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Collective situation analysis and individual decision-making: modeling and simulation of virtual pedestrian interactions in urban environment

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THÈSE DE DOCTORAT

Analyse de situation collective et prise de décision individuelle : modélisation et simulation des interactions du piéton virtuel en environnement urbain

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Laboratoire Perception, Interactions, Comportements &
Simulation des usagers de la route et de la rue (PICS-L)
École Doctorale Mathématiques et STIC (ED MSTIC)

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Abstract

This thesis aims to increase the heterogeneity of pedestrian interactions in a virtual urban environment. The interactions focus on collision avoidance and street crossing. My first contribution consists in allowing the pedestrian agents to avoid the collisions by adapting their behavior according to the neighbor agents with which they interact. Simulations show the expected adaptation during the avoidance interactions by increasing or decreasing the avoidance effort depending on the behavior of the perceived neighbors. Then, in the cases of unidirectional flows, the pedestrian agent will seek to overtake their slower neighbors. Based on the position, the speed, and the size of the neighbors, the pedestrian agent will consider particularly the neighbor in front of them (called the leader), who constraints them the most. Therefore, my second contribution combines a collision avoidance model with a queuing model by considering the leader differently from the rest of the perceived neighbors. These two contributions rely on the perception of the perceived neighbors' physical characteristics (size, position, and speed). However, the temporal dimension (how long the agent has been in a situation) and the social influence from the neighbors behaviors are important factors in decision-making.

My main contribution is the development of a decision model for street crossing, which considers the waiting time on the sidewalk of the pedestrian agent and the actions of his neighbors (to cross or wait). The model is assessed under two scenarios, 1) a street crossing with a pedestrian light, without road traffic, and 2) a street crossing with traffic without a pedestrian light. The model is based on three assumptions. The first one is that waiting time is an important factor in the decision to cross. On one hand, we assume that a pedestrian agent is willing to wait a certain amount of time before crossing (a sort of patience) and beyond that, the pedestrian will want to cross even at a red light. On the other hand, we assume that the waiting time plays a role in the perception of the vehicle in front of which the pedestrian plans to cross. Indeed, literature shows that the time-to-contact with an oncoming vehicle can be overestimated or underestimated before the crossing decision. The next two hypotheses are based on Rosenbloom's work, who suggests that a pedestrian waiting

at a red light may be influenced by those crossing and those waiting. Combining these two hypotheses forms what we call the social influence, which will modulate both the patience of the pedestrian agent and his perception of the time-to-contact of the oncoming vehicles.

In a first study, the simulations show that pedestrians supposed to cross at the red light may wait for the green light, influenced by waiting neighbors. Conversely, neighbors crossing at the red light will encourage the agent to cross during the red light, leading to a different decision compared to being alone in this situation. Moreover, pedestrians with similar characteristics (patience, speed) and perceiving the same situation (color of the pedestrian light and number of neighbors) but arriving at the crossing location at different times, will make different decisions.

In the second study, crossing in front of road traffic, the combination of social influence and waiting time will induce a bias in the perception that may lead the pedestrian agent to overestimate or underestimate the time-to-contact with the vehicle. The pedestrian agent may thus decide to wait when he could normally cross, missing an opportunity; he also may decide to cross when the situation does not allow it, which leads to an inadequate decision.

Keywords : Pedestrian modeling and simulation, heterogeneous collision avoidance, social influence, waiting time, street crossing, transgression of traffic rules, inadequate crossing decision

Résumé

Les simulations de piétons seraient plus réalistes si les comportements des piétons étaient similaires à ceux observés dans une situation réelle. De nombreuses simulations de piétons manquent ainsi d'hétérogénéité dans les comportements produits en raison des simplifications des modèles, ce qui diminue leur réalisme. Cette thèse vise à augmenter l'hétérogénéité des interactions des piétons en milieu urbain. Les interactions traitées sont l'évitement des collisions et la traversée des rues. Ma première contribution consiste à donner aux agents piétons la possibilité d'éviter les collisions en s'adaptant au contexte rencontré, c'est-à-dire en fonction des agents voisins perçus avec lesquels l'agent piéton peut interagir. Le modèle proposé conduit à des simulations dans lesquelles on observe une adaptation du comportement de l'agent durant les interactions d'évitement, par une augmentation ou une diminution de l'effort d'évitement en fonction du comportement du voisin perçu. Mais, l'interaction d'évitement ne se limite pas aux rencontres de type face à face, elle existe également dans des flux monodirectionnels dans lesquels l'agent piéton va chercher à doubler ses voisins plus lents. En se basant sur la position, la vitesse et la taille des voisins, l'agent piéton va tenir compte plus particulièrement du voisin devant lui qui le contraint le plus, nommé leader, quand il existe. Ma seconde contribution a ainsi consisté à combiner un modèle d'évitement de collision avec un modèle de file d'attente en considérant différemment le leader du reste des voisins perçus. Ces deux contributions reposent sur une analyse des voisins perçus et des seules données dites physiques (taille, position, vitesse). Ainsi, l'aspect temporaire des situations rencontrées et les actions des voisins ne sont pas considérés. Pourtant, la dimension temporelle, depuis combien de temps l'agent est dans cette situation et l'influence sociale provenant des voisins perçus sont des facteurs importants dans les prises de décision d'un agent piéton dans ses déplacements. Pour illustrer ces phénomènes d'influence sociale et de temporalité d'une situation, ma contribution principale porte sur le développement d'un modèle de prise de décision pour la traversée rue qui considère le temps d'attente sur le trottoir de l'agent piéton et les actions de ses voisins, qui attendent, ou qui traversent. Dans un premier temps, le modèle sera utilisé pour une traversée de rue au feu piéton rouge, sans trafic routier, puis dans un second temps pour une traversée de rue face à un trafic routier et sans feu, situation

pour laquelle l'interaction avec le véhicule sera surestimée ou sous-estimée en fonction du temps d'attente et de l'influence sociale.

Le modèle ainsi développé repose sur trois hypothèses. La première est que le temps d'attente est un facteur important dans la prise de décision de traverser. D'un côté, nous supposons qu'un agent piéton est prêt à attendre ou dépenser un temps donné avant de vouloir traverser, que nous appelons patience, et qu'au-delà le piéton voudra traverser même au feu piéton rouge. D'un autre côté, nous supposons que le temps d'attente joue un rôle dans la perception du véhicule devant lequel il envisage de traverser. Les deux hypothèses suivantes reposent les travaux de Rosenbloom qui suggèrent qu'un piéton qui attend au feu piéton rouge peut être influencé par ceux qui traversent devant lui, suggérant ainsi qu'il y a des opportunités pour traverser, mais également par ceux qui attendent, l'encourageant ainsi à attendre le feu piéton vert. La combinaison de ces deux hypothèses forme ce que nous appelons l'influence sociale ; influence sociale qui va moduler la patience de l'agent piéton et sa perception de l'arrivée du véhicule devant lequel il envisage de traverser.

Dans une première étude, les simulations montrent que les piétons supposés traverser au feu piéton rouge peuvent attendre le feu vert en raison de voisins qui attendent, et réciproquement, des voisins traversant au feu rouge vont influencer l'agent à traverser alors qu'il aurait attendu le feu piéton vert s'il avait été seul dans cette situation. On peut noter également que des agents piétons similaires en termes de caractéristiques propres (patience, vitesse) et percevant la même situation (couleur du feu, nombre de voisins traversant et nombre de voisins en attente) mais arrivant sur le bord du trottoir à différents moments vont prendre des décisions différentes (traverser ou attendre) conduisant ainsi à une production de comportements hétérogènes et non nécessairement prédictibles dans le cas où un sujet humain interagirait avec des piétons virtuels, les uns et les autres pouvant s'influencer mutuellement. Dans la seconde étude de traversée face à un trafic routier, les résultats montrent des comportements jusqu'à présent peu fréquents dans le cadre des simulations de piétons. Ainsi, aux comportements de traversée et aux refus de traversée justifiés du point de vue de la sécurité routière, l'agent piéton peut décider d'attendre alors qu'il pourrait traverser manquant ainsi une opportunité, mais également peut décider de traverser alors que la situation ne le permet pas, ce qui le conduit à prendre une décision inadaptée à la situation. Le modèle repose une comparaison temporelle entre le temps nécessaire à l'agent piéton pour traverser et le temps d'arrivée au point de conflit du véhicule devant lequel l'agent envisage de traverser. La combinaison de l'influence sociale et du temps d'attente va constituer un biais sur la perception du temps d'arrivée du véhicule. C'est l'utilisation

de ce biais qui peut conduire l'agent piéton à surestimer l'arrivée du véhicule et peut le conduire à prendre une décision inadaptée, ou à sous-estimer l'arrivée du véhicule l'amenant à attendre plus longtemps et peut-être manquer ainsi une opportunité de traverser. Pour ces deux études, les résultats sont comparés à la littérature disponible pour déterminer la pertinence du modèle et de la démarche.

Mots clé : Modélisation et simulation piétonne, évitement de collision hétérogène, influence sociale, temps d'attente, traversée de rue, transgression des règles de circulation, décision de traversée inadaptée.

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List of Abbreviations

CA	C ellular A utomata
FD	F undamental D iagram
NPC	N on- P layer C haracter
ORCA	O ptimal R eciprocal C ollision A voidance
PT	P atience T hreshold
RVO	R eciprocal V elocity O bstacles
SE	S hared E ffort
SFM	S ocial F orce M odel
SI	S ocial I nfluence
TH	T ime H orizon
TPed	T ime T o C ontact Time from the position of a pedestrian to the offside of a vehicle
TPed_near	T ime T o C ontact Time from the position of a pedestrian to the nearside of a vehicle
TTC	T ime T o C ontact Time from the front bumper of a vehicle to the position of a pedestrian
TTC_rear	T ime T o C ontact Time from the rear bumper of a vehicle to the position of a pedestrian
VO	V elocity O bstacles
VR	V irtual R eality

Chapter 1

Introduction

1.1 Overview

Research on pedestrian modeling is multidisciplinary, involving cognitive science, virtual reality, social science, and transportation. It is not a new topic; many scientists have been working on the subject since the late 1950s [Coh18]. Most models developed during that period were macroscopic, where an aggregate term describes the dynamics of pedestrian flow [Hoo+14]. In 1974, Henderson formalized the crowd to an average velocity from all pedestrians composing the crowd. Then, represents the movement of the crowd as continuous, like the movement of fluids [Hen74]. I use the definition of the crowd from [TDP15] in this thesis. It describes an aggregation of individual pedestrians at the same location, but each pedestrian has distinct properties. Then, in the mid 1980s, a new class of models comes into play, that are the pedestrian microscopic models. [Hoo+14] presented the microscopic models as a flow of pedestrians, described at individual levels. Gipps developed the first pedestrian microscopic model, where each pedestrian has its properties, was developed in 1985 [GM85]. He uses a cellular automaton for this first pedestrian simulation, and he discretized the environment into different pedestrian-sized cells [GM85].

In 1995, Helbing developed a social force model (SFM) [HM95], which was the first collision avoidance pedestrian model, inspired by Henderson's work. The SFM is a force-based model composed of several forces to allow the pedestrians to reach their destinations and avoid collisions with other pedestrians and obstacles. The SFM also is considered a pioneer in pedestrian models, leading to various derivations of the model, including the creation of new models. As such were the velocity-based models, Reciprocal Collision Avoidance for Real-Time Multi-Agent Simulation (RVO2), in 2011 [VDB+11]. Moreover, the number of works published on pedestrian models started to

grow after 1995s, probably because of the increase in computation power in that period, in table 1.1.

A model is a simplification of reality [Don+08]. The model can be used to test hypotheses [KMP11], or to simulate pedestrian behaviors. One of the advantage of simulation is the possibility to work on dangerous situations, such as underestimating the arriving time of an oncoming vehicle and crossing in front of this vehicle.

Although walking is the oldest form of transportation that ever existed, pedestrian behaviors receive less interest than vehicular traffic [She+21]. [Dia02] proposed a pedestrian street crossing model based on questionnaires designed for drivers. [TGD14] developed a model of macroscopic pedestrian flow, derived from a vehicular traffic model, to exhibit emerging behavior. Furthermore, crowd simulations have more interest than pedestrian simulations (see table 1.1). [Lem+12; RRW14] extended leader following in cars to leader-following in pedestrians. In some works, pedestrians are considered a perturbation and delay to the traffic flow [Wan+21].

Table 1.1: Google Scholar search comparison results of all work published on each designated date, when the keywords “pedestrian simulation”, “crowd simulation” and “vehicle simulation” are used, (Consulted in December, 2021).

keyword	1960	1970	1980	1990	1995	2000	2005	2010	2015	2020
“Pedestrian simulation”	1	2	9	20	27	63	257	947	2380	4140
“Crowd simulation”	3	3	3	9	17	65	416	1780	4540	7720
“Vehicle simulation”	11	41	203	463	554	758	1320	2770	5950	11300

1.2 Pedestrian simulation challenges

Microscopic pedestrian simulations still have many challenges to overcome, explaining the number of published works in this field that still increases. Many existing pedestrian simulations are drastic simplifications of the real situation [Don+08]. Pedestrian simulations use rules or mathematical formulations, and the pedestrian agent in each simulation uses the same rules or the same mathematical formulations. The differences between agents are mostly related to their individual characteristics, such as speed, destination, or perception distance. Moreover, pedestrian agents process only physical information such as their neighbors’ position, speed, or shape. These simplifications lead to homogeneous interaction behavior, and simulating heterogeneous behavior would lead to a more realistic crowd [Guy+11; LLB11].

The simplification also can lead to symmetrical interactions. For example, pedestrians anticipate and avoid collisions the same way [Cur+13]. Real pedestrians do not always avoid collisions the same way with each other. Maybe because of time reaction differences, cultural reasons, or the preferences. Moreover, pedestrians interactions are not limited to collision avoidance; they can also follow and overtake another slower pedestrian.

Wooldridge presents an agent as an autonomous entity with objectives and reacting to the perception of the environment [Woo99]. In the context of crowds, a pedestrian has an objective, which may be to reach a destination, and the perception of another pedestrian who may cause a collision may create a collision avoidance reaction. In many situations, this reaction is rarely planned, leading to an adaptation to the situation. There are different ways to react to the environment, and individuals can react differently even to the same situation perceived. This variability of individuality could help to increase the heterogeneity of the crowd.

1.3 Street crossing

It is recommended to walk an average of 10,000 steps a day [TL+11]; however, walking is not always safe, especially when crossing streets. Most accidents involving pedestrians happen during street crossings, when the pedestrians are exposed to vehicles [KSG09; Lav+09]. Indeed, crossing a street is a complex task. A pedestrian has to make a quick decision, and a wrong crossing behavior could lead to a dangerous situation, even an accident.

Pedestrians are the most vulnerable road users because they do not have a car body and helmet to protect them from others. They also have lower inertia than vehicles, which means they can maneuver more easily. However, they do not have flashing lights or horns to prevent others, increasing the risk of an accident. In addition, not all pedestrians follow the traffic rules.

Pedestrians can have different crossing behaviors. Some of them violate the traffic rules. The violation rates in major European cities, like Paris, Brussels, and Hamburg, are around 20 to 25% [Die19]. Traffic violations are more likely to lead to an accident [Lav+09] than rule-compliant behavior, and around 39% of the pedestrian accidents at marked crosswalks occur during red light violation [Die19].

Pedestrians are influenced by neighbors in their decision during street crossings [Ros09; FKK10]. Few simulated street crossing models consider the social influence.

[FKK10; Yan+06] simulated pedestrians influenced from neighbors to cross, but they did not implement the influence from neighbors to wait.

1.4 Objective and application domains

The behaviors of real pedestrians are often heterogeneous and vary according to the situations. Pedestrians do not always behave the same way for the same situation. However, the behaviors of pedestrians developed in most models lack variety [TM12]. This is because many existing pedestrian models consider few contextual information, leading to homogenous behaviors. The temporal dimension (how long the pedestrian has been in a situation) and the social influence from the neighbor's behaviors are important factors in street crossing decisions. Thus, the objective of this thesis is to limit the gap between what is observed in real situation and what is developed in the models. To reach that goal, I propose to increase the heterogeneity of the interaction of pedestrians in urban environments.

Producing heterogeneous pedestrian behaviors can increase the realism of simulations. The application domains of this thesis are to populate a scene with virtual and convincing pedestrians. Then, the developed tools can be given to researchers in experimental psychology to experiment with more realistic pedestrians in a controlled environment. For example, to propose virtual pedestrians crossing at the red light in front of an autonomous vehicle in order to study the behavior of the driver or a passenger [RAB21].

1.5 Contribution

In the first part, I developed the interaction between pedestrians. I start with the face-to-face interaction during collision avoidance. My first contribution is giving pedestrians the ability to adapt the collision avoidance based on perception of neighbors, so they can avoid and anticipate differently. But, the interaction between pedestrians is not limited to collision avoidance.

I extended the collision avoidance with the following behavior, so pedestrians can avoid and overtake someone with slower speed named leader, depending on the situation. Thus, my second contribution consists of combining a collision avoidance model with a queuing model, and considering different interaction between the leader and the

rest of the neighbors. Interaction in an urban environment also implies pedestrians interacting with a pedestrian light or road traffic during street crossings.

My main contribution is the development of a street crossing decision model. I hypothesized that pedestrians are violating the traffic rules because they lose patience, and they are influenced by the number of neighbors crossing and waiting. To illustrate this situation, I implemented a street crossing scenario with a pedestrian light without road traffic. If pedestrians arrive during a red light, they start to wait and can be influenced by the neighbor's decision to violate or comply with the traffic laws. My third contribution is the utilization of social influence, which is the behaviors of neighbors (crossing/waiting) to modulate the patience. Then, the pedestrians decide to cross if their patience runs out.

Street crossing also imply an interaction with road traffic. I hypothesized that pedestrians have an inaccurate crossing decision because they biased the estimation of the time-to-contact of an oncoming vehicle, and the bias is based on waiting time and the social influence. To illustrate this scenario, I implemented a street crossing with road traffic without a pedestrian light. If pedestrians perceive an approaching vehicle, the pedestrians can overestimate or underestimate the time-to-contact of the oncoming vehicle. My fourth contribution is the development of the bias on the time-to-contact of an oncoming vehicle. These two situations lead to an adaptation of crossing decisions based on the situation, and they would have a different decision if they were alone, leading to heterogeneous interaction behaviors.

1.6 Plan

Chapter 2 reviews the literature on pedestrian models, pedestrian behaviors, and different data on pedestrians.

Chapter 3 develops the problem statement. Using the literature review on pedestrians models, and the behavior of pedestrians, I propose to bridge the gap. In this chapter, I specify the direction of the thesis, and the approach used.

Chapter 4 develops my two contributions to increasing the heterogeneity during collision avoidance between pedestrians. The first contribution gives pedestrians the possibility to adapt the collision avoidance based on the perception of the neighbors. The second contribution combines the collision avoidance with a queuing model.

Chapter 5 presents my main contributions to the development of an agent-based model for street crossing. The model uses the social influence from the actions of neighbors, and the pedestrian agent waiting time for crossing decision. My third contribution will be for a street crossing model at a red light without road traffic. My fourth contribution will be for a street crossing facing road traffic and without a pedestrian light.

Chapter 6 describes the first scenario for implementing the street crossing model at a red light without road traffic, and the second scenario for implementing the street crossing facing road traffic and without a pedestrian light. I also present the initial condition setup for the two scenarios.

Chapter 7 shows the simulations results of the street crossing model for the two scenarios.

Chapter 8 concludes the work presenting a summary, describing the major contributions, and some limitations of the contributions. Then, I proposed some short-term and long-term perspectives.

Chapter 2

State of the art

In the current pedestrian model, the heterogeneity of interactions and the variety of possible behaviors are limited. These limitations reduce the realism of pedestrian simulations. My objective is to increase the heterogeneity of the pedestrians behaviors. This literature review presents different simulations and models used for pedestrian interactions. The interactions can be between pedestrians or between the pedestrians and the urban environment. Then, I present the agent-based approach, which is those I will use. In the third section, I present some data and characteristics of real pedestrian behavior.

2.1 Pedestrian interaction models and simulations

This section presents models of the interaction between pedestrians. I identified three types of interactions: collision avoidance, group behavior, and the leader-following. A fourth interaction can be described between pedestrians and the urban environment during the street crossing.

2.1.1 Collision avoidance

Since 1950, some pedestrian models have been built, but these are mainly statistical models to improve the environmental design [Coh18]. In 1974, Henderson developed a fluid-based model [Hen74]. He formalized the crowds using the Maxwell-Boltzmann velocity space of gas law and the theory of conservation of mass. The first microscopic model emerged in 1985. Different categories of models were then built after this date, starting from rule-based in 1987 [Rey87], force-based in 1995 [HM95], velocity-based in 1998 [FS98], and vision-based 2010 [Ond+10].

In 1985, Gipps developed a cell-based model [GM85]. It was the first microscopic model where each pedestrian had its characteristics. He used a cellular automaton (CA). CA was developed by John von Neumann in 1948, for the objective of simulating artificial life [BCE97]: CA follows four principles. First, the space is divided into two-dimensional uniform cells. Second, each cell can only have one state at a time (dead or alive). Third, the state of any cell depends on the state of its closest neighbors. Finally, the definition of uniform transition rules to move from one cell to another cell [BCE97]. Gipps discretized the environment into uniform cells, and each cell has a pedestrian's size. However, the displacement of an adjacent cell limits pedestrian displacement.

In 1987, Reynolds developed a rule-based model, also called Boids. Boids are composed of three rules, each defined for specific reactions. The first rule is separation for collision avoidance. The second is for alignment, making the agent follow the same direction. The last rule is cohesion, which allows the agents to stay together. (Figure 2.1).

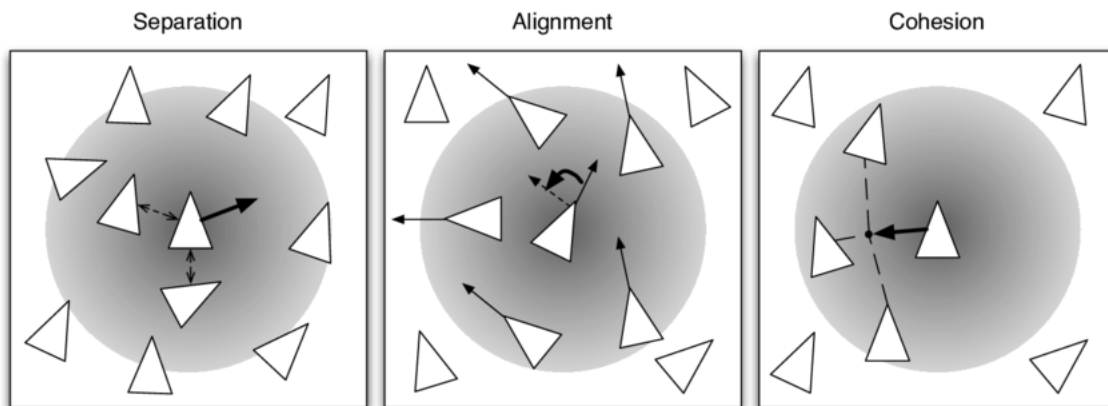


Figure 2.1: Illustration of the three Boids' rules model[BDD09].

Reynolds developed the Boids model initially to simulate a group of wild animals for computer graphics. In 1999, he extended the model for pedestrians [Rey+99]. He created a virtual environment with human-animated characters. He also extended the model by introducing the leader-follower concept, where the follower stays close to and follows a leader. The leader has a destination, and the group follows. The model produces a relative realistic displacement of a group and synchronization of each individual without centralized information. However, each agent in this model perceives the position and velocity of all other agents, which is physically impossible for a pedestrian, especially if the group has a hundred or a thousand individuals. This

model may be good for simulating a group of pedestrians with a defined leader, but it is not suitable to simulate an individual pedestrian with their destination.

In 1995, Helbing developed the first collision avoidance model from a concept of Henderson in 1974, combined with Lewin’s social behavior [Coh18]. SFM is a forced-based model, and it is composed of several forces (attraction to destination, repulsion to avoid collision with other pedestrians, another repulsion to avoid obstacles) [HM95]. A new acceleration is computed at each time step from several opposite forces to move the agent to a new position. This model is a pioneer in transportation research and crowd simulation. It led to different derivatives of SFM and other models, such as velocity-based models. This model works well in medium or high pedestrian densities, but it produces less realistic behavior at lower densities by moving backyards with negative velocity [Stu+19]. The model only considers the position of other agents around to compute the acceleration. Thus, the agent cannot anticipate the future position of other agents, and collision avoidance cannot always be correct. For instance, an agent moving in the same or opposite direction or not moving at all is considered the same. Thus, the agent always reacts the same way, even if the other agents around him do not represent any collision risk. [ZIK11] adds velocity to the input of the SFM model to predict future collision threats, and the agent may have a different interaction if the neighbors are moving in the same or opposite direction.

In 1998, Fiorini introduced a velocity-based model for static and dynamic disk-shaped robots. The model is called Velocity Obstacle (VO), and uses linear programming to approximate the trajectories of other robots. It expects the other robots to have a constant displacement, which leads to their future positions [FS98]. To avoid colliding with B_1 , A chooses a velocity V_A . V_A should be located outside the cone of collision CC_{A,B_1} , also known as the velocity obstacle. This is shown in figure 2.2, which is between V_A and V_{B_1} . Each robot takes a velocity outside the combined velocity obstacles associated with each robot.

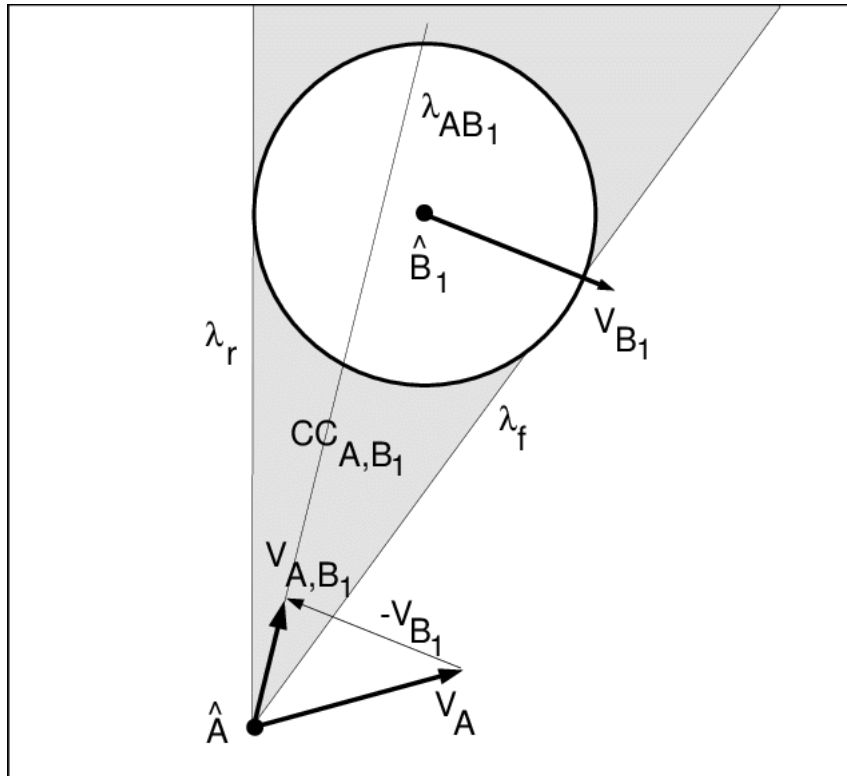


Figure 2.2: Cone collision CC_{A,B_1} between two robots A and B_1 by [FS98].

VO offers several advantages; it can deal with high-speed objects and anticipate collisions. Nevertheless, VO has a few limitations. It is computationally expensive to explore the velocity obstacles of all other objects. An undesirable oscillation in the trajectory can happen in certain situations [BLM08]. The oscillations happen when robots have a strong variation of the velocity direction at every step. Consider a robot R_A with a preferred velocity V_{R_A} and a required velocity V_{VO} , to avoid colliding with another robot R_B . The oscillation occurs when the velocity of R_A is switched between the two velocities (V_{R_A} and V_{VO}) successively, leading to a change of velocity cap at each time step.

In 2002, Daamen and her colleagues developed a model based on the three-level theory approach [CHD14]. Their goal was to standardize a single microscopic model. Under the name NOMAD, the project was developed over 12 years [CHD14]. Instead of focusing mostly on the operational level, as most collision avoidance models do, they integrated three distinct levels: strategic, tactical, and operational. The first level is strategic and is used to list and select activities. The second level is tactical and is used to select an alternative activity different from initially planned, such as deciding

to follow someone. The last level is operational and is used to calculate the physical movement of the pedestrian during its displacement (new speed and position).

In 2008, Van Den Berg developed the Reciprocal Velocity Obstacles (RVO model) [BLMo8], extended from VO to resolve the oscillation problem. He modifies the selection of velocity during collision avoidance. Instead of selecting a velocity outside the velocity obstacle V_{VO} , when a collision is imminent, he selects the velocity between the actual velocity and V_{VO} . RVO is a pioneer in gaming and in computer graphics. In 2011, a velocity-based model for pedestrian simulation called Optimal Reciprocal Collision Avoidance (ORCA) was developed from the same authors [VDB+11].

In 2010, Ondrej and Pettré developed a vision-based approach for pedestrian simulation. Inspired by work from cognitive science, he said that pedestrians rely on visual information for locomotion [Ond+10]. They used a bottom-up approach, and the agent pedestrian reacted to perceived obstacles. The information processed from the perceived objects is the bearing angles and the time-to-collision. As a response, the agent pedestrian can turn the obstacles or decelerate. This model has certain limitations regarding its cost of computation. They extend their work from a velocity-based model, and they use the position and velocity from neighbors to compute the bearing angle. Thus, they create more computation than a basic velocity-based model.

In 2011, Guy used a Personality Trait Theory to increase the heterogeneity of the behaviors of crowds during collision avoidance [Guy+11]. The number of personality treated were six: aggressive, impulsive, assertive, active, shy, and tense. As results, the aggressive ones take the straightest path and avoid less the collision with other pedestrians of different personalities. Conversely, the shy ones avoid more the collision compared to the other pedestrians with different personalities.

From 1950s to 2010s is a long period, but the gap between the major works is rather long. Most of the models cited above use physical information (position, velocity, and size) to perform collision avoidance. That limits the consideration of the social context. Velocity-based models can handle better collision avoidance than other force-based models, allowing an anticipation of a possible collision. The anticipation allows a correction of a possible detected collision. Thus, pedestrians to react differently to another pedestrian moving in the same, opposite direction, or if the pedestrian is stationary. Velocity-based models are also cheaper than vision-based models. Nevertheless, the interaction between pedestrians is not limited to collision avoidance; for instance, they can also walk in groups or follow each other.

2.1.2 Group behavior

[Ave77] describes a crowd as an aggregation of individuals in groups, and isolated individuals. A group can have different proprieties, such as individual characteristics, group size, relationships among groups, and influences among group members [QH10]. Different works have been developed on the subject since Reynolds.

In 1987, Reynolds developed the Boids model, well known for group behaviors [Rey87]. This model works for both group and pedestrian simulation.

In 2010, Moussaid developed a model for groups. They observed that crowds are frequently an aggregation of individual pedestrians, and in most situations, pedestrians are walking in small groups as friends or couples. Pedestrians favor positions that allow verbal and social communication [Mou+10]. To maintain visual contact, they change positions and follow a certain spatial pattern rather than turning their heads [Mou+10]. The dynamic positions also depend on the size of the group. With three people walking together, they tend to follow a “V-like” shape, and the person in the middle is a little behind the two others. When the group is composed of four people, the positions change to form a “U-like” shape, where the two persons in the middle are a little behind the first and fourth person in the group [Mou+10], they developed this model from the SFM.

In 2011, Karamouzas developed another pedestrian group behavior using a velocity-based model [KO11]. They state that the velocity-based model performs better than the SFM for collision avoidance. When confronted with different densities (low or medium) in their model, a group can change shape. Pedestrians can avoid collisions with groups as one entity, rather than avoiding each member individually.

In 2016, Lemerrier and Auberlet extended the collision avoidance with group interaction [LA16]. The particularity of this model is the group composition. The groups are not based on a special relationship among the group members, but on the position and velocity of each pedestrian. Agents moving with approximately the same speed and velocity are considered by others as a group. Thus, if an agent perceives a group, the agent avoids the whole group as an entity. This concept of an occasional group is interesting since, in many situations, pedestrians do not know if pedestrians are walking together are a real group or not, but they just avoid them as a cluster of pedestrians. This model focuses more on improving the interaction during collision avoidance than considering a social group. Nevertheless, the model has a limitation regarding its implementation. The group identification is centralized, but not individual

to each agent.

2.1.3 Leader-following

Leader-following interactions receive less interest than group dynamics or collision-avoidance interactions. In many situations, pedestrian-following interaction models are derived from vehicular traffic models [RRW14].

In 2014, Rio and Warren developed six pedestrian leader-follower models extended from vehicular traffic models [RRW14]. Then, they used their six models to experiment with subjects by asking the subjects to follow a leader, and the leader altered its speed during the experiment. The six models tested were: 1) speed matching between leader and follower, 2) constant distance, 3) constant speed, 4) time-to-contact, 5) ratio (based on the inverse of the time-to-contact), and 6) a linear combination of speed and distance. They found a better performance for the speed matching model and hypothesized that pedestrians are better at matching speeds in normal conditions (normal pedestrian speed) and within a few meters. Their models were tested for special circumstances, such as waiting in a queue and not overtaking the leader. However, in real situations, pedestrians can follow and overtake someone.

In 2016, Lemercier and Auberlet combined a collision-avoidance model (ORCA) with a queuing model [Lem+12]. Unlike pure queuing models, where a pedestrian just follows another pedestrian in front of him, the pedestrian can overtake. Thus, this model is suitable for an urban environment. In this model, a pedestrian can follow another pedestrian in front of him, moving in the same direction but slower. In this case, the pedestrian does not consider the one in front of him the same as the rest of the neighbors. This model is an improvement of the collision avoidance model.

2.1.4 Street crossings

[DC11; ZWM18] used logistic regression to predict the crossing decision. [FKK10] use the decisions of the neighbors to build a probabilistic model for the crossing decision. In this model, the closer the acting neighbor, the higher the probability of following. They do not use many variables: the model relies on the positions and decisions of their neighbors. However, the crossing decision is more complex than that. [May+15] developed a binary logit model. They use the personal characteristics, spatial factors, and neighbors' decisions to make the crossing decision. Models with several parameters are difficult to reproduce in different situations.

Many street crossing models combine various factors: physical (gap [YPT13]), environmental (presence of illegal parked cars [Dom+15]), and social (behaviors of neighbors [FKK10]). However, the results are difficult to generalize to different crossing locations or countries. For example, according to [Lav+09], the configuration of the environment can impact the crossing decision. Social culture also can have an impact on the crossing behaviors [Pel+17]. Most of the models presented above are based on data at specific crosswalks. Moreover, relying uniquely on data also has its limitations. To collect data, the experimenters isolate the variables they want to study in many situations.

The models cited above are not developed for simulations. [FKK10] developed a street crossing simulation using the distance between crossing neighbors. [FKK10] found with their model that a person was more likely to cross 1.5 – 2.5 times if their neighbors had started to cross.

[Yan+06] developed a street crossing simulation and pedestrian crossing at a pedestrian light. The simulations produce law-obeying and opportunistic pedestrians. The distribution of gaps was extracted from a video recording. Decisions are based on a gap comparison between the arriving time of an oncoming vehicle and the time needed by pedestrians to reach a safe position. At the beginning of the simulation, they generate a proportion of law-obeying and opportunistic pedestrians. The opportunistic behavior is based on the observation of pedestrian crossing during red. This work, however, has limitations regarding its implementation, all pedestrians who were waiting on red become opportunists after seeing someone crossing at red.

