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Department of Measurement

Human motion modeling and data generation tool for tracking algorithms development

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BACHELOR‘S THESIS ASSIGNMENT

I. Personal and study details

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Guidelines:

1. Study the literature of human motion modeling using mutli-agent systems and finite state machines.
2. Study the literature on (human) motion filtering and probabilities for better familiarity of the application of the simulated data.
3. Propose and implement your own simulation environment with configurable behavior and simple physical interactions.
4. Develop a simple graphical visualization of the generated data.

Bibliography / sources:

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III. Assignment receipt

The student acknowledges that the bachelor’s thesis is an individual work. The student must produce her thesis without the assistance of others, with the exception of provided consultations. Within the bachelor’s thesis, the author must state the names of consultants and include a list of references.

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I would like to express my deepest gratitude to my supervisor for the acceptance of the role of providing me with guidance. This endeavor would not have been possible without my brother, who had introduced me to the programming world and the possibilities and a feeling of freedom that it offers. It pushed me to the path, where the studies at CTU have shown me new ways of thinking about problems, taught me things that have blown my mind, helped me understood a little better how the world around me works. Also, I could not have undertaken this journey without my close friends, who keep me grounded, inspire me to be a better person, and enrich my life in ways I have not thought to be possible.

Declaration

I declare that this work is all my own work and I have cited all sources I have used in the bibliography.

Prague, May 20, 2022

Prohlašuji, že jsem předloženou práci vypracovala samostatně, a že jsem uvedla veškerou použitou literaturu.

V Praze, 20. května 2022

Abstract

Acquiring data for development and testing of human motion tracking algorithms is difficult and costly. A good alternative would be to model human motion and generate the data instead. However, the intrinsic complexity of the human behaviour makes it a challenge to develop a model of human motion. From many various approaches tackling this problem, the Headed Social Force Model has been chosen as the main algorithm for creation of a program for generating simulation data for the testing of a tracking algorithm that takes an input in the form of projections of humans moving thought the indoor environment onto the ground. The advantage of the Headed Social Force Model lies in offering a set of parameters that can be explicitly configured and as a result human motion simulations can be designed with a higher degree of variety. In order to simulate also complex scenarios, the human motion model is accompanied by a Probabilistic Roadmap algorithm that computes feasible paths through an environment cluttered with obstacles, which are subsequently smoothed out by B-spline interpolation.

Keywords: human motion, simulation, social force model

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Abstrakt

Získávání dat pro vývoj a testování algoritmů pro sledování lidského pohybu je obtížné a nákladné. Dobrou alternativou by místo toho bylo modelování lidského pohybu a generování dat. Avšak složitost lidského chování činí vytvoření modelu lidského pohybu výzvou. Z mnoha různých přístupů, které tento problém řeší, byla jako hlavní algoritmus pro vytvoření programu pro generování simulačních dat pro testování sledovacího algoritmu vybrána forma modelu sociálních sil. Vstup sledovacího algoritmu má podobu projekcí pohybujících se lidí na zem. Výhoda modelu spočívá v nabídce sady parametrů, které lze explicitně konfigurovat a v důsledku toho lze simulace lidského pohybu navrhovat s vyšší mírou rozmanitosti. Aby bylo možné simulovat i složité scénáře, je model lidského pohybu doprovázen algoritmem pravděpodobnostní cestovní mapy, který počítá proveditelné cesty prostředím zaplněným překážkami, následně vyhlazeny B-spline interpolací.

Klíčová slova: lidský pohyb, model sociálních sil, simulace

Překlad názvu: Nástroj pro modelování pohybu lidí a generování dat pro vývoj sledovacích algoritmů

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Chapter 1

Introduction

1.1 Overview

There are many factors that are, some consciously, some subconsciously, taken into account and evaluated while moving by foot from one location to another. There are obstacles to avoid, social norms to conform to, interactions with other people, environment with own its specific topology and semantics, possibly a need for a path planning ability, all of them contributing and building up the complexity of the problem of modelling human motion [16].

1.2 Motivation

The impracticality of using real data from motion capture for the testing of tracking algorithms arises from multiple points of view. Firstly, with tight privacy laws regarding the commercial use of the recordings and many of highly visited places being in fact privately owned, the possibilities for a suitable venue can start getting narrowed down fast. Secondly, even with a venue secured, another substantial deterrent is the cost of obtaining the real data, which includes the hardware for the recording, subsequent video processing and most importantly, the cost of the annotation of the ground truth by people. Thirdly, it would be hard to capture human motion behaviour highly specific to certain conditions or extreme cases, such as evacuations. On the other hand, there is an option of going for the simulated data, where the specific extreme conditions would be able to be configured, and that will be the focus of this thesis.

With a goal of implementing a human motion simulator that works upon 2D data, i.e. projections of humans on the ground-level, the scope of this work as well as the term human motion itself will be limited to 2D human motion.

Developing models of human motion and pedestrian flow for both normal and extreme conditions, such as crowded places, has also a multitude of other usages. It is beneficial for evaluation of the design of pedestrian facilities[2], navigation of robots in spaces in human domains, designing believable non-player characters in games, or trajectory prediction of pedestrians in case of self-driving vehicles.

1.3 Related Work

1.3.1 Traditional Approaches

The traditional human motion microscopic models can be classified as force-based, grid-based and agent-based. Force-based approaches like Social Force Model (SFM)[8] and Centrifugal Force Model (CFM)[4] are based on the idea that a motion performed by an agent is driven by the virtual forces representing attraction towards a goal and repulsion from obstacles and other agents. Social Forces Model has been further elaborated onto by many newer studies that have integrated features such as group formation[5], categories of humans[19], or more complex human representation than a particle[13] into the model. While the forces models are instances of continuum models, grid-based models such as Cellular Automata and Lattice Gas models offer only a limited number of directions for movement since they represent spaces as discretised cells. In [7] the interactions between pairs of pedestrians and obstacles are described by a nonlinear function of the corresponding distance. A newer work done in the area that proposes a non-Marcovian lattice-gas cellular automata models for moving agents with memory[15]. Agent-based approach can be represented by the C-Nav (Coordinated Navigation) model[6], in which agents choose their velocities in such a way that they help also other agents to move to their goals, or also by [20], where a stochastic motion-control algorithm based on a hidden Markov model was developed. A worth mentioning approach is also modelling human decision making during navigation by non-cooperative game theory and theory of Nash equilibria, trying to minimise a cost function while avoiding collisions. [17] [3].

1.3.2 Machine Learning Approaches

Rigorous research in the domain of machine learning allowed for many new approaches to be applied to the modelling of the human motion.

[14] uses real-life dataset to train an artificial neural network with a multi-layered perceptron to infer microscopic pedestrian movement behavior. Particularly, the recurrent neural networks, having internal states allowing for processing a sequence of input, allowed for working training on trajectories, as paths can be viewed as sequences of locations, velocities and accelerations. Similarly, the machine learning approaches use long short-term memory units, which can be considered as the upgrade of RNN units as they do not suffer from the vanishing gradient problem. Such approach was used e.g. in [1].

Imitation learning is a technique where agents mimic human behavior in performing a task by learning a mapping between observations and actions from demonstrations. Its great advantage lies in teaching complex tasks with minimal expert knowledge of the underlying decision making process model[10]. [9] comes up with a model-free imitation learning algorithm, further improved by the framework of Social-Aware Generative Adversarial Imitation Learning (SA-GAIL), where the social aware components in the generator of the future trajectories are intention inference, collision avoidance regularization and social-aware LSTMs for human-human simulation[21]. [18] shapes the reward function by combination of reinforced learning an knowledge distillation.

