonnMotion mobility model is a model to move a node using a trace file. A trace file provides the movement pattern in terms of X, Y, and Z coordinates.

The OMNeT++ simulation environment allows us to set up a scenario based on a real crosswalk scenario as in the considered dataset. In the simulation, the attempt is to transfer information between the source node and the destination node. The intermediate nodes are mobile and follow real pedestrian trajectories (based on the trajectory data considered for the project). The MANET routing protocols need to adapt to changes in the network topology and maintain routing information to be forwarded to the destination. A visualization of an intersection scenario with thirteen nodes is shown in Figures 8.2 and 8.3.

Steps for the implementation in OMNeT++ involves following step by step procedure:

Step 1: Two hosts communicating wirelessly

Step 2: Adding more nodes and decreasing the communication range

Step 3: Setting up static routing

Step 4: Configuring node movements

Step 5: Configuring AODV (reactive) MANET protocol

Step 6: Configuring DSDV (proactive) MANET protocol

Step 7: Configuring OLSR (proactive) MANET protocol

Figure 8.2: A view of DUT intersection with thirteen college students walking

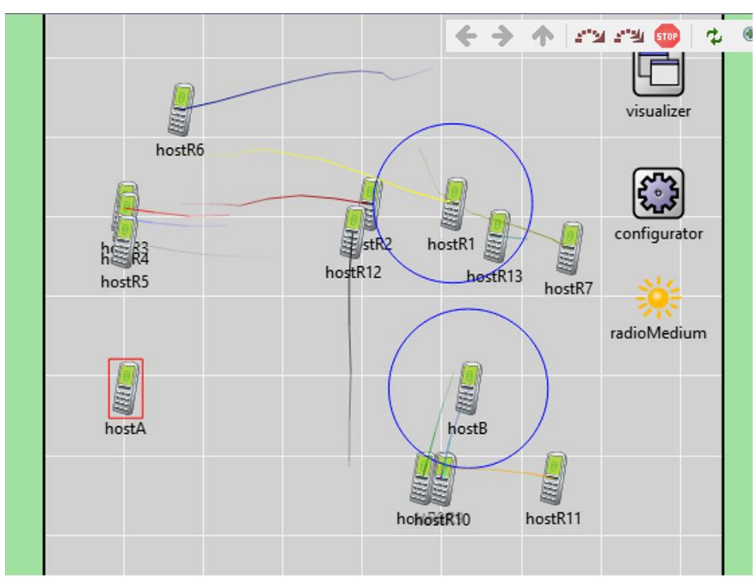


Figure 8.3: OMNeT++ visualization shows mobile nodes based on real trajectories

The visualization of step 5 can be seen in Figures 8.4 and 8.5. In Figure 8.4, we can see the route formation for packet transfer between host-source and host-destination with a solid blue arrow. This is because the nodes are mobile and continuously change position. The blue circle around each node is the communication range of each node. The routing table stored at each node contains updated location information for any other node in the network. This helps in route discovery and route formation. Figure 8.5 shows the functioning of the network layer in route discovering and maintaining the routing table for establishing communication. The table 8.2 shows the performance metrics comparison for AODV protocol, DSDV protocol and OLSR protocol created after manually analyzing the result log generated by OMNeT++ simulator. Still, efforts are to be made to automatically generate results logs from the OMNeT++ simulator environment using user-readable charts and tables.

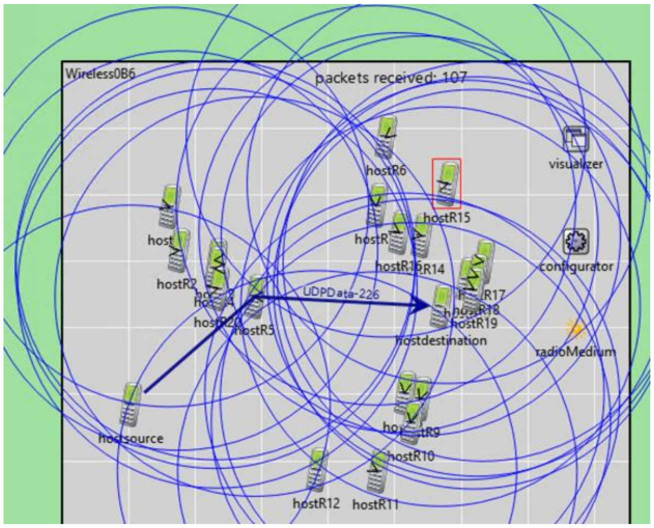


Figure 8.4: AODV protocol working to transmit messages between host source and host destinationwith twenty mobile nodes