2.1.5 Synthesis of pedestrian models and simulations

The development of pedestrian simulation has increased since 1950. The first models were mostly macroscopic [Coh18], where the dynamics of pedestrian flow is described by an aggregate term [Hoo+14]. The development of the first microscopic simulation was in 1985 and the first pedestrian collision avoidance model was in 1995. Most of the crowd navigation models process the new position based on physical information (position, velocity, and size), limiting the behavior variability. Thus, pedestrians react the same if another pedestrian with the same physical characteristics (position, speed, and size) is perceived in this situation. Regarding the interaction between pedestrians: the group and leader-follower receive less attention. Most group models use social interaction, but the social interaction is often limited to the members of each group, and each member has a fixed group. Most leader-follower models are extensions of

leader-follower models in vehicular traffic and focus on the queuing situation. The queuing situation is not very adaptable for the urban environment.

Another way to simulate pedestrians is to use a data-driven model. A data-driven model has different principles compared with traditional knowledge-based model. This last one model requires understanding pedestrian behaviors in order to model it, but a data-driven does not [Son+18]. The two models have a limitation: a knowledge-based may lead to a bias from the modeler [Son+18], and a data-driven may lead to a bias from the data inputs. Moreover, the data-driven model works only with a certain amount and a certain quality of data. An alternative to the pure data-driven methods is the Reinforcement Learning (RL), which consists of finding the optimal behavior to the situation [LL18]. RL uses a data-driven approach to find the action and then correct it in order to reach the optimal behavior [LL18]. Nevertheless, even if RL can find the optimal behavior for the situation, pedestrians in the real world do not always follow the optimal behavior. For example, pedestrians can decide to wait, even if they have time to cross in front of an oncoming vehicle [LC07]. Or, in another situation, pedestrians can decide to cross, even if they do not have time to cross in front of an oncoming vehicle [oxley2005crossing.]

Regarding the street crossing models, most use data from a limited number of crosswalks for the interactions between pedestrians and the urban environment during street crossings. This allows identifying some factors affecting pedestrians' decisions, but limits the generalization of the results to different crosswalks. Besides, few street crossing models have been developed for simulation. [Yan+06; FKK10] developed a pedestrian street crossing simulation and pedestrians can influence each other to cross the street and break the traffic rules, but they cannot influence each other to wait and follow the traffic rules. [LBM55; Ros09] observed that some pedestrians could see someone following the traffic rules and be influenced to follow them as well.

2.2 Agent-based approach

A crowd is described as a composition of individuals at the same location [TDP15]. Woodridge defined an agent as “a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objective” [Woo99]. Thus, each individual can be considered to be an agent. Different other definitions of an agent exist. Ferber defines an agent as an autonomous entity, capable of perceiving the environment and reacting according to its capability

[FW99]. The main idea of agent-based modeling is the ability of an agent to perceive, interact and decide according to situations. The agent approach is considered to be closer to the reasoning in real situations [KMP11], where everyone has a certain autonomy in their actions.

2.2.1 Agent characteristics

An agent is autonomous in its activities to meet its objective [Woog9]. The agent is flexible if it has these three characteristics: 1) reactivity to perceive and respond to a dynamic environment. 2) Pro-activeness to have goal-directed behaviors. 3) Social ability to interact with other agents [Woog9]. An agent has a perception capacity to observe the environment, a repertoire of actions to react to his perception, and a specific goal. Not all the action in the repertoire should be applied in all situations [Woog9]. Ferber defined the action as the response to the stimulus perceived [FW99]. The agent should be capable of balancing the goal-directed behavior and the pro-activeness of the environment. A pure goal-directed behavior would reach its goal but would be too rigid in a dynamic environment, and a pure pro-activeness would not reach its goal.

2.2.2 Agent interactions

The agent approach is based on the interaction between agents [Don+08]. The interaction is a succession of semantic actions resulting from stimuli perceived in the environment [KMP11]. The interaction is not limited to verbal communication; it can also be physical. For instance, agents in the ORCA model interact with each other without explicit communication, but through position, velocity, and size [VDB+11].

Intelligent behavior can emerge from interactions [Woog9]. Intelligent behavior, which is also called emerging behavior, is not conditioned by a central approach [Mou+12]. The Boids model was the first producing emergent behaviors from the interactions of individual agents [Rey87]. Pedestrian behaviors are complex, each pedestrian can have different goals, but they share the same environment. Thus, they have to interact with each other. Nevertheless, pedestrians do not always behave the same way, which makes their behaviors complex. Helbing presented that pedestrian behavior is not chaotic, as everyone follows their individual objectives [Hel+01]. Some regularities may happen in some situations, where pedestrians self-organized. Helbing defines self-organization as non-predefined pedestrian interaction, without prior communication or planning, that gives rise to spontaneous patterns [Hel+01]. Self-organization is

illustrated by the formation of lanes, when a bidirectional flow of pedestrians in a lane meets and pedestrians from each direction follows a spontaneous lane [MHT11].

Agent interactions are not limited to physical characteristics (positions, velocity, and space available). Lhomme and Lourdeaux developed an emotion contagion model using personality and special relationship, and implemented the contagion model in the context of crowd crisis-simulation [LLB11]. They described the emotional theory as the state of an agent affected by the actions of another agent or an event. Thus, the decision of each agent is affected by the emotion coming from the perception of the others.

2.2.3 Computation model and scheduling

Agent-based is an approach for building a model. A computer simulation is a production of behavior from the model [Don+08]. Different programming languages exist, leading to different ways of implementing the same model. The same programming language is used in some situations but with different scheduling, leading to different results. Regarding scheduling, three approaches exist.

The first approach is sequential. Each agent moves sequentially from the other. The advantage of this approach is the absence of collision. Each agent cannot move to the same position at the same time. The disadvantage of this approach is that the sequential movement of each agent does not reflect the real-world situation, where each individual is more likely to move in parallel.

The second approach is pseudo-parallel. Each agent computes its position sequentially and moves together at the same time. To illustrate, let us have three agents A_1 , A_2 and A_3 compute their positions at time t , and the three agents could select the same position at time t . The ORCA model uses this approach. That means a collision could occur. However, the collision risk is reduced by the anticipation capacity of the ORCA model.

The last one is parallel. Each agent moves in parallel. This approach could be realized using a thread to allow each agent's position computation in parallel. This last approach could also lead to collisions because two agents can simultaneously choose the same position. The advantage of this approach is the similarity with a real-world situation.

2.3 Pedestrian behavior

Different factors can affect the decision of pedestrians. Regarding the behavior during street crossing decisions, it can be impacted by cultural or environmental factors. I focus on some pedestrian physical capacities and some social factors affecting crossing decisions in the following.

2.3.1 Pedestrian speeds variation

Pedestrians are more flexible compared to other road users [Lav+09]. They can adjust their speed, run, or step back [Jay+20]. Pedestrians have different speeds during the street crossing or a simple walk. To illustrate, they tend to have a higher speed when crossing a street than when doing a simple walk [IN08; KWC14; Bro+13; Rus+18; Pet+15]. They also walk faster when crossing during a red light than when crossing during a green light [IN08; KWC14; Bro+13; Rus+18; Pet+15].

Pedestrians adjust their speed as needed and can walk faster or run, according to the situation [Zhu+20]. For example, when the light turns red just when they arrive, some may speed up and cross at the beginning of the read cycle [Vir98]. Or, when they are almost finished crossing, they tend to decrease their speed [KWC14].

Depending on the context, for example, after waiting a long time on the sidewalk, they tend to have a higher speed, presumably to compensate for the delay [IN08]. A pedestrian alone walks faster compared to a group [IN08; Pet+15]. Pedestrians also tend to walk faster when crossing wider streets compared to narrower streets [FBT06; GN].

The speed can vary depending on physical characteristics. Young pedestrians cross the street faster than older ones [FBT06]. Men cross faster than women [FBT06].

2.3.2 Perception characteristics

Pedestrians perceive the majority of the information from traffic through visual input [FD20]. Pedestrians can perceive up to 8 millions bit/s, but process only 7 bit/s [FD20]. In cases of attention overload, humans can ignore helpful information [GS04]. Thus, pedestrians can process limited information. According to [SO03], a human can only process from 4 to 10 information simultaneously.

Pedestrians sometimes process the distance rather than the time gap between two vehicles to decide to cross, especially when they are constrained by time [LC07]. It is probably more difficult to estimate the speed than the distance of an oncoming vehicle.

Each pedestrian has a distance limit for perceiving the speed of an oncoming [YS21]. The distance depends on the height of the pedestrian. The taller the pedestrian, the longer the distance. As an illustration, a pedestrian 1.5 m tall can perceive an oncoming vehicle moving at 80 km/h at about 60 m, and a pedestrian 2 m tall can perceive an oncoming vehicle moving at 80 km/h at about 70 m (in the figure 2.3).

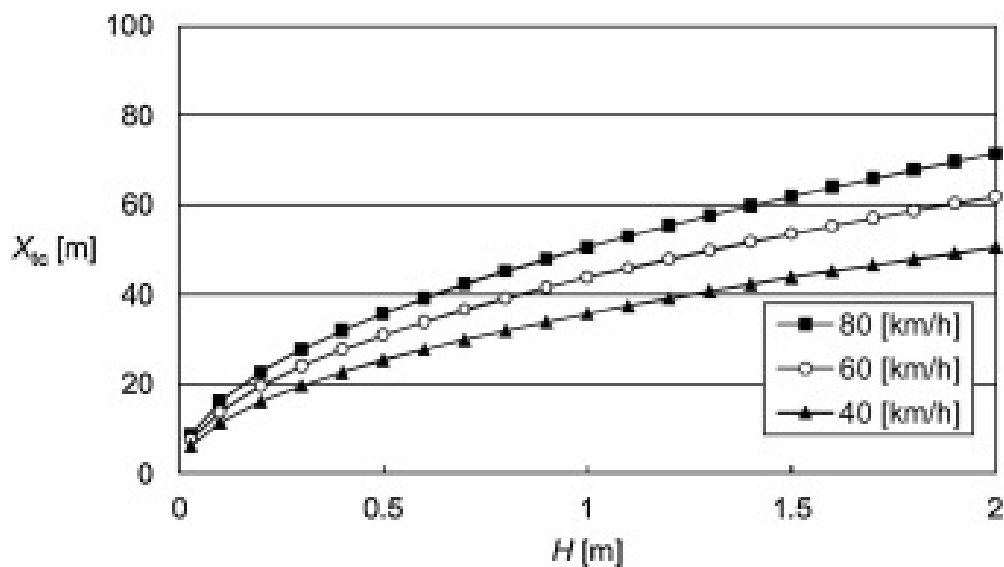


Figure 2.3: The relation between the maximal distance of the oncoming vehicle, and the height of the pedestrian, for three vehicle speeds, according to [YS21].

Pedestrians can perceive a limited number of objects simultaneously, and they can estimate the speed of an oncoming vehicle up to a certain distance. These perception limitations could lead to an inadequate crossing decision.

2.3.3 Social influence during street crossings

Seeing someone crossing the street can influence pedestrians' decisions. [DMM05] found that even if pedestrians are not traveling together, they can be influenced by the crossing decision of others. When pedestrians arrive at an intersection with a pedestrian light, they are regulated by traffic rules. They are supposed to cross during green and wait during red. But not everyone follows the traffic rules, and some cross even if the pedestrian light color is red. Then, when someone crosses, it may encourage other pedestrians to follow [Ros09]. Some pedestrians may think that if someone is crossing,

then it is safe [FKK10]. Knowing that someone is breaking the rules increases the likelihood of infractions [LBM55]. This can create a cascade of decisions not adapted to the situation, starting from the decision of one person [FKK10]. [Har91] explain this phenomenon by saying that pedestrians delegate responsibility to a group and that they are more cautious alone. In some situations, pedestrians use other people as a cue and do not look at a pedestrian light [Har91]. Influence from neighbors also works in the opposite direction. Seeing someone waiting increases the conformity of pedestrians to follow the rules [Ros09]. More people will conform to the traffic rules if they see someone who has already conformed to the traffic rules [LBM55].

Social influence can come from both familiar and unfamiliar neighbors [FKK10]. But the power of influence depends on the person perceived [LBM55]. [LBM55] hypothesized that high-status persons who violate the rules influence more, leading to more violations, than low-status persons. Conversely, a high-status persons who wait leads to more people who conform to the rules. Their experiments confirm the first hypothesis, but not the second, since the conformance was already high. Their results could mean that the influence of crossing or conforming pedestrians does not have the same power. They also found that when someone violates the traffic rules, and the person who violates is perceived as low or high-status, then the violation always increases. Still, the violation is higher with high status.

More recently, [GP01] conducted an experimentation in France, following the results of [LBM55]. The experimentation was done in the street with low traffic volume and few risks for pedestrians. A confederate waits on a sidewalk, and when ten pedestrians arrive, the confederate crosses the street. To produce the situation with low and high status, the confederate wears different clothes representing the two situations (suit / dirty clothes). Two observers counted the number of waiting and crossing pedestrians to collect the data. As a result, in the control group, the violation rate was about 15 %, and in the cases of high, low, and medium, the violation was 54.5 %, 9.3 %, and 17.9 %, respectively. Their results indicate higher violations for high status compared to the control group, and the opposite for low status. The results for the low status are different in the two experiments; the violation rate decreased with low status crossing the street in the last experiment.

2.4 Observation of pedestrian behaviors

Data collection on pedestrian behavior can be done in two approaches: during an experiment or natural observation. For the first approach, participants are asked to

follow a protocol, and the experimenter observes the participants' behaviors. The first approach can be conducted through a physical experiment, virtual reality, online or mixed methods. In the second approach, participants may not be aware of the experimentation, and the experimenter directly collects behaviors. This second approach can be realized with video cameras or an observation grid. In what follows, I present different observed pedestrian behaviors. The first observation concerns the behaviors during collision avoidance. The rest of the observations concern the behaviors during street crossings.

2.4.1 Physical experiment for collision avoidance

Olivier investigated the collision avoidance between two human walkers during an experimentation [Oli+12]. Two pedestrians were invited to move simultaneously from the diagonal position of the experimental area. When the two starts moving, they do not see or hear the footsteps of each other. She starts to see each other when they pass a 3 meter wall long (Figure 2.4). She found that walkers can accurately estimate the distance and the time of the collision and adapt their walk. However, the estimation might not always be accurate in real situations, where pedestrians can be distracted. This experiment has the advantage of a high control of the situation. The experimenter can isolate the defined variables. This approach has a limitation, the experimenter could not find the motivation of pedestrians, and one way to identify the motivation is to ask pedestrians.

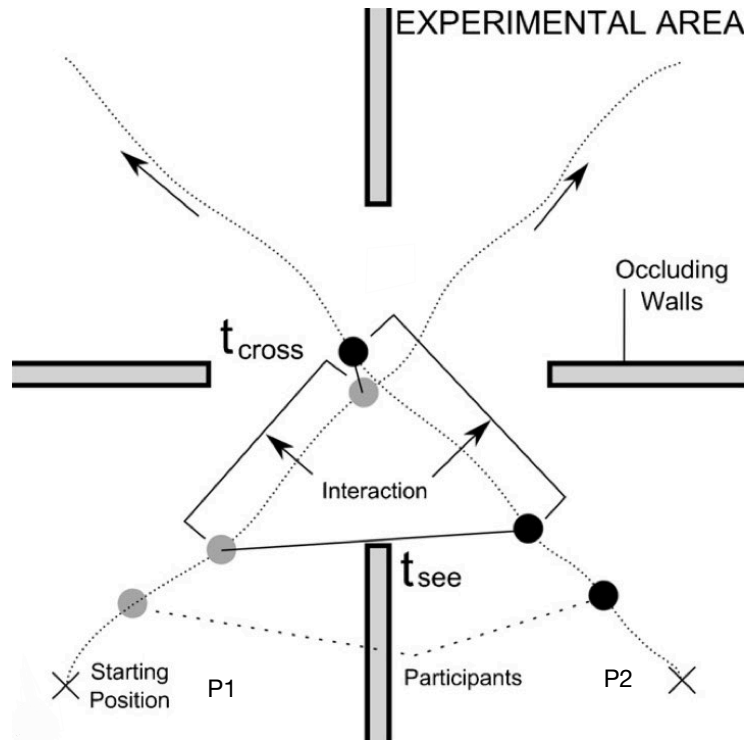


Figure 2.4: Description experimentation realized by [Oli+12]. Two pedestrians P_1 (disk gray) and P_2 (disk black) start moving from the diagonal of an experimental area, and meet at the central position of the experimental area.

2.4.2 Questionnaires

Granie developed a questionnaire for pedestrians to measure their behaviors [GPG13]. She and her colleagues found that about 21.09% of her participants admit violating a pedestrian light. Among the reasons reported was that they forgot to check because they were thinking something else or wanted to join their group. 7.73% of the participants have lapsed and made violations accidentally. The total violation rate was about 28.82%, which is close to the average violation rate in Lille (France) 32% [Dom+15]. Self-reports, however, can lead to a social-desirability bias [CAR15], where pedestrians want to give a response that is viewed favorably. Granie said that it is better to use questionnaires as a complementary tool [GPG13]. The questionnaire does not consider the impact of the environment, unlike direct observation [GPG13]. Direct observation can be realized during video analysis or experimenting with virtual reality.

2.4.3 Video recording analysis

Video analysis is broadly used for analyzing pedestrian behaviors. It can be used to estimate the waiting time before crossing a street. Different data on waiting times

are available in the literature, depending on the configuration of road. For example, pedestrians wait a shorter time in the case of unmarked compared to marked crossing [ZW11]. [ZW11] found that pedestrians wait a shorter time (around 3 s), but never more than 25 s, and [ZRA19] found between 1 to 6 s. In the case of crossing at a marked crosswalk, [DMM05] found that 63.7% of pedestrians wait for at least 20.8 s. The two situations indicate that pedestrians wait a shorter time when crossing at unmarked interactions. At an unmarked street, pedestrians tend to wait more actively, looking for new information, and wait for the next available gap to cross [ZW11]. If a pedestrian fails to cross at his first attempt, he will wait longer before the second attempt [SMM18]. [Bro+13] observed seven similar intersections in Sherbrooke (Canada), with only the red phase varying from one place to another. They found that a longer duration leads to higher violations rates. People tend to wait less time when the vehicle flow is low [Ham01].

[KO03] observes that after waiting for more than 20 s, pedestrians start taking more unsafe crossings and violate the traffic rules. During rush hour, there was a record number of crossing violations [CSH11; Guo+11; KWC14], suggesting that pedestrians have less patience to wait the pedestrian light turns to green. Younger pedestrians tend to wait a shorter than older pedestrians [Nol+08]. Trip purpose impacts patience [Guo+11]. Younger pedestrians, for example, frequently have a specific purpose, such as going to work, and have less patience than older pedestrians. A group of pedestrians is found to wait a longer time than an individual [Guo+11; Ham01].

The configurations of the crossing location can impact the patience of pedestrians. The patience required at an intersection with a pedestrian light is longer than the patience required at an intersection with no pedestrian light. With a pedestrian light, pedestrians are constrained by social rules, and with no pedestrian light, pedestrians cross when a gap is available. The pedestrian's patience is also not the same.

Regarding the pedestrian's waiting time recorded, it lacks a description of the situation around the pedestrian during the crossing decisions. Using a camera to record the waiting time based on the subtraction of the arriving time and crossing time is not enough to describe how long a pedestrian would accept to wait. I suppose patience and waiting time are different. Waiting time is the time spent by a pedestrian on a sidewalk, and patience is the time he accepts to wait.

Video recording can also be used to visualize pedestrian violation rates. Different crossing violation rates have been observed in different sites and countries. The crossing violation can be different in different countries: 15% in Israel [Ros09]. In China, the

average is about 23.3%, and the rate may be 66.7% at certain intersections [Yan+06]. The average is about 39.88% in mid-block crosswalks in Beijing during peak-hour [Guo+11].

Regarding the average violation rates, a gender difference is found in Japan and France: men are around 40.6%, and women are around 25.7% [Pel+17], averaged from different sites. The number of lanes varies from 1 to 6, and the car speed on each site was limited to 50 km/h. The violation rates are different in France (41.9%) and Japan (2.1%).

These different observations indicate that the crossing violation can vary depending on several factors. In some countries, it can be as low as 2.1%, and in some areas, it can reach 66.7%. These differences between countries are associated by [Pel+17] with cultural differences. In cities like Hong Kong, for example, violating the red light can lead to a fine if caught by a police [Zhu+22b]. On the other hand, it is just a warning for some countries, like Ireland [Ros09].

Using a video camera to observe pedestrian behaviors has the advantage of avoiding desirability bias. Pedestrians may not be aware of the situation, and they would not act to please an experimenter. Nevertheless, this technique has a certain limitation: it cannot produce motivational factors.

2.4.4 Observation using grid

Dommes combines observation grid and questionnaires to study the human red light crossing motivation [Dom+15]. She established observation of 15 urban crosswalks in Lille (France). Each urban crosswalk was marked, with a pedestrian light, in two-way streets, with no pedestrian refuge islands. Pedestrians were unaware of the first observation phase and were asked using a questionnaire after finishing the crossing. The observation consisted of identifying if they made a violation, the waiting position, the speed, and the crossing path. As a result, an average violation rate of about 32% was found. She also found that violations were planned behavior rather than opportunistic.

2.4.5 Experiment street crossings in virtual environment

[Oxl+05] experimented street crossing using video. Subjects were invited to press a button if they found the gap was large enough to cross. They proposed several gaps, between 1 to 13 s, and a car speed of 40, 60, and 80 km/h. As a result, they observed that about 19% of young (20 to 30 years old) and adult (60 to 70) pedestrians selected

a negative margin (between 0 and -2 second). For older pedestrians, 70 to 80 years old, about 70% selected a negative margin gap (between 0 and -10 second).

The gap theory is often used during street crossings. According to [PYG09], every pedestrian has a critical gap used for street crossings. [LC09] has set up experiments on pedestrian street crossings. 78 pedestrians were invited to cross a street in a virtual environment with virtual vehicles. The street was one-way with a width of 4.2 m, and participants were invited to cross between two oncoming vehicles at the same speed. The scenario was the same for all crossings: the total number of vehicles was three, and the participants were asked to cross between the two last vehicles; the vehicles did not interact with pedestrians. The participants were split into three groups: 26 young people, 26 adults, and 26 older people. Each group had a balanced distribution of women and men. The experimenter set up the speed of the car's at 40, 50, and 60 km/h. For each speed, the time between the two oncoming cars (gap) varied between 1 and 8 seconds, leading to 8 gaps in total. Therefore, all the participants experienced $8 \text{ gap} \times 3 \text{ vehicle speeds} = 24$ situations. Each pedestrian was positioned at the edge of the sidewalk, and for each situation, they decided if they could cross or not. If they can cross, the crossing time was measured. As a result, about 17% of pedestrians missed opportunities to cross. The average gap selected by all pedestrians was 3.756 s.

2.4.6 Synthesis of pedestrian observation behaviors

Different technics exist to collect data on pedestrian behavior. [Oli+12] found that pedestrians can estimate the collision with another pedestrian accurately. But the estimation might be different if the subjects are distracted or influenced. During a queuing experiment, [RRW14] found that the follower pedestrians were better in speed matching. Regarding street crossings, some pedestrians violating the traffic rules, some say wanted to follow their friend [GPG13]. According to [Dom+15], violating the traffic rules is mainly a planned behavior rather than an opportunistic one. Violation rate varies at different crosswalks. Pedestrians wait a shorter time when crossing at unmarked crosswalks compared to marked crosswalks [ZW11]. Pedestrians also wait more actively at unmarked crosswalks compared to without crosswalks. Regarding the gap selected during street crossing with road traffic, some pedestrians selected unsafe gap [Oxl+05] and some others miss the crossing [LC09].

2.5 Conclusion

I could see the discrepancy between models, simulations, and observed behaviors from this literature review. Crowd models focus mainly on collision avoidance and use as physical input information, limiting the consideration of the contextual situation. For the case of groups, most models are focused on social interaction, and the groups are already defined at the beginning of the simulation. For the case of leader-following, most models focus on the queuing situation.

Regarding street crossings, most models are focused on identifying the street crossing factors. These models often rely on data from a limited number of crosswalks. Observations and experimental data on street crossing show that pedestrians have heterogeneous behaviors. Pedestrians have different waiting times, and some pedestrians violate the traffic rules. But waiting times and the violation rates observed are often measured empirically, leaving the contextual situation unknown. During experimentation with street crossings, [Oxl+05; LC09] found pedestrians have an inaccurate estimation of the gap between vehicles. Some existing simulation models for street crossing mainly consider motivating the crossing, not the factor encouraging the waiting. I will start from this literature review and develop in the problem statement in the next chapter the approach I will follow during my PhD.

Chapter 3

Problem statement

This thesis aims to increase the realism of pedestrian interactions in virtual environments. Interaction can be between pedestrians in a crowd in which they can avoid each other or follow someone, for example. I use the crowd definition of [TDP15], that a crowd is an aggregation of autonomous pedestrians near the same location. It can also be between pedestrians and the urban environment during street crossings. To achieve my goal of improving the realism of pedestrian's interactions, I propose several ways to consider and to compute interactions, which increase the behavioral heterogeneity of the crowds.

3.1 Pedestrian behaviors

In a real situation, pedestrians do not avoid collisions with each other identically. Pedestrians may have an accurate anticipation of the time of collision between them [Oli+12], but only if they are fully attentive. Depending on several factors, pedestrians can anticipate collision differently. These factors can be the size of personal space (a friendly person required less space than those who are less friendly [EH73]), the attentional state (a pedestrian wearing a headphone is less attentive than those who do not wear anything [CSH11]), or the physical constraints (older people have longer reaction time than younger ones [Fug+00]). These different factors contribute to heterogeneous pedestrian's interactions.

The interaction between pedestrians is not limited to collision avoidance. In some situations, they can follow someone in a crowd. For instance, a pedestrian in a crowd does not always interact in the same way with all of his neighbors, especially if someone in front of him is walking more slowly than him [LA16]. Thus, pedestrians in a crowd can avoid collisions, follow someone else, or combine the two methods.

From a pedestrian perspective, avoiding collisions or following someone is not an objective. In many situations, they have destinations to reach, like going to university. On their route, they can avoid a collision, follow someone, or cross a street. Pedestrians have heterogeneous street crossing behaviors, when crossing with a pedestrian light or with road traffic. Observations from the literature indicates different violation rates at signalized intersections across different cities. According to these observations, the violation rates are most of the time lower than 50%, meaning that the majority of pedestrians follow the traffic rules.

During an experimentation for street crossing with road traffic in a virtual environment, [Oxl+05] observed pedestrians had inadequate decisions and selected a gap that could lead to a collision. They found that about 19% of young and adult pedestrians had a margin gap (between 0 and -2 second). During another experimentation, [LC09] observed that around 15% of young and adult pedestrians missed crossing opportunities. These results show that pedestrians do not always select an accurate decision when crossing with road traffic.

3.2 Pedestrian models

There is a discrepancy between the observed behavior of real pedestrians and the developed pedestrian models. Many models have been developed since 1950, and they can be categorized as rule-based [Rey87], force-based [HM95], and velocity-based [VDB+11]. These models mainly address collision avoidance, possibly due to its higher constraint. Furthermore, pedestrian models process mainly physical information, such as position, velocity, or size. This limits the consideration of the contextual situation.

Some of these models are drastic simplifications of the real situation [Don+08]. An example of simplification is that in a given model, each agent uses the same mechanism for collision avoidance. The mechanism can be a mathematic formulation, equation, or some rule. This simplification can lead to a symmetric collision avoidance [Cur+13]. For instance, the ORCA model expects pedestrians to avoid half of the collision [VDB+11].

Some models individualize the action of each agent. [Der+19] was interested in the impact of social factors during collision avoidance in face-to-face interaction. They selected three factors: sex, speed, and distraction. They used the ORCA model to simulate pedestrians, moving from opposite sides in a narrow sidewalk and meeting in the middle of the sidewalk. The sidewalk is not wide enough to allow the crossing,

and one of them must step down when they meet. According to their results: speed and attention contributed the most for stepping down from the sidewalk. [Cur+13] was interested in breaking the symmetry during collision avoidance and allowing each agent to manage their collision. For that, they extended the ORCA model by adding a concept of priority. The one with lower priority avoided more than the one with lower priority.

To avoid collisions, one strategy may be to follow someone walking in the same direction. In many situations, the pedestrians leader-following models are extensions of vehicle's leader-following models. In most of the cases, these models are used in queuing situations, and pedestrians are not supposed to overtake each other. In urban environments, a pedestrian may follow and then overtake someone. Lemercier and Auberlet combined a queuing model with ORCA for crowds [LA16]. In their model, a pedestrian agent processes the position, speed, and size of its neighbors. Then, the pedestrian agent will particularly take into account the front neighbor who is the most constraining.

In an urban environment, pedestrians do cross streets. Several models are available for pedestrian street crossing. Many of these models use the behaviors of pedestrians from cameras [FKK10], questionnaires [GPG13; Dia02] or both sources [YS13; Dom+15]. These approaches limit the replicability of the models for different crosswalks from those where the data was collected. In the case of crossing with road traffic, many models use the gap theory. According to [PYG09], each pedestrian has a critical time gap for street crossing. Few street crossing models are used for simulation, and fewer simulate social influence. [Yan+06] simulated law obeying and opportunistic pedestrians for street crossing. However, in these simulations, the influence to comply with the traffic rules are not considered.

My first contribution to this research was to provide the pedestrians the possibility of avoiding collisions by adapting to the context encountered, i.e., according to the perceived neighboring pedestrians with which he can interact. The proposal leads to simulations in which we observe the agent behavior adaptation while avoiding interactions, by an increase or a decrease in the avoidance effort according to the behavior of the perceived neighbor.

3.3 Contributions

From a literature review on the observation of pedestrian behaviors and on simulation models, I started by working on the interaction between pedestrians by giving them possibility to avoiding collisions by adapting to the context encountered, based on perception of the neighbors. My first contribution is to allow pedestrians to manage anticipation and collision avoidance. This method results in asymmetrical interactions with neighbors. The simulations shown are demonstrated by simulating two pedestrians with the same speed starting to move from the two opposite sides of a corridor. They avoid collision when they meet at the central position of the corridor. The major result of this simulation is that pedestrians adapt their collision avoidance.

Lemercier extended ORCA with a queuing model [LA16]. In this model, the pedestrian perceives position, velocity, and size information from his neighbors. Then, from the neighbor's position, velocity and size, a pedestrian P may find a pedestrian leader P_L that constraint him in his displacement, and processes P_L differently from the rest of the neighbors. In this context, my contribution was to enrich the model of [LA16], by defining several other interactions between the pedestrian, the potential leader, and the rest of the neighbors. I have implemented a model and simulated a unidirectional crowd in a corridor composed of several pedestrians with different speeds. As a result, when a pedestrian finds a leader, he behaves according to the defined interaction. This combination of collision avoidance and "following" behavior creates heterogeneous observable behaviors. Pedestrians also adapt their behaviors according to the situation.

To go further in pedestrian interactions, I allow pedestrians to consider social information in addition to physical information. They can perceive the actions of their neighbors and be influenced by them, leading to a temporary change in their behavior. In some situations, they can behave differently over a period of time, for example they become impatient and violate the traffic rules. Regarding street crossing scenario, pedestrians can also be influenced by the behaviors of neighbors (crossing/ waiting). [KO03] found that some pedestrians start violating the pedestrian light after waiting around 20 seconds, meaning they have different behavior before and after 20 seconds.

I started to work on street crossings based on social influence. According to [Harg1], pedestrians do not behave the same way when they are alone or surrounded by other pedestrians. Researches on social influence shows that crossing pedestrians influence others to cross, and reciprocally, waiting pedestrians encourage others to follow the traffic rules [Ros09; FKK10].

I hypothesized that these violations are related to the pedestrian's patience, which can be considered the time excepted time by a pedestrian to spend on the sidewalk. Then, I hypothesized that patience can be modified by the behaviors of neighbors so that the patience is not constant. My contribution is the development of a crossing decision model based on patience and social influence.

In other scenarios, pedestrians cross with road traffic, and I use time-to-contact for the crossing decision. Observations of pedestrian's behavior show that they can make an inaccurate crossing decision. This may be due to the misinterpretation of the pedestrian's crossing time or the time-to-contact of an oncoming vehicle. [INo8] found that pedestrians base their crossing decision on the pedestrian's crossing time, pedestrian's waiting time, and the interpretation of the perception of the oncoming vehicle. I supposed that estimating the time-to-contact of an oncoming vehicle is more difficult than estimating the crossing time, since the oncoming vehicle is moving. Thus, I hypothesized that a pedestrian can have an inaccurate perception of the oncoming vehicle. I propose a model where the estimation of the time-to-contact is biased by social influence and waiting time, allowing some pedestrians to make unsafe crossing and to miss some opportunities, as is found in real life.

3.4 Conclusion

The objective of this thesis is to increase the heterogeneity of pedestrian interactions. The observations of pedestrian behaviors present more variability in their behaviors during pedestrian interactions or with the urban environment, than what is found in most models. To reach the objectives, my first work consists in developing the interactions between pedestrians during collision avoidance and leader-following behavior. My second and main work is the development of pedestrian interactions with the urban environment during street crossing. In this second part, pedestrians can cross the street with different scenarios with a pedestrian light or with road traffic. For the first scenario, the pedestrian bases its crossing decision on patience during red lights, and the patience is modulated by social influence. For the second scenario, the pedestrian bases its crossing decision on time-to-contact is modulated by social influence and waiting time.

Chapter 4

Heterogeneous collision avoidance models

Different models address the interactions between pedestrians. These models are mainly working on the collision avoidance. However, models are often a simplification of the real situation [Don+08]. One example of simplification is the utilization by each agent of the same formula or equation, leading to asymmetric collision-avoidance behavior. This is not common in real situations because of different factors, such as different reaction times, attention, or size of personal space. Another example of simplification is that most models are developed for one situation, such as collision avoidance or leader-following. However, these interactions can be found in the same crowds.

In this chapter, I present two ways to increase the heterogeneity for the collision-avoidance interactions. In the first section, I gave each pedestrian more ability to anticipate and avoid collisions with each other. This approach led to asymmetric collision avoidance in space-time dimensions.

In the second section, I defined several interactions between the pedestrian, the leader, and the neighbors. The pedestrian can follow, avoid a collision, or follow and avoid collisions. This approach leads to an adaptation of the behavior according to the situation.

4.1 Asymmetric collision avoidance model

In most pedestrian simulations, pedestrians avoid each other the same way. For example, the ORCA model is based on the symmetry and translation invariant [BLMo8]. This section aims to allow each pedestrian to manage their collision avoidance and anticipation, during a face-to-face interaction (Figure 4.1). To reach that objective, I

broke the symmetry of the interaction on the anticipation and on the collision avoidance.



Figure 4.1: Illustration of a face-to-face interaction between two pedestrians.

I based the proposed model from two works. The first work was interested in breaking the symmetry during collision avoidance. [Cur+13] extended the ORCA model by adding a concept of priority. Then, a pedestrian with lower priority avoids more than those with higher priority. The second work was interested in the impact of social factors during collision avoidance in face-to-face interaction. [Der+19] simulated two pedestrians moving toward each other on a narrow sidewalk, and one must step down to let the other pedestrian pass. To allow one of them to let pass the other, different anticipation times was set for the two pedestrians using the ORCA model.

My contribution consists in enriching the ORCA model by combining the priority model and the anticipation model. This combination corresponds to the two questions: when and how to avoid the collision. To evaluate the model, I check that the proposed model has the same characteristics as the original ORCA model, i.e., no collision and no oscillation.

4.1.1 Collision avoidance with ORCA model

ORCA is a pedestrian simulation model, which allows pedestrians to avoid collisions and reach their destinations. It allows the pedestrians to reach their destination and avoid collision with each other. The model ORCA is extended from the VO model [FS93], which is developed for robots. In the ORCA and VO models, each agent uses

neighbors, velocity, position, and size to compute its new velocity. To illustrate the collision avoidance with the default ORCA model. Suppose two pedestrians P_1 and P_2 with the same characteristics (disk shape with 0.6 meter of radius and perception distance of 10 meter). P_1 and P_2 are initially at the two opposite ends of the corridor, with 20 meter distance from each other (in figure 4.2). They start to move toward each other at the same time. Then, they start to perceive each other and begin to avoid simultaneously. In the central position of the corridor ($X = 0$), they reach their maximal collision avoidance and the distance between the two is 1.2 meters, which is also the sum of their sizes. Moreover, the shapes of their trajectories are perfectly symmetric.