The learning techniques' weaknesses lie in that many factors affecting the movement of pedestrians cannot be directly captured by the camera, datasets feature only a limited number of samples, the higher the difference to the setting and environment between the training and testing data, the lower the success rate, do not capture the non-deterministic nature of human decision making, i.e., there are more than one trajectories a human expert can take in the same setting[18].

1.4 Evaluation of the Suitability of Approaches

After obtaining some understanding of possible approaches here follows discussion on their suitability for the purpose of this work.

Multi-agent systems have shown to encompass a large number of immensely different approaches under the one term. On one hand, there are primitive ones where collisions are handled by backtracking or can even lead to deadlocks.

On the other hand, there are multiple very able looking machine learning approaches, which would be, however, highly dependent on the available datasets. Multiple of the studies presenting machine learning technique applied to the human motion show simulations focused only on collision avoidance with other agents, and with no obstacles [18], which leaves the question open, of how good they would perform in a cluttered environment. The negative prospects on this front are based on the exploration of the available datasets on the human motion, which had been documented summarised in [16]. In the study it can be seen that out of 16 well prepared and used datasets, only 4 were made in indoor environment. Furthermore, even in these 4 datasets, there are few if any obstacles and for the most part they are large open spaces. Some of the studies had own self-made datasets, but these were open not made public, included only a low number of participants, and were too specific to the purposes of the study.

Furthermore, a common characteristics of multi-agent systems is that they are only aware of their surroundings, about which they get information from their sensors, and do not know of what lies behind a certain distance. This would be undesirable for modelling situations when, for example, a customer arrives into a shop, and already has at least some idea, where to find his desired goal. Humans do not explore new pathways, but can visit

1.5 Outline

As has been shown, there is a huge variety on how to grasp the topic of human motion. However, the machine learning approaching and multi-agent systems have been found lacking or limiting in multiple directions. For that reason, a force-based approach will be chosen.

The reader will be acquainted with the implementation and simulation results, which will be evaluated, whether they are suitable for the purposes of a human motion simulator for tracking algorithms.

Chapter 2

Theoretical Background

From the force-based approaches, Social Force Model will be further investigated, since throughout the years, it has been often picked-up and improved in one way or another.

2.1 Social Force Model

Helbing in [8] further explores the concept formulated by Lewin[12] that behavioral changes can be modelled by social fields, resp. social forces. He reasons that pedestrians react to stimuli (i.e. perception of their environment and their inner motivation) by making a certain behavioural change while trying to maximize utility. He neglects a fact that human motion is inherently multimodal[11], meaning that multiple futures of different probabilities are plausible for a given state by assuming that pedestrians tend to make automatic reactions based on their past experience with such situations. Based on this premise he models the behavioural reactions of pedestrians by an equation of motion.

Social force $\mathbf{f_i}$ represents a motivation of an agent to act. In the case of pedestrian motion, the force describes how does environment affect a pedestrian's behaviour and is formulated as a immediate change in the desired velocity.

Social Force Model views agents as particles and describes the interactions between agents and obstacles as a forces derived from Newton's Law of Motion that, which are components of the social force. The individual forces are virtual and serve as a measure of the internal motivation of agents to make a movement in a certain direction with certain velocity. The social force components are namely:

- attractive force acting towards the destination $\mathbf{f_i^g}$;
- repulsive force acting from other pedestrians $\mathbf{f_i^p}$;
- repulsive force acting from obstacles $\mathbf{f_i^{obs}}$.

The social force is equal to the sum of attractive force acting towards the destination and all repulsive forces, multiplied by their respective weights:

$$\mathbf{f_i} = \mathbf{f_i^g} + \mathbf{f_i^e} \qquad \text{(Eq. 2.1.1)}$$

$$\mathbf{f_i^e} = \mathbf{f_i^p} + \mathbf{f_i^{obs}} \qquad \text{(Eq. 2.1.2)}$$

Such design leads to collision avoidance. The model, while modelling microscopic characteristics, such as position and velocity, belongs to those that are capable of macroscopic emergent behaviours from a perspective, such as lane formation or clogging effects.

2.1.1 Attractive Force Towards the Destination

Even though the model can handle avoiding collisions with small static and dynamic obstacles, it requires a global path planning algorithm in order to not get stuck in a local minimum, to successfully navigate in a more complex environment. A path for agent i can be expressed as a sequence of position vectors $(\mathbf{w_i^0}, \mathbf{w_i^1}, ..., \mathbf{w_i^{wn}})$, which act as waypoints on the path towards the goal. There is an underlying assumption for calculation of the attractive force towards the destination that humans want to reach their goal by passing the shortest distance between their current and final location, so the desired direction of motion $\mathbf{e_i}$ is at any moment a normalized vector difference between the next waypoint vector $\mathbf{w_i^k}$ and current position vector of agent i $\mathbf{r_i}$:

$$\mathbf{e_i} = \frac{\mathbf{w_i^k} - \mathbf{r_i}}{|\mathbf{w_i^k} - \mathbf{r_i}|}. \qquad \text{(Eq. 2.1.3)}$$

An agent of mass m_i and desired velocity of magnitude v_i^d is attracted to its goal by the force

$$\mathbf{f_i^g} = m_i \frac{v_i^d \mathbf{e_i} - \mathbf{v_i}}{\tau_i}, \qquad \text{(Eq. 2.1.4)}$$

where relaxation time tau_i characterizes the time it takes an agent i to adjust its velocity to a new situation after changes in the environment.

2.1.2 Repulsive Forces from Other Pedestrians

The repulsive force from other pedestrians is calculated as a sum of repulsive forces from all of them and is modelled as elliptical equipotential lines, where the semi-major axis is aligned with the direction of the velocity vector of an agent j, as to take into account that the agent will be making a step in that direction. The repulsive force decrease exponentially with increasing distance between the pedestrians.

$$\hat{\mathbf{f_{ij}}} = -V^0 \nabla_{\mathbf{r}_{ij}} e^{\frac{-b_{ij}}{\sigma}}, \qquad \text{(Eq. 2.1.5)}$$

$$2b_{ij} = \sqrt{(\mathbf{r_{ij}} + ||\mathbf{r_{ij}} - \mathbf{v_j} \Delta t \mathbf{e_j}||)^2 - (\mathbf{v} \Delta t)^2}, \qquad \text{(Eq. 2.1.6)}$$

where V^0 is a constant.

2.1.3 Repulsive Forces from Obstacles

The repulsive force from other obstacles and walls reflects the tendency of humans to keep distance from walls and obstacles and is calculated as a sum of repulsive forces from all obstacles, i.e. $\mathbf{f_i^{obs}} = \sum_w \mathbf{f_{iw}^{obs}}$. It decreases exponentially with increasing distance $||\mathbf{r_{iw}}||$ between an agent and a nearest point of an obstacle:

$$\mathbf{f_{iw}^{obs}} = -U^0 \nabla_{\mathbf{r}_{iw}} e^{\frac{-||\mathbf{r_{iw}}||}{r_i}}, \tag{Eq. 2.1.7}$$

where U^0 is a constant.

2.1.4 Attractive Forces from Other Pedestrians or Objects

There are many cases when also attractive forces between pedestrians and objects are present, but Hilbert models only a temporary flare of attraction that decreases both with distance and time.

2.1.5 Effective angle of sight

In order to account for the fact that pedestrians mainly accommodate to the situation in their effective angle 2ϕ of sight, meaning that they either interact with other pedestrians or avoid them, forces can be given directional dependent weights that can have a value of 1 in a case that a pedestrian lies in front of them and some constant value c with $0 < c < 1$ if they lie out of the sight:

$$w(\mathbf{e}, \mathbf{f}) = \begin{cases} 1 & \text{if } \mathbf{e} \cdot \mathbf{f} \geq ||\mathbf{f}|| \cos\varphi \\ c & \text{otherwise} \end{cases} \tag{Eq. 2.1.8}$$

$$\mathbf{f_{ij}} = w(\mathbf{e_i^g}, -\hat{\mathbf{f_{ij}}})\hat{\mathbf{f_{ij}}} \tag{Eq. 2.1.9}$$

Such weights are applied only to the forces between pedestrians, as it has been suggested that humans tend to keep distance from static obstacles.