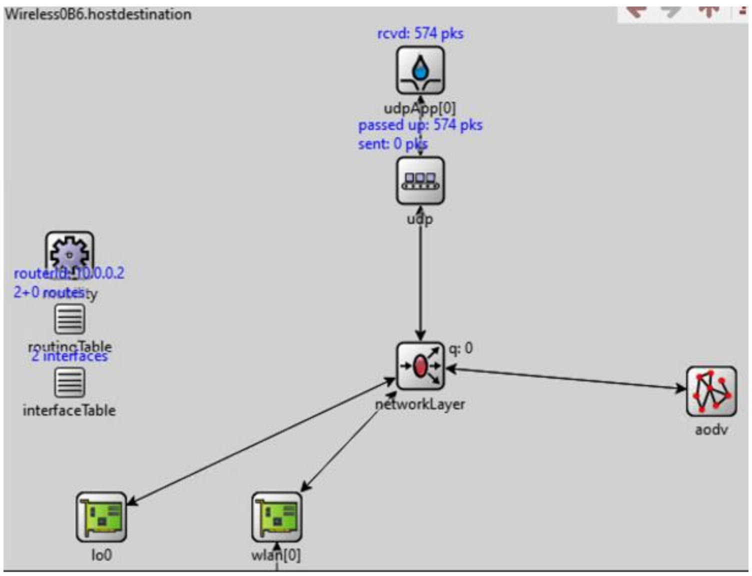


Figure 8.5: Inside view of host destination node in OMNeT++

Table 8.1: OMNeT++ Result logs for AODV Protocol

Number of Packet Sent by Source	Number of Packet Received by Destination	Communication Range	Number of Nodes (/Pedestrians)
29213	0	150m	7
29213	0	150m	13
29213	251	150m	20
29213	1240	250m	7
29213	7304	250m	13
29213	15902	250m	20
29213	1479	300m	7
29213	7304	300m	13
29213	15902	300m	20

Table 8.2: Comparing performances Metrics for AODV, DSDV and OLSR Routing Protocol result logs from the OMNeT++ simulator environment in the forms of user-readable charts andtables.

Number of Nodes	Performance Metrics	OLSR	DSDV	AODV
13	End to End Delay	Low	High	Very High
	Throughput	High	Low	High
	PDR	High	Low	High
20	End to End Delay	Low	Low	Low
	Throughput	High	High	High
	PDR	Very High	High	High

The following performance metrics are considered:

- Throughput: It measures how well the network can constantly provide data to the destination. It is derived in Mbps. For achieving better performance, it should be high.
- Packet Delivery Ratio: The ratio of the number of data packets delivered to the destination nodes and the number of data packets sent by source nodes. The performance would be better when it is high.
- End-to-end delay: The average time interval between the generation of packets in a source node and the successful delivery in a destination node. The performance would be better when it is low.
- In the preliminary study, we have achieved the following objectives: we have performed a thorough literature review of the existing state of the art routing protocols and performed the preliminary simulation study that is the initial step to set up the standard to compare the network durability and QoS for the existing routing algorithms and the proposed prediction-based routing algorithm.

CHAPTER 9
FUTURE WORK AND DISCUSSION

9.1 <u>Future Work</u>

Urban transportation needs to be sustainable, and it needs active collaboration among transportation and infrastructure planning agencies and policymakers to handle the enormous challenges of urbanization. A holistic redesign of existing mobility infrastructure and promoting non-motorized transportation promotes physical activity, and at the same time, reduces traffic congestion, accident risk, energy consumption, and pollution emissions. Our research aims to develop a framework that helps to simulate active mobility in shared spaces and enhance peer-to-peer communication among the shared space participants.

As part of Phase-I of the project, we have developed an agent-based pedestrian trajectory generation model and performed the case studies involving two agents' group, three agents' group, and an agent's obstacle avoidance maneuvers. The model calibration and validation are also completed, demonstrating that the developed pedestrian trajectory generation model generates quite realistic trajectories with RMSE values of less than one in most performed case studies. We are in the process of writing one journal paper based on the accomplished research work.

The Phase-II of our research aims at developing a mobility-aware adaptive routing protocol for MANETs. We have performed a thorough literature review of the present state of art MANET routing protocols and performed a preliminary simulation study analyzing the shortlisted state-of-the-art MANET routing protocols while inputting real pedestrian trajectories. Next, we will focus on improving an existing MANET routing protocol that enhances the communication between moving nodes.

9.2 Discussion

The developed trajectory generation algorithm will aid in improving a routing technique that establishes and maintains a robust and stable pedestrian MANET. A new adaptive MANET routing algorithm will ensure that there always exists connectivity in a pedestrian MANET, enabling safer shared space traffic by prompt dissemination of useful real-time information to the end-users. A robust communication network can share information reliably with all the participating nodes in a network and, therefore, can be used to address challenging times of disaster evacuation, emergency evacuation, and occasional times of limited connectivity and break-ins.

This research addresses a mobility challenge that we are going to see in the coming future. Therefore, if there already exists a framework that can allow testing the scenarios of urban mobility, this gives traffic enforcement agencies an upper hand in handling the challenges and allows the government to have a holistic redesign of existing mobility infrastructure, which provides a better traffic safety.

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