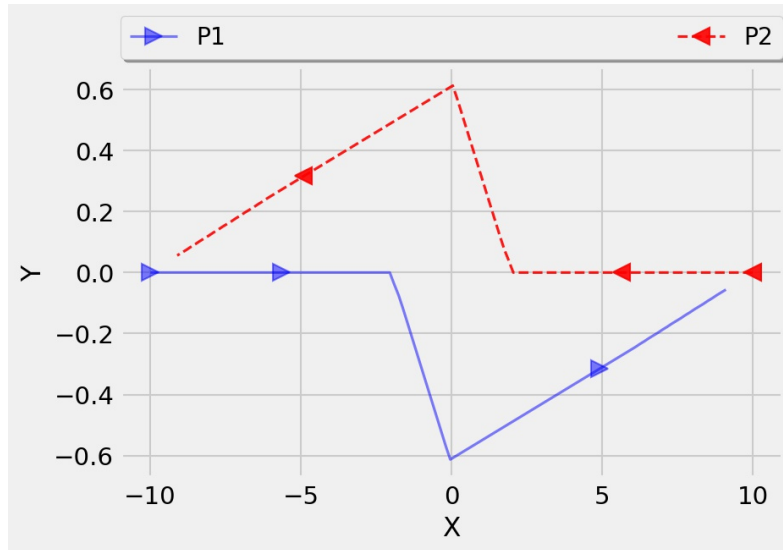


Figure 4.2: Illustration of the symmetric interaction of the trajectories of pedestrian P_1 and P_2 , with the ORCA model. P_1 and P_2 have the same characteristics (disk shape with diameter of 0.6 meter and perception distance of 10 meter). The continuous line is P_1 and the dashed line is P_2 . P_1 and P_2 moves toward each other inside a corridor with 20 meter distance from each other. P_1 from left to right, P_2 moves in the opposite direction.

Equation 4.1 presents the formulation of the collision avoidance in the ORCA model between two pedestrians P_1 and P_2 (Equation 4.1). The model has several parameters. u is the minimal change needed for P_1 to avoid collision with P_2 and reciprocally for P_2 to avoid P_1 . The $\frac{1}{2}$ in u means the two agents share equally the minimal change during the collision avoidance. The minimal change also means that the two agents will touch each other. v_1^{opt} is the optimized velocity of P_1 that allow the collision avoidance. n is the number of agents. t_H is the time horizon when the

agent starts to proceed to the collision avoidance. More details about the descriptions of the parameters are available in the original version of the ORCA model [VDB+11].

$$ORCA_{1|2}^{t_H} = \{v | (v - (v_1^{opt} + \frac{1}{2}.u)) .n \geq 0\} \quad (4.1)$$

4.1.2 Asymmetric anticipation and collision avoidance model

The model I proposed is based on the formulation of the collision avoidance in 4.1, but I transferred to the agent the Shared Effort (SE) parameter. It is set to $\frac{1}{2}$ in the ORCA model for each pedestrian. In the proposed model, it is split individually between a pair of pedestrians SE_1 and SE_2 , during a collision avoidance:

$$ORCA_{1|2}^{t_H} = \{v | (v - (v_1^{opt} + SE.u)) .n \geq 0\} \quad (4.2)$$

This breaks the symmetry for collision avoidance between pedestrians P_1 and P_2 , if they have different SE values. Furthermore, giving P_1 and P_2 different values of t_H will break the symmetry for the anticipation of collision avoidance. Pedestrians will start to avoid each other at different times. Figures 4.3 illustrates an asymmetric interaction between P_1 and P_2 . The question “when?” corresponds with the parameter t_H , and the question of “how?” corresponds with the parameters SE .

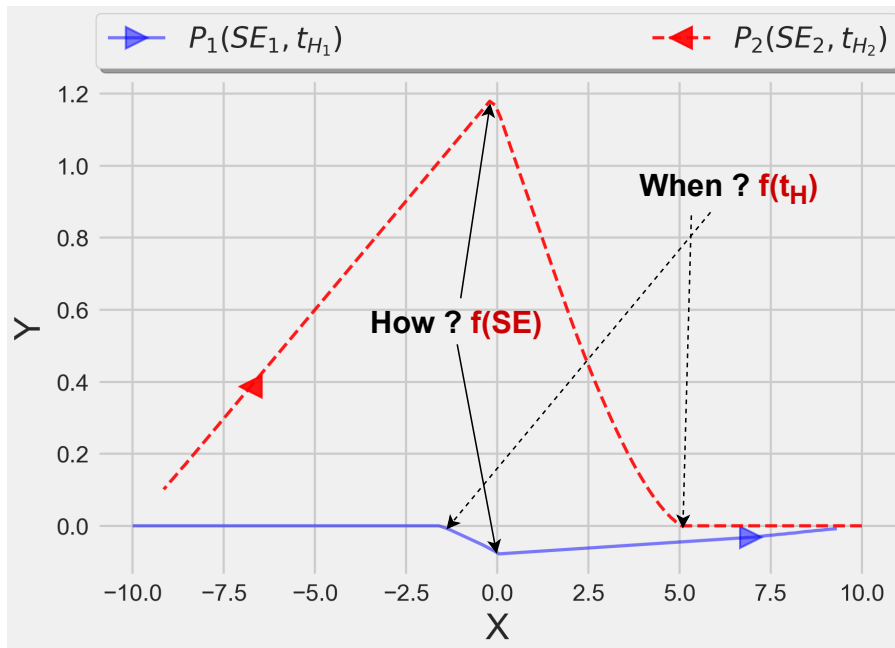


Figure 4.3: Collision avoidance using SE and t_H .

4.1.3 Asymmetry measurement

To quantify the asymmetry produced by the proposed model, I measure the distance between the two pedestrians P_1 and P_2 when they crossed each other. I use the same configuration used during the presentation of the trajectory symmetry of the original ORCA model (Figure 4.1.1). I identify their Y positions on y-axis, then I consider the interaction symmetric if $|Y_1| = |Y_2|$, in figure 4.4.

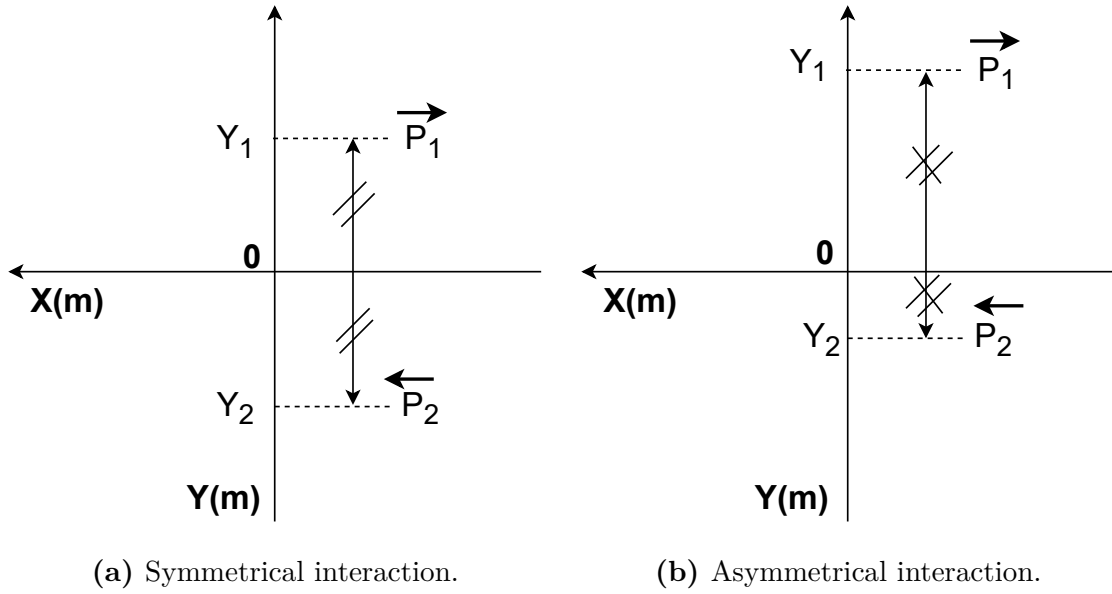


Figure 4.4: Comparison interaction between P_1 and P_2 , during collision avoidance.

I implemented the model by simulating two pedestrians moving in the opposite direction with the same individual characteristics: the preferred speed $V_{pref} = 1.5$ m/s, the maximal distance of perception (10 m). The pedestrians have a $2D$ disc shape with a diameter of 0.6 m. At first, the pedestrians are 20 m from each other. The simulation time is discrete with uniform discrete steps. At each step, each agent computes the information [KMP11]. The simulation stops when they finish crossing each other, and the time step is set to 10 steps for one second, leading to a simulation of 13.3 simulated seconds if the trajectory is straight.

4.1.4 Identification oscillations

To assess the proposed model if it respects the two characteristics of the ORCA model, which are oscillating-free and collision-free models. Oscillation happens when pedestrians avoid collision with each other, and one of them switches between two directions (velocity to avoid collision and preferred velocity); successively over a period of time

[BLMo8]. I started checking the oscillations by simulating two pedestrians with different values of SE , and set $t_H = 3$ for the two pedestrians. In the formulation of the ORCA model, a variable u is defined to be the smallest change needed to avoid a collision between two pedestrians (in 4.1). Then they propose to divide the u by half, so each pedestrian takes half of the collision. I suppose an oscillation is more likely to occur with high SE . The pedestrians can react strongly, to avoid the collision; then, in the next step, they select their preferred speed because there is no more risk of collision; but the risk appears again in the next step. Thus, why I simulated two pedestrians with high SE values, 0.9 for both, and decreased it by 0.1 for each new simulation. Then, I plot the velocity on the y-axis to see if the velocity has a constant value (Figure 4.6), which would mean that there is no oscillation.

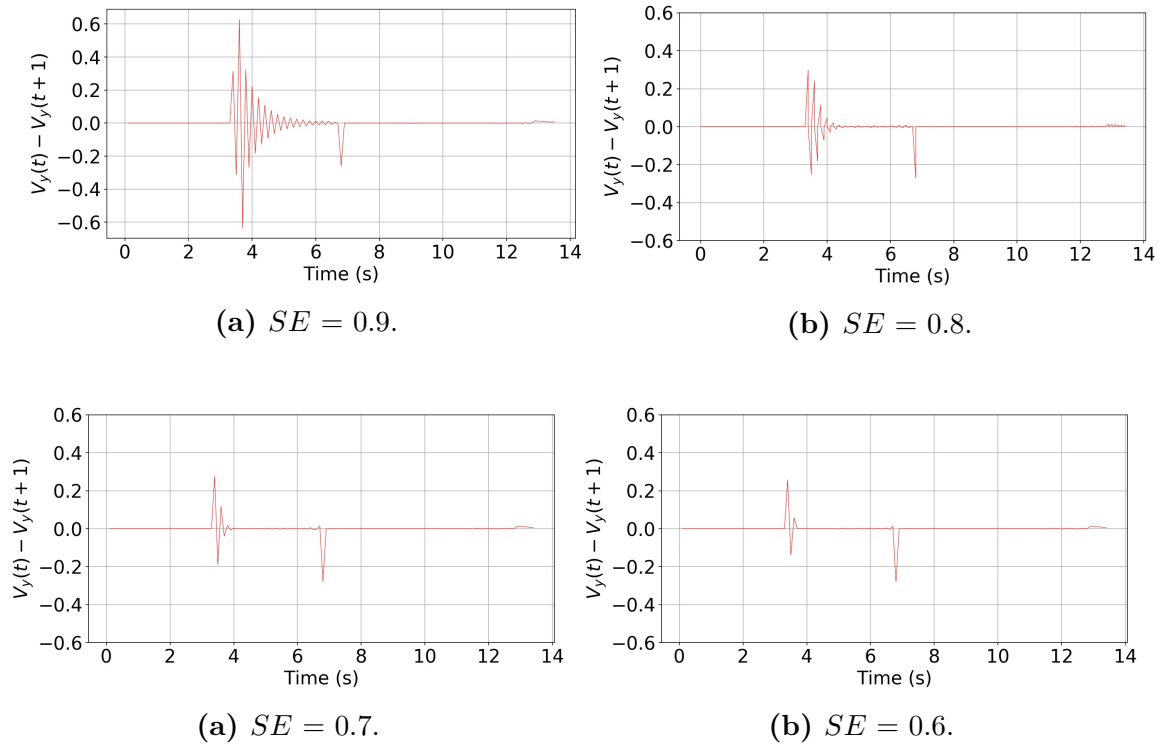


Figure 4.6: Identification oscillations between P_1 and P_2 . The two pedestrians have the same $t_H = 3$ s, and various $SE = \{0.9, 0.8, 0.7, 0.6\}$.

The velocity on Fig 4.6 shows oscillations for $SE = 0.9$ and 0.8 . The difference between the max and min values is high at the beginning of the interaction, decreasing and disappearing when the interaction ends. The variability is higher with high SE , and this variability corresponds to the oscillations.

To quantify the oscillations, I define when the oscillations can be considered negligible. For that, I count how many times the velocity moves from one value to another

one in two successive time steps, corresponding to a change of direction. Then, I identify the maximum and minimum values of the velocity. Considering that the average pedestrian speed is approximately 1.2 m/s [FBT06], I choose that if the difference between two successive velocities is greater than 0.1 m/s, in formula 4.3. Below 0.1 m/s, the change is too small compared to the average pedestrian speed.

$$|V_y(t) - V_y(t + 1)| > 0.1 \quad (4.3)$$

If two pedestrians cross paths and choose the same side to avoid each other, it can lead to a collision. When this happens, the two pedestrians try to choose different sides. If both pedestrians choose the same side several times, it is called in [BLM08] as a dance. I suppose, it can be a dance if the pedestrians repeat the selection of sides more than three times. In this situation, I also considered the selection of velocity more than three times to be an oscillation as well (Eq. 4.4). Using this formulation, I found in my results (Figure 4.6) that the oscillation is acceptable when ($SE \leq 0.7$).

$$\begin{aligned} |V_y(t) - V_y(t + 1)| &> 0.1 \\ |V_y(t + 1) - V_y(t + 2)| &> 0.1 \\ |V_y(t + 2) - V_y(t + 3)| &> 0.1 \end{aligned} \quad (4.4)$$

4.1.5 Identification collisions

I simulated two disk-shaped pedestrians P_1 and P_2 , with the same radius R_1 and R_2 . Comparing $R_1 + R_2$ and the distance between P_1 and P_2 , allows checking a collision (Eq. 4.5). Moreover, since the trajectories are smooth only if after $SE \leq 0.7$, then I test the model only for $SE \leq 0.7$.

$$is_collision = \begin{cases} True, & \text{if } \sqrt{(Y_2 - Y_1)^2 + (X_2 - X_1)^2} \leq R_1 + R_2 \\ False, & \text{otherwise} \end{cases} \quad (4.5)$$

Following the same reasoning, a collision is more likely to happen with a low SE . Thus, why, I started the simulation with $SE = 0.1$ for both pedestrians, then increased the SE by 0.1 until 0.7; leading to a total of 28 combinations. On the other hand, I simulate with two values of t_H . With the default value, $t_H = 1$ second, and another

$t_H = 3$ seconds. I collected the distance and the position of P_1 and P_2 , when they meet each other.

The figure 4.7 presents the distance between P_1 and P_2 when they meet. A collision happens when the distance between the two pedestrians is less than 1.2 m. The results show a small interpenetration, about 10 cm max, with $t_{H_{1,2}} = 1$ s ($SE_1 = 0.6_SE_2 = 0.6$), ($SE_1 = 0.6_SE_2 = 0.7$) and ($SE_1 = 0.7_SE_2 = 0.7$), in square dots. The interpenetration is small compared to the size of the two pedestrians of 120 cm. These results indicate a larger distance avoidance with a small SE . This means that the choice of SE impacts the choice of the velocity, and if the two pedestrians have a small SE , then they select velocities less direct to the destination for the two pedestrians. Conversely, if the two pedestrians have high SE , they select velocities more directly to the destination for the two pedestrians. However, if P_1 and P_2 have different SE , the one with lower SE will select the velocity more directly to the destination.

No collisions when $t_{H_{1,2}} = 3$ s, in star dots, and the distance between the two pedestrians are almost the same for all values of SE , with an average of ($|Y_1| + |Y_2| \approx 1.21$ m). These results mean, if the two pedestrians have higher anticipation $t_{H_{1,2}} > 1$ s, they will have time to avoid each other. If the pedestrians detect a collision, they will have time to correct the trajectory on time.

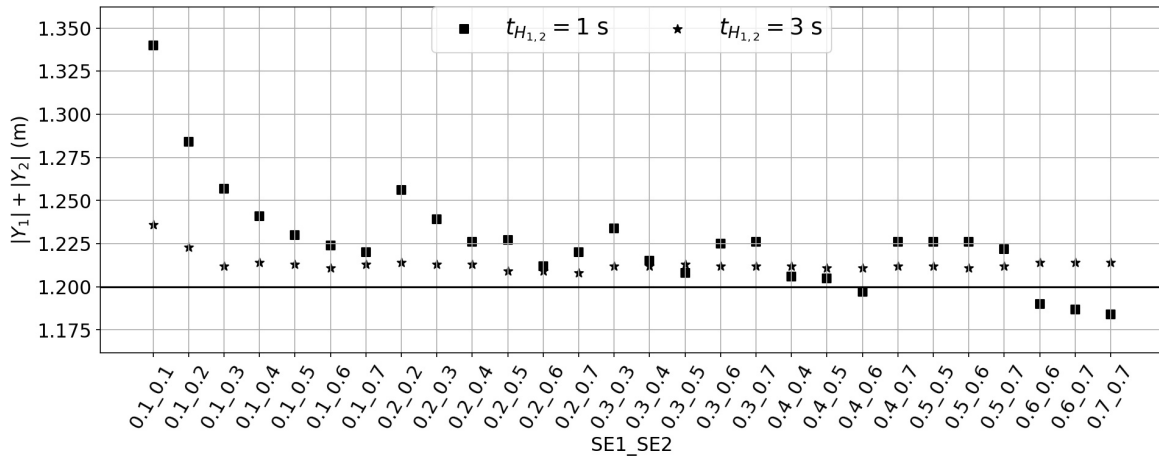


Figure 4.7: Distance between P_1 and P_2 when they met, with different initial conditions: $t_{H_{1,2}} = 1$ s in square dots, $t_{H_{1,2}} = 3$ s in star dots, and $(SE_1, SE_2) \in [0.1, 0.7]$.

4.1.6 Adaptation behaviors

Figure 4.8 shows two different interactions between two pedestrians: the first in a continuous line (P_1 and P_2 have the same t_H , but different SE), the second in a

dashed line (P_1 and P_2 have different t_H and SE).

When the two pedestrians have the same t_H , they start avoiding the collision simultaneously. The pedestrian with higher SE (P_1 in continuous blue) takes the velocity less directly to the destination and avoids the collision more than P_2 , in continuous red.

When t_H and SE are different, the one with the higher t_H (P_2 in dashed red) takes the velocity less directly to the destination and avoids the collision more than the one with the lower t_H (P_1 in dashed blue). Thus, the one with higher anticipation always avoids more the collision. If one pedestrian has higher SE and lower t_H , it starts avoiding the collision lately because the time for the pedestrian to avoid the collision is short, so it does not allow the pedestrian with low t_H to avoid on time.

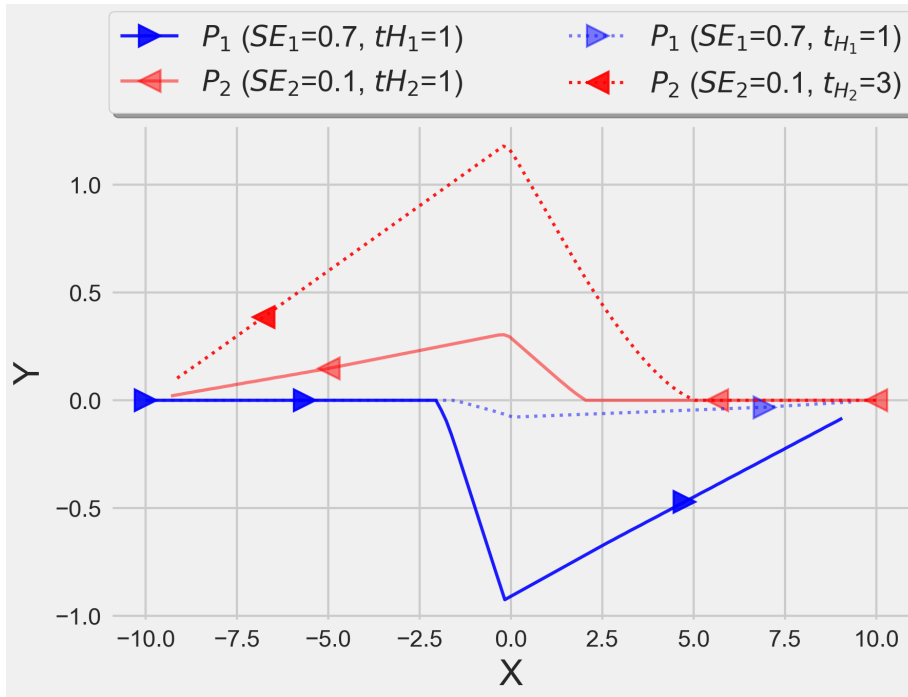


Figure 4.8: Trajectories of two pedestrians interacting with each other. The first interaction with continuous line $\{P_1(SE_1 = 0.7, t_{H1} = 1)$ and $P_2(SE_2 = 0.1, t_{H2} = 1)\}$ and the second with dashed line $\{P_1(SE_1 = 0.7, t_{H1} = 1)$ and $P_2(SE_2 = 0.1, t_{H2} = 3)\}$. For the two interactions: the blue pedestrian moves from left to right, and the red in the opposite direction.

The figure 4.9 presents another illustration of the adaptation of pedestrians. I used the asymmetric measurement, in section 4.1.3, to compare 7 interaction between two pedestrians P_1 and P_2 . I measured the absolute value of Y position of P_1 and P_2 when they meet, on the y-axis, and different value of SE of P_2 on the x-axis. P_1 parameters

are set to $t_H = 1$ and $SE_1 = 0.5$ each time. P_2 has different set of parameters for the 7 interactions, the anticipation is set to $t_H = 1$, and different value of SE each time ($SE_2 \in [0.1, 0.2, \dots, 0.7]$). The results show as expected P_1 and P_2 avoid evenly ($|Y_1| = |Y_2|$) with the default parameter value $SE_1 = SE_2$. When the two have different SE values, they avoid each other differently. What is interested in this figure is that, even P_1 has the same set of parameters, P_1 reacts differently depending on the behavior of P_2 . With $SE_2 \leq 0.4$, P_1 avoid more than with his default parameter because P_2 does not avoid enough. With $SE_2 = 0.7$, P_1 avoids less than with his default parameter value because P_2 already avoid enough. P_1 and P_2 has different SE values when $SE_2 = 0.6$, and $SE_2 = 0.5$ but they avoid each other with approximately the same, meaning that the difference is not significant enough to create a difference.

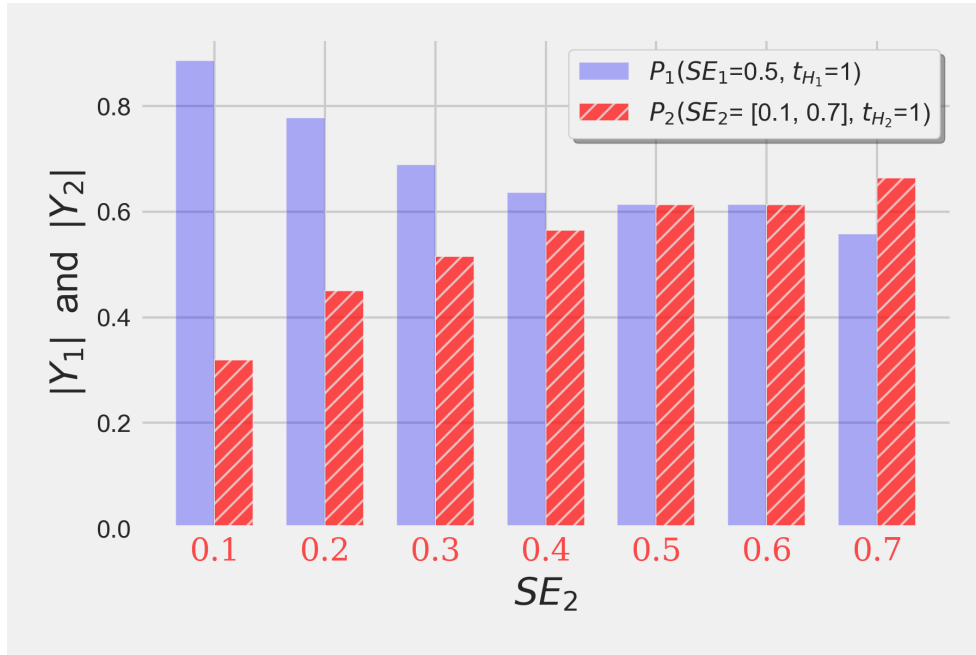


Figure 4.9: Asymmetric measurement between two pedestrians P_1 and P_2 . The crossing was repeated 7 times, with P_1 having the same parameters ($t_H = 1$, $SE_1 = 0.5$) and P_2 with different SE values ($t_H = 1$, $SE_2 \in [0.1, 0.2, \dots, 0.7]$).

4.1.7 Conclusion on asymmetrical collision avoidance

I presented in this section an asymmetric collision avoidance model that can increase the heterogeneity of pedestrian interactions. Each agent can have different anticipation or collision avoidance intensities. I based the heterogeneity of anticipation on work on social collision avoidance [Der+19]. The asymmetry of collision avoidance on a work interested in breaking the symmetry during collision avoidance [Cur+13]. I identified

the presence of oscillations or collisions with the model. The oscillation can happen if the two pedestrians have $SE > 0.7$. This means the value of SE impacts the selection of the velocity. Another major result is the capacity of adaption of pedestrians. One pedestrian may potentially avoid but decide not to do if the other pedestrians already avoided him. Conversely, one pedestrian can avoid more than its potential if the other does not avoid enough. These results have been published at an international conference on computer animation and social agents [RAB19].

My work opens different perspectives. It would be interesting to implement this agent model in the context of a crowd. However, I did not have data to set the model's parameters SE and t_H . Data on the interactions of different individuals would help in that situation. For example, pedestrians can have different behaviors depending on the person to avoid. For example, older pedestrians tend to have a longer reaction time than younger pedestrians [Fug+00]. This model has the potential to adapt to contextual situations. However, the adaptation is based on the physical perception of neighbors, which are position, velocity, and size. That means the agent is not interested in whom the pedestrian is. To allow an agent to adapt its behavior to the contextual situation, the agent should process the other agents differently, depending on their status, age, and sex.

Furthermore, the interactions between pedestrians are not limited to collision avoidance. Pedestrians can follow each other and avoid a collision at the same time. In the next section, I present a model for crowd simulation, where an agent can have different interactions with the neighbors.

4.2 Collision avoidance and leader-following model

In the context of crowds, pedestrian interactions are not limited to collision avoidance. They can follow a person, even if they do not know the person [LA16]. However, pedestrians' leader-following mode is usually a pure queuing model, where pedestrians do not overtake. Lemercier extended the collision avoidance model (ORCA) with a pure queuing model [Lem+12]. As a result, pedestrians can follow a leader if they are found and avoid collisions simultaneously, depending on the situation.

My work enriches the collision avoidance interactions of the model developed by Lemercier. In their model, when a pedestrian finds a leader, the pedestrian computes the minimal acceleration produced by the queuing and collision avoidance models. My contribution is to propose another interaction between the pedestrian, the Leader, and

the neighbors. I propose another computation of the accelerations of the pedestrian from the collision avoidance and queuing models. This definition of new accelerations leads to different interactions.

I start this section by presenting Lemercier’s model, which I use as a reference. Then, I present my acceleration-based model. I implement the model in the context of crowds, and I compute a fundamental diagram to describe the propriety of the crowd produced.

4.2.1 Collision avoidance and queuing model

Lemercier was interested in improving the variety of behaviors during collision avoidance [LA16]. He extended the collision avoidance model ORCA [VDB+11] with a queuing model [Lem+12]. A pedestrian P proceeds with simple collision avoidance if no particular neighbor constrains his displacement. Otherwise, if a neighbor constrains his displacement, P combines the collision avoidance and the queuing model. This particular neighbor is considered as a “Leader”.

To combine the two models, they set the acceleration of P to the minimal acceleration produced between the ORCA and the queuing model (Figure 4.10). They decomposed the acceleration on the x-axis and the y-axis. ORCA is a velocity-based model, and they derivate the velocity for the acceleration produced by ORCA (a_{ORCA_x}, a_{ORCA_y}). On the other hand, the queuing model is not developed for overtaking, so the queuing model only produces a one-dimensional acceleration (a_{follow}). Thus, the acceleration produced by the queuing model is compared with a_{ORCA_x} .

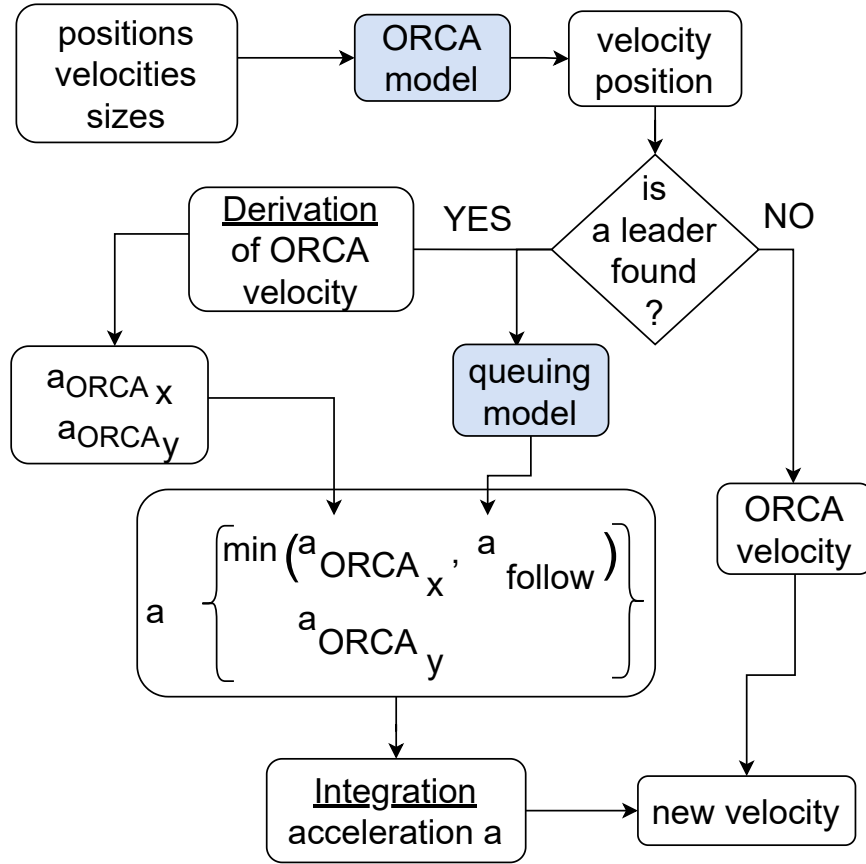


Figure 4.10: Computation of the acceleration at a time t from the acceleration of ORCA and the queuing model, if a leader is found, based on [LA16]. a_x is computed from the mixed model; however, the acceleration on y -axis is always from ORCA $a_y = a_{ORCA_y}$. Then, the acceleration is used for computing the new velocity.

P identifies the Leader P_{Leader} , presenting the greatest constraint among the other pedestrians in his neighborhood. The conditions for that are:

- P and P_{Leader} follow the same direction, P_{Leader} is in front of P .
- P_{Leader} has a lower speed than P .
- P_{Leader} should be closer than a certain distance Dx .
- The distance (Dy) between the central positions of P and P_{Leader} must be less than the sum of the radii of the Leader and the follower.
- The angle formed by the velocities of P and P_{Leader} is smaller than $\epsilon_{\alpha f}$.

If a neighbor meets these conditions, then the neighbor becomes the Leader. If several neighbors meet these conditions, then the closest neighbor becomes the Leader. Figure 4.11 illustrates the distance of perception of an agent P and the two distances Dx

and Dy for the identification of the Leader. The intersection between these distances presents a space for the potential leaders if the pedestrians inside this area have a slower speed than P and if the angle between the two velocities is smaller than $\epsilon_{\alpha f}$.

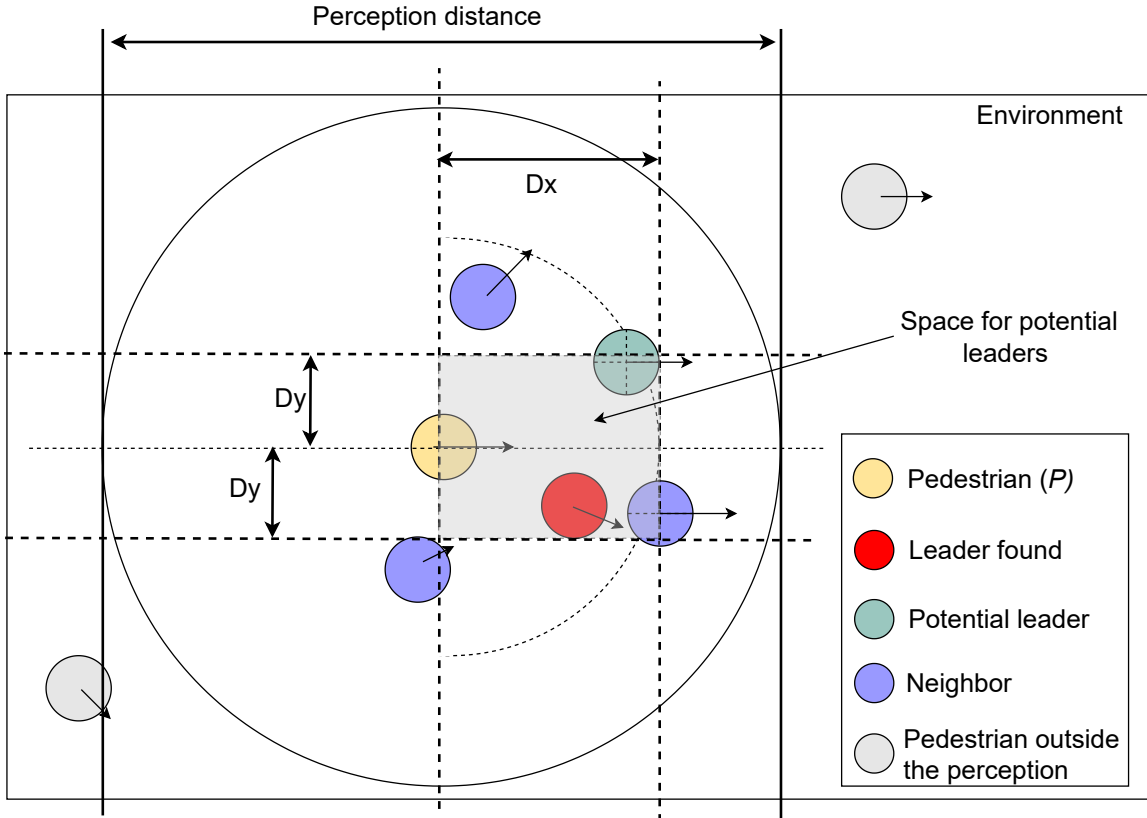


Figure 4.11: Perception of neighbors and identification of a leader. The potential Leader is inside the intersection between Dx and Dy . The pedestrians are attributed to a defined area depending on the position of their center. A yellow pedestrian P perceived several neighbors in blue. P has a potential leader in green and identifies the Leader in red among the green, based on closest distance. The gray pedestrians are outside the perception of P .

4.2.2 Acceleration-based model

The proposed model computes the acceleration from the collision avoidance and queuing models. However, instead of selecting the minimum acceleration between the areas computed by the ORCA and the queuing model, I propose different possible combinations of the accelerations.