2.1.6 Extensions to the Social Force Model

The Social Force Model has been frequently explored by others over the years since its publication. Some of the noteworthy works:

- in [19] different categories of agents – luggage-laden, ordinary and panic pedestrians, are introduced;
- in [2] Alonso-Marroquín et al. proposed a model that represents humans as spheropolygons and add up also viscoelastic contact forces, contact friction, and ground-reaction forces; they applied the model to the situation from 2012, when 3 persons have died in a stampede at a nightclub in Madrid, to analyze the crowd behaviour in a dense counterflow;
- in [13] humans are represented by a three-circle representation;
- [5] incorporates also a concept of heading and torque.

Chapter 3
Implementation

The goal of the implementation is to develop a program which for certain input pedestrian characteristics will generate trajectories with available visual presentation as well as in a textual form.

The designed simulator has following components:

- Headed Social Force Model for local path navigation
- Probabilistic Roadmap algorithm for finding a global path
- Finite State Machine architecture for an agent's behaviour

3.1 Headed Social Force Model

Proposed by Farina et al., the Headed Social Forces Model[5] further elaborates upon the Social Force Model by Helbing, enriching it with more aspects of human motion behaviour, with the goal of generating more realistic trajectories than the original Social Force Model does.

Additional features:

- generation of smoother trajectories without lateral motions in open spaces, with an ability to adapt also to a cluttered environment
- possibility of modelling a group of people that moves together

For these purposes, changes in translational dynamics and rotational dynamics have been made to the original Social Force Model.

3.1.1 Translational dynamics

The original forces attraction force towards destination $\mathbf{f_i^g}$ and interaction force vbf_i^e are projected on the forward direction of motion, i.e. the one where the pedestrian is heading, and the orthogonal direction:

$$\mathbf{u_i^f} = (\mathbf{f_i^g} + \mathbf{f_i^e})^T \mathbf{r_i^f}, \qquad \text{(Eq. 3.1.1)}$$

$$\mathbf{u_i^o} = k^o \mathbf{f_i^e}^T \mathbf{r_i^o} - k^d \mathbf{v_i^o} \qquad \text{(Eq. 3.1.2)}$$

for constants $\mathrm{R}^o > 0$, $k^d > 0$.

Addition of a term that dampens the lateral motions.

3.1.2 Rotational dynamics

A newly introduced term representing magnitude of torque is:

$$u_i^\theta = -k^\theta(\theta_i - \theta_i^g) - k^\omega \omega_i. \qquad \text{(Eq. 3.1.3)}$$

With a dynamic model

$$\ddot{\tilde{\theta}}_i + \frac{k^\omega}{I_i}\dot{\tilde{\theta}}_i + \frac{k^\omega}{I_i}\tilde{\theta}_i = -\frac{k^\omega}{I_i}\dot{\theta}_i - \ddot{\theta}_i^g \qquad \text{(Eq. 3.1.4)}$$

of the orientation error $\ddot{\tilde{\theta}}_i \approx \theta_i - \theta_i^g$, i.e. the angle between the heading direction and the destination direction $\mathbf{f_i^g}$ Farina formulated the equations for the poles as functions of the magnitude of $\mathbf{f_i^g}$. Such formulation allows us to control how susceptible to the orientation error the pedestrian will be by configuring the constants k^θ and k^ω:

$$k^\theta = I_i k^\lambda ||\mathbf{f_i^g}|$$

$$k^\omega = I_i(1+\alpha)\sqrt{\frac{k^\lambda ||\mathbf{f_i^g}||}{\alpha}}$$

3.1.3 Formation of Groups

An additional term modelling an attraction force of members of a group that holds them together was formed. A centroid of the group of pedestrians is calculated, and the attraction force compels the individuals to stay within an area shaped a rectangle with side d^f, f^o that has the centroid as its center.

The centroid is the mean of all position vectors of the pedestrians in the group. If $\mathbf{p_i}$ is the distance of pedestrian i from the centroid, then the projection of the group cohesion force in the forward motion is $k_2^8 h(\mathbf{p_i}, \mathbf{r_i^f}, \mathbf{d^f})$ and the its projection in the orthogonal direction: $k_2^8 h(\mathbf{p_i}, \mathbf{r_i^o}, \mathbf{d^o})$, where $k_1^8 > 0$ and $k_2^8 > 0$. For h(x,y,z):

$$h(\mathbf{x}, \mathbf{y}, z) = \begin{cases} 1 & \text{if } \mathbf{x} \cdot \mathbf{y} > z \\ c & \text{otherwise} \end{cases} \qquad \text{(Eq. 3.1.5)}$$

3.1.4 Changes in Interaction Forces

The original interaction forces consisting of only an exponential term were enlarged by two additional terms representing compression and friction forces. These terms have a nonzero value only when the distance between a pedestrian and another person d_{ij} is smaller than the sum of their radii r_{ij}, or when the distance between a pedestrian and a nearest point of an obstacle d_{iw} is smaller than the pedestrian's radius r_{ij}

The Headed Social Force Model upgraded equation for the pedestrian repulsive force from the Social Force is:

$$\mathbf{f_{ij}^p} = [A_i e^{\frac{(r_{ij}-d_{ij})}{B_i}} + k_1 g(r_{ij} - d_{ij})]\mathbf{n_{ij}} - k_2 g(r_{ij} - d_{ij}) \mathit{\Delta} v_{ij}^{(t)} \mathbf{t_{ij}}, \qquad \text{(Eq. 3.1.6)}$$

The upgraded equation for the obstacles repulsive force from the Social Force Model:

$$\mathbf{f_{iw}^{w}} = [A_w e^{\frac{(r_i - d_{iw})}{B_w}} + k_1 g(r_i - d_{iw})]\mathbf{n_{iw}} - k_2 g(r_i - d_{iw}) \Delta v_{iw}^{(t)} \mathbf{t_{iw}} \quad \text{(Eq. 3.1.7)}$$

For

$$r_{ij} = r_i + r_j,$$

$$d_i j = ||\mathbf{r_i} - \mathbf{r_j}||,$$

$$n_{ij} = \frac{\mathbf{r_i} - \mathbf{r_j}}{||\mathbf{r_i} - \mathbf{r_j}||},$$

$$\mathbf{t_{ij}} = [-\mathbf{n_{ij}}(2), \mathbf{n_{ij}}(1)]^T,$$

$$\Delta_{ij}^{(t)} = (\mathbf{v_j} - \mathbf{v_i})^T \mathbf{t_{ij}}$$

$$g(x) = max\{0, x\} \quad \text{(Eq. 3.1.8)}$$

3.1.5 Usage

Prior to the start of the motion simulation, initialization of the following variables is needed:

- a position vector $\mathbf{r_i}$,
- a velocity vector $\mathbf{v_i^B} = [v_i^f, v_i^o]^T$, where v_i^f and v_i^o are projections of the velocity vector $\mathbf{v_i}$ on the forward and orthogonal direction,
- a vector $\mathbf{q_i} = [\theta_i, \omega_i]^T$ containing the angle θ_i representing the angle between the forward motion direction and the goal destination, and $omega_i$ representing angular velocity,

for each pedestrian. Usually these are initialized as not moving. Based on the chosen simulation time and the desired number of generated frames we get time duration t of one frame. In intervals t, equations of motions with be evaluated and the respective changes integrated to the current state of the variables.

$$\dot{\mathbf{r_i}} = \mathbf{v_i} = R(\theta_i)\mathbf{v_i^B}$$

$$\dot{\mathbf{v_i^B}} = \frac{1}{m_i}\mathbf{u_i^B}$$

$$\dot{\mathbf{q_i}} = \mathbf{A}\mathbf{q_i} + \mathbf{b_i} u_i^\theta$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \mathbf{b_i} = \begin{bmatrix} 0 \\ \frac{1}{I_i} \end{bmatrix} \quad \text{(Eq. 3.1.9)}$$

3.2 Global Path Planning

Most of the human motion models take care only of the task of performing a locally-constrained motion, meaning that they strive to keep their direction of heading aligned with the desired direction of motion, while reacting to stimuli in their closest neighbourhood. However, if reaching a goal requires navigating through an environment filled with obstacles, global path planning algorithm is needed to provide such feasible path, if any exists. Path can be understood as a sequence of actions or points following which will lead an agent from the starting state/point to the destination. For this path finding, only the static parts of the environment are considered and the map with obstacle coordinates is known.

3.2.1 Selection of the Global Path Planning Algorithm

There are search-based techniques that discretise the map to a grid and work with a graph structure, going through reachable unvisited nodes and calculating the cheapest way to reach the node and its cost. Then there are sampling-based methods that do not find the optimal solution, namely Rapidly exploring random tree (RRT), RRT with heuristics applied: RRT*, and a Probabilistic roadmap algorithm PRM. RRT sequentially generates sampling points and connects them to the nearest node in the graph. PRM generates the sampling points at once and makes connections between them by connecting the k-nearest neighbours.

Even though humans strive to reach their destination in the shortest time possible, they do not use the optimal paths, but rather along smooth trajectories. Therefore, a non-optimal and more time efficient algorithms would be preferred. Between RRT and PRM, PRM holds the advantage of generating a roadmap only once, and then a search-based algorithm is used to find a path through this simplified roadmap of the environment. As this would let all the pedestrians use the same generated roadmap to find their path, it was chosen as the global path planning algorithm for the implementation.

3.2.2 Probabilistic Roadmap Algorithm Implementation

As for the specifications for this algorithm, a number of points (1/10 of the total number of points in the map has been used) is randomly generated within the borders of the map, and each of the points is checked, whether it collides with any of the obstacles. Additionally, also a space of 1 meter around the obstacles was left unexplored, in order to avoid walking right next to the walls. On the unique uncolliding points, as well as on the all points of interests that attract walkers, algorithm k-nearest neighbors is performed in order to join points lying close to one another together. Value of the parameter k of the kNN algorithm k=5 has been used. The connections between the neighbour points as suggested by the algorithm will be candidates, from which those that collide with any obstacle are discarded. A graph structure is generated, with sample points as vertices and connections as edges, with a cost proportional to their length. On this graph, Dijkstra algorithm will be repeatedly run with a task of finding the shortest path between two vertices. If it happens that there is no path found, additional sample points are generated, along with their connections once again done according to the kNN algorithm.

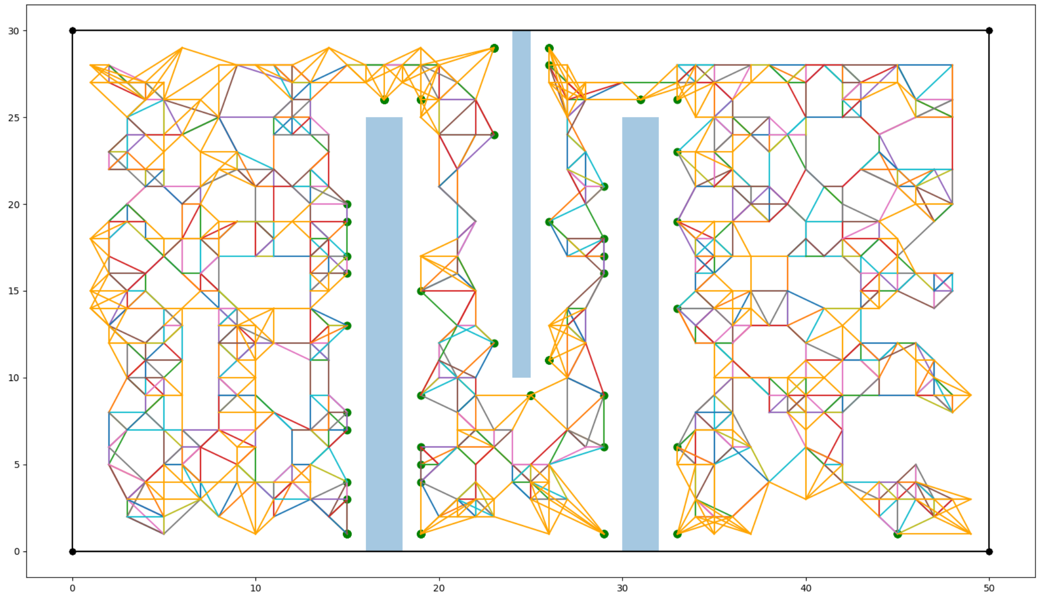

Figure 3.1: Probabilistic Roadmap pathways

3.2.3 Trajectory Smoothing

Since humans perform smooth trajectories, the output path by the Probabilistic Roadmap Algorithm is smoothed out by B-spline interpolation performed for each section of the path section separately, therefore the trajectory is discontinuous at the points at which the pedestrian stops (marked red in the image below). This reflects that once a person stops at some location and performs an activity that takes some time, they choose their path anew.

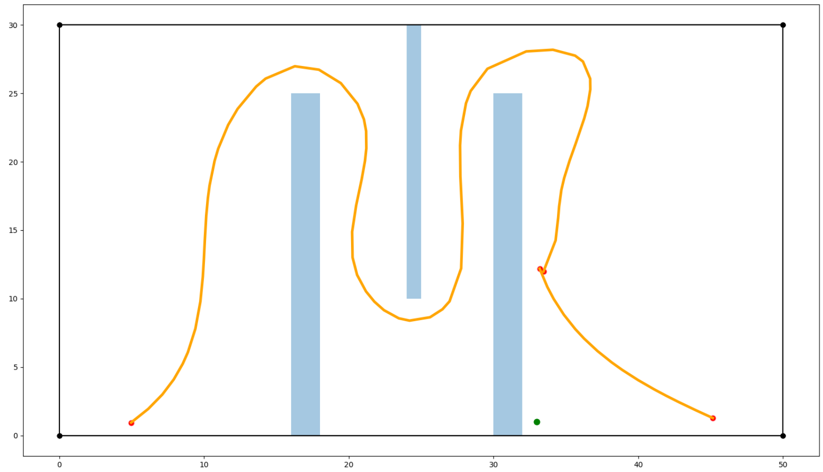

Figure 3.2: Smoothed Out Trajectory

3.2.4 Subgoals

With a more complex environment, such as a shop or a museum, while the end goal of such visit is to get to the exit, the path itself is even more important. Humans stop for a short time in front of display cases, shelves or even just walls. This pattern of behaviour can be generalized to the idea of points of interest, locations through which the walkers should pass on their way to the end point. As a result, more diverse paths will be explored.

In the implementation, these points of interest are generated as random point on the circumference of the selected sides of some obstacles. The sides can marked as attractive to humans in the input file for the map of the environment. For a randomly generated set points of interest that a walker will have to pass through, a travelling salesman problem arises, as we have to come up with a plan in which order to visit the desired points of interest.