1. **Minimal acceleration:** it is the “following” model developed by [LA16]. Pedestrians avoid collision and follow a leader if they find one. In this case, the acceleration is the minimum value between the acceleration computed from the collision

avoidance model and the following model (Algorithm 1). The minimum acceleration implies that the agent wants to satisfy the strongest constraint between the ORCA and the Leader following behavior.

Algorithm 1: Acceleration of the “minimal acceleration” model.

```

1 if LeaderFound = True then
2   |  $a_x(t) \leftarrow \min(a_{ORCA_x}(t), a_{Follow}(t))$ 
3 else
4   |  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 
5 end

```

2. **Smallest acceleration:** this model is developed by considering the accelerations from the two models, as the “minimal acceleration” model; however, the acceleration is computed as the smallest absolute value of the two accelerations (Algorithm 2). Taking this smallest value leads to a small slope, so pedestrians can minimize the speed variation.

Algorithm 2: Acceleration of the “smallest acceleration” model.

```

1 if LeaderFound = True then
2   | if  $|a_{ORCA_x}(t)| < |a_{Follow}(t)|$  then
3     |  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 
4   | else
5     |  $a_x(t) \leftarrow a_{Follow}(t)$  // takes the smallest between  $|a_{ORCA_x}(t)|$  and  $|a_{Follow}(t)|$ 
6   | end
7 else
8   |  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 
9 end

```

3. **Maximal acceleration:** this model computes the maximal acceleration between $a_{ORCA_x}(t)$ and $a_{Follow}(t)$, when the pedestrians have a leader (Algorithm 3). In this situation, pedestrians can follow a leader but stay as short of time as possible. This situation is more likely to occur during rush hours, such as at a metro station, when most pedestrians rush, and crowd density is high. Movement is limited, and pedestrians follow someone because they don't see an opportunity and pass as soon as an opportunity arises.

Algorithm 3: Acceleration of the “maximal acceleration” model.

```

1 if LeaderFound = True then
2   |  $a_x(t) \leftarrow \max(a_{ORCA_x}(t), a_{Follow}(t))$ 
3 else
4   |  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 
5 end

```

4. **Pure following:** in this model, when a leader is found, the pedestrians use the acceleration from the Leader (Algorithm 4). This situation is more likely to occur when pedestrians are distracted by other tasks, such as checking a smartphone. So, when they find a leader, they use him as a shield to complete their task.

Algorithm 4: Acceleration of the “pure following” model.

```

1 if LeaderFound = True then
2   |  $a_x(t) = a_{Follow}(t)$ 
3 else
4   |  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 
5 end

```

5. **ORCA:** serves as a reference [VDB+11]. Pedestrians in this model do not pay special attention to a particular neighbor and treat everyone the same. In this situation, the acceleration is therefore computed by the ORCA model (Algorithm 5).

Algorithm 5: Acceleration of the “standard ORCA” model.

```

/* This model is not based on the presence or not of a leader. */
1  $a_x(t) \leftarrow a_{ORCA_x}(t)$ 

```

4.2.3 Simulation

A one-way pedestrian flow is simulated inside a corridor $10 \text{ m} \times 30 \text{ m}$. The pedestrians are randomly positioned at $t = 0$ and move from left to right. They are spawned on the left side of the corridor when they reach the right end, and this method keeps the number of pedestrians and the density constant during the simulation. The pedestrians may accelerate at the end of the corridor because they do not see anyone in front of them. Therefore, I use an artifact: pedestrians always perceive other pedestrians in front of them when they are at the end of the corridor, keeping their speed constant.

For each simulation, I ran simulations with 6 different numbers of pedestrians, ranging from 100 to 600. Each simulation lasts 300 simulated seconds, with a fixed step of 0.1 s. Above 600 pedestrians, the available space inside the corridor is not enough given the representation of pedestrians as non-deformable discs. Moreover, if the space is full about 40 to 65%, then a stop-and-go phenomena can emerge [MHT11]. The stop-and-go happens when the speed of pedestrians follows the shape of waves, and the emergence of stop-and-go is a cue to indicate that the space is too full [SPS10]. Regarding my configuration, with 600 pedestrians, the space is covered at about 56.52%.

I use a normal distribution for the pedestrian's speed with an average speed of 1.4 m/s [FBT06; KPN96], and a standard deviation of 0.3 m/s (large enough to produce some variability). All pedestrians have the same size radius of 0.6 m, the same perception distance up to 10 m, and simultaneously process up to 10 neighbors. The model parameter $\epsilon_{\alpha f} = \pi/6$ is the maximal angle between the velocity of the pedestrian and of his potential Leader. Dx is set to 1.5 m, the distance between the centers of two agents. Because the radius of pedestrians is 0.3 m, the distance Dy is below 0.6 m.

4.2.4 Illustration of pedestrian trajectories

Figure 4.12 present an illustration of the trajectory of 400 pedestrians. On the left, the model with minimal acceleration (Algorithm 1) and on the right the model with maximal acceleration (Algorithm 3). This illustration shows that pedestrians with minimal acceleration are homogenous and tend to follow a lane. On the other hand, the pedestrians with maximal acceleration have more heterogeneous trajectories. The trajectories are not straight, meaning that they overtake more often.

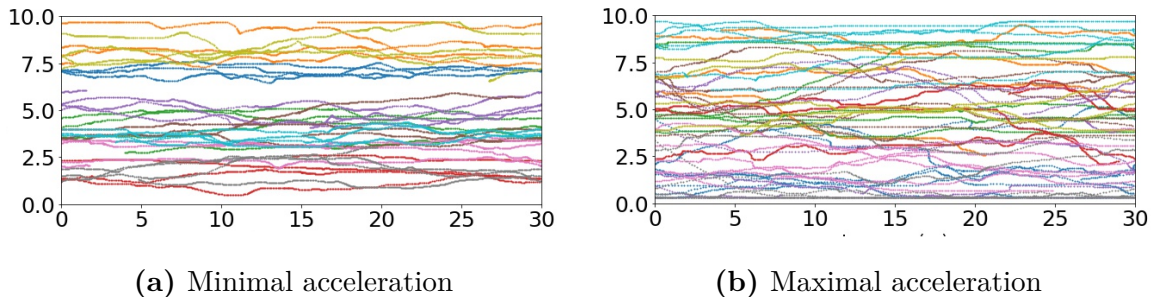


Figure 4.12: Illustration of pedestrian's trajectories produced by two models (Algorithm 1 on the left and algorithm 3 on the right). 400 pedestrians are randomly positioned inside a $10\text{ m} \times 30\text{ m}$ corridor. The pedestrians are moving from left to right.

4.2.5 Description of pedestrians using fundamental diagrams

The fundamental diagram (FD) describes the relationship between speed, density, and flow. The FD is very popular in vehicular traffic modeling and for pedestrian work with emerging behaviors [SPS10; MHT11]. I compute the FD in this work to describe the propriety of the simulated flow of pedestrians.

At lower density, the pedestrians can move at their comfortable speed [Xia+16]. I suppose this leads to a higher and more heterogeneous speed. In this situation, the average speed is expected to reach its initial value of $\mu = 1.4$ m/s. At higher pedestrian density, each one is constrained to adapt their speed to the slowest pedestrian in the flow [Mou19], leading to a more homogeneous speed. The normal distribution $\mathcal{N}(\mu = 1.4 \text{ m/s}, \text{std} = 0.3 \text{ m/s})$ used to generate the speeds has a standard deviation of 0.3 m / s, and that leads to the estimation that 99 % of the speed will be higher than $V_{min} = 0.5$ m/s (in formula 4.6). Thus, I suppose that the average speed will be around this minimal value in a dense crowd.

$$V = \begin{cases} V_{\mu} & = 1.4 \text{ m/s} \\ V_{min} & = \mu - (\text{std} \times 3) \end{cases} \quad (4.6)$$

I construct the FD in these simulations from the speed of pedestrians inside an area A_{FD} with dimensions $2.5 \text{ m} \times 10 \text{ m}$, positioned at 17.5 m from the end of the corridor. The idea of choosing a subarea was to avoid the two edges of the corridor with possible perturbations during the spawning. The width is 2.5 m, which corresponds to the size of 4 pedestrians in a queue (see figure 4.13).

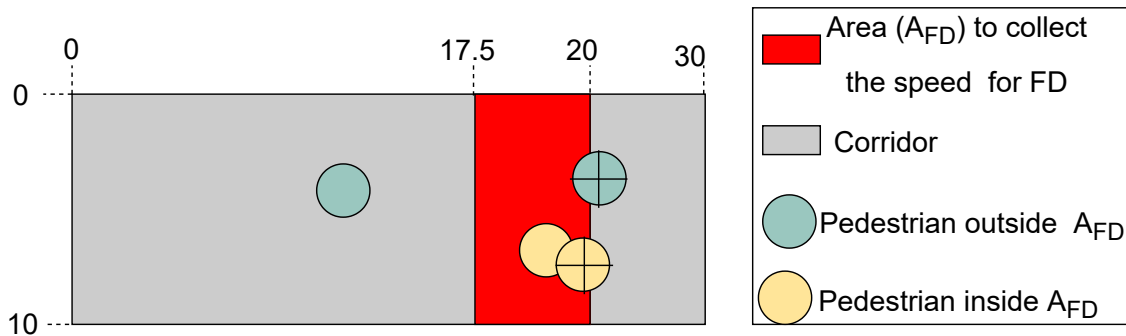


Figure 4.13: Area A_{FD} (2.5×10) inside the corridor where the fundamental diagram collects the speed. The corridor is $30 \text{ m} \times 10 \text{ m}$. A_{FD} is positioned at 17.5 m from the end of the corridor. A pedestrian is counted inside A_{FD} depending on the position of its center.

The FD from the five proposed models is compared to another FD with a similar scenario (Figure 4.14). [Xia+16] simulated flow of unidirectional pedestrians inside a corridor of $10 \text{ m} \times 3 \text{ m}$. Each pedestrian has a radius of 0.2 m , and are distributed randomly over three rows inside the corridor. Their density is from 0.1 to $5 \text{ ped}/\text{m}^2$, and each simulation lasts 100 s .

The figure 4.14 shows that at lower density, the pedestrian's speeds are close to the mean of the initial distribution; then, it decreases with increasing density, which is the expected form of a fundamental diagram. Model 1 (minimal acceleration) has a slower speed than the other models because it uses the minimum acceleration between the collision avoidance and the following models. Unlike other models, pedestrians with model 1 almost stop moving above $2 \text{ ped}/\text{m}^2$. On the other hand, the model 3 (maximal acceleration) has a higher speed compared to the other models, which makes sense since this model uses the maximum acceleration between the “collision avoidance”, and the “following” models. Furthermore, models 2 (minimal acceleration), 4 (pure following), and ORCA have the same characteristics, significantly above $1 \text{ ped}/\text{m}^2$. Finally, the addition of new rules increases the diversity of behaviors, but it does not change the global characteristics of the crowd.

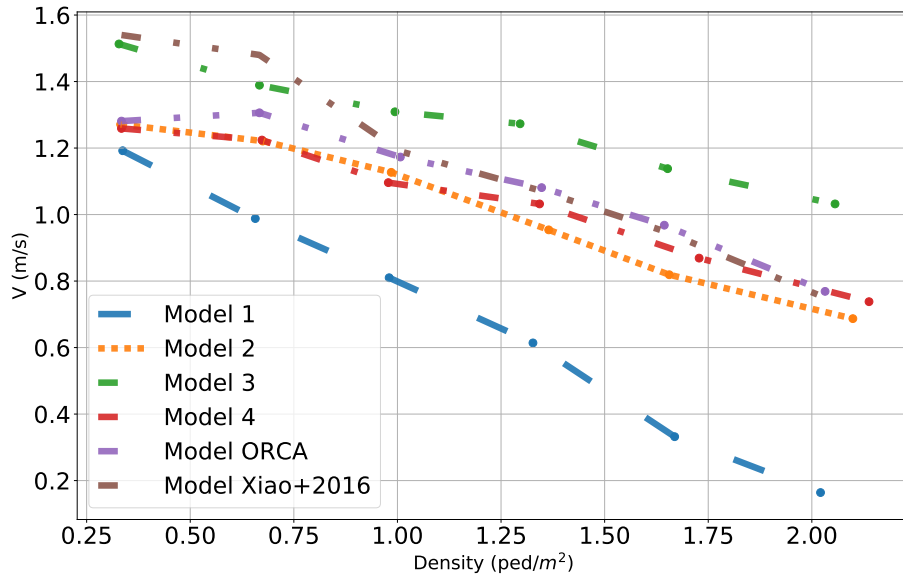


Figure 4.14: Fundamental diagrams for the five proposed models and the model used for comparison [Xia+16].

4.2.6 Conclusion in collision avoidance and leader-following

In this section, I have presented 5 models derived from the works of [LA16]. The model extended the collision avoidance with queuing behavior. Pedestrians can have two interactions during the same simulation. If a pedestrian finds a leader, the pedestrian moves from the minimal acceleration produced by the collision avoidance and the queuing. My contribution consists of allowing the pedestrian to have different interactions when a leader is found. Thus, instead of using only the minimal acceleration between the two models, I have compared 5 rules. 1) the model developed by Lemercier, used as a reference. 2) the smallest acceleration. This allows the pedestrians to maintain their actual speed. 3) the maximal acceleration. This allows the pedestrians to follow someone, but as short as possible. 4) the acceleration from queuing model. This allows pedestrians to follow someone. 5) the ORCA model was used as a reference. To compare these 5 models, I compute a Fundamental Diagram (FD). The FD simulated are compared to another result [Xia+16] with similar initial conditions. As a result, the shape of the 6 FD has the same tendency: the speed decreases when the density decreases, which is the standard shape of FD. Moreover, the trajectory between the minimum and maximum acceleration shows more heterogeneous pedestrian trajectories with maximum acceleration. The results of this work have been published in the international conference on multi-agent system [RAB20]. Nevertheless, the proposed models have certain limitations. The modification of the velocity on the X-axis can lead to a selection of a new velocity that is not permitted by ORCA, and can lead to collisions. However, ORCA is an anticipation model, making the possibility that an agent correct the new velocity selected in the next step, if collisions are anticipated. Moreover, no collisions are observed during all the simulations, probably because the time step was small enough. The perspective of this work would be to find a new permitted velocity that is closest to the velocity proposed by one of my models.

4.3 Conclusion

In this chapter, I proposed two models to increase the heterogeneity of pedestrian interactions. I give each pedestrian to adapt the collision avoidance based on the perception of neighbors. Each pedestrian can anticipate and avoid a collision differently from another pedestrian can adapt its collision avoidance, according to the potential of the other pedestrian. The model, however, has limitations. The adaptation results from physical characteristics (positions and velocities of the other agents). Then an agent with the same position and velocity will be processed the same.

The second model is based on the accelerations produced by the ORCA model and by a queuing model [Lem+12]. In this model, I allow the agent to behave differently from its neighbors. The agents process the position and velocity of other agents. However, an agent leader can be identified and processed differently. Pedestrians can both follow and avoid collisions. I presented 5 types of interactions between the pedestrian, the Leader, and the neighbors. 3 among the 5 presented are the contributions, which are the smallest, the maximal and the pure following. Pedestrians in this model can adapt their behavior according to the contextual situation. This model also has limitations. Each pedestrian uses the same interaction model during the simulation. The adaptation is based on the physical characteristics of neighbors, and the agent does not consider the social situation. Moreover, the behaviors of the agents are not impacted by the time.

The pedestrian interaction is not limited to the interaction between pedestrians. They interact with road traffic during street crossings. Moreover, they can be influenced by social influence to conform to a certain behavior, and their behaviors also are impacted by the time they spend on the crossing location. Someone who has just arrived at a crossing location may have different behavior than someone who already waits for a longer period. My main contribution in this thesis is developing a street crossing model based on social influence, and I present this model in the next chapter.

Chapter 5

A pedestrian crossing decision model based on social influence

Tolmie developed computer-based training for street crossings [TTF02]. He described the street crossing as a series of four steps taken by a pedestrian. The first step is identifying a safe place on the sidewalk. Then, the second step is the awareness of the contextual situation. This may be the presence of a pedestrian light or of oncoming vehicles. The third step is the estimation of the gap. The last step is the anticipation of the behavior of the oncoming vehicle, assuming the vehicle will have a constant speed, for instance. In this chapter, I propose a model for pedestrian street crossing. This will address the second and third steps, which are the awareness of the situation around the crossing location and the time estimations (crossing time and time-to-contact with an oncoming vehicle). I use an agent-based approach to develop a street crossing decision model, where the decision takes social information and waiting time into account.

I start with a presentation of the overall model and the description of the agent pedestrian. Then, I implement the model under two crossing scenarios. The first scenario is a crossing with a pedestrian light and without road traffic. In this situation, pedestrians may cross the street during a red light if they lose patience. Observations of pedestrian behavior show that some pedestrians violate the traffic rules, and that they do not cross immediately when they arrive at a crossing location. This could mean that pedestrians have limited patience, impacting their crossing decisions. The literature review also shows that pedestrians can influence each other, and they do not always behave the same way alone or with people around. This leads to different crossing behaviors depending on the contextual situation. Therefore, I propose a model where the patience of pedestrians is modulated depending on the behavior of neighbors (crossing or waiting). When their patience runs out, the pedestrians cross the street

at a red light. The modification of patience can lead to compliance with the rules if patience increases and violation if patience decreases.

The second crossing scenario is composed of a crosswalk with road traffic and without a pedestrian light. In this situation, pedestrian agents cross the street using estimation of time-to-contact as the main cue for the crossing decision. Experiments realized by [Oxl+05; LC09] show that pedestrians can select an unsafe gap, and they can also miss a crossing when they have enough time to pass. These two experiments show that pedestrians can misjudge the gap. [INo8] formulate the crossing decision on road traffic as a trade-off between crossing time, waiting time, and the representation of the time-to-contact of an oncoming vehicle. I choose to modify the interpretation of the time-to-contact of the oncoming vehicle, using social influence and waiting time. A modification (bias) of the estimated time-to-contact is expected to produce several types of behavior, some of which cannot be produced by a standard street crossing model, such as unsafe or missing crossing opportunities.

5.1 Agent pedestrian definition

I use an agent approach to model the crossing decisions of pedestrians. I use the ORCA navigation model to navigate pedestrians to their destinations while avoiding collisions with their neighbors while crossing the street. I added a crossing decision model to the navigation model, where pedestrians can make a trade-off between their characteristics (patience, speed, etc.) and social influence from neighbors' behaviors.

An agent pedestrian P uses the decision model only for crossing streets and moves into the virtual environment using a navigation model. P does not update its crossing decision once it decides to cross. I based the crossing decision on physical and social information. The physical information considered is the color of a pedestrian light or the time-to-contact of an oncoming vehicle, and the social information is restricted to the behavioral status of neighbors (crossing, waiting) (section 5.1.2). The social information is processed using a formula combining the number of crossings and waiting neighbors (section 5.2). The social information can then modify the decision of the agent pedestrian. The action of one agent pedestrian affects the environment, modifying the decision of neighbors in the neighborhood.

5.1.1 Agent pedestrian perception

I define an agent pedestrian with a complete awareness of its neighborhood. The pedestrian can perceive the exact position and velocity of neighbors and vehicles, as well as the pedestrian light colors and the actions of neighbors within their perception range.

Pedestrians have a memory limitation to process information simultaneously. Human eyes can perceive more information than the brain can process [FD20]. [SO03] found that people process around 7 plus or minus 3 information simultaneously, leading to an approximation value between 4 to 10. I limit the number of information perceived simultaneously by the pedestrians in the model. I also limit the perception distance for neighbors (Z_{Ped}), and road traffic (Z_{Car}), see figure 5.1.

To approximate the distance Z_{Ped} , Hall in his work about proxemics found that 7.6 meters is an estimate of the public distance [Hal+68]. This is the largest distance between pedestrians, no matter their relationship (intimate, personal, or public). I suppose this is the approximate distance where pedestrians start to process information from another pedestrian. This distance can also depend on the sidewalk's width and on the width of the street. A pedestrian standing on a sidewalk, for instance, should see the width of the street for estimating his crossing time.

For the case of Z_{Car} , [SF09] estimated that the visual angle threshold for the perception of the time-to-contact with an oncoming vehicle is about $0,17^\circ/\text{s}$. [YS21] found that for an average male pedestrian around 1.54 meters, a distance around 62.7 meters is needed to perceive an oncoming vehicle moving at 80 km/h. To implement Z_{Ped} and Z_{Car} , I define two discs centered at the center of the physical body of the pedestrian (Figure 5.1). Z_{Car} is larger than Z_{Ped} .

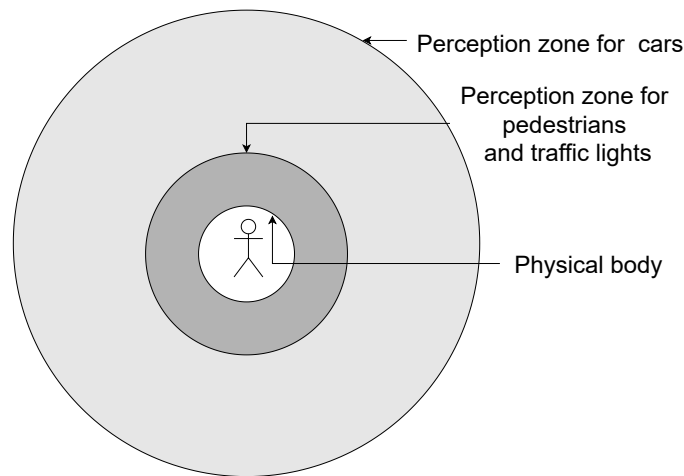


Figure 5.1: The two perception zones of a pedestrian. Z_{Car} is the largest disk, used for the perception of cars. Z_{Ped} is the intermediate disc used for the perception of neighbors and the pedestrian light colors. The smaller disc represents the physical body.

5.1.2 Definition of social information

The decision model processes both physical and social information simultaneously for crossing decisions. Developing a model for simulation which processes social information is not common; it can consider the behaviors of others [GVT02], or their social status [LBM55]. I choose to use the definition of social influence by [GVT02], who limits the social information to a description of the action of neighbors. I start by describing the activities of pedestrians during and before street crossings. They can walk, wait, stop, move, or cross. They can also mix wait-walk, wait-idle, and cross-walk (table 5.1). The activities are composed of two actions, which I defined as the status of pedestrians. The first action represents what the pedestrian physically does (idle and walk) and what he cognitively does (wait and cross).

The first status (walk/wait) is for pedestrians who are walking on the sidewalk, waiting to cross, and trying to reach the position where they want to wait. The second status (idle/wait) occurs when a pedestrian arrives at a crossing location on the sidewalk where he wishes to wait. The last status (walk) corresponds to a pedestrian moving to the crossing location. The last status (walk/cross) pertains to pedestrians who are crossing the street. These statuses allow characterizing the pedestrian's situation during the simulations. More behavioral classes, such as running or stepping back, can be added as new statuses in the future. However, in this work, I limit the

social information to the most important in the sub-actions associated with pedestrian status: cross and wait.

Table 5.1: Pedestrian behavior status during a simulation.

Action	Status	Description
wait	(walk/wait)	The pedestrian arrives at a crossing location and walks without crossing the street.
wait	(idle/wait)	A pedestrian arrives at a sidewalk and does not move.
cross	(walk/cross)	The pedestrian crosses the street.
	(walk)	A pedestrian is not on the crossing location and is not crossing the street. This situation occurs when the pedestrian walks towards the crossing location.

5.2 Social influence modeling

5.2.1 Hypotheses about social influence

According to [Ros09; FKK10], when arriving at a crossing location with a pedestrian light, and if the pedestrian light color is red, illegal crossing pedestrians influence the agent to cross (H_1). Reciprocally, seeing someone waiting encourages the agent to follow the traffic rules (H_2). These two aspects of social influence can be described as “conformism” because people are influenced by what other people do. This leads to the model hypothesis:

H_1 crossing neighbors influence the agent to cross;

H_2 waiting neighbors encourage the agent to wait.

5.2.2 Formulation of social influence

To implement the model hypothesis, I define the influence $\Delta^i(t)$ received from the behaviors of neighbors, using a linear combination of the number of waiting pedestrians $N_W^i(t)$ and crossing pedestrians $N_C^i(t)$ perceived by an agent pedestrian i at time t . To combine H_1 and H_2 , I weight $N_W^i(t)$ and $N_C^i(t)$ with two social parameters p_W and p_C , respectively.

$$\Delta^i(t) = p_W \times N_W^i(t) - p_C \times N_C^i(t) \quad (5.1)$$

p_W and p_C are associated with the social influence of waiting and crossing pedestrians and should be set according to existing evidence. For instance, pedestrians might be more rule-followers in some locations (country, city, neighborhood, crosswalk, etc.), and in this case, p_W would be higher than p_C . In another locations, pedestrians might be more compliant with the traffic rules, so the weights would be more balanced because pedestrians can follow someone crossing or waiting. In the following, the social parameters remain constant throughout the simulation, and all agents have the same p_W and p_C values, for the model's simplicity.

5.2.3 Approximation of social influence value

To illustrate the formulation of the social influence Δ , I define a pedestrian P^i who can simultaneously perceive up to ten neighbors, because of limited perception [SO03]. These neighbors can have a “crossing” or “waiting” status (table 5.1), leading to $\frac{10 \times 10}{2}$ possible combinations. The table 5.2 shows a matrix with the values of Δ computed from the possible combinations. Two examples are given (matrices M_1 and M_2) with different values for p_W and p_C . For M_1 (table 5.2.1), $p_W = p_C = 0.5$, I give the same importance to the neighbors who are waiting and to those who are crossing, which can serve as a reference. In a real situation, during red light crossings, often N_W is greater than N_C . Thus, to allow the pedestrians to violate the traffic rules, p_C should be greater than p_W , and I give greater importance to crossing pedestrians than to waiting pedestrians. Then, I use M_2 , $p_W = 0.1 < p_C = 0.9$ for M_2 (table 5.2.2).

M_1 is symmetric because $p_W = p_C$, so that $\Delta = 0$ on the diagonal. When there is more waiting than crossing pedestrians, $\Delta > 0$. For M_2 , the matrix is not symmetric. The number of positive and negative values of Δ is not the same. It depends on the difference between p_W and p_C . As $p_W < p_C$, M_2 has more negative values.

If p_W and p_C have small values, this leads to small Δ values and reduces the impact of social influence. Otherwise, If p_W and p_C have large values, this leads to large Δ values and increases social influence.

M_1 and M_2 present different possible values of Δ . However, an agent pedestrian may not encounter all these possible values.

Table 5.2: Social influence values for a pedestrian at the sidewalk, perceiving up to ten pedestrians. The cell color is green when $\Delta > 0$, which is a positive influence encouraging waiting; it is red when $\Delta < 0$, meaning a negative influence which could lead to a rule violation. The cell is blue when there is no social influence ($\Delta = 0$). The white cells are not explored because $N_C + N_W > 10$.

$N_C \setminus N_W$	0	1	2	3	4	5	6	7	8	9	10
0	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
1	-0.5	0	0.5	1	1.5	2	2.5	3	3.5	4	
2	-1	-0.5	0	0.5	1	1.5	2	2.5	3		
3	-1.5	-1	-0.5	0	0.5	1	1.5	2			
4	-2	-1.5	-1	-0.5	0	0.5	1				
5	-2.5	-2	-1.5	-1	-0.5	0					
6	-3	-2.5	-2	-1.5	-1						
7	-3.5	-3	-2.5	-2							
8	-4	-3.5	-3								
9	-4.5	-4									
10	-5										

5.2.1: Δ values for the social parameters $p_C = 0.5$ and $p_W = 0.5$.

$N_C \setminus N_W$	0	1	2	3	4	5	6	7	8	9	10
0	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
1	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0	
2	-1.8	-1.7	-1.6	-1.5	-1.4	-1.3	-1.2	-1.1	-1		
3	-2.7	-2.6	-2.5	-2.4	-2.3	-2.2	-2.1	-2			
4	-3.6	-3.5	-3.4	-3.3	-3.2	-3.1	-3				
5	-4.5	-4.4	-4.3	-4.2	-4.1	-4					
6	-5.4	-5.3	-5.2	-5.1	-5						
7	-6.3	-6.2	-6.1	-6							
8	-7.2	-7.1	-7								
9	-8.1	-8									
10	-9										

5.2.2: Δ values for the social parameters $p_C = 0.9$ and $p_W = 0.1$.

5.3 Street crossing decision model

5.3.1 Framework for a street crossing decision model

This section presents the framework for the street crossing decision model. The framework includes the properties of an agent pedestrian P , the environment, and the interface linking the agent pedestrian and the environment.

Crossing decisions imply the interaction of P with the urban environment and the neighbors. The urban environment includes a pedestrian light, crossing locations, crosswalks, vehicles, sidewalks, and streets.

Between the urban environment and the internal mechanism of the agent, the model uses an interface. The interface contains the perception of the urban environment and the actions of other agents. Then, the actions of P changes the current state of the urban environment as perceived by neighbors.

P receives information from perception and processes the information using two models: the first for the crossing decision-making and the second for navigation. If P is at a crossing location, P uses the decision-making model at each time step, until he crosses. This model receives the number of neighbors waiting and crossing, the width of the street, the information from oncoming vehicles (position/speed), and the light traffic color (red/green), if any. Then, it processes the information for deciding to cross or to wait.

P used the navigation model if the decision is to cross or if P is not at a crossing location. This model receives information inputs from the neighbors (position, velocity, and size), and a predefined destination. Then, it processes a new velocity and position to reach a destination and avoid collisions with neighbors.

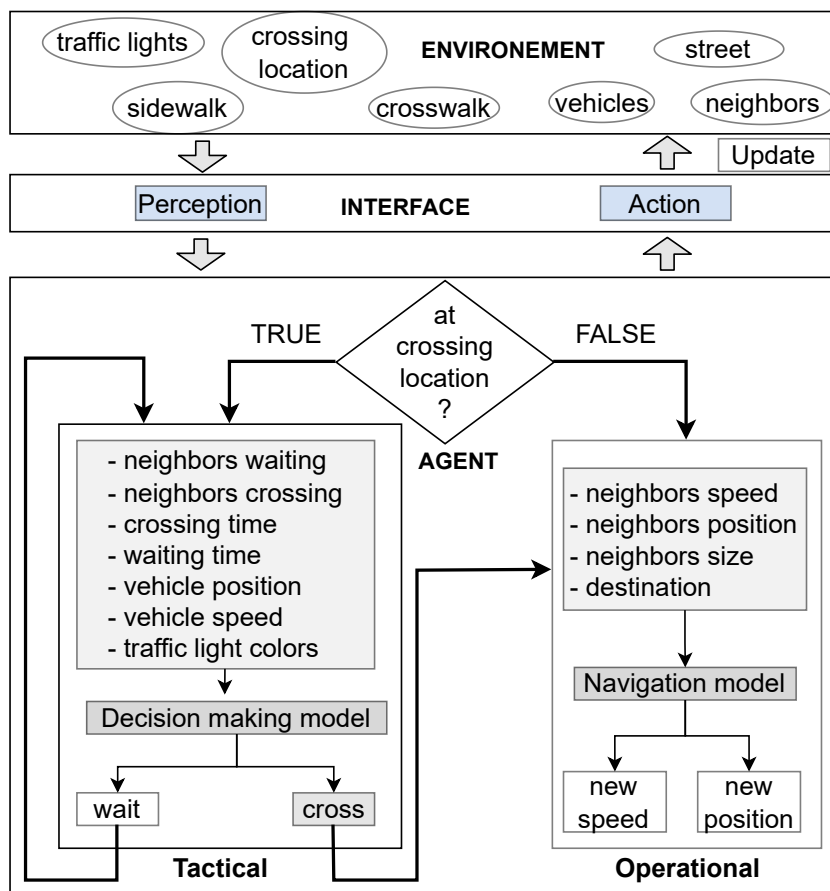


Figure 5.2: Framework for pedestrian street crossing.

5.3.2 Crossing decision categorization

Street crossing implies an interaction between pedestrians and the urban environment. To simplify the model, I limit the urban environment to road traffic and a pedestrian light. The interaction between pedestrians and the urban environment can be described by four possible scenarios.

The first scenario is the situation where the street has no pedestrian light and no road traffic. This is equivalent to no interaction with the urban environment and does not require a decision model.

The second scenario is composed of a street with a pedestrian light without road traffic. In this situation, the traffic rules apply, but some pedestrians violate it. Observations of pedestrian behavior indicate that pedestrians wait some time before crossing. I hypothesized that it is because of patience limitation, modulated by the influence from neighbors.

The third scenario is without a pedestrian light and has road traffic. Pedestrians have to estimate their crossing time ($TPed$) and the time-to-contact (TTC) with the oncoming vehicles for crossing decision. An agent pedestrian P can estimate its $TPed$ based on its speed and the crosswalk width, and estimate the TTC based on the speed and velocity of an oncoming vehicle. Pedestrians are not constrained by traffic rules in this scenario but by the possible oncoming vehicles. The existence of some pedestrians with unsafe crossings (negative margin) [Oxl+05], may indicate that pedestrians can misestimate TTC or $TPed$. Estimating a moving object is more difficult than a static object. Thus, I hypothesized that pedestrians could misestimate the TTC . Moreover, pedestrians cannot unlimitedly estimate the TTC of incoming vehicles, so I limit the perception to a maximal distance α . If an incoming vehicle exceeds the distance α (Figure 5.1), the pedestrian does not perceive the incoming vehicle and crosses immediately.

The fourth scenario is a street crossing with road traffic and with a pedestrian light. This combines the behavior of the second and third scenarios sequentially. In this scenario, the pedestrian is expected to wait longer than in the third scenario because pedestrians are constraints by both the traffic rules and the presence of possible oncoming vehicles.

Figure 5.3 implement the four possible interactions in an urban environment. Then, among the four scenarios, I have assessed in more details the second and third scenarios in this work. The two scenarios are described in figure 5.4.

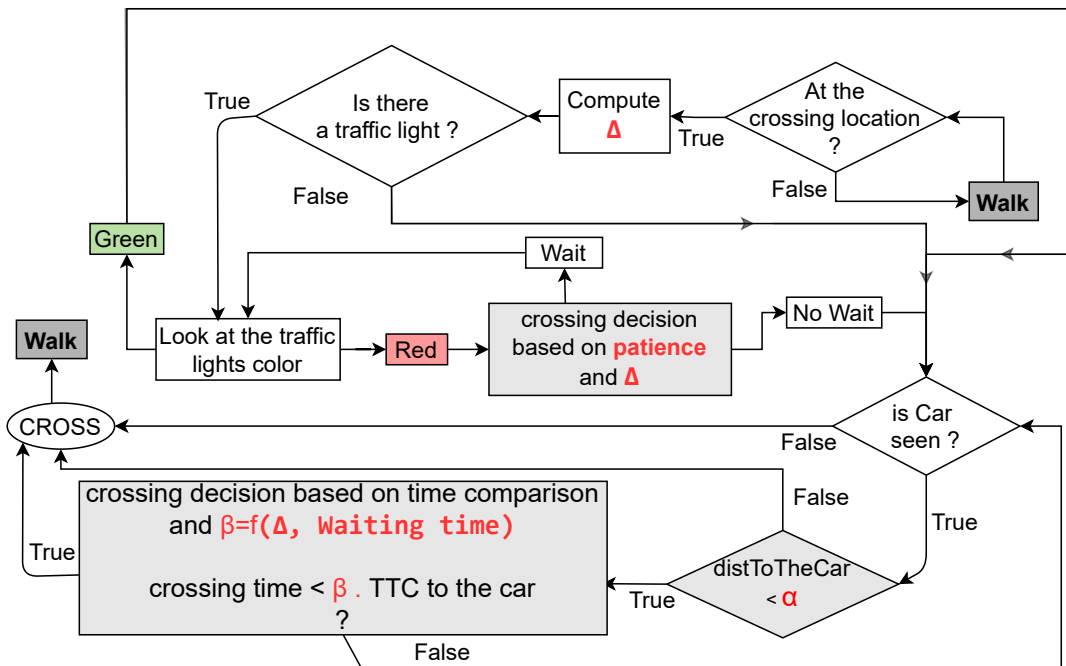


Figure 5.3: Street crossing decision model.