Rather than searching for a path passing all selected locations repeatedly for all agents, which would significantly increase the computation overhead, a heuristic approach was preferred. A general path passing through the corner points of attractive sides of obstacles is generated. For each point of interest, its closest corner point is determined. Afterwards, the points of interest can be sorted according to the order of the corner points, to which they belong to.

Regarding the order of the order of the points of interest from one set, belonging to one specific corner, their order was left as random, for the purpose of mimicking the behaviour of humans when they stick to a section longer time, perhaps for exploring details of a specific exhibit or searching for a desired merchandise.

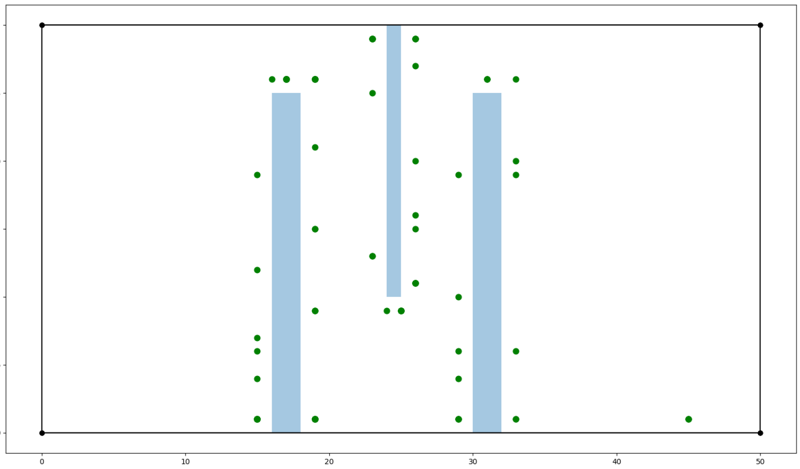

Figure 3.3: Pool of Generated Points of Interests

3.3 Agent as a Finite State Machine

Even though it is reasonable to assume that people try to reach their destination in the shortest time possible, they often encounter unexpected situations as a result of which they have to alter their plans. To account for such random actions, the agent's behaviour is represented by a finite state machine.

After transitioning from the state *absent* in time t after the beginning of the simulation, a walker starts undertaking an active part in it by passing though a list of in beforehand planned locations. Most of the time they spend in the *normal walking* state.

The state *standing* is entered whenever any point of an interest along the planned path is reached.

Transitions from *normal walking* to States *accelerated movement* and *freezed* are in default happening with a percentage of 1%.

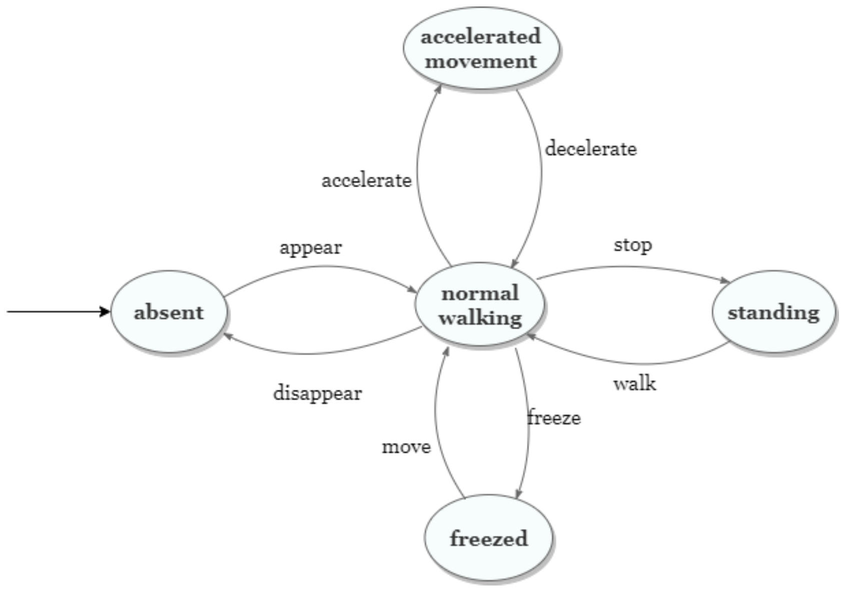

Figure 3.4: Finite State Machine diagram

3.4 Map

Maps consist of a set of obstacles that either have a form of a line or a rectangle. The program accepts a text file as an input where each line specifies points defining an obstacle, with a possibility to mark edges as the ones that attract people.

If a new map is generated, it is written to a file in the format: 2 points defining a line segment (the starting point and the ending point) or a rectangular (any two opposite corners), with sides that should serve as obstacles and as attraction surfaces specified. One does not exude the other, as e.g. in a supermarket shoppers are attracted to the walls of the corridors where the merchandise is displayed. The sides are specified by their initials: 'L', 'R', 'B', 'T' for the left, right, bottom, top. example : 0;32,25;L,T,R;L,R

3.5 Implemention Specification

Agent Characteristics	
Parameter Name	Distribution
radius	N(u,sd)
mass	N(u,sd)
desired speed	N(u,sd)
duration of state standing	N(u,sd)
duration of state accelerate	N(u,sd)
duration of state accelerate	N(u,sd)

Chapter 4

Simulations and Results Discussion

Firstly, a methodology for the evaluation of the model with be presented, followed by demonstrations from the simulation and their discussion.

4.1 Methodology

The evaluation of simulations will be conducted in 3 parts.

The first one will be focused on the implementation itself, how well it models human motion in various conditions and environments, displaying its characteristic features in specifically for that purpose tailored situations, but also giving space to unveil errors, inconsistencies and weak spots of the algorithm.

The second part of the evaluation will be based on comparison of the generated data with the data generated by other models. An instance of a multi-agent system will be provided, as well as real data.

The third part of the evaluation of the model will lie in collection of responses from real humans, how do they perceive the generated data. Multiple people will be shown example animations of human movement generated by various models and asked two questions.

4.2 Part I: Simulations

Descriptions of the Simulated Scenarios:

1. Scenario #1: Swap of walkers' positions – collision avoidance
   - Walkers arranged in a circle at the start will trade their spots together, meeting in the middle all at one while aiming for their desired position. The ability to smoothly avoid other pedestrians will be evaluated;
2. Scenario #2: Crowded corridor
   - The purpose of a crowded corridor is to investigate how do the emergent properties such as line formation of the Social Force Model hold up;

3. Scenario #3: Open space

   - In order to capture the distinctions in the movement of various people and clearly show the differences in their behaviour, a large area with one big obstacle in the middle will been presented;

4. Scenario #4: Cluttered space with a shop-like structure

   - To show off global path navigation, passing obstacles of various shapes and generation.

4.2.1 Scenario #1: Swap of walkers' positions – collision avoidance

Ability to avoid other walkers represents the core function of any human motion model. For human trajectory predictions implemented in robots, errors in collision avoidance mean safety risks. In the generation of testing data for tracking algorithms, collisions could incorrectly lead to doubts about the performance of the tested software.

Two formats of the location swap animations were undertaken. One for 6 walkers and the other one for 12 walkers.

Both on the animations and on the trajectory plots of the walkers it is clearly visible, the walkers just to the dynamic changes in their environment, i.e. other walkers, by rotating their body. Also, after the collision has been successfully avoided, the walkers do not sharply turn back to their former path, but rather gradually rotate and walk towards their goal position.

On the other hand, it has to be mentioned that at first, head on collisions have occurred. The walkers adjusted their paths, but only after a small rebound caused by the collision. After this result, parameters k^o and k^d of the Headed Force Model, which control how much influence does the lateral repulsive force holds an how much is the lateral speed being suppressed, has were changed. In general, lateral movements are undesired, since a person under normal conditions prefers to walk forwards. However, these lateral movements are needed in situations like collision avoidance.

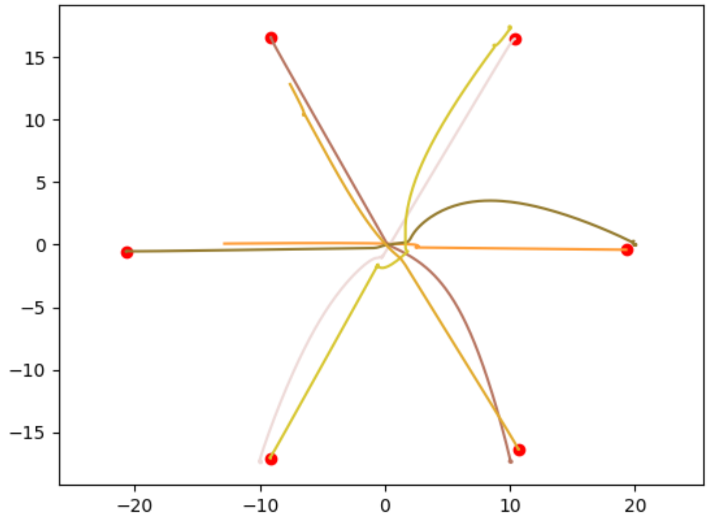

Figure 4.1: Location Swap Simulation: Trajectory Plot (6 walkers)

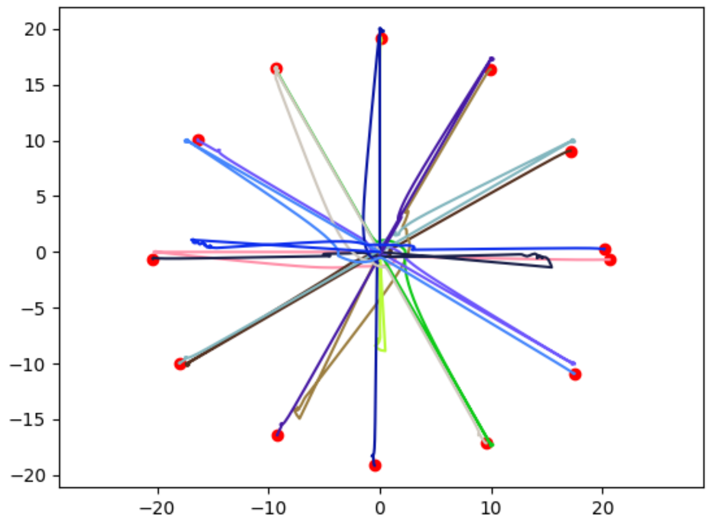

Figure 4.2: Location Swap Simulation: Trajectory Plot (12 walkers)

4.2.2 Scenario #2: Crowded corridor

In the second simulation example, collision avoidance is approached from another perspective. Two group of walkers walking in the opposite direction meet at the center of the corridor.

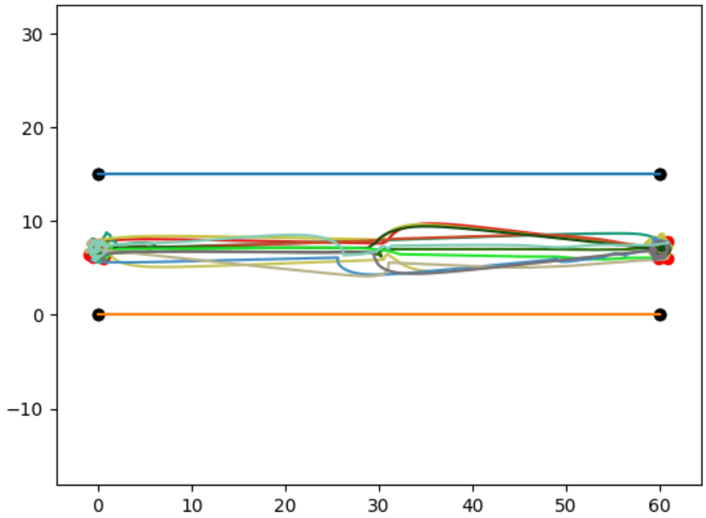

Figure 4.3: Corridor Simulation: Trajectory Plot

Once again, smooth rotations are performed in order to avoid a collision, even more pronounced in this case.

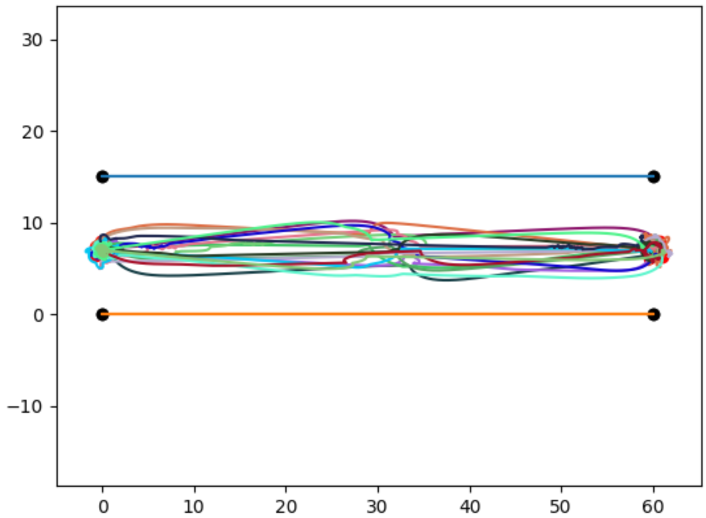

Figure 4.4: Corridor Simulation: Denser Trajectory Plot

4.2.3 Scenario #3: Open Space Simulation

A rapid movement through the space is demonstrated by the third scenario. There is no global path finding algorithm in use yet, what has as a consequence that some walkers became stuck in the between the obstacles. Otherwise there is almost like a bubble of unexplored space around the obstacles. If the goal does not lie exactly on the other side of the obstacle, there is a clear effort to avoid them. There seems to be little to none of the unnecessary lateral movement.

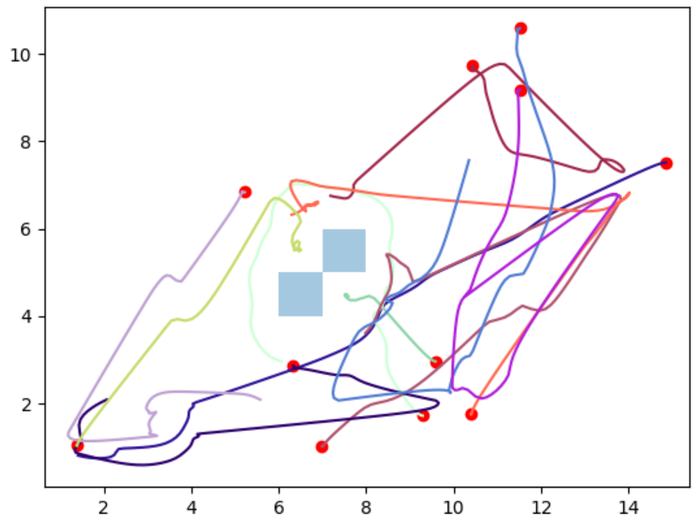

Figure 4.5: Open Space Simulation: Actual Trajectory Plot

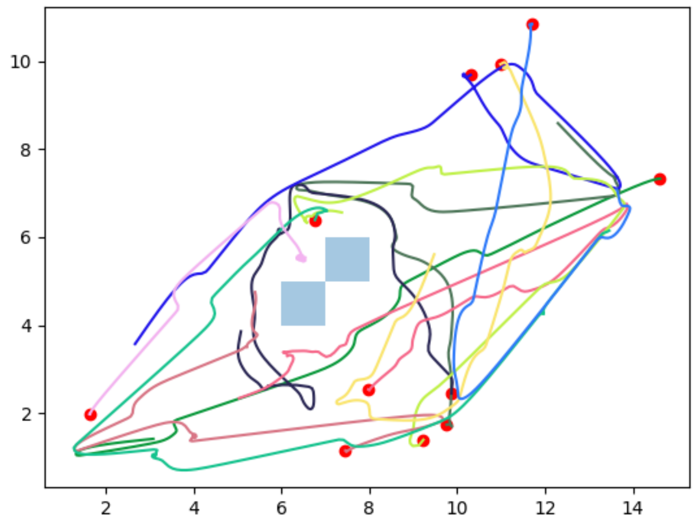

Figure 4.6: Open Space Simulation: Actual Trajectory Plot

4.2.4 Scenario #4: Cluttered Space with a Shop-like Structure

The forth category culminates with the most complex scenario: generation of points of interest, finding a path going from the start, through the points, and terminated at the exit. Examples of such paths are visualized 4.7, with pink spots marking the points of interest, and green spots marking the corner points.