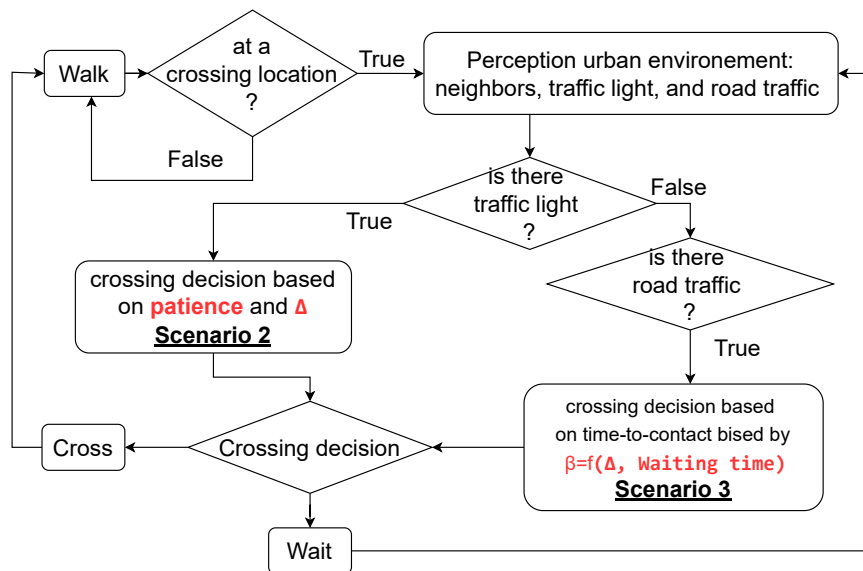


Figure 5.4: Description scenarios selected for the street crossing decision model.

5.4 Patience and social influence

The waiting time is often measured empirically using cameras, for example [ZWM18]. Literature review on social influence indicates that seeing someone crossing or waiting

may impact the crossing decisions. [Harg1] attributes the phenomena of following someone crossing as a delegation of responsibility, leading to a decision less cautious in a group than alone. Various violation rates are observed in several intersections or cities [Dom+15; Die19]. The influence of neighbors to conform to their behavior may indicate that patience can be modified depending on social influence. Thus, I have hypothesized that patience is not constant and can depend on social influence. I base the crossing decision on patience when a pedestrian crosses at a pedestrian light color red to produce this behavior. The patience value then can evolve depending on social influence, and the pedestrian decides to cross when it runs out.

5.4.1 Hypotheses

I define my street crossing model based on hypotheses H_1 and H_2 on social influence (section 5.2). The literature review also indicates that after waiting around 20 seconds, some pedestrians become impatient and want to violate the traffic rules [KO03]. Thus, I hypothesized that they have some level of patience, and when the patience runs out, they may violate the traffic rules. Therefore, I suppose a pedestrian has an individual level of patience (H_0). As a pedestrian can be influenced to cross or to wait, I suppose the pedestrian's patience can evolve depending on the social situation and may lead to a violation when the patience runs out.

H_0 pedestrians have a patience limit;

H_1 crossing neighbors influence the agent to cross;

H_2 waiting neighbors encourage the agent to wait.

5.4.2 Patience mechanism

Arriving at the sidewalk, an agent pedestrian P perceives the traffic color light. If the traffic color is green, then P crosses. Otherwise, if the traffic color is red, P waits, and crosses when the pedestrian light turns to green or when P 's patience runs out (in this case, P violates the traffic rules).

During the red light, P starts to wait, his waiting time (WT) increases every time step TS , starting from 0. The modified patience MIP is initialized to $MIP(0) = IP$. Then, the crossing decision happens when ($WT > MIP$).

Modeling patience is not something common in street crossing simulations. A reference is needed to compare the results. It is why I have considered modeling

standard patience, with a restriction of the patience and social influence model, where $\Delta = 0$, leading to a null influence ($\psi = 1$). The figure 5.5 presents the crossing decision with the standard patience model and with the patience and social influence model. In the two situations, an agent pedestrian can violate the traffic rules, but the agent pedestrian with the standard patience model would behave the same, no matter the neighbors' behaviors.

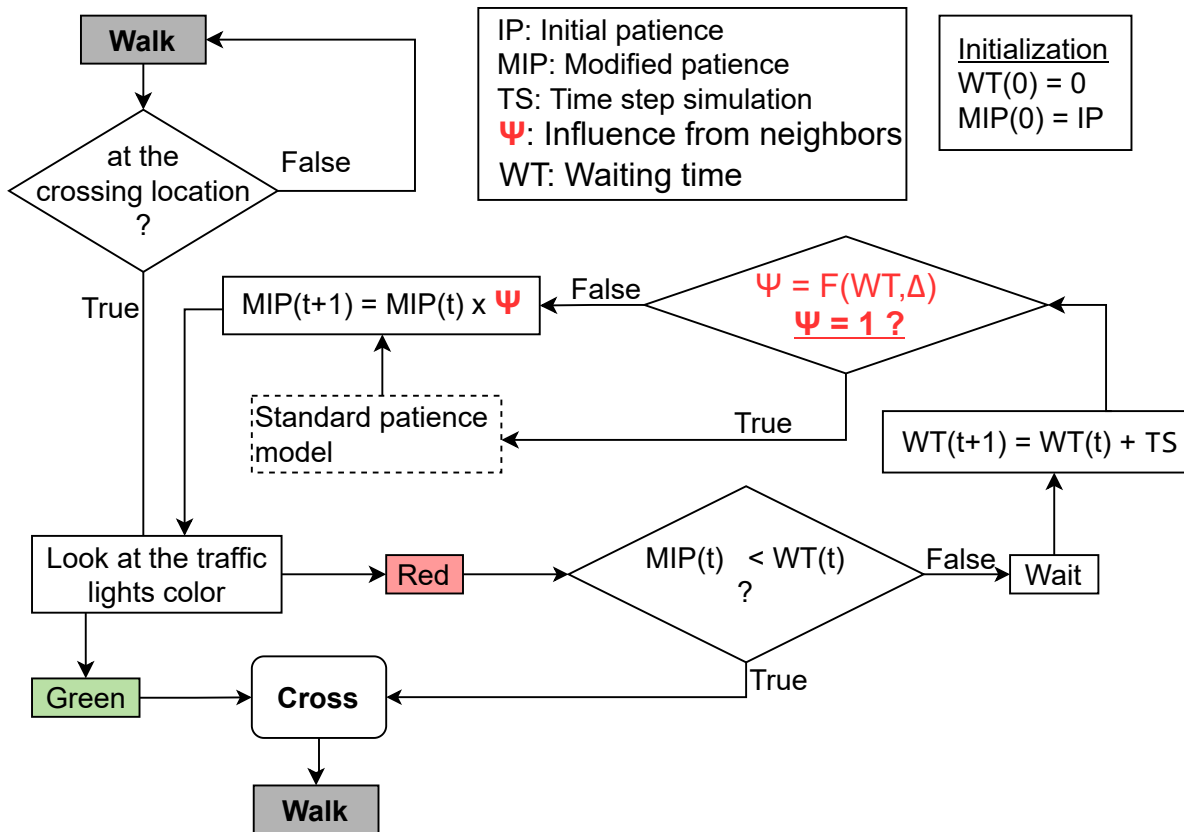


Figure 5.5: Patience model modified by social influence. A pedestrian crosses if the pedestrian light color is green, or if its patience runs out ($WT > MIP$). The social influence modifies the patience with ψ , and if $\psi = 1$ the model corresponds to the standard patience.

5.4.3 Impact of social influence on patience

When pedestrians start waiting, their patience MIP is modified due to the neighbor's influence. To express the modification, I use the linear combination Δ , which integrates into a single value the number of crossings and waiting (see formula 5.1). Δ is computed at time step t , and the influence ψ is computed from Δ in such a way that $\psi > 1$ when ($\Delta > 0$), $\psi < 1$ when ($\Delta < 0$), and $\psi = 1$ when ($\Delta = 0$):

$$\psi^i(t) = \left[1 + \frac{\Delta^i(t)}{100} \right] \quad (5.2)$$

$MIP^i(t)$ is computed from $MIP^i(t-1)$ and modified by ψ (formula 5.3). This modification allows $MIP^i(t)$ changing during the waiting phase. Due to Eq. 5.2, ψ is close to 1, so the evolution of $MIP^i(t)$ is not too quick. If ($\psi < 1$), then MIP decreases, and if ($\psi > 1$), then MIP increases. If ($\psi = 1$), then MIP remains constant, as in the standard patience model at time t :

$$MIP^i(t) = MIP^i(t-1) \times \psi^i(t) \quad (5.3)$$

To explore the possible values of ψ , let us suppose a pedestrian P can perceive up to 10 crossing or waiting neighbors, forming a matrix M with $\frac{10 \times 10}{2} = 50$ possibilities (Figure 5.6). The cells show the values of ψ , with the parameter $p_C = 0.9$ and $p_W = 0.1$, using the matrix M_2 , with more weight on the crossing pedestrians than on the waiting ones (section 5.2.3).

Figure 5.6 shows that ψ ranges between 0.91 to 1.01, and most values are close to 1, meaning that the evolution of MIP is not too quick. In this example, if only one neighbor is crossing, then MIP will not decrease (define by a blue rectangle). At least MIP will be constant if nine neighbors are waiting and one crossing.

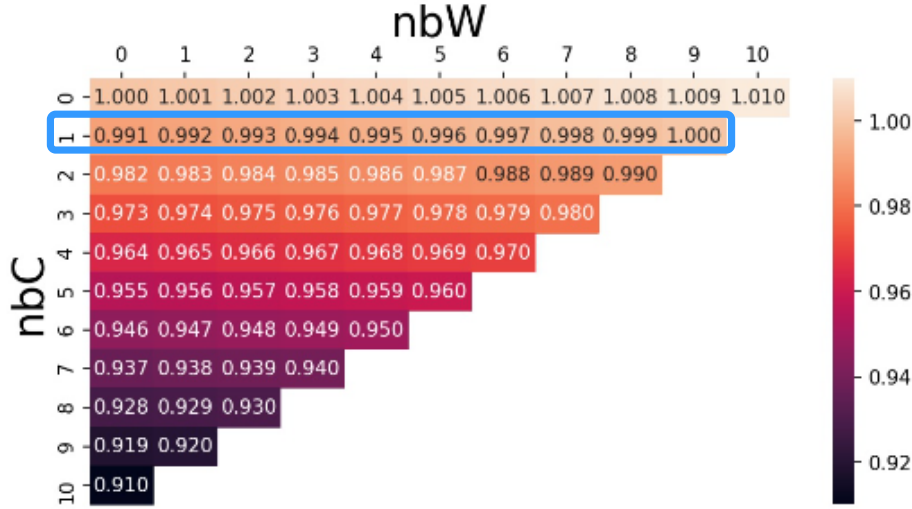


Figure 5.6: Computation of the influence $\psi = \left[1 + \frac{\Delta}{100}\right]$ used to modify the individual patience, when the number of neighbors perceived is limited to ten, $p_C = 0.9$ and $p_C = 0.1$.

5.4.4 Limitation patience threshold

The definition of patience allows patience to evolve depending on the situation, following the value of $\psi \in [0.910, 1.01]$ for the case of 10 perceived neighbors. Over a period of time, with a continuous value of ψ , the patience can increase to an extreme value quickly. Thus, I limit the increase of the patience.

Considering the duration of short cycle (green and red) pedestrian lights' at about 60 seconds [NAC], MIP can exceed largely this 60 seconds duration. To illustrate that situation, suppose a pedestrian P^i with initial patience $MIP^i(0) = 40$ seconds, continuously perceiving 8 waiting neighbors, which leads to $\psi^i = 1.008$. If the simulation step is fixed to $TS = 0.1$ second, then MIP^i can reach 88.74 seconds after 10 seconds waiting, which is relatively high. Thus, I limited the increase by defining a threshold PT in percentage. PT prevents the individual patience to be higher than threshold $T = IP \times PT$ (algorithm 6, line 1 to 5).

Algorithm 6: Patience and social influence.

```

1  $T^i \leftarrow IP^i \times PT$  ; // Processd only during the initialization process.
   /* Patience Threshold (PT) in %,  $PT > 100$  %,  $PT$  is a parameter model. */
2  $MIP^i(t) \leftarrow MP^i(t-1) \times \left[1 + \frac{\Delta^i(t)}{100}\right]$  ;
3 if  $MIP^i(t) > T^i$  then
4   |  $MIP^i(t) \leftarrow T^i$ 
5 end
6 if  $[WT^i(t) > T^i]$  then
7   | cross()
8 else
9   | if  $[(MIP^i(t) < IP^i) \text{ AND } (MIP^i(t) < WT^i(t))]$  then
10  | | cross() ; // The waiting time reaches the  $MIP^i$ , then cross.
11  | else
12  | |  $WT^i(t) \leftarrow WT^i(t-1) + TS$  ; // Wait
13  | end
14 end

```

5.4.5 Illustration of the evolution of patience

The figure 5.7 illustrates the evolution of patience of one pedestrian, influenced by several neighbors. In this figure, the waiting time is on the x-axis, and the difference $MIP - WT$ is on the y-axis. When $MIP < WT$, the pedestrian crosses the street. In this example, $MIP - WT$ decreases straight from the beginning. This period may correspond to a situation where the number of neighbors crossing or waiting is not changing. After about 4.3 seconds, $MIP - WT$ decreases more quickly. It means that some more pedestrians are crossing. The evolution of patience would be different if the pedestrian is alone or with the standard patience reference model (with $\Delta = 0$).

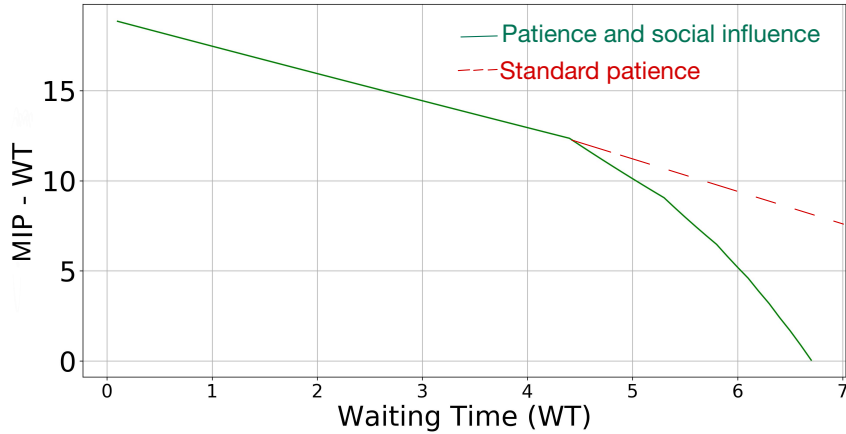


Figure 5.7: Patience evolution comparison of the standard (dashed line) and of the social influence model (continuous line). The pedestrian crosses the street when $MIP < WT$.

5.4.6 Conclusion on patience and social influence

The proposed model of agent pedestrians' bases the crossing decisions on patience when crossing on a crosswalk with a pedestrian light and during red lights. I developed the pedestrians' patience with hypotheses based on observed pedestrian behavior. The hypotheses are that a pedestrian can be influence by crossing neighbors to violate the traffic rules (H_1). Or, conversely, a pedestrian can be influenced by waiting neighbors to comply with the traffic rules (H_2). My approach combines both H_1 and H_2 in a single formulation of social influence Δ . Δ can be positive when the influence to comply with traffic rules is greater than the motivation to cross. Conversely, Δ can be negative when the motivation to violate is greater than the influence to wait. I use Δ to modify the patience of a pedestrian, while the pedestrian waits during red lights. The MIP can evolve until $MIP < WT$; then, the pedestrian may violate the pedestrian light. This modification of patience is expected to produce some pedestrians violating and complying with the traffic rules. In the next section, I present the time-to-contact model, where pedestrians cross a street with road traffic and without a pedestrian light.

5.5 Time-to-contact biased by social influence

This section considers a street crossing scenario with only road traffic, without a pedestrian light. Suppose a pedestrian P arrives at a crossing location and perceives an oncoming vehicle. In that case, he compares the time-to-contact TTC with the oncoming

vehicle to its crossing time $TPed$, and crosses if $TPed < TTC$. If P does not perceive any oncoming vehicles, P crosses immediately.

Many works on street crossings use the gap theory: pedestrians estimate if they can cross between two vehicles [Oxl+05; LC09]. In this work, I use time-to-contact for the crossing decision. This allows pedestrians to interact only with one oncoming vehicle. To use the time-to-contact, pedestrians estimate the speed and position of an oncoming vehicle, the length of the crosswalk, and their speed. Estimating a moving object is more difficult than estimating a static object, and the estimation can be inaccurate.

This section shows how to use the time-to-contact for crossing decisions when pedestrians perceive an oncoming vehicle. The estimation of the time-to-contact can be inaccurate. If pedestrians do not perceive any oncoming vehicle, then they cross immediately. To develop this time comparison model, I start by presenting the decision process, the selection of perception inputs, and the formulation of the influence of the contextual situation.

5.5.1 Vehicle perception

The perception of information is a composition of three steps executed by pedestrians before crossing a street: selection, projection, and identification.

a) Selection of the vehicles presenting a constraint for crossing a street. P has a perception field and can perceive oncoming and outgoing vehicles. The oncoming vehicles move towards the pedestrians, and the oncoming ones represent the constraint for crossing decisions. If no oncoming vehicle is perceived, then pedestrians can cross immediately. Figure 5.8 illustrates P perceiving vehicles in its perception range. Four vehicles are in the perception range, the oncoming ones are in red.

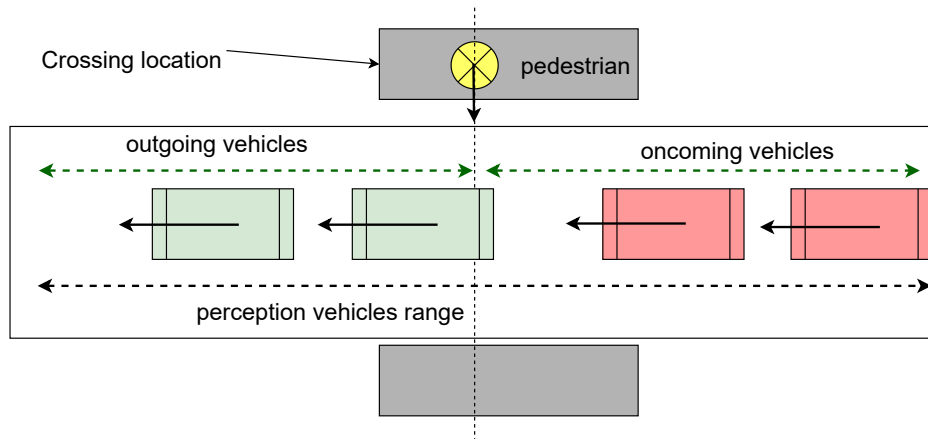


Figure 5.8: Pedestrian perception vehicle range from the crossing location, in gray rectangle. The two oncoming vehicles are in red, and the two outgoing vehicles are in green.

b) Projection of the future position of a vehicle (VP) among the oncoming vehicles that would not be a constraint for crossing because its rear bumper will reach the conflict area before P . To proceed, is shown in figure 5.8, P perceiving four vehicles, and two are the anticipation ones. P compares the arriving time of the rear bumper TTC_rear to his time of arrival at the nearside of an oncoming vehicle $TPed_near$, for each oncoming vehicle, from the nearest position. [TTF02] described this process of projecting the of the position of the oncoming vehicle in the four stages before crossing a street. [LC09] also observed some pedestrians start to cross before the rear bumper of an oncoming vehicle passes the pedestrians' positions.

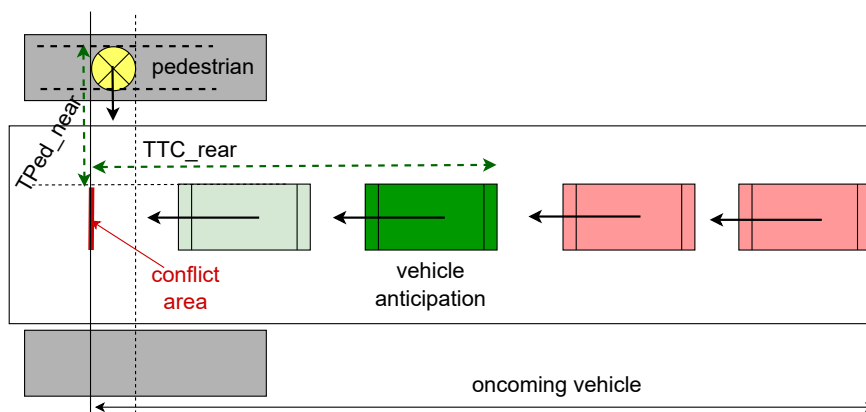


Figure 5.9: Identification of the anticipation vehicle from an oncoming vehicle that would not present a constraint for crossing. The condition is verified by comparing $TTC_rear < Tped_near$. The two green vehicles are not supposed to be a constraint for crossing, and the furthest vehicle is the anticipation, in dark green.

c) **Identification** of the vehicle to interact with (VI), presenting the first constraint for the crossing decision of P . This vehicle would be the first vehicle after the anticipation vehicle, if any. If $TTC_rear > Tped_near$, then it is the vehicle to interact with for the crossing decision. See in figure 5.10 illustrates the vehicle red to be the vehicle to interact with.

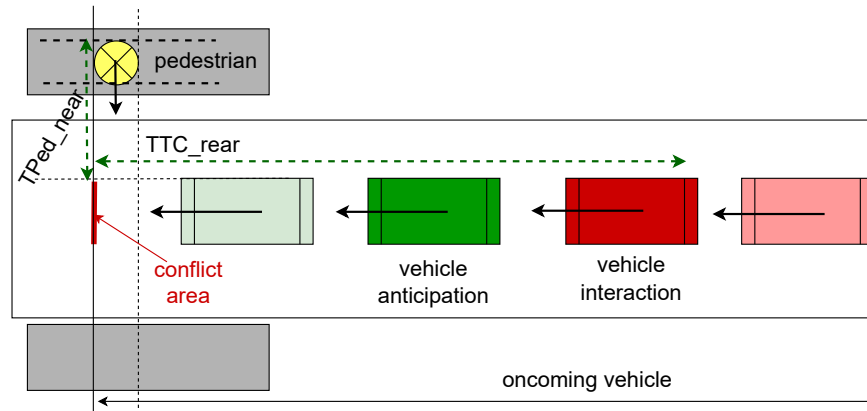


Figure 5.10: Identification of the vehicle (in dark red) to interact with by comparing $TTC_rear > Tped_near$.

5.5.2 Trade-off between waiting and crossing

When pedestrians arrive at a crossing location with no road traffic, the goal is to cross as soon as the situation allows. The situation allows when no oncoming vehicle is perceived, or an oncoming perceived is perceived but far enough allowing the pedestrians to cross. For the case of perceiving an oncoming vehicle, this vehicle is the one identified during the perception phase in 5.5.1. The pedestrians have to compare their crossing time ($TPed$) to the time-to-contact of the front bumper of the oncoming vehicle (TTC) for crossing decision.

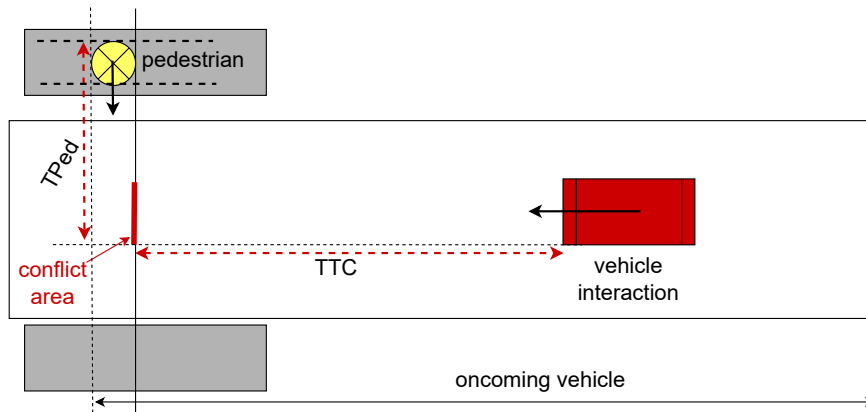


Figure 5.11: Definition of the pedestrian crossing time ($TPed$) and the time-to-contact of the front bumper of the oncoming vehicle (TTC) for crossing decision. The pedestrian crosses the street if $TTC \geq TPed$, or wait otherwise.

If everyone had a perfect perception of the environment, and pedestrians can accurately estimate their $TPed$ and the TTC . Then, a standard comparison time would suffice to describe street crossings. However, [Oxl+05] observed that some pedestrians selected a time that would lead to a collision. Another experiment observed some pedestrians missed crossing opportunities [LC09]. The two observations indicate that pedestrians can have an inaccurate estimation of time, which can lead to an overestimation or underestimation of the crossing decision.

The inaccurate estimation can be caused by multiple factors, such as environmental (presence of an illegal parked vehicle [Dom+15]), physiological (perception limits [SO03]), or social (influence to conform to the behaviors of others [FKK10]). I limit this work to social factors. Moreover, pedestrians can have an inaccurate estimation of $TPed$ and TTC . For the model's simplicity, I choose to address TTC because it is more difficult to estimate.

[IN08] found that the pedestrian's crossing decision is based on a trade-off between the crossing time, the waiting time, and the perception of the oncoming vehicle. [IN08] also presented that faulty perception leads to inadequate crossing decisions. Furthermore, an agent with inaccurate perception of the environment is more convincing [LLB11]. Thus, I propose modifying the perception of the time-to-contact of an oncoming vehicle by a bias β , which combines the waiting time and the social influence due to the neighbors' behavior. The modification of the TTC allows some variability in the crossing decisions. The variability can lead to unsafe, safe crossings or missed opportunities.

$$\beta \times TTC \geq TPed \quad (5.4)$$

5.5.3 Modified perception of time-to-contact

The bias β is based on the social influence of neighbors and on the pedestrian's waiting time. H_1 and H_2 are observed both with and without a pedestrian light. I supposed they are also relevant when pedestrians interact with road traffic. Nevertheless, pedestrians may not follow a crossing neighbor without estimating a possible collision with an oncoming vehicle.

I express β using the same formulation of the neighbor's influence Δ , as before in formula 5.1, and the waiting time WT . To counterbalance Δ and WT , I use two parameters a and b to weight WT and Δ (formula 5.5).

$$X = b \times \Delta - a \times WT \quad (5.5)$$

Using two parameters a and b allow weighting importance for each of the two factors WT and Δ . Then, the combination of the two factors is introduced into a sigmoid function, and limited by a threshold c , to compute β (formula 5.6).

$$\beta = \frac{2 \times (1 - c)}{1 + e^{-X}} + c \quad (5.6)$$

Let us take a closer look at the formulation of β . The sigmoid and the numerator value 2 allow β being between c and $2 - c$ and the values of the parameter c are between 0 and 2, illustrated in figure 5.12. If $\beta > 1$, the crossing decision is overestimated. In the opposite case, if $\beta < 1$, the crossing decision is underestimated. If $\beta = 1$, then the crossing decision is not biased.

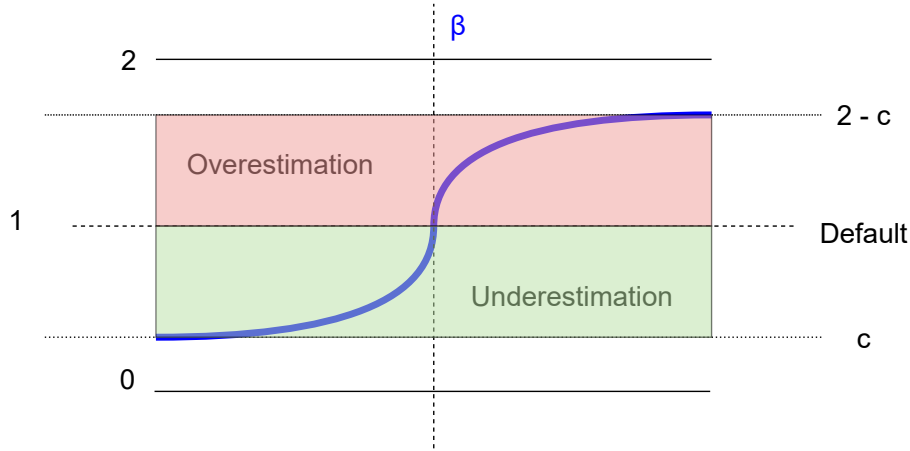


Figure 5.12: Domain definition of the bias β . $\beta \in [c, 2 - c], c \in [0, 2]$.

Δ can have positive or negative values. WT on the other hand, only has positive values and increases linearly. Thus, depending on the sign of the two β parameters (a and b), Δ can reinforce or counterbalance the impact of WT . Since WT increases linearly, it is possible to identify three phases. The first phase is when pedestrians just arrived. X depends mainly on Δ at the beginning. The second phase is when WT increases and counterbalances Δ , in the computation of X . The last phase happens if the pedestrians wait longer, WT has more importance than Δ , and X depends mainly on WT .

Algorithm 7 implements the crossing decision using the bias β on the perception on the TTC . The β allows a pedestrian to have an inadequate decision. The inadequate is an unsafe decision if $TTC < TPed$, or is a missed crossing if $TTC \geq TPed$.

Algorithm 7: Time-to-contact biased model.

```

1  $X = b \times \Delta - a \times WT$ 
2  $\beta = \frac{2 \times (1 - c)}{1 + e^{-X}} + c$ 
3 if  $\beta \times TTC \geq TPed$  then
4   | cross()
   | /* IF  $TTC \geq TPed$ , THEN it is a safe crossing */
   | /* IF NOT, THEN it may be an unsafe crossing //  $\beta > 1$  */
5 else
6   | wait(); //  $\beta \times TTC < TPed$ 
   | /* IF  $TTC \geq TPed$ , THEN it may be a missed crossing //  $\beta \leq 1$  */
   | /* IF NOT, THEN it is impossible to cross, speed not enough */
7 end

```

Figure 5.13 presents the four possible crossing decisions for pedestrians perceiving an oncoming vehicle. The pedestrians have two options, whether crossing or waiting, based on the comparison of TTC and $TPed$. If the pedestrians decide to cross ($\beta \times TTC \geq TPed$), the crossing decision can be “safe” or “unsafe” based on the comparison of the difference between TTC and $TPed$, as I named the margin. The decision is “unsafe” if the margin ($TTC - TPed < 0$) and “safe” in the opposite case. The “unsafe” decision can only happen if $\beta > 1$.

If the pedestrians decide to wait ($\beta \times TTC < TPed$), the crossing decision can be “missed” or “impossible” based on the comparison of the difference between TTC and $TPed$. The decision is “missed” if the pedestrians can cross ($TTC \geq TPed$), but due to social influence, the decision is to wait. The “missed” can only happen if $\beta < 1$. The decision is “impossible” if pedestrians do not have the crossing time enough ($TTC < TPed$) without being hit by the oncoming vehicle.

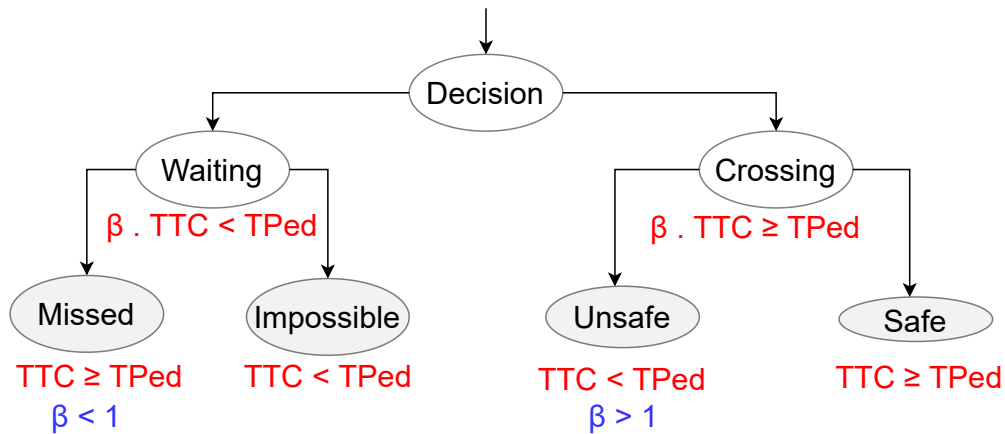


Figure 5.13: Expected behavior output. Missed opportunities and unsafe crossings can only happen using the bias β . Missed opportunities happen only if $\beta < 1$, and unsafe crossings if $\beta > 1$.

5.5.4 Illustration of the bias β

Figure 5.14 illustrates the evolution of β for five pedestrians arriving at different times at the crossing location. β starts when $WT = 0$, until the pedestrians cross the street (red star). When Δ is constant, the situation on the crossing location is stationary; no new pedestrian is coming or crossing. If Δ is constant, β is roughly linear because WT evolves linearly.

The evolution of β can be described in three phases. During the first phase, WT is low and β mainly depends on Δ . Unlike WT , Δ is not linear. During the second phase,

WT increases, and β depends on WT and Δ . During the last phase, WT becomes relatively higher than Δ , and β depends mainly on WT .

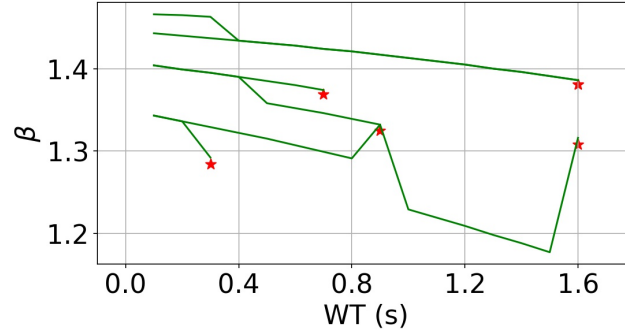


Figure 5.14: Illustration of the evolution of β for five pedestrians waiting at the crossing location.

To analyze the formulation of β , I initialized the three parameters with ($a = 1, b = 1, c = 0$), where I used these values for simplification. Then I initialized the parameters for Δ with ($p_C = 0.7, p_W = 0.3$). Then I compute X_{low} for a low value of $WT = 0.3$ s and X_{high} for a high value of $WT = 30$ s.

$$X = \begin{cases} X & = \Delta - WT \\ X_{low} & = \Delta - 0.3 \\ X_{high} & = \Delta - 30 \end{cases} \quad (5.7)$$

$$\beta = \frac{2}{1 + e^{-X}} \quad (5.8)$$

With this simplified formulation, let us explore four different scenarios (A, B, C, and D), which can be experienced by a pedestrian P (in the figure 5.15). If $\Delta > 0$, then the pedestrian is influenced to wait; otherwise, the pedestrian is influenced to cross. For the two situations (A and B), both have $\Delta > 0$, but WT is low for A and high for B. In these situations P is influenced to wait; but in A, P just arrived, and in B, P already waits for a long time. In the two last situations (C and D), both have $\Delta < 0$, but WT is low for C and high for D. In these situations P is influenced to cross; but in C, P just arrived, and in D, P already waits for a long time.