As can be also seen, there is a collision on the planned path, that has likely occurred due to the path smoothing. After path smoothing, there is a check only for a point collision (not path line section collision), so that may be the reason why such undesired path could be generated.

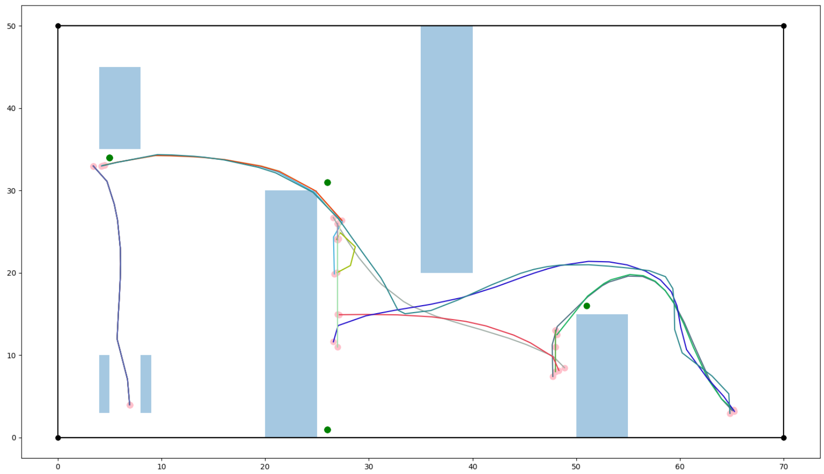

Figure 4.7: Shop Simulation: Planned Trajectory Plot

As can be seen on the image 4.8, the walker can successfully navigate through the shop, with a smooth trajectory for the most part, with deformations near obstacles.

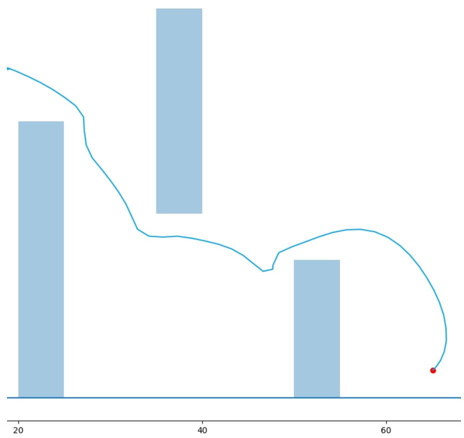

Figure 4.8: Shop Simulation: Trajectory by Motion Capture (1 walker)

Last example is a close up on the path of a group of walkers (the lower trajectory 4.9),

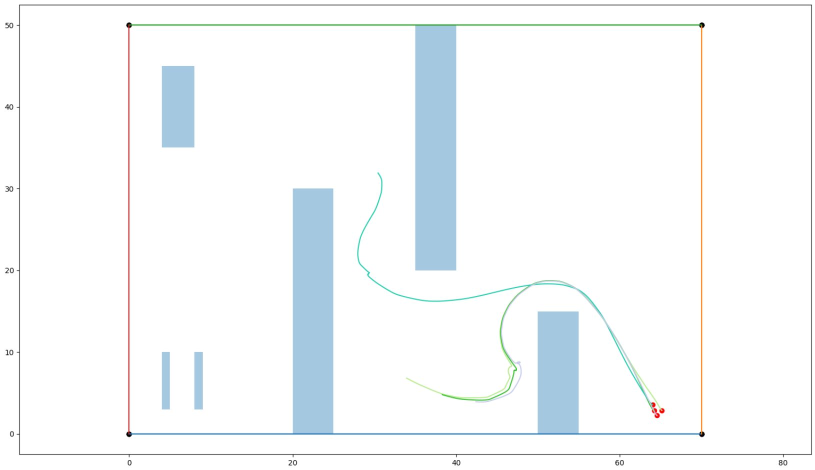

Figure 4.9: Shop Simulation: Trajectory by Motion Capture

4.3 Part II: Comparison with Data Generated by Other Models

[18] features a scenario for which comparisons between trajectories collected by motion capture, the model from the study - multi-agent system using knowledge distillation, reinforced learning and optimal reciprocal collision avoidance. This scenario has been reproduced and is displayed in figures *Figure 4.1: Location Swap Simulation: Trajectory Plot (6 walkers)* and *Figure 4.2: Location Swap Simulation: Trajectory Plot (12 walkers)* above.

A short comparison of the data generated by our model and data from the algorithms from the study will be supplied. It is emphasized that the purpose of the comparison is not to compare the algorithms themselves, but rather to provide the reader with an idea what are some shared characteristics, advantages, or missing features of the Social Force Model, when compared with other approaches.

While the reinforced learning model, successfully handles all the walkers without collisions, the resulting trajectories are too well coordinated and seem unnatural. In this regard, the unexpectedness of our model is preferred, as it better captures the diversity in human motion behaviour.

The trajectories by the optimal reciprocal collision avoidance algorithm feature multiple sudden changes in direction, conflicting with the human nature to walk along smooth trajectories. Also, the model seemingly accelerates all the walkers at the same time, another unnatural action.

More pronounced rotations than preformed by humans (when comparing against the reference animation) seems to be a common feature of the multi-agent system using knowledge distillation and the social force model.

On the other hand, all 3 featured algorithms keep the walkers a greater distance from one another, instead of the touches that occur in the social force model.

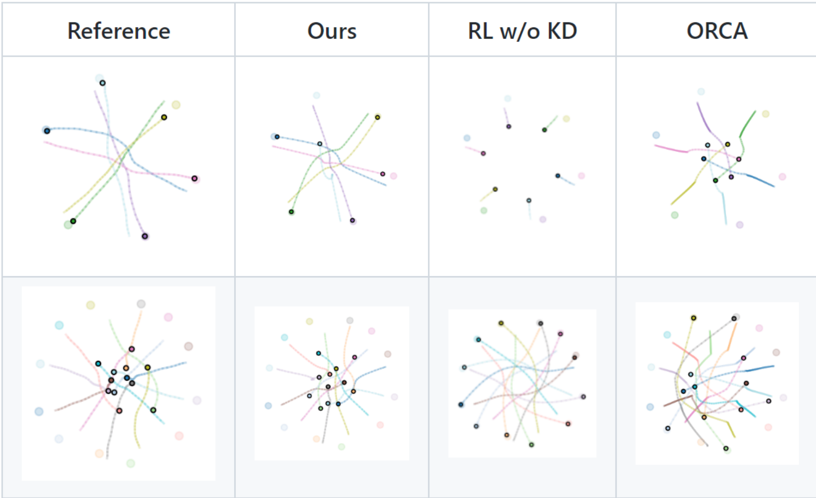

Figure 4.10: Comparison of human motion modelling approaches by [18]

4.4 Part III: Survey

A survey has been conducted, in which each participant was shown 4 unlabeled animations and was asked 2 questions:

- to what extend they think the data could have been generated human motion
- to what extend they think the data reflects human motion

They were asked give an answer on a scale 1 to 10 so as to obtain a quantifiable measure of the performance of the model. The survey responders were offered no context about the background of the data in order to not give out any hint or introduce a bias.