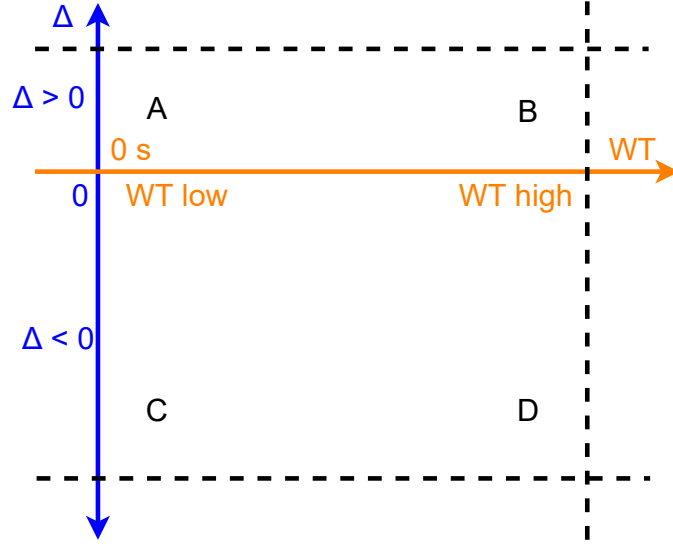


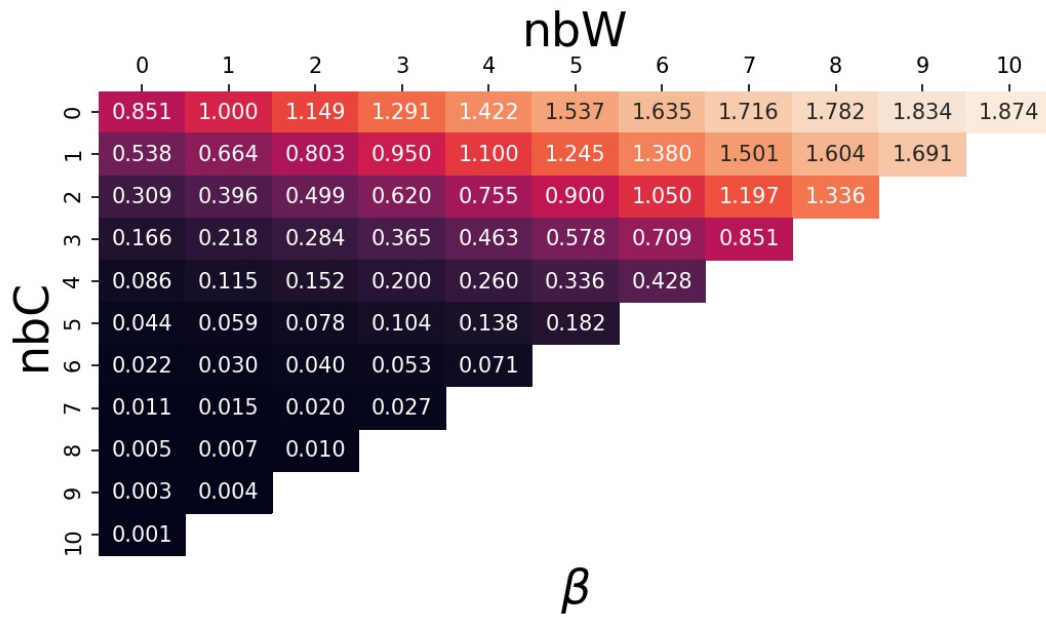
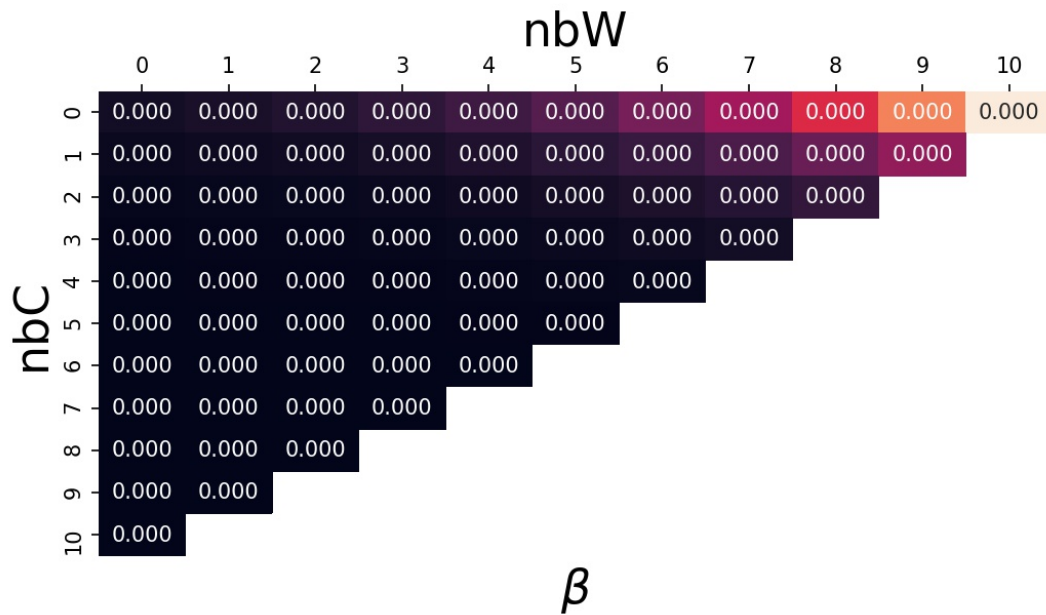
Figure 5.15: Illustration of the four scenarios A, B, C, and D.

My objective with this illustration is to test the potentiality of the model to simulate various scenarios. I expected that if these four scenarios can be covered with this model, then it can work for scenarios in between.

I computed two matrices 10×10 for low and high WT, for a pedestrian who can perceive up to 10 pedestrians. Then, X_{low} , X_{high} , β_{low} and β_{high} are computed using equation 5.8. Figure 5.16(a) shows the matrix for β_{low} . The values of β_{low} can be below or above one, this means that the pedestrian can overestimate or underestimate the perception of TTC.

Figure 5.16(b) shows the matrix for β_{high} . The values of β_{high} are always 0, which means the pedestrians are only overestimating the perception of TTC. Thus, for the four scenarios, three scenarios A, B, and C can be simulated with the chosen parameters. Regarding the case of D, pedestrians cannot underestimate the crossing after waiting a longer time, with the selected set of parameters.

To identify the β values for the four scenarios, I use the two matrices, in figure 5.16. A low Δ is located in the bottom left of the matrices, and a high Δ is located in the top right. Scenarios A and C uses the matrix with low WT, in figure 5.16(a), giving their values $\beta_A = 1.87$ and $\beta_C = 0.0$. Scenarios B and D uses the matrix with high WT, in figure 5.16(b), giving their values $\beta_B = 0$ and $\beta_D = 0$. These results show that the same value ($\beta_B = \beta_C$) can produce two different behaviors at different moments of time (WT_{low} and WT_{high}).

(a) β values for $X_{low} = \Delta - 0.3$ s.(b) β values for $X_{high} = \Delta - 30$ s.**Figure 5.16:** β_{low} and β_{high} values with low and high WT computed. With β ($a = 1$, $b = 1$, $c = 0$, $p_C = 0.7$ and $p_W = 0.3$).

5.5.5 Conclusion on time-to-contact biased by social influence

Street crossing is not a simple time comparison of crossing time and time-to-contact of an oncoming vehicle. If pedestrians accurately estimate these times, no accidents and no missed opportunity crossings would occur. Results from experimental observations show that pedestrians can have inadequate crossing decisions. Different factors can be the cause of the inaccuracy. I hypothesize the factors can be the social influence and the waiting time. To formalize my hypothesis, I use a trade-off between crossing time, waiting time, and the perception of the oncoming vehicle formalized by [IN08]. I proposed that the perception of the time-to-contact of an oncoming vehicle is modified based on waiting time and social influence.

This modification produces variability in the pedestrian's street-crossing behavior, and the model can produce several behaviors such as having a safe or unsafe crossings, having missed crossings. Unsafe and missed crossings could not be produced in a standard time comparison model. I also assess the model using simple scenarios, without running any simulations, to observe the model's potential. The model can produce situations where a pedestrian with a low waiting time can be influenced to wait or influenced to cross. With a longer waiting time, the pedestrian can be influenced to wait. To allow the pedestrian to wait longer and be influenced to cross, a different set of parameters is needed.

5.6 Conclusion

This chapter presented the street crossing model under two scenarios: crossing with a pedestrian light and without road traffic, and crossing with road traffic without a pedestrian light. The model considers the social influence and the waiting time for the crossing decisions. This choice is expected to produce several crossing behaviors. Pedestrians can violate the pedestrian light if their neighbors influence them, or they become impatient after waiting some time. They can also decide to comply with the traffic rules when seeing someone waiting, also observed by [Ros09]. In some other situations, pedestrians can decide to cross even if an oncoming vehicle is approaching or wait even if they can cross safely, behaviors also observed by [Oxl+05; LC09]. Thus, the model is expected to produce behaviors that are observed in the literature, with more behavioral variability than existing models I present in chapter 7, the results of the simulation of the model. Before simulating the model, I present the scenario and initial conditions requirements in the next chapter.

Chapter 6

Street crossing scenario description

Following the four steps taken by pedestrians before crossing a street [TTF02], a pedestrian starts by identifying the crossing location on a sidewalk, selecting the information, deciding to cross, and physically crossing the street. In the chapter 5, I developed a street crossing decision model. This chapter 6 aims to describe the corresponding scenarios, virtual environment and the initialization parameters, required to simulate the street crossing model. The street crossing decision model is performed under two scenarios: in section 6.1, the pedestrians interact with a pedestrian light and without road traffic. Then, I simulated an intersection with a controlled and marked crosswalk. In this scenario, pedestrians followed an itinerary, moved to a defined crossing location on the sidewalk, selected information from the pedestrian light colors and from the behavior of neighbors (crossing/ waiting), decided and physically to cross the street. The pedestrian light has two colors (red and green), and a crossing is considered illegal if a pedestrian decides to cross while the traffic color is red; otherwise, it is a legal crossing. To run the simulations, I set different values for each pedestrian's speed and individual patience, leading to different waiting times and crossing decisions. To see the impact of the collective situation on individual decisions, I created populations with homogeneous and mixed pedestrians (in terms of speeds), and with low and high pedestrian flow. To analyze the consistency of the generated pedestrian's speed and individual patience values, I confront these values with the duration of the traffic light colors (green and red).

For the second scenario in section 6.2, the pedestrians interact with road traffic and without a pedestrian light. Then, I simulated an uncontrolled crosswalk environment in this scenario, corresponding to a mid-block intersection. Road traffic is composed of vehicles moving in a one-way direction at a constant speed, even if someone was crossing. As in the previous scenario, the pedestrians follow an itinerary, move to a defined crossing location, select information from the oncoming vehicle and the crossing

behaviors of neighbors, and then physically cross the street. In these simulations, pedestrians have the individual speed set up from a normal distribution, leading to different crossing decisions. Vehicles are randomly distributed with different inter-vehicle distances along their itinerary, and they are set up with three constant speeds (40, 50 and 60 km/h), leading to constant gaps between vehicles. To analyze the consistency of the generated pedestrian's speed and the inter-vehicle distances values, I confronted these values with the width of the street.

6.1 Street crossing scenario with a pedestrian light

6.1.1 Scenario description

Pedestrians followed a predefined itinerary. When pedestrians reached a defined crossing location (waiting zone), which was a zone inside the sidewalk, they started to select information from the pedestrian light and the crossing behaviors of their neighbors. If the pedestrian light color was green, pedestrians cross. Otherwise, they started waiting and move inside the waiting zone. Once they have decided to cross, the pedestrians physically crossed the street, and they do not update their decision. Their behavioral status was changed to “crossing”.

The pedestrian light has two colors, red and green, with different duration for each color, turning in a loop (color cycle) during the simulation. A crossing was labeled as illegal if a pedestrian crossed while the light traffic color was red; otherwise, it was labeled as a legal crossing. Then a legal crossing may happen when someone arrived during the green phase or when someone arrived during the red phase and waited for the next green to cross.

6.1.2 Virtual environment

The pedestrians follow an itinerary in a loop, and the itinerary has a distance about 67.64 m, depending on the position of pedestrians on the sidewalk when they crossed the street, in figure 6.1). The pedestrian light was near this waiting zone: it appears as a red-colored square with a dotted line (on figure 6.1). Pedestrians can cross directly from the start of the waiting zone if the light is green. If the light is red, they move inside the waiting zone to find a spot to wait. If a crossing opportunity arises when they reach the spot, they can cross. When they finished crossing the street, they go to the beginning of the itinerary and make a new lap.

The dimension of the waiting zone is $2.4 \text{ m} \times 6.72 \text{ m}$, which was a rectangular area inside the sidewalk. It contained two rows of 10 positions, each position can comprise up to two pedestrians, leading to a maximum capacity of 40 pedestrians waiting simultaneously. The maximum surface capacity was around 0.405 m^2 for one pedestrian, corresponding to a high density with a level of service F in Fruin's work [Fru71].

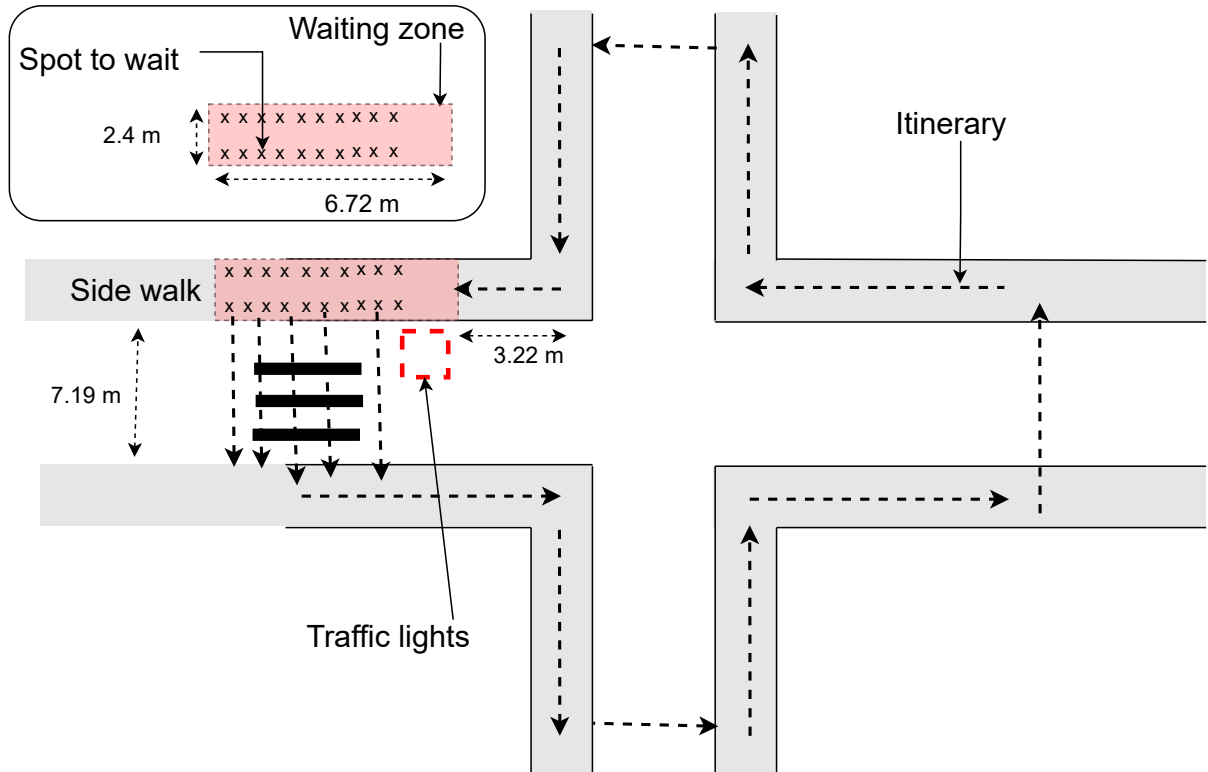


Figure 6.1: Virtual environment for the street crossing scenarios with a pedestrian light. The pedestrians follow a closed-loop itinerary, they cross the controlled interaction from the waiting, then pedestrians continue for another lap on the itinerary.

6.1.3 Initial conditions

A pedestrian is perceived by other pedestrians as a 2D disc, and all pedestrians have the same diameter size (0.4 m). The pedestrian also has the same information related to its perception characteristics: the maximum number of neighbors perceived was set to ten and within a radius of ten meters with angles up to 360 degrees (using both visual and auditory information [Lav+09]). The sum of the width of the waiting zone (2.4 m) and the street (7.19 m) is 9.59 m, and the length of the sidewalk is 6.72 m. Thus, 10 m is enough for a pedestrian to perceive neighbors on the sidewalk and crossing the street. Pedestrians have individual patience (IP) and personal speed ($VPed$) generated

from a normal distribution. According to [Liv10], a normal distribution can be used to represent human characteristics. [FBT06] observed the average speed for younger and older pedestrians at a two-way street intersection, comparable with my selected virtual environment. The younger pedestrians had an average of 1.45 m/s compared to 1.16 m/s for the older pedestrians. The average waiting time of pedestrians at a controlled intersection was recorded. According to the literature, pedestrians became less patient after 20 s of waiting, and only 25% wait more than 60 s [UFT04]. [INo8] also found that pedestrian's impatience becomes noticeable after 15 s. Therefore, I used a minimum waiting time of 20 s:

$$IP = \begin{cases} IP_{min} = 20 \text{ s} \\ IP_{Third\ quartile} < 60 \text{ s} \end{cases} \quad (6.1)$$

I created two populations, first one was homogeneous H and another one was with a mixed M population in terms of speed. I used the average speed of younger and older pedestrians from [FBT06] to build normal distributions for the two populations. I simulated the homogeneous population using only the older pedestrian's speed (1.16 m/s) and a low standard deviation of 0.05 m/s, to make the population homogeneous. The $SD = 0.05$ leads to a maximal and minimal pedestrian speed of $v_{min} = 1.01$ and $v_{max} = 1.31$:

$$homogenous = \begin{cases} v \in \mathcal{N}(\mu = 1.16 \text{ m/s}, SD = 0.05 \text{ m/s}) \\ v_{min} = 1.01 \text{ m/s} \\ v_{max} = 1.31 \text{ m/s} \end{cases} \quad (6.2)$$

For the mixed population, I used the average speed (1.3 m/s) from the younger (1.16 m/s) and older pedestrians (1.45 m/s), with a larger standard deviation (0.3 m/s). I chose a larger SD to give more variability, since a mixed population combines the younger and older pedestrians. Moreover, younger pedestrians have larger variability in terms of speed than the older ones [INo8]. For $SD = 0.3$ m/s, the minimal speed can be as low as 0.4 m/s, and as high as 2.2 m/s. A threshold was applied for the speed to be between 0.8 and 2 m/s

$$mixed = \begin{cases} v \in \mathcal{N}(\mu = 1.3 \text{ m/s}, SD = 0.3 \text{ m/s}) \\ v_{min} = 0.8 \text{ m/s} \\ v_{max} = 2 \text{ m/s} \end{cases} \quad (6.3)$$

I did not find quantitative data in the literature about the average individual patience of younger and older pedestrians, so I used the same distribution for both homogeneous and mixed populations. I hypothesized the mean IP to be 40 s, with a minimum value set to 20 s and the 75th percentile set to 60 s from [UFT04]. I selected an $SD = 8$ s, so the average individual patience can reach the minimal value and exceed the 75th percentile:

$$(homogenous \text{ and } mixed) = \begin{cases} IP \in \mathcal{N}(\mu = 40 \text{ s}, SD = 8 \text{ s}) \\ IP_{min} = 20 \text{ s} \\ IP_{max} = 64 \text{ s} \end{cases} \quad (6.4)$$

In the model, the number of perceived neighbors impacted on the collective situation, and the collective situation impacted on the individual decision. To study the relationship between collective situations and individual decisions, I simulated different levels of pedestrian flow. A low flow was simulated with 10 pedestrians in a loop, following the itinerary, leading to an average flow of one pedestrian every 6.76 m. A high flow was simulated with 40 pedestrians, with an average flow of one pedestrian every 1.69 m.

Pedestrians cross at an intersection with a pedestrian light, with a cycle duration of 45 seconds for the red phase and 15 seconds for the green phase, leading to a complete cycle of 60 s. The red duration adheres to MUTCD's recommendation for minor streets: the green phase should last more than 7 seconds [NAC]. MUTCD is a document from the Federal Highway Administration of the United States.

At the beginning of each simulation, the pedestrians are randomly positioned along the itinerary but outside the waiting zone and the crosswalk. Each simulation lasts 600 s, ten complete cycles. The pedestrians follow the itinerary (67.64 m) in a loop, with the same walking and crossing average speeds of 1.16 and 1.3 m/s for H and M population, and altered by the pedestrian light colors, leading to several laps between six and ten, with a median of seven for H and eight for M .

The simulation time step is fixed with 0.1 s, and the simulation starts at a red light. To avoid a particular case, each simulation is repeated three times, leading to 3 repetitions \times 2 of populations (homogeneous and heterogeneous) \times 2 pedestrian flows (low and high), for a total of 12 simulations.

The preferred speeds and individual patience values are given for all distributions (figure 6.2). The colored red zone in each figure represents the length of the red light phase. It can be used as a global indicator of the number of pedestrians who are expected to cross at red lights if pedestrians arrive at the start of the red phase and if social influence does not alter their patience. The pedestrians below this colored red zone are more likely to violate the pedestrian light. The number of pedestrians with $IP > 45$ s is 19 (resp. 49) for $n = 10$ (resp. $n = 40$), which leads to violation rates of 31.67% (resp. 20.41%). These percentages correspond to the violate rates if pedestrians arrive at the beginning of the red phase and if social influence does not modify their patience.

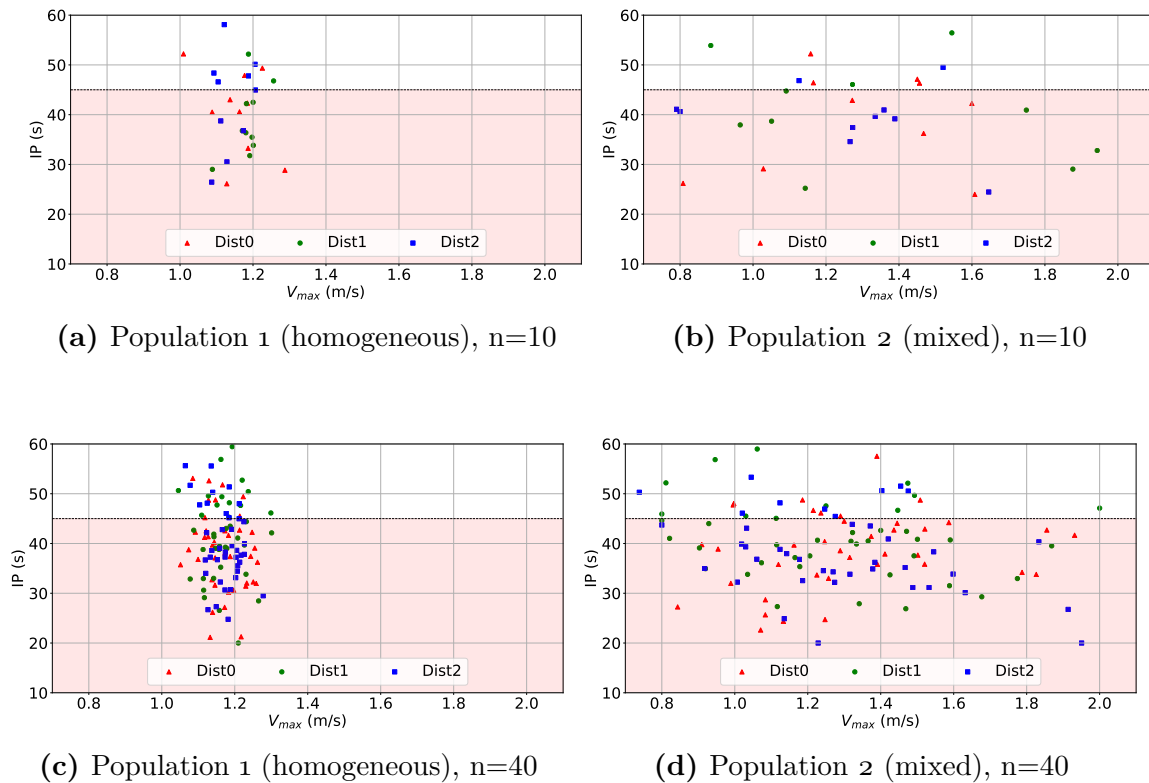


Figure 6.2: Individual patience and desired pedestrian's speed used for the simulations. Pedestrians are categorized with homogeneous and mixed population, and with low and high pedestrian flow. The horizontal dotted line in each figure represents the duration of the red light phase.

6.2 Street crossing scenario with road traffic

This section presents the second scenario for pedestrian street crossing with road traffic and without a pedestrian light. The crossing location corresponds to an uncontrolled crosswalk at a mid-block intersection. To implement the street crossing model with this scenario, I present the scenario, the description of the virtual environment and the initial condition requirement in this section.

6.2.1 Scenario description

Pedestrians have different individual speeds and follow a predefined itinerary for pedestrians. The pedestrians follow the itinerary in a loop, and they are spawned to the initial position when they reach the end of the itinerary, forming the loop.

Pedestrians start perceiving oncoming vehicles when they reach the crossing location on the itinerary. If a pedestrian does not perceive any oncoming vehicle, he can cross immediately. Otherwise, they compare the time-to-contact of the oncoming vehicle to their crossing time, leading to a crossing decision. Pedestrians have the same walking and crossing speed and do not change their decisions once they start crossing.

The road traffic comprises vehicles with a constant speed, and the vehicles do not interact with pedestrians. The inter-distance between vehicles is different, using a uniform distribution. The vehicles follow a predefined itinerary for vehicles itinerary. The itinerary is also in a loop, making the vehicles lap in an infinite loop.

6.2.2 Virtual environment description

The crossing location is positioned on a mid-block street 188 m length and with two lanes with a width of 4.1 m each (Figure 6.3). At this crossing location, a pedestrian can perceive up to 60 m. It is described as the maximal distance for a normal pedestrian to accurately estimate the speed of an oncoming vehicle [YS21]. In this scenario, I only consider one lane, and pedestrians based their decision on the width of one lane.

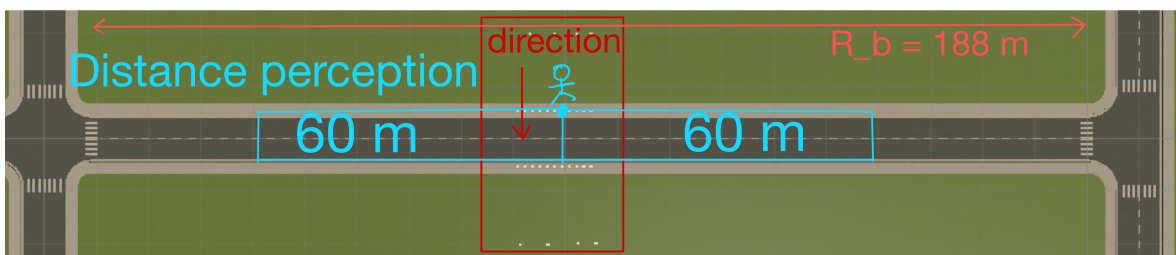


Figure 6.3: Crossing point position on the road.

Pedestrians follow 4 successive positions in their itinerary: (P_0) a position behind the crossing location, (P_1) the crossing location, (P_2) the sidewalk on the other side of the street, and (P_3) a position in the front of the sidewalk (Figure 6.4). When the pedestrians reach P_3 , they are spawned to P_0 .

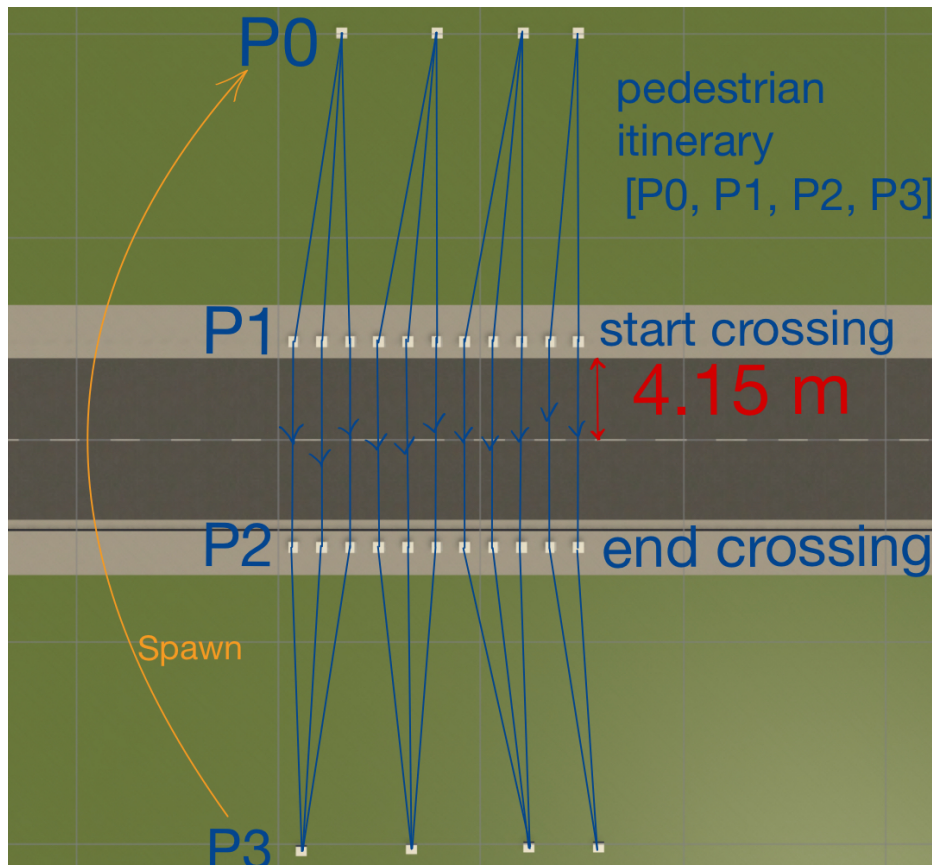


Figure 6.4: Pedestrian itineraries.

Regarding the road traffic, the vehicles follow an itinerary of 752 m, composed of three roads ($R_1 = 188$ m, $R_2 = 188$ m and $R_3 = 376$ m). The crossing is only on one lane, so the vehicle moves in one direction, from right to left. The crossing location is positioned on the road R_3 , in figure 6.5.

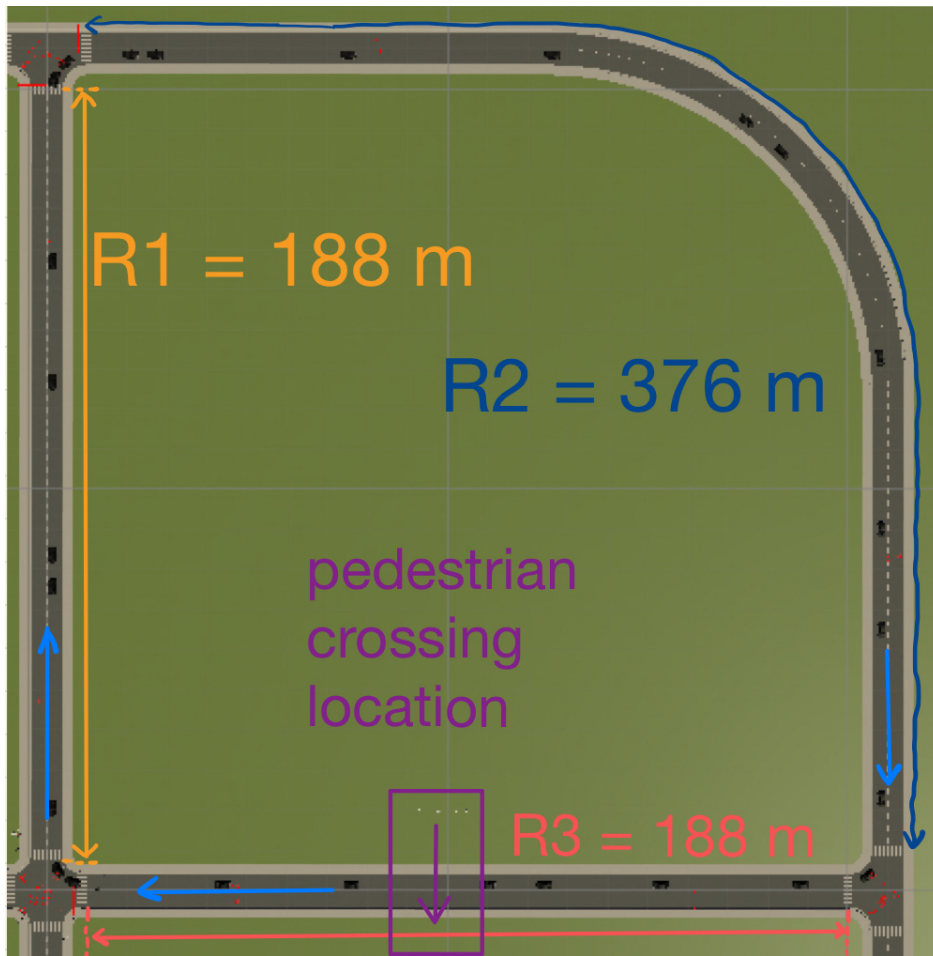


Figure 6.5: Presentation from eagle View of virtual environment.

6.2.3 Initial conditions

I ran three distributions of pedestrian speeds and three distributions of gaps. Then, I used the six distributions to simulate the standard and biased time-to-contact models, leading to a total of 18 simulations. Each simulation lasts 600 simulated seconds, with a fixed time-step of 0.1 s. Finally, I removed the first 100 s as a warm-up for the data analysis.

6.2.4 Pedestrian perception setup

I set the perception of neighbors as in section 6.1.2, with maximal perceived neighbors set to 10, and a maximal distance set to 10 meters. Regarding the perception of the oncoming vehicle, the maximal perception distance is set to 60 meters ($AP2$), based on the perception limit of a moving vehicle [YS21]. I do not limit the number of vehicles inside the $AP2$ area, since the number of oncoming vehicles inside $AP2$ would not be

greater than ten in these simulations. To illustrate it, let us consider a vehicle speed of 40 km/h, which is close to the average vehicle speed on an arterial road in an urban city in France (42,3 km/h in 2020) [ON120], with an inter-vehicular time of one second. A vehicle's length of five meters would lead to a total of four vehicles, inside the 60 meters of perception distance. Each pedestrian processes the neighbors and the oncoming vehicles are based on the closest distance.

6.2.5 Pedestrian speed distribution

To compare the results of these simulations with experimental data, I set up the simulated pedestrian's speed with the subjects' speed during experimentation for street crossing realized by [LCog]. [LCog] developed a street crossing experimentation, and they invited subjects to cross a street between two oncoming vehicles with a constant speed.

Table 6.1 shows the results of the gap selected by all participants. The results indicate that young pedestrians choose approximately the same gap, with different vehicle speeds. Young male pedestrians were very consistent when they estimated the gap. Thus, to avoid the possible ambiguity between distance and speed as the visual cue used to take a decision, I chose the average speed of young male pedestrians in these simulations.

Table 6.1: Average gap selected by subjects during street crossing experimentation realized by [LCog].

		40 km/h		50 km/h		60 km/h		Mean	
		avg(s)	std(s)	avg(s)	std(s)	avg(s)	std(s)	avg(s)	std(s)
20-30	Women	3.51	1.3	3.24	1.1	3.25	1	3.34	1.1
	Men	3.26	1.3	3.20	1.4	3.22	1.1	3.23	1.2
60-70	Women	4.14	0.9	3.71	1	3.53	0.7	3.79	0.9
	Men	4.17	1	3.78	0.9	3.53	0.9	3.83	1
70-80	Women	4.68	1.7	3.95	1.2	3.65	1	4.09	1.4
	Men	4.73	1.3	4.23	1.2	3.83	1	4.26	1.2

Table 6.2 presents the crossing time of pedestrians. The average crossing time for men pedestrian is 3.97 s, and the street width is 4.2 m; this leads to an average speed of 1.06 m/s. Then, with a standard deviation of 0.4 s, the lowest and highest crossing times are $3.97 - (0.4 \times 3) = 2.77$ s and $3.97 + (0.4 \times 3) = 5.17$ s. That leads to the lowest and highest pedestrian speed of 0.81 m/s and 1.51 m/s.

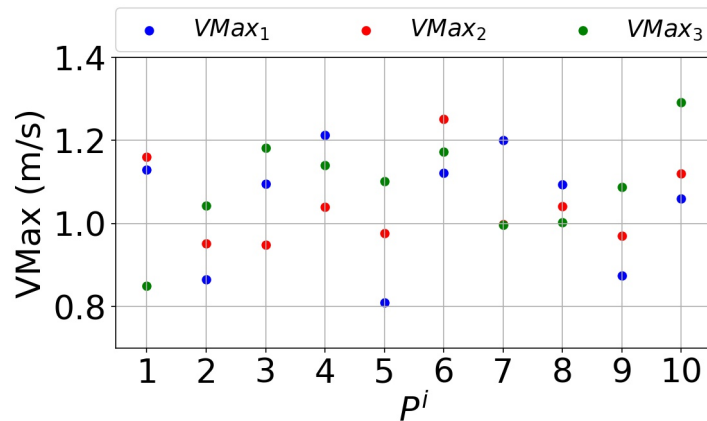
Table 6.2: Average crossing time by subject during street crossing experimentation was realized by [LC09], with the width of the street 4.2 m.

		40 km/h		50 km/h		60 km/h		Mean	
		avg(s)	std(s)	avg(s)	std(s)	avg(s)	std(s)	avg(s)	std(s)
20-30	Women	3.95	0.6	3.93	0.6	3.89	0.5	3.92	0.6
	Men	3.98	0.4	3.96	0.4	3.96	0.4	3.97	0.4
60-70	Women	4.49	0.3	4.52	0.3	4.55	0.3	4.52	0.3
	Men	4.18	0.4	4.23	0.4	4.24	0.4	4.21	0.4
70-80	Women	4.53	0.2	4.57	0.2	4.61	0.2	4.57	0.2
	Men	4.44	0.4	4.58	0.4	4.65	0.4	4.55	0.4

In the following, I used the normal distribution in (equation 6.5) for the distribution of pedestrian speed. Then, I limited the pedestrian speed to 0.81 m/s and 1.51 m/s, according to their crossing times in [LC09].

$$V \begin{cases} V \in \mathcal{N}(\mu = 1.06 \text{ m/s}, \text{std} = 0.15 \text{ m/s}) \\ V_{min} = 0.81 \text{ m/s} \\ V_{max} = 1.51 \text{ m/s} \end{cases} \quad (6.5)$$

For the sake of generality, three distributions of speed were used, and each distribution for a different simulation. Figure 6.6 shows the speeds of the 10 pedestrians for the three distributions $VMax_1$, $VMax_2$, and $VMax_3$.

**Figure 6.6:** Pedestrian speed $VMax$ for the three distributions $VMax_1$, $VMax_2$, and $VMax_3$.

6.2.6 Gap distribution

[INo8] observed the gap selected by pedestrians when the pedestrians crossed a street of 7 m. [INo8] also found that 92% of the pedestrians would cross if the gap between vehicles exceeds 7 s, and no one would cross if the gap was below 1.5 s.

Computing gaps between two vehicles requires the speeds and the distances between two successive vehicles. During their experimentation on pedestrian street crossings, [LC09; Ox1+05] used three vehicle speeds: 40, 50, and 60 km/h, and each time the vehicle has constant speed.

I need a minimal and maximal values of gap to run a uniform distribution of gaps. The maximal distance perception of an oncoming vehicle was set to 60 m, and I chose the three vehicle speeds 40, 50, and 60 km/h used by [LC09] in their experimentation. From the minimal and maximal gaps presented by [INo8], I identified the travel distance for each gaps from the minimal value 1.5 s until the travel distance exceeded the 60 m. Since [INo8] had a wider road (7 m) compared to the width of the road in my simulation (4.1 m), I reduced the minimal gap to 1 s. Table 6.3 presents the travel distance with the three vehicle speeds and with the different values of gaps. Then, I collected the first gap when the travel distance exceeded 60 m. 6 s for 40 km/h and 5 for 50 and 60 km/h. I use 5 and 6 s for the maximal value of the gap for each vehicle speeds.

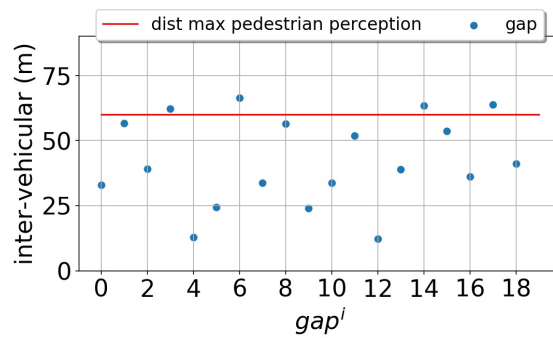
Table 6.3: Identification travel distance for different gaps (1, 1.5, 5, and 6 s) and different vehicle speeds (40, 50, and 60 km/h). 60 m is the maximal perception distance of an oncoming vehicle.

vehicle speed	1 s	1.5 s	5 s	6 s
40 km/h \approx 11.11 m/s	11.11 m	16.67 m	55.55 m	66.66 m > 60 m
50 km/h \approx 13.89 m/s	13.89 m	20.84 m	69.45 m > 60 m	83.34 m >> 60 m
60 km/h \approx 16.67 m/s	16.67 m	25.01 m	83.35 m > 60 m	100.02 m >> 60 m

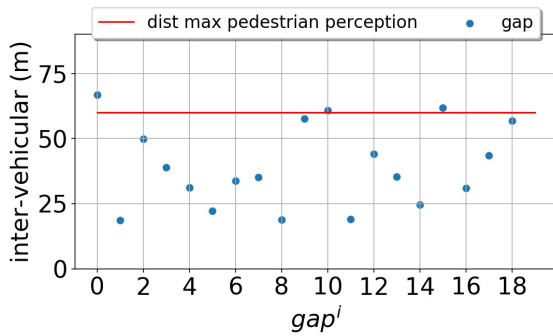
I run three samplings from uniform distributions of the gaps using the minimal and maximal value of gaps chosen, selected for each vehicle speed, in table 6.3. Figure 6.7 presents the three samplings of the inter-distance $inter - dist_1$, $inter - dist_2$ and $inter - dist_3$ for the three different VCar 40, 50 and 60 km/h. Each gap in the sampling has an ID gap^i on the horizontal axes. The number of $gap^i + 1$ lead to the number of vehicles during a simulation. The vertical axis is the inter-vehicular distance. The

horizontal red line in each figure is the maximal distance of perception on an oncoming vehicle (60 m).

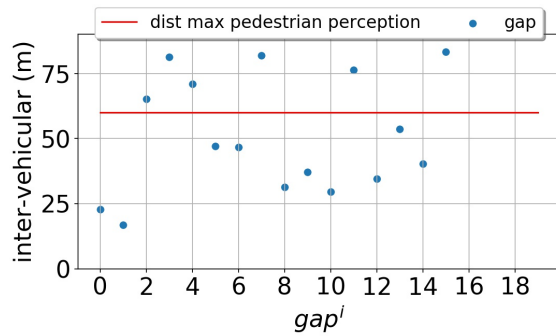
The number of vehicles is not the same for every sampling, since it depends on the space available on the vehicle itinerary and the distance between them. The samplings for 40 km/h indicate that most inter-vehicular distances are lower than 60 m. It means that each pedestrian should find a gap for crossing. For 50 and 60 km/h, the inter-vehicular distance can be above 60 m. In this case, pedestrians would not see the oncoming vehicle and cross immediately.



(a) VCar = 40 km/h.



(b) VCar = 50 km/h.



(c) VCar = 60 km/h.

Figure 6.7: Inter vehicular distance for VCar = 40, 50 and 60 km/h, for the three inter-distance samplings $dist_1$, $dist_2$ and $dist_3$. x-axis is the ID of each gaps during the sampling, and y-axis is the inter-vehicular distance.

6.3 Conclusion

This chapter presents the scenario, design, and initial condition requirements for the street crossing model implementation. The street crossing model is simulated under two scenarios: the first one scenario is with a pedestrian light and without road traffic, and

the second one scenario is with road traffic and without a pedestrian light. The value of individual patience can produce a portion of pedestrians violating the pedestrian light, as required in the first scenario. Regarding the second scenario, each pedestrian would find an adequate gap for crossing. The model and the virtual environment have been developed, and agent parameters are set. Thus, I can run the simulations and present the results in the next chapter.

Chapter 7

Street crossing simulations

In the last two chapters (5 and 6), I developed a street crossing model and presented a scenario to assess the model. In this chapter, I present the results of the simulations, addressing the objective of increasing the heterogeneity of pedestrian behaviors during street crossings. The street crossing model is developed under two scenarios: the first is a street crossing with a pedestrian light and without road traffic, and the second scenario is a street crossing with road traffic but without a pedestrian light.

In the first scenario in section 7.1, pedestrians base their decision to cross on the perception of the light traffic color and the perception of their neighbors' behaviors (crossing/ waiting). The perception of neighbors' behavior influence pedestrians, leading to a modification of patience. The pedestrian decides to cross the street at some moment of time to break the traffic laws. Thus, I propose a function that combines the number of crossing and waiting neighbors; this function modifies the individual's patience.

In the simulations, when exploring the crossing decision of pedestrians arriving at the crossing location at the red light, some of the pedestrians who violated the traffic rules had individual patience longer than the remaining red light duration. This means they are initially expected to cross at the green light and would not have crossed at the red if they have not been influenced, so they were negatively influenced. Conversely, some of the pedestrians who crossed at the green light had individual patience shorter than the duration of the remaining red lights. This means they are initially expected to cross on red and would have crossed on red if they had not been influenced, so they were positively influenced. In my simulations, most pedestrians were positively influenced. To analyze the consistency of the results, I compared the crossing decision in my model and with a standard patience model, where individual patience is constant, and pedestrians cross at red lights if their individual patience runs out. I also compared the violation rates produced by the model with violation rates published in the literature,

which indicates fewer illegal crossings than legal crossings. In the initial version of the model, the social influence function, which modifies the individual patience, does not allow the simulation with different time steps, limiting the usability of the model for real-time simulation. Thus, I developed a new function in the context of a group crossing in virtual reality.

Regarding the scenario with interaction with road traffic and without a pedestrian light in section 7.2. In this scenario, the vehicles do not interact with pedestrians. I assume that the model's hypothesis demonstrated in the scenario with a pedestrian light is still valid without a pedestrian light: seeing someone crossing or waiting influences pedestrians on their decisions. Moreover, pedestrians do not have patience but waiting time. Without patience, a pedestrian crosses immediately when a crossing opportunity arise. They also behave differently depending on how long they wait on the sidewalk. For crossing decisions, pedestrians compare the estimation of the time-to-contact with an oncoming vehicle (TTC) with their estimation of crossing time ($TPed$). Then, the estimation of the time-to-contact of the oncoming vehicle is modified based on the waiting time of the pedestrians and the behaviors of neighbors (social influence). This modification of TTC leads to several types of behavior: crossing safely, crossing unsafely, missing the crossing, and crossing impossible.

In my simulation, some pedestrians decided to cross even though they did not have the speed required to do so safely. Some others missed the crossing, even though they had the speed required to cross safely. To analyze the consistency of my results, I compared my results with different works with similar initial conditions. First, I compare the gap observed by pedestrians when they decide to cross with the results of gap selected by pedestrians at a street crossing experimentation realized by [LC09]. Then, I compared the percentage of unsafe crossing decisions with an observation realized by [Jay+20]. Finally, I compare the negative margin during the unsafe crossing decision with the result of an experimental street crossing realized by [Oxl+05].

7.1 Street crossing: scenario with a pedestrian light

7.1.1 Crossing violation rate

Pedestrians have individual patience (IP) initialized with normal distribution. When pedestrians wait at the crossing location, their modified patience by social influence (MIP) is initialized with IP . MIP can evolve depending on the social situation, but the increase is limited by a parameter model patience threshold (PT). After waiting

some time (WT), pedestrians decide to cross if $MIP < WT$, or the light traffic color turns to green. The pedestrian light turns in a loop (color cycle), with 45 s of red and 15 s of green, and a violation occurs if the pedestrian crosses at the red light.

Table 7.1 presents the crossing violation rates for all simulations. “Expected” is the decision based on the difference between the individual patience (IP) and the remaining red light duration when a pedestrian arrived in the waiting zone. “Observed” refers to the decision made by pedestrians when they cross. “V1” represents the violation percentage of all pedestrian crossings (crossing on red VS crossing on green). “V2” the violation rate restricted to pedestrians arriving at red lights and compared those who crossed and those who did not. P is the standard patience model, and SI is the social influence and patience model. SI_1 is for the defined weight for waiting and crossing: $p_C = 0.5$ and $p_W = 0.5$. SI_2 is for $p_W = 0.1$ and $p_C = 0.9$. The modified individual patience $MIP^i(t)$ is initialized with the individual patience IP^i , and limited by a model parameter threshold PT :

$$MIP^i \leq IP^i \times PT \quad (7.1)$$

Table 7.1: Crossing rate violations for all simulations. The standard patience model is denoted P , while the social influence model is denoted SI , with PT representing the patience threshold. SI_1 is the social influence model with parameter for $p_C = 0.5$ and $p_W = 0.5$, and SI_2 for $p_C = 0.9$ and $p_W = 0.1$. H and M refer to the homogeneous and mixed population. n refers to the number of simulated pedestrians

			Expected		Observed			
Pop	Models	PT (%)	Red phase only PV (%)		Global V_1 (%)		Red phase only V_2 (%)	
			n=10	n=40	n=10	n=40	n=10	n=40
H	P		23.96	34.33	9.50	18.46	23.96	34.33
	SI_1	110	31.27	33.53	9.03	11.98	24.57	22
		120	33.16	33.87	7.46	6.91	20.53	13.45
	SI_2	110	28.16	31.75	12.23	14.08	32.65	26.31
		120	29.17	34.39	10.83	10.08	27.08	20.25
	M	P		6.91	14.52	5.28	9.67	6.91
SI_1		110	8.77	14.73	5.09	6.74	6.71	10.03
		120	8.25	15.10	3.12	4.90	4.12	7.44
SI_2		110	8.70	15.09	5.09	8.45	6.65	12.52
		120	7.23	15.35	2.74	9.92	3.61	14.23

“Expected” is the decision resulting from the difference between the individual’s patience and the remaining time of the red light when pedestrians begin to wait at the crossing location. The “Expected” is the result with the standard patience model or when $\Delta = 0$. The percentage of violation (PV) is the result of the total expected in red and the total expected in green. “Observed” is the percentage violation. V_1 percentage violation when comparing the number of pedestrians crossing at a red light and the crossing at green lights. V_2 is the percentage violation when comparing the number of pedestrians crossing and waiting at red lights.

Before presenting my results, I analyze the consistency of my results by comparing the “Expected”, and the “observed” V_2 decision with the standard patience model, where the patience is constant. The results show the same violation rates for both.

To verify the assumption that the patience can evolve, I compare whether the patience changed when they cross. The comparison of the violation rates between “Expected”, and the V_2 indicates lower V_2 values, meaning the individual patience is modified, and the pedestrians are more influenced by waiting pedestrians rather than crossing pedestrians. These results are consistent with the observation realized by [Ros09] that waiting pedestrians have greater power than crossing pedestrians. In other words, a positive influence can have more impact than a negative influence.

According to the literature review, the percentage of rule-followers is lower than rule-breakers in real life. For example, the violation rates in major European cities are around 20 to 25% [Die19]. The average expected violation for all my simulations is 21.412%. The observed violation for all simulations is 16.594%, lower than the average, so that it can correspond to a neighborhood with more rule-following pedestrians. Moreover, the violation rate is low compared to the initial conditions: the average waiting time is about 40 s and the red light length (45 s). However, the violation also depends on the arrival time on the sidewalk.

To see the impact of the collective situation, I compare the violation rates for the homogeneous H and the mixed M population. The two populations have different speeds. The H population has a lower average and lower standard deviation speed, and the M population has a higher average and higher standard deviation speed (section 6.1.3). The results indicate that the H population has greater violation rates than the M population. Indeed, the pedestrian’s speed in the H population has a small standard deviation ($SD = 0.05$ m/s). This leads to the formation of groups walking at approximately the same speed, which leads to higher violation if someone in the group has low individual patience and the patience threshold is not large enough to

maintain the impatient pedestrian for waiting. On the other hand, there was a larger standard deviation ($SD = 0.3$ m/s) in the M population. This condition leads to more individual crossings, and the more impatient pedestrians have less influence on other pedestrians.

As expected, the model parameters have an impact on the violation rates. Increasing the threshold PT decreases the violations in V_1 and V_2 for most simulations. This is because pedestrians wait longer and have more positive influence on each other. Moreover, the violation rate decreases less in population H than in population M , for the same condition. Indeed, people in population M are more likely to cross alone than people in population H , so the change in PT does not greatly alter the decision to cross. Parameters p_C and p_W also impact the crossing violation rate. By giving more weight to the crossing than waiting pedestrians ($p_C > p_W$), people are more likely to follow someone crossing illegally.

The difference between the violation rate V_2 and the violation rate “Expected” indicates the individual’s patience is modified in the social influence model. Pedestrians tend to wait longer than what would have happened if they were alone. The present results do not show whether a pedestrian wanted to violate the traffic law and decide to wait, or wanted to wait and decide to violate. I present this discrepancy in behaviors in the following.

7.1.2 Impact of social influence on crossing decision

When social influence modifies pedestrians’ individual patience, they may have different expected and observed decisions. To quantify the difference between the two decisions, I denote “R” for the pedestrian light color red and “G” for green, and the combination of the two letters forms the two decisions. The combination leads to the creation of four classes: “RR”, “RG”, “GR” and “GG”. The descriptions of each class are in table 7.2. The percentages of all simulations in each of the four classes (“RR”, “RG”, “GR”, and “GG”) are shown in the tab 7.3.

Table 7.2: Denotation of the expected and observed crossing decisions in table 7.2.

Label	Description
Green-Green (GG)	Crossing at the green light expected, observed crossing at the green light
Green-Red (GR)	Crossing at the green light expected, observed crossing at the red light
Red-Red (RR)	Crossing at the red light expected, observed crossing at the red light
Green-Red (RG)	Crossing at the red light expected, observed crossing at the green light

Table 7.3: Proportion of crossing violations for each crossing class: RR, RG, GR, GG for each experimental condition of the Social Influence model, for all simulations.

Pop	Models	<i>PT</i> (%)	RR (%)		GR (%)		GG (%)		RG (%)	
			n=10	n=40	n=10	n=40	n=10	n=40	n=10	n=40
H	<i>P</i>		23.96	34.33	0	0	76.04	65.67	0	0
	<i>SI</i> ₁	110	21.41	22	3.16	0	65.57	66.47	9.87	11.53
		120	17.16	13.45	3.37	0	63.47	66.13	16	20.43
	<i>SI</i> ₂	110	20.76	21.68	11.89	4.63	59.95	63.62	7.4	10.07
		120	16.67	16.46	10.42	3.8	60.42	61.82	12.5	17.93
M	<i>P</i>		6.91	14.52	0	0	93.09	85.48	0	0
	<i>SI</i> ₁	110	6.71	10.03	0	0	91.23	85.27	2.06	4.71
		120	4.12	7.44	0	0	91.75	84.9	4.13	7.66
	<i>SI</i> ₂	110	6.65	11.31	0	1.2	91.3	83.71	2.05	3.78
		120	3.61	8.38	0	5.89	92.77	78.76	3.62	6.97
mean	(<i>P</i>)		15.44	24.43	0	0	84.46	75.58	0	0
mean	(<i>SI</i>)		12.14	13.84	3.61	1.94	77.06	73.84	7.2	10.39

The results show that the sum of $GR + RG > 0\%$ for the social influence and patience model, and $GR + RG = 0\%$ for the standard patience model. This means that the patience has been modified for *SI*. Moreover, the sum of $GR + RG$ is lower than the sum of $RR + GG$ for *SI* model. This means that pedestrians who have different expected and observed crossing decisions are a minority. However, if a pedestrian has the same expected and observed crossing decision, it does not mean the pedestrian has not been influenced. It means the pedestrian has not been influenced enough.

The model's parameters impact the proportion of crossing violations. The number of violations is higher with *SI*₂ than with *SI*₁, with a higher weight on the influence of crossing pedestrians. For instance, with 40 pedestrians, the mean *RR* is 13.23% with *SI*₁, and 14.46% with *SI*₂. More importantly, the proportion of pedestrians who predict they will wait (based solely on patience) and then cross rises from $GR = 0.00\%$ with *SI*₁ to $GR = 3.88\%$ with *SI*₂. The proportion of crossing violations also seems to depend on the *PT* threshold: there are more crossing violations with a lower *PT*.

Looking at the crossing classes, several trends can be highlighted. First, the *GG* percentage is always lower in the homogeneous population (between 60% and 70%), compared to the mixed population (between 80% and 90%), meaning that the *H*

population appears to be more rule compliant than the M population; they have lower speed and have a lower number of crossings compared to the M population.

The percentage of RR violations with the P model is always greater than with the SI model, indicating that waiting pedestrians influence more than crossing pedestrians in the SI model (SI_1 and SI_2). The differences between the two models are higher with 40 simulated pedestrians than with 10 simulated pedestrians, due to the greater impact of social influence on a higher number of neighbors. The GR is always zero in the P model, as expected.

Presenting the percentage of all simulations that differ between the expected and observed crossover decisions helps quantify the impact of the model globally. In the next section, I present some illustrations of the impact of social influence at an individual level.

7.1.3 X/Time diagrams of crossing pedestrians

The crossing decisions of pedestrians are impacted by the pedestrian light colors and the behaviors of their neighbors (crossing/ waiting). If the pedestrian light color is green when they arrive, the pedestrians cross. Otherwise, they wait until their individual patience runs out. Figure 7.1 shows an example of X/Time representation of pedestrians crossing the street from the waiting zone (bottom of the figure) to the other side of the street (top of the figure). The time represented is one cycle of the pedestrian light (45 s for red and 15 for s green), which is used as a background for the figure. The waiting zone's dimensions are $6.20 \times 2.40 m^2$, and the street's width is $7.19 m^2$. The vertical axis is oriented to the opposite sidewalk, and the origin is set to the roadside near the waiting zone. The horizontal axis is set to the simulation time. Pedestrians are waiting at a red light are placed in two rows inside the waiting zone, described in section 6.1.2. Pedestrians crossing at a green light have their trajectory colored in green.

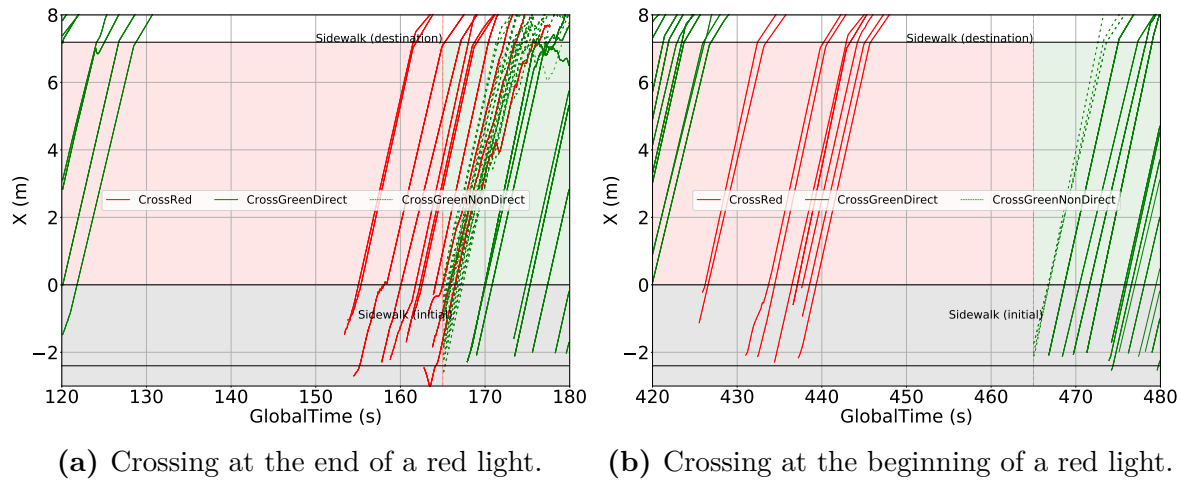


Figure 7.1: X/Time diagrams of crossing pedestrians. The vertical axis represents the spatial position X of pedestrians, and the horizontal axis is the simulation time. The color of the light (green or red) are displayed as a background of the figure. The origin of the vertical axis is set to the roadside near the waiting zone. The trajectories of the pedestrians start from the waiting zone, when they decide to cross, and each plot represents the trajectory of an individual. The color of the trajectories depend on the colors of the pedestrian light colors, when pedestrians decide to cross: green for pedestrians starting to cross at a green light and red for pedestrians starting to cross at a red light. If pedestrians cross at a green light, and they arrived a green light, then I named their crossings “CrossGreenDirect”, and their trajectories is plotted in a continuous green line. Otherwise, their crossing are indirect if they arrived at a red light and cross at a green light “CrossGreenNonDirect”, and their trajectories is plotted in a dashed green line.

Figure 7.1 illustrates different situations of crossings during different cycles (red and green phase) of a simulation that last 600 seconds and have 10 cycles in total. Three situations of crossing can happen. For the first situation, the pedestrians arrived at a red light and crossed at the red light “CrossRed”. For the second situation, the pedestrians arrived at a red light and crossed at a green light “CrossGreenNonDirect”. For the last situation, the pedestrians arrived at a green light and crossed immediately “CrossGreenDirect”.

Figure 7.1(a) illustrates several pedestrians crossing. The presence of “CrossGreenNonDirect” indicates that several pedestrians are waiting together while the pedestrian light color is red. Then, some of them decide to violate the traffic rules, and others decide to wait for the green light. This is interesting to see different pedestrians take opposite decisions (wait or cross) based on the perception of the same situation. Thus, they have different interpretation of the perceived situation. It is possible because

each pedestrian has his patience, and the modification of the patience is based on the patience at $t - 1$ and the social influence.

Figure 7.1(b) illustrates several pedestrians crossing together at the end of a green light. Some of these pedestrians have not finished crossing at the green light and continue at the red light (top left of the figure). At the same time, several other pedestrians arrived at the beginning of the red light and perceived these pedestrians crossing at the red light. This perception of pedestrians crossing at the red light influenced the new coming pedestrian to violate the traffic rules, leading them to cross at the beginning of the red light.

The X/Time diagram illustrates the individual decisions of pedestrians, and it shows when the pedestrians decide to cross and what color the pedestrian light is when they start to cross. The observation trajectories of pedestrians are consistent with the model's hypotheses, and these behaviors can be observed in a real situation. For one situation, some pedestrians can violate the pedestrian light after waiting 20 seconds [KO03]. For another situation, [Lip+13] found that pedestrians are more likely to violate the traffic laws with countdown for the first and last 4 seconds. In this scenario, there is no countdown, but seeing several pedestrian crossings may indicate to pedestrians coming onto the sidewalk that the color has just turned red, increasing the violation rate. Alternatively, [INo8] presented that pedestrians do not necessary become impatient after waiting a longer time, they may become more compliant because they know the pedestrian light will turn to green soon. The X/Time does not illustrate the evolution of individual pedestrians waiting on the sidewalk.

7.1.4 Evolution of patience modified by social influence

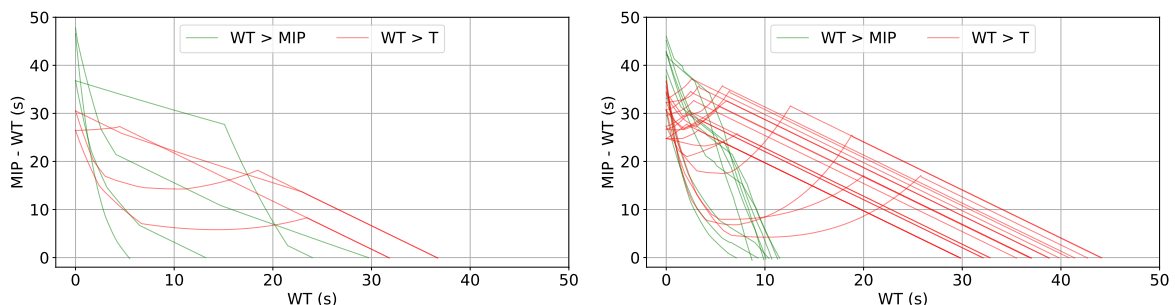
When pedestrians arrive at the crossing location at red lights, they can perceive the crossing and waiting neighbors. This perception leads to a social influence that modifies their patience MIP . Crossing neighbors influence them to violate the traffic rules and decrease MIP . Waiting neighbors motivate them to wait and increase MIP . Then, the pedestrians decide to cross if $MIP < WT$, meaning they lose patience.

Figure 7.2 illustrates the evolution of MIP of several waiting pedestrians for the patience and social influence model for 10 and 40 pedestrians. $MIP^i(0)$ starts from its initial value, the individual patience IP^i at waiting time $WT^i(0) = 0$, and stops when $MIP < WT$, meaning the pedestrian loses patience. Individual patience can increase or decrease according to the situation. The threshold PT limits the increase.

Thus, I denote the results with “WT>T”, if the pedestrians reach their threshold when crossing at red, and “WT>MIP” for the rest of the crossings.

If MIP reaches the threshold “WT>T”, MIP does not have a visible decrease anymore. This is due to the situation encountered by pedestrians, where the influence is mostly positive. Moreover, I limit the increase in MIP using the patience threshold T , so the MIP cannot have a too large values. Regarding the decrease, I do not allow the pedestrians to cross between their individual patience (IP) and (T) (section 5.4.4). Thus, MIP is outside (IP) and (T) for “WT>MIP”, then pedestrians tend to have shorter patience. In the other case, when MIP is inside (IP) and (T), pedestrians have longer patience.

These results show to allow patience to evolve. It can increase or decrease depending on the social situation. Pedestrians can have several crossing behaviors. Some wait for shorter waiting times, and others for longer waiting times. In a certain situation, pedestrians are influenced to cross, and they almost cross ($MIP - IP \approx 0$), but other pedestrians influence them to wait (Figure 7.2(b)). This behavior is difficult to compare in a real situation. To my knowledge, no work supposes that patience can evolve. In most situations, it is the waiting time that is measured.



(a) Number of simulated pedestrians 10.

(b) Number of simulated pedestrians 40.

Figure 7.2: Illustration of the evolution of the patience modified by the social influence MIP , with 10 (on the left) and 40 (on the right) simulated pedestrians, with the parameters of SI_2 , $PT = 120$, and the homogeneous population H. The pedestrian violates the pedestrian light if $MIP < WT$.

The formulation of individual patience has a limitation. It is not independent of the time step. I use a time step of 0.1 second for all simulations, and the result is not reproducible with different time steps. The non-player character (NPC) pedestrians

should be simulated in real-time for virtual reality applications. The pedestrian behavior should be the same at different time steps. This problem is addressed in the next section.

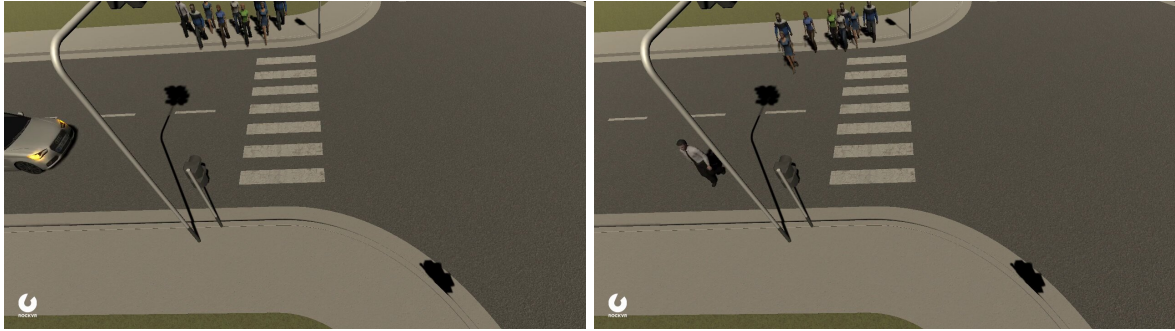
7.1.5 Influencing a group of NPC pedestrians to cross

Other pedestrians influence pedestrians in this simulation for their crossing decisions. To go further with the interaction, I wanted to see what happens if a person could influence the behaviors of the simulated pedestrians. To reach this goal, I have to make sure that the model can be simulated in real-time and produce the same behaviors with different time steps TS . The actual model could not produce the same evolution of patience with different TS . Thus, I have to create a new formulation.

The individual patience $IP^i(t + TS)$ depends on its precedent value $IP^i(t)$, and on the social influence Δ . I assume that patience of pedestrians is not linear, and it can evolve depending on Δ . If $\Delta > 0$ then pedestrians are influenced to wait; and if $\Delta < 0$, pedestrians are influenced to cross. If $\Delta = 0$, pedestrians are supposed to have constant patience. An exponential function meets this condition: it can receive negative or positive values, increasing with a positive value and decreasing with a negative value. Then, I weight the exponential to limit the evolution by a model parameter n . I tested empirically several values of n , and I could achieve the shape of the evolution of individual patience from the previous results with $n = 7$. The equation is:

$$IP^i(t + TS) = IP^i(t) \times e^{\left(\frac{\Delta^i(t) \times TS}{n}\right)} \quad (7.2)$$

I have developed a new scenario to test this new function. A group of NPC pedestrians accompanied by one bot controlled by an experimenter are waiting on the sidewalk. The bot is triggered by the experimenter to cross, influencing the rest of the group to cross (in figure 7.5). The NPCs and the bot have the same characteristics (speed, size, distance perception, and number of perceived neighbor maximal). The NPCs have individual patience, and the bot does not have individual patience since the experimenter triggers it.



(a) NPCs and bot waiting at the sidewalk. (b) The bot and a few NPCs start crossing.

Figure 7.3: Scenario simulation with nine pedestrians (bot and eight NPCs).

The individual patience of the NPCs is scripted using an arithmetic progression, where the difference between two consecutive IP is the parameter α . The experimenter chooses the number of NPCs (N) in the group, including the bot, and the individual patience IP_i of the first NPC in the group (ω):

$$\begin{aligned}
 IP^1 &= \omega \\
 IP^2 &= IP^1 + \alpha \\
 &\dots \\
 IP^N &= IP^{N-1} + \alpha
 \end{aligned}
 \tag{7.3}$$

The evolution of the individual patience was simulated with the new function, with different fixed time steps 0.01, 0.02 and 0.1 second, and the last one with variable time step, in real-time (Figure 7.4). In real-time, the time step is not fixed. It depends on the resources available on the computer and the duration of the execution of each step.

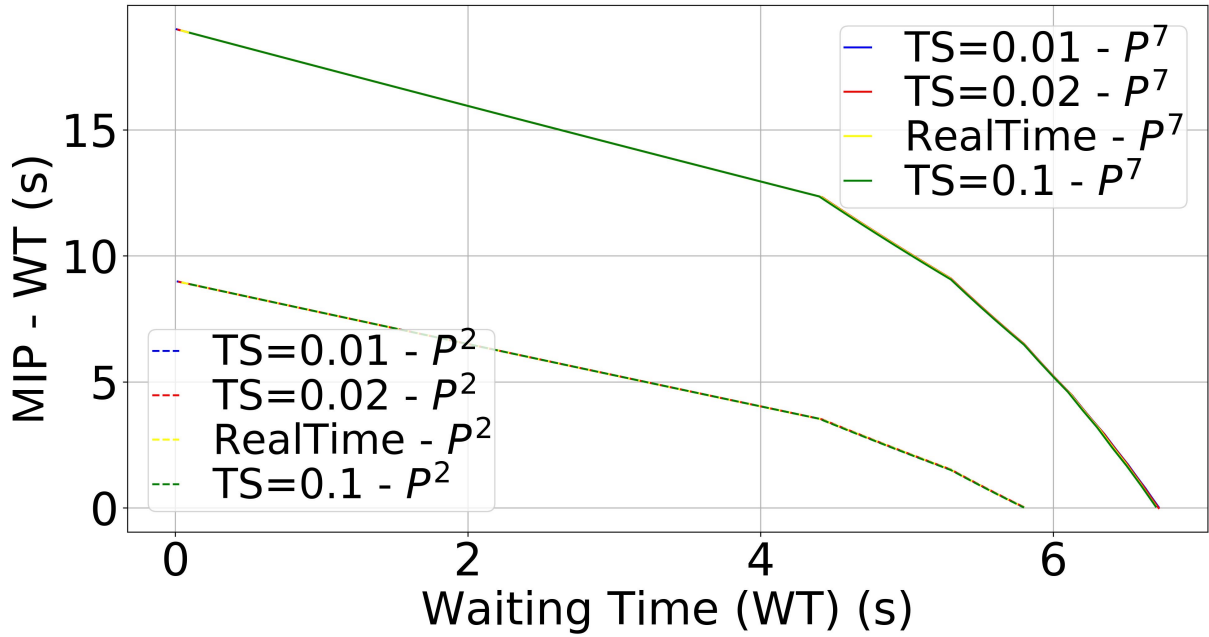


Figure 7.4: Comparison evolution of $MIP - WT$ of two NPC pedestrians (P^2 and P^7) from the group of pedestrians, with different TS values: 0.01 s, 0.02 s, 0.1 s and real-time.