The first animation holds an actual trajectory of a person, while the second one was a reproduction of the first one by using the same initial and terminating coordinates, but generating all the in points between by the headed social force model.

In the same manner, the second pair consists of a ground truth and its reproduction by the Social Force Model.

Examples can be found attached in the Appendix: image A4.11, image B4.12, image C4.13, image D4.14

Unfortunately, not enough samples had been collected to present any meaningful drawn conclusions. However, it can be at least mentioned, that even though the real dataset had been, as was expected, given a higher score or the same score, the differences were not huge. As for the differences in the scores given to the 2 questions within one dataset, all the responders had given almost the same score, as if to express, that they do not see a difference between what is the source of the data and whether it reflects the characteristics of the source.

Figure 4.11: Survey: A Screenshot from Animation A (taken from [18]), i.e. trajectory of a person

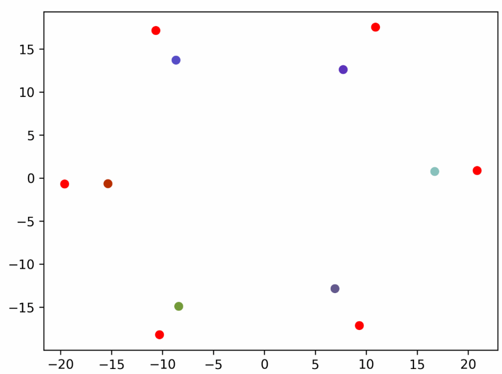

Figure 4.12: Survey: A Screenshot from Animation B, trajectory generated by the Social Force Model

Figure 4.13: Survey: A Screenshot from Animation C (taken from [18]), i.e. trajectory of a person

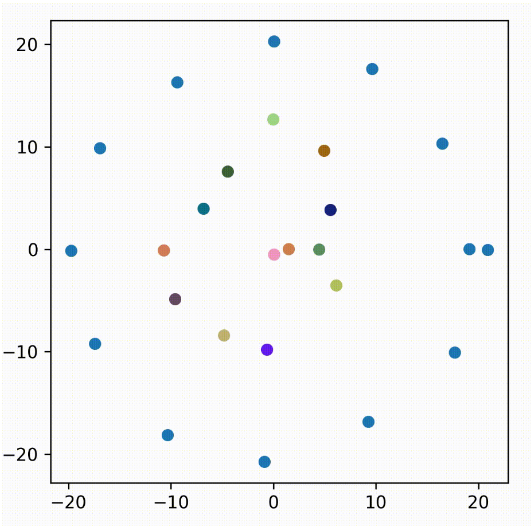

Figure 4.14: Survey: A Screenshot from Animation D, trajectory generated by the Social Force Model

Presented results will be evaluated and summarized in the following chapter.

Chapter 5

Evaluation

In the most basic terms, the algorithm has been proved to generate human-like trajectories. However, there are several limitations that should be kept in mind.

5.1 Limitations of the Solution

Some of the observed weaknesses of the algorithm is that it does not reflect the human trait that a different path might be chosen when walking between two coordinates. Due to the use of the of the Dijkstra algorithm that goes through the edges supplied by the Probabilistic Roadmap, for one combination of a starting point and an end point, the same path will be always generated.

Another weakness is that in certain cases, a different parameters settings might be required to get the best results. However, this needs to be done manually. For example, in the case of the head on collisions simulated in the corridor, after configuring a constant that controls how much of an influence does the force driving the lateral movements have, the simulation were smoother. On the other hand, in general scenarios, the lateral movements are desired to be minimized.

As for the formations of groups, in environments as shops, with many turns, it is unproductive to give various group members an option to have different preferred speeds (what would reflect the reality, since, for example, family groups consist of members with highly different characteristics), because in the simulations, the slowest member would get sooner or later stuck behind an obstacle due to being attracted to the center of the group, what would deform his supposed direction around an obstacle.

5.2 Time Complexity

Regarding the time complexity, in order to calculate one frame, a system of differential equations needs to be solved to determine the changes in position, velocity, angular velocity and the angle between the direction of heading and the goal position. For those calculations, we first need to find what are the forces affecting each walker, what translates to looping through all other walkers and all obstacles in the environment. So need to do also all other agents, what leads to the quadratic time complexity in the number of walkers as well as the number of obstacles.

There is also much overhead added before the simulation event starts despite the attempt at cutting it down, such as with the generation of the probabilistic roadmap in path finding process and also the idea of using only a few selected points to determine the order of the points in the path. Use of the probabilistic roadmap lies, and relies on the fact that the examined environments will be reasonably free to explore. There is also an assumption that there exists a viable path between the inputted points.

The overhead might be reduced by exploring further heuristic approaches. Instead of calculating a repulsion force from every obstacle, only those in some close vicinity would be selected. That could be achieved by division of the space in to smaller subsections, where each subsection would keep knowledge about the nearest obstacles...

Additionally, this program would be suitable for parallelization, since the time consuming calculations (forces affecting humans) are performed independently from each other.

5.3 Ideas for Improvement

The map design offers a lot of space for improvements, namely automatic generation of new maps based on specified characteristics that would be inputted by the user. Also, more diverse shapes of obstacles would bring new opportunities for actions and would expand the range of possible movements to display, such as running around a circular obstacle.

Regarding the Headed Social Force Model, additional characteristics of human motion could be integrated from other already existing implementations (various categories of people or more realistic shapes for people representation other than a sphere). Furthermore, the collision avoidance does not take into account social norms, such as preferring the right side for the process of avoidance.

As for the possibility of the use of other algorithms for the human motion modelling, this rather leads to the question of obtaining an appropriate dataset. Regarding other available datasets, described in detail in [16], could be analyzed to distinguish various types of behaviour (e.g. frantic, slow, organized) to categorize the instances of human motion and train a learning algorithm upon such data in order to be able to model various characteristics, what would generate more realistic output.

Chapter 6

Conclusion

The focus of this thesis was the problem of a lack of affordable solutions for testing of tracking algorithms. An alternative to the costly acquisition of the human motion data has been supplied - a simple program, that generates human trajectories based on the input data parameters.

Based on the conducted research on the topic of how to model human motion, various approaches were considered. Ultimately, the machine learning approaches were rejected due their limitations caused by a small number of datasets conducted indoors being available. Also, the existing datasets do no focus on the distinction in the behaviour of an individuals, what would be important for the purpose of the simulator for the tracking algorithms. Multi-agent systems were rejected due to the fact that they do not represent well human behaviour, as they are not aware of the environment from the global perspective.

A popular example of the force-approach had been selected, the Social Force Model[8], more specifically, its extension: [5]. The model describes the human motion using Newton's laws of motion, and adds up rotational dynamics, the idea of a heading direction and a possibility of a group formation.

This thesis builds up on its implementation and enriches it further with the possibility of generating points of interests to be visited in a certain order, generating new routes from a passed map of the environment, smoothing the paths with a B-spline interpolation, following a path and a simple user interface for the input.

The performance of the model has been evaluated using multiple scenarios. The model can successfully navigate through the environment and exhibits randomized actions.

On the other hand, it has certain limitations, for example the collision avoidance is happening too close to one another together.

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