Figure 7.4 shows that the crossing behavior of the group changes depending on the parameters set and not on different time steps. In figure 7.5(a), the whole group crossed almost at the same time. The individuals in the second group crossed more sequentially in figure 7.5(b). The crossing time difference between the first, the second, and the third pedestrian was more than one second. This time difference is similar to the reaction time to the traffic signal, which is within one second according to [Fug+00].

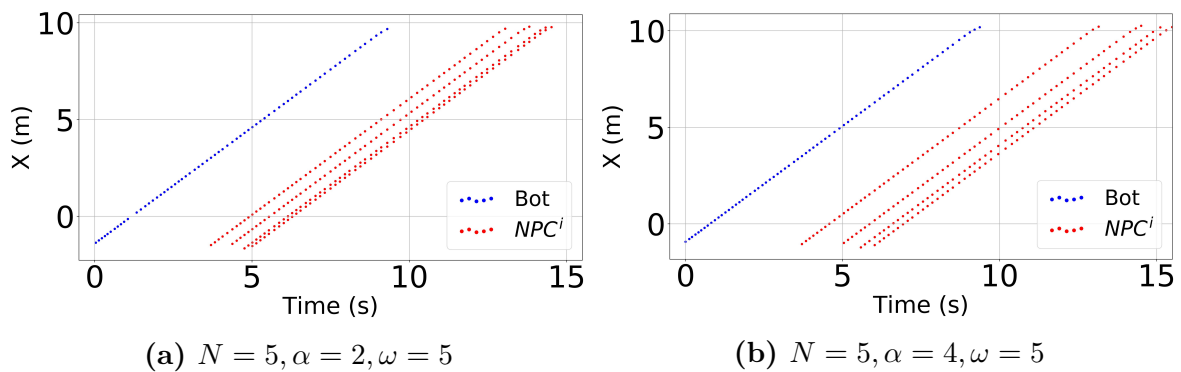


Figure 7.5: An illustration of the X/Time diagrams of four NPCs (red plots) and the bot (blue plots) a street.

The new formulation was tested with different time steps, using a scenario of a group of pedestrians crossing a street. The evolution of individual patience shows the same evolution with different time steps. Pedestrians behave differently in street crossing scenarios depending on the parameter values. This scenario could manage a group of pedestrians, and this could help social scientists experiment with pedestrian behavior. The results of this work were presented at an international [RAB21].

7.1.6 Conclusion from the scenario with a pedestrian light

My objective is to increase the heterogeneity of pedestrian's interaction, so they can adapt their behaviors according to the situations. In this first scenario in 6.1, pedestrians cross a street with a pedestrian light, and they base their crossing decision on the pedestrian light colors and the neighbor's behavior (crossing/ waiting). To achieve the objective, I have developed a patience model in which the neighbors' behaviors modify the individual patience of pedestrians. The model hypothesis is that crossing pedestrians influence pedestrians to cross, and waiting pedestrians encourage pedestrians to wait. If the pedestrians were not influenced, this would lead to a crossing decision sooner or later than expected. Based on the difference between the individual's patience and the red light remaining, a crossing decision can be expected when the pedestrians arrive at the crossing location and compare with when pedestrians cross the street. As a result, some pedestrians cross at red lights, although they are expected to cross at green lights; conversely, some cross at green lights. This means that the behavior simulated with this model is consistent with the hypothesis. Moreover, the percentage of crossing violations is similar to some observations of pedestrian behavior. The violation rate produced is approximately 16,594%, which is not far from the violation rate in the major European countries, which is between 20 to 25%.

Street crossings also include interaction with road traffic. I present in the following section the results of the street crossing model under the second scenario. A street crossing with road traffic and without a pedestrian light.

7.2 Street crossing: scenario with road traffic

In this second scenario, pedestrians cross a street with road traffic and without a pedestrian light. The road traffic is composed of several vehicles with a constant speed and different constant gaps between vehicles. The pedestrians base their crossing decision on the comparison of the time-to-contact and the crossing time if an oncoming vehicle

is perceived; they cross immediately if not. [Oxl+05; LC09] found during their experiment that pedestrians can have an inadequate crossing decisions. This inadequation of estimation can be caused by several factors (physiological, environmental, contextual, or social). In the proposed model, I suppose the influence from the behaviors of neighbors and the waiting time create a bias for the perception of the time-to-contact of an oncoming vehicle. The bias leads to four crossing behaviors (safe, unsafe, missed, and impossible), and these crossing behaviors are observed during experimental works [Oxl+05; LC09].

I start this section by comparing the gap observed by pedestrians during a simulated street crossing and the gap selected by pedestrians during an experimentation, realized by [LC09]. Then, I show that different crossing behaviors emerge in the simulations. Finally, the evolution of social influence and the bias on the crossing decisions while waiting to cross is illustrated.

7.2.1 Time-to-contact

The Gap is often used during pedestrian street crossings [Oxl+05; LC09]. Pedestrians estimate the time between two vehicles and their crossing time to decide to cross. [LC09] experimented with pedestrian street crossings with road traffic, constant vehicle speed, and without a pedestrian light. They invited pedestrians to cross a street in a virtual reality environment when they found the gap is enough. They proposed each pedestrian 8 different gaps (gap_{LC09}) and 3 vehicle speeds. gap_{LC09} were between 1 and 8 seconds, and the vehicle speeds were 40, 50, and 60 km/h. Then, they collect the gap selected by pedestrians (gap_{select}). During their experimentation, every pedestrian follows the same protocol.

The proposed time-to-contact model does not use the gap for crossing decisions. It compares the time-to-contact with an oncoming vehicle (TTC) and the crossing time of a pedestrian ($TPed$) for crossing decision. To compare the gap from simulations using my model and a gap model, I collect the gap observed gap_{obs} by pedestrians in the simulations when they decide to cross. Then I compare the gap_{obs} with the gap_{select} of [LC09].

In my simulations, pedestrians can cross in two situations. The first situation is when an oncoming vehicle is perceived, leading to a crossing “with interaction” with the oncoming vehicle. The second situation is “free of interaction” because no oncoming vehicle is perceived. Pedestrians can have gap_{obs} only if they cross with interaction and a leaving vehicle exits. Figure 7.6 shows the process of collection of the gap_{obs} .

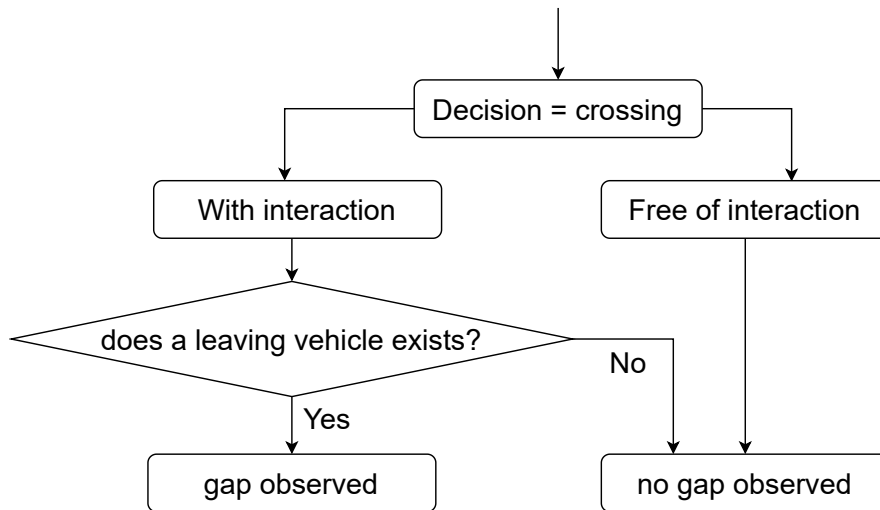


Figure 7.6: Process of collection of the gap observed

I compare the number of gaps observed and the crossings with interaction to see if it is statistically significant. Table 7.4 presents the total number of crossing, crossing with interaction with an oncoming vehicle, gap_{obs} , and crossing free of interaction. This table shows that almost all pedestrians crossings with interactions have a gap observed.

Table 7.4: Number of crossings, crossing with interactions, gap observed, and crossing free of interaction for all simulations.

vCar (km/h)	total crossing	with interaction	with interaction and gap observed	free of interaction
40	939	326	324	613
50	994	287	276	707
60	1104	167	164	937

Before comparing the gaps, let us look into the environment's configuration in my simulations and in [LC09] experimentation. Firstly, the width of the street for the two situations is approximately ≈ 4.2 m. Secondly, the crossing speed in these simulations are obtained from the crossing times of pedestrians during their experimentation, $\mathcal{N}(\mu = 1.06 \text{ m/s}, \text{std} = 0.15 \text{ m/s})$. Finally, the vehicle speeds are the same for the two situations (40, 50, and 60 km/h). The difference between the two situations is the gaps proposed to pedestrians. In this simulation, different gaps are proposed to the pedestrians. Between 1 and 6 seconds at 40 km/h, and between 1 and 5 seconds at 50 and 60 km/h. I use a uniform distribution for the gaps used to initialize the road

traffic along the itinerary, and the average gaps are about 3.5, 2.8, and 2.98 seconds for 40, 50, and 60 km/h. In their experimentation, they propose to each pedestrian 8 gaps between 1 to 8 seconds.

They did not have any unsafe decision, where a pedestrian selected a gap that led to a collision. In my simulation, some pedestrians had unsafe crossing decisions. Thus, I split my results into three groups. The first group includes the gap_{obs} observed with the bias β on the time-to-contact (“global” that is, with all the data). The second group includes the gap_{obs} observed with the bias β , restricted to the safe crossing decisions (“safe”). The last group includes the gap_{obs} observed with the time-to-contact “standard” model (unbiased). The average gaps for the three groups and the gaps from [LC09] are available in table 7.5.

Table 7.5: Comparison of the average gap_{obs} in simulations and gap_{select} in experimentation.

	40 km/h		50 km/h		60 km/h		all speeds km/h	
	μ (s)	std (s)	μ (s)	std (s)	μ (s)	std (s)	μ (s)	std (s)
[LC09]	3.26	1.3	3.20	1.4	3.22	1.1	3.23	1.2
Standard	4.13	0.86	3.44	0.5	2.88	0.39	3.48	0.58
Global	4.34	1.12	3.59	0.73	3.06	0.8	3.66	0.88
Safe	4.52	1.0	3.74	0.57	3.41	0.65	3.89	0.74

The average gaps show that “safe” biased crossings have the highest gaps values. It is expected because most pedestrians overestimate the TTC during safe crossings. “global” also higher than “standard” unbiased gaps, meaning that pedestrians tend to be more cautious when using the bias on the perception on TTC . At the general level, “standard”, “global”, and “safe” indexes tend to be higher than the $gap_{selected}$ from [LC09]. This difference may be due to the distribution of gaps proposed to pedestrians. They proposed 8 gaps between 1 to 8 seconds, and participants were invited to cross with each of the 8 gaps. In my simulations, pedestrians have proposed gaps from a uniform distribution and may not experience the small gaps. According to [INo8], pedestrians can start to cross with a gap of 1.5 seconds. This leads to higher gaps in my simulations.

Let us examine the gaps in more details. Figure 7.7 presents the cumulative values of the gaps. In this figure, the x-axis is the gap, and the crossing decision probability is on the y-axis. The curve increases from 0 to 1 crossing probability, based on the gap selected by participants. Probability 0 means no pedestrians are crossings, probability

1 means all pedestrians are crossings. The continuous line is the curve computed from [LC09], and the dashed line from the simulation (standard in triangle, global β in square, and safe crossings in triangle), in table 7.5. I also present in this figure the results for my simulations at 40, 50, and 60 km/h.

Overall, the shapes of the curves are similar. They start to increase around 2 seconds and reach the maximal probability around 5 seconds. No one can cross when the gap is lower than 1.5 seconds, and 92% of the pedestrians cross when the gap reaches 7 seconds [INo8]. All simulations and the experimentation have approximately the same high probability above 5 seconds. In my simulations, pedestrians did not necessarily encounter low gap situations, decreasing the probability for a gap lower than 5 seconds. Then, the probability increases because the average gap_{obs} for 40 km/h is around 4 seconds, so most pedestrians cross around the 4 seconds (table 7.5). For 50 and 60 km/h, the gap_{obs} has a low standard deviation, and the curves do not increase gradually like the other curve with different vehicle speeds.

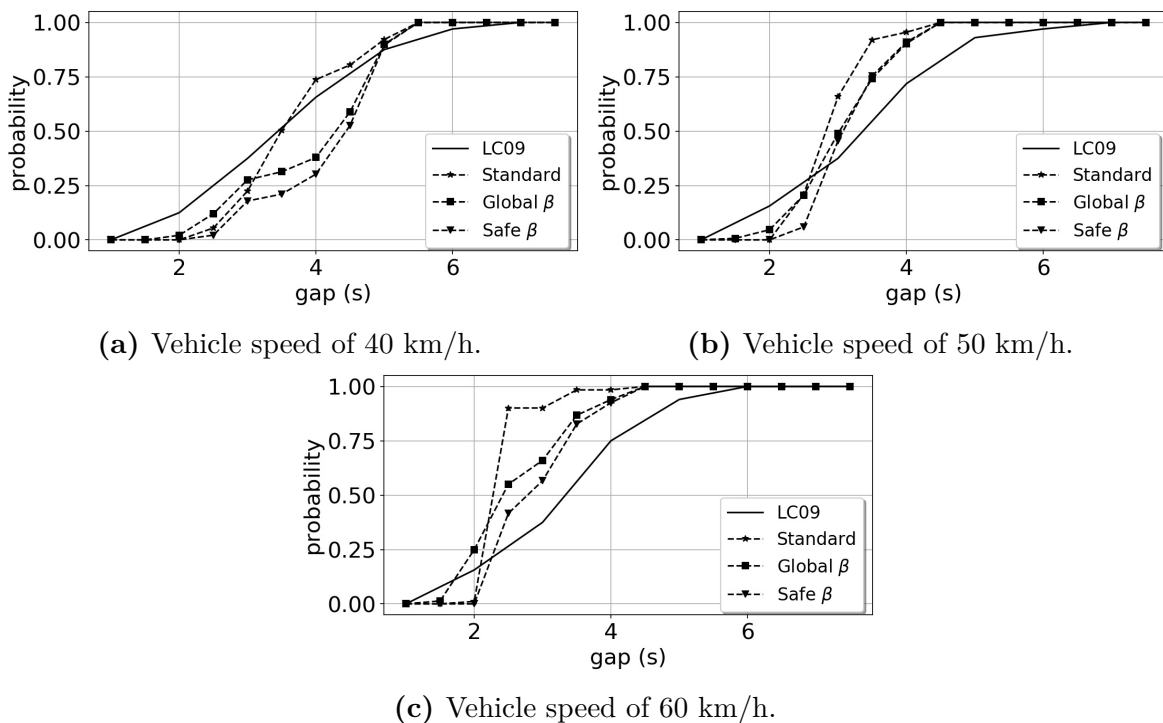


Figure 7.7: Comparison of the cumulative gap from [LC09] and our simulations. The gap_{obs} shows the average of all simulations. The gaps are sorted by the three vehicle's speeds.

7.2.2 Presentation of the different crossing behaviors

In this model, I use a bias β to modify the perception of the time-to-contact TTC of the pedestrian during a street crossing decision. The model allows pedestrians to have four types of crossing behaviors: “safe”, “unsafe”, “missed”, and “impossible”. The two first: “safe” and “unsafe” are defined based on the margin from the difference between TTC and $TPed$, when a pedestrian decides to cross. If $TTC > TPed$, then it is “safe”, and otherwise, it is “unsafe”. The two last: “missed”, and “impossible” are related to the capacity of pedestrians to cross. If a pedestrian decides to wait but $TTC > TPed$, it is a missed crossing; otherwise, it is an impossible crossing.

To check whether these four behaviors can be found in the simulations, with the proposed model, I decompose the crossing condition $TTC \times \beta \geq TPed$, using variables $T = \frac{TPed}{TTC}$ and β (Table 7.6). This gives to a 2D representation of each 4 crossing behaviors, with a definite definition domain. The “safe” behavior happens only if two conditions are meet: $1 \geq \beta > T$ (E) and $\beta > 1 > T$ (F). Intuitively, “safe” crossing would be (F), since the pedestrians overestimate when β is below one; but when an oncoming vehicle is further away $TTC \gg Tped$, even an underestimation would not lead to an unsafe crossing. The second “unsafe” behavior happens with only one condition $\beta > T > 1$ (A), during an underestimation of the TTC . The third behavior, “missed” is possible with one condition: $1 \geq T > \beta$ (D). The fourth (“impossible”) happens for two conditions: $T > \beta > 1$ (B) and $T > 1 > \beta$. “impossible” and “safe” behaviors can happen with both $\beta \leq 1$ and $\beta > 1$.

Table 7.6: Classification of the situations A to F, depending on $T = \frac{TPed}{TTC}$ and $\beta \in [\beta_{min}, \beta_{max}]$.

Situation	Behavior	T	β	Domain
A	unsafe	$T > 1$	$\beta > 1$	$\beta > T > 1$
B	impossible ($\beta > 1$)		$\beta > 1$	$T > \beta > 1$
C	impossible ($\beta \leq 1$)		$\beta \leq 1$	$T > 1 \geq \beta$
D	missed	$T < 1$	$\beta \leq 1$	$1 \geq T > \beta$
E	safe ($\beta \leq 1$)		$\beta \leq 1$	$1 \geq \beta > T$
F	safe ($\beta > 1$)		$\beta > 1$	$\beta > 1 > T$

The four crossing behaviors lead to 6 situations. To illustrate these 6 situations over a 2D representation β on x-axis and $T = \frac{TPed}{TTC}$ on y-axis (Figure 7.8); let consider β between β_{min} and β_{max} . The figure is divided by a diagonal line, separated by the decision to cross (safe or unsafe), or not to cross (missed or impossible).

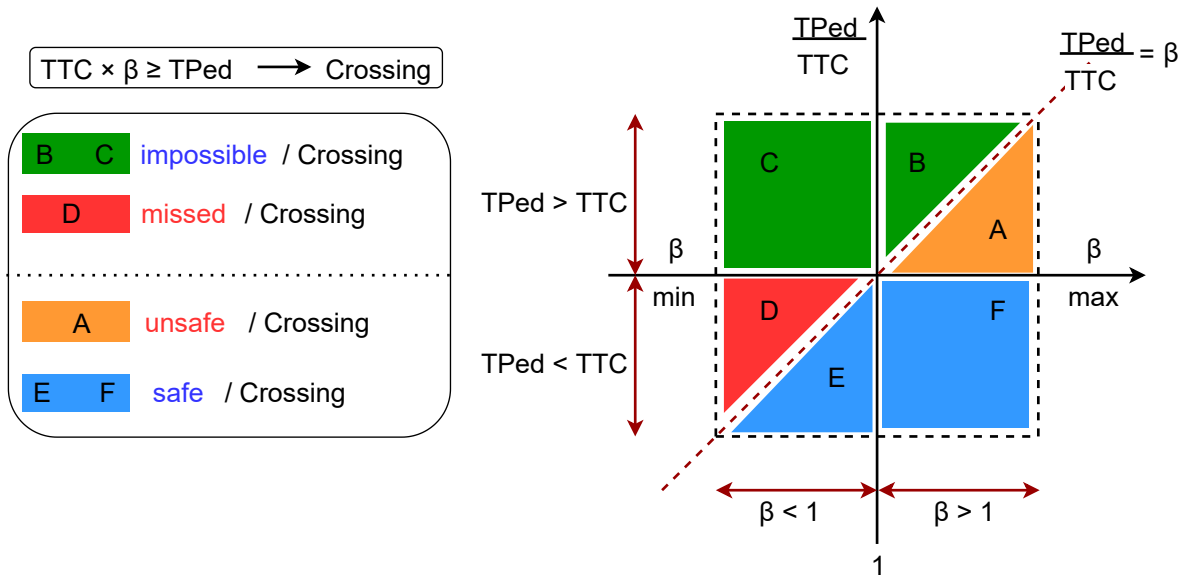
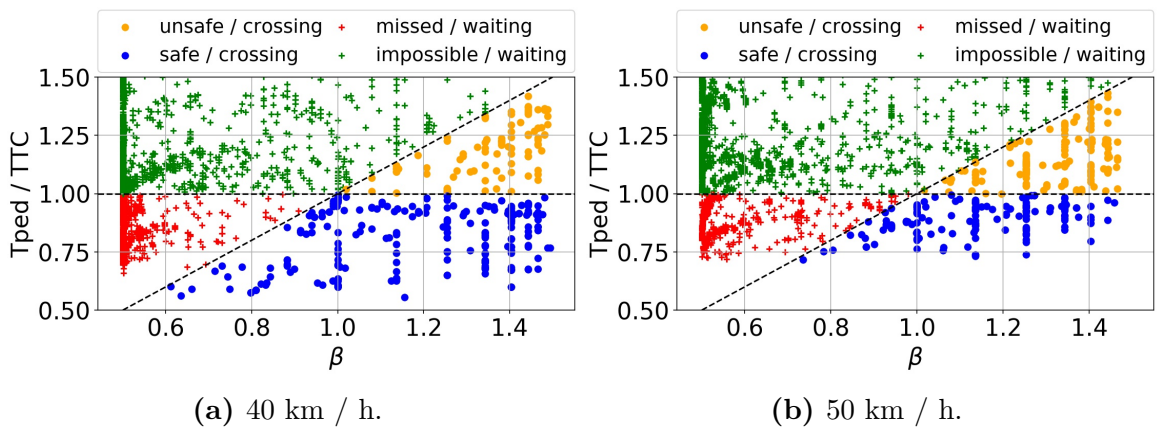


Figure 7.8: Representation of the 6 situations from A to F in a 2D dimensional representation, using axis β and T .

Now, let us apply this formulation to my simulations, with $\beta \in [0.5, 1.5]$. As we can see in the figures 7.9(a), 7.9(b), and 7.9(c) all six situations are available and are in the expected position. The different values of β create the two crossing behavior “missed” and “unsafe” not available for a standard time-to-contact unbiased model, in figure 7.9(d), with the standard model, $\beta = 1$, leading to homogenous one dimensional representation.



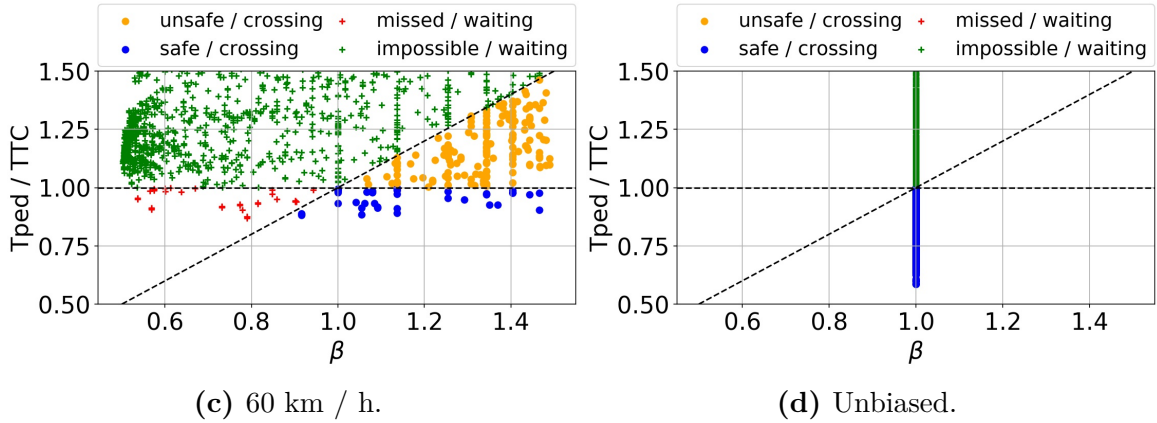


Figure 7.9: Pedestrian behaviors for all simulations using the 6 situations in terms of β and T .

7.2.3 Unsafe crossing decisions

According to the model's hypotheses, pedestrians are expected to have sometimes unsafe crossing decisions in these simulations. An unsafe decision happens if $\beta > 1$, in situation (A) in section 7.2.2. The value of β depends on two factors: the waiting time WT and the social influence Δ .

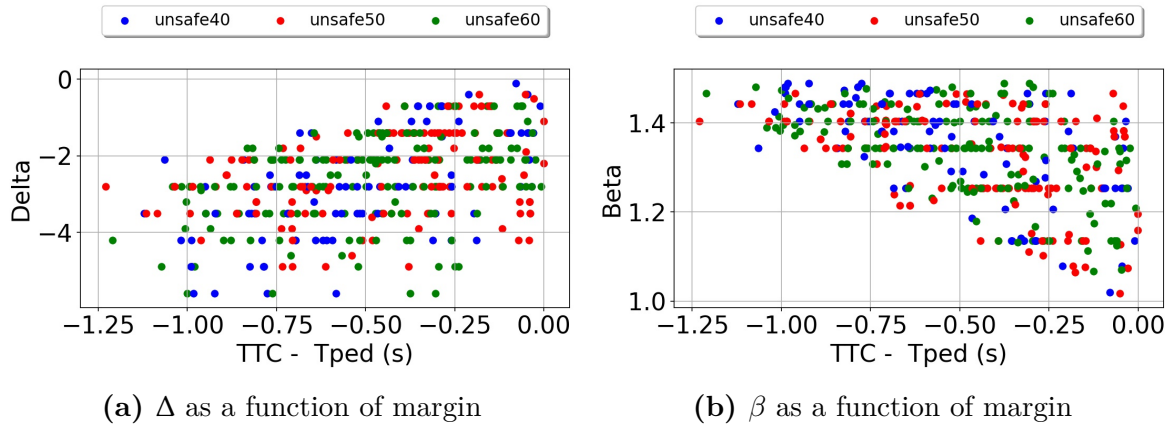
Figure 7.11 shows several unsafe crossing decisions during the simulations. As expected, the simulations show that the bias β is lower than one for unsafe crossings, and the greater the β , the greater the negative margins, in figure 7.10(b).

Regarding the factor Δ alone, the neighbors influence the pedestrian to cross if $\Delta < 0$ and the neighbors influence the pedestrian to be more cautious if $\Delta > 0$. The neighbors do not influence the pedestrians if $\Delta = 0$. However, WT and Δ are used to compute β . Thus, even with $\Delta < 0$, some pedestrians still can miss the crossings, in figure 7.10(a).

I quantify unsafe decisions by measuring the margin ($TTC - TPed$). If $TTC < TPed$, then it is an unsafe decision. Pedestrians in my simulations have negative margins up to -1.25 seconds (Figure 7.11). This margin is close to the negative margin observed by [Oxl+05] and up to -2 seconds for young and adult pedestrians.

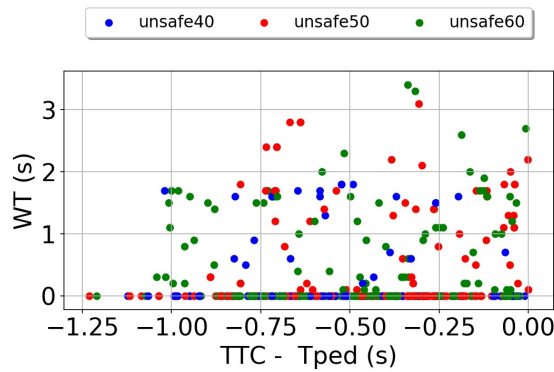
The unsafe decisions in these simulations happen within the first 4 seconds of waiting (Figure 7.11(a)). As the longer the waiting time increases, the number of unsafe crossings decreases. Related to these results, several works observed that pedestrians become impatient after waiting a longer time, and wanted to cross [Bro+13; INo8].

Alternatively, [DK70] observed that some pedestrians chose safer gaps after waiting a longer time.



(a) Δ as a function of margin

(b) β as a function of margin



(a) WT as a function of margin

Figure 7.11: Δ , β , and WT during unsafe crossing decision, for all simulations. Unsafe crossing decisions happen if $TTC - Tped < 0$.

Why does the unsafe crossing only happen during the first 4 seconds? To respond to this question, I may first point out that an unsafe crossing decision only happens if $\beta > 1$. To understand what happens, I used a simplified formulation of $\beta = \frac{2}{1+e^{-X}}$, with $c = 0$, for the identification of the conditions. If $\beta < 1$, then $e^{-X} < 1$, and X combines Δ and WT . This leads to $WT > \frac{b}{a} \times \Delta$, with $a = 0.8$ and $b = -0.5$ in my simulations. If 10 neighbors are crossings, it leads to $\Delta = -7$. Then, the unsafe crossings happen before $WT = 4.4$ seconds, for the defined set of parameters in this simulation.

I have compared the unsafe decision with [Jay+20], that was interested in street crossing violations and hesitation behaviors, and this happens when a pedestrian crosses a street and realizes that they incorrectly estimated the necessary time to cross during

their crossing. Then, the pedestrians run or steps back to the sidewalk (they modify their initial crossing decisions). The authors used natural observation of pedestrians crossing the street at rush hour, with pedestrians uninformed of the purpose of the work, to avoid bias. They compare different results from two cities (in France and Japan). They found 5 % and 10 % of hesitation (modified their decisions) in France and Japan. I have compared unsafe crossing decisions in my simulations to the hesitations in [Jay+20]. I measured the percentage of unsafe decisions (Table 7.7). The percentage of unsafe decision is around 11.03% for 40, 50, and 60 km/h.

Table 7.7: Percentage of unsafe crossing. For all simulations

Vehicle speed	40 km/h	50 km/h	60 km/h
Free	613	707	937
Safe	52	187	33
Unsafe	92	89	131
Unsafe (%)	12.15%	9.05%	11.89%
Total	757	983	1101

Figure 7.12 illustrates a few pedestrians who just started waiting and were influenced by neighbors to cross. If $\beta \times TTC - TPed > 0$, then the pedestrian cross. If $TTC - TPed < 0$, the pedestrians do not cross the street. My objective in this illustration is to compare the unsafe and unbiased decisions of the same pedestrians. The unsafe crossing for each pedestrian is a red star, and the decision if the pedestrians were unbiased in a black square. This illustration shows that these pedestrians would cross if their perceptions were unbiased.

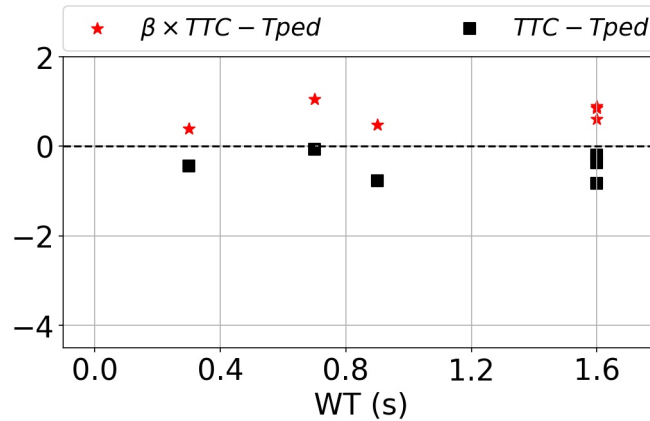


Figure 7.12: Illustration of a few pedestrians waiting and influenced to cross by their neighbors, and deciding to take an unsafe crossing decision. The red star represents the unsafe, biased perception, and the black square represents the corresponding unbiased perception.

7.2.4 Missed crossing decision

In to the situation D in section 7.2.2, a missed crossing may happen if $\beta \leq 1$. Δ as a function of β is plotted in figure 7.13(a), and Δ as a function of WT in figure 7.13(b).

Figure 7.13 shows some pedestrians influenced to cross, but still missed opportunities, because β depends on Δ and WT , not only on Δ . The figure 7.13(b) shows that the number of missed crossing decisions is different with the three different vehicle speeds. At 40 km/h, some missed crossings happen after waiting more than 30 seconds. At 50 km/h, some missed crossings happen after waiting 17.5 seconds due to the environment's configuration. The vehicles follow the same itinerary for the three vehicle speeds and have approximately the same gaps. Thus, the number of vehicles following the itinerary decreases if the speed increases, reducing the potential interaction between a pedestrian and an oncoming vehicle.

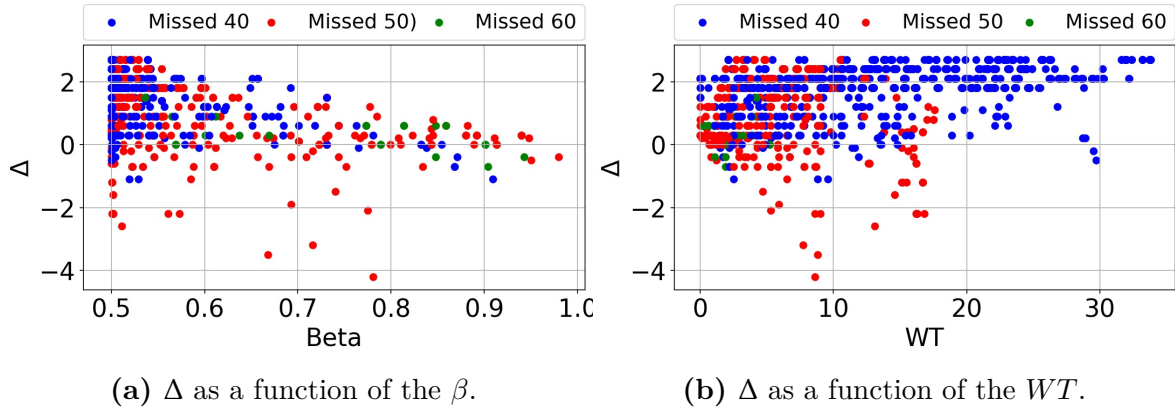


Figure 7.13: Δ as a function of β and Δ as a function of WT , during missed crossings.

To illustrate a missed crossing decision, let us see the case of one pedestrian P who waits for 30.3 seconds. His Δ evolution is plotted in figure 7.14(a) showing a negative value starting from -2 , and then increasing, corresponding to a situation where P is influenced to cross. His Δ stabilized at $WT = 5$ seconds, corresponding to a stabilization of the number of neighbors crossing and waiting. The first blue dots appear after $WT = 7$ seconds. These blue dots correspond to missed crossings. If the perception of P was unbiased, he would have crossed at the first missed crossing, at $WT = 7$ seconds. P missed five opportunities before crossing at $WT = 33$ seconds. When P crosses the street, his Δ drops, meaning several pedestrians are crossing together, corresponding to a pedestrian not perceiving any oncoming vehicle, or an oncoming vehicle is perceived, but at a large enough distance to allow the crossing.

Figure 7.14(b) corresponds to the β of P . It drops quickly and reaches its minimal value of 0.5, after $WT = 7.5$ seconds, and stabilizes until the end. Reaching its lowest value means the pedestrian becomes very cautious and overestimate the TTC in this situation.

Figure 7.14(c) compares the biased missed crossings (blue dots) and the decision if the perception was unbiased (red dots). Each line corresponds to an interaction with an oncoming vehicle, and the line decreases when the oncoming vehicle approaches. A new decreasing line appears when pedestrians perceive another oncoming vehicle, forming a saw toothed waveform. I only plot dots for the missed crossing and the unbiased crossings in this illustration. Thus, if the interaction with an oncoming vehicle is impossible, I do not plot a point at the beginning of the new decreasing line. A pedestrian missed a crossing if $\beta \times TTC - T_{Ped} < 0$, and the illustration shows that

the blue dots are only on the negative side. Then, since it is a missed crossing, a pedestrian would cross if his perception of the TTC was unbiased.

The figure 7.14(d) shows the missed and impossible crossings encountered by P , while he was waiting. A crossing is impossible if $TTC - TPed < 0$, and seven situations meet this condition (black dots). The rest five dots in blue are missed crossings. Then, P has 13 interactions with oncoming vehicles before crossing the street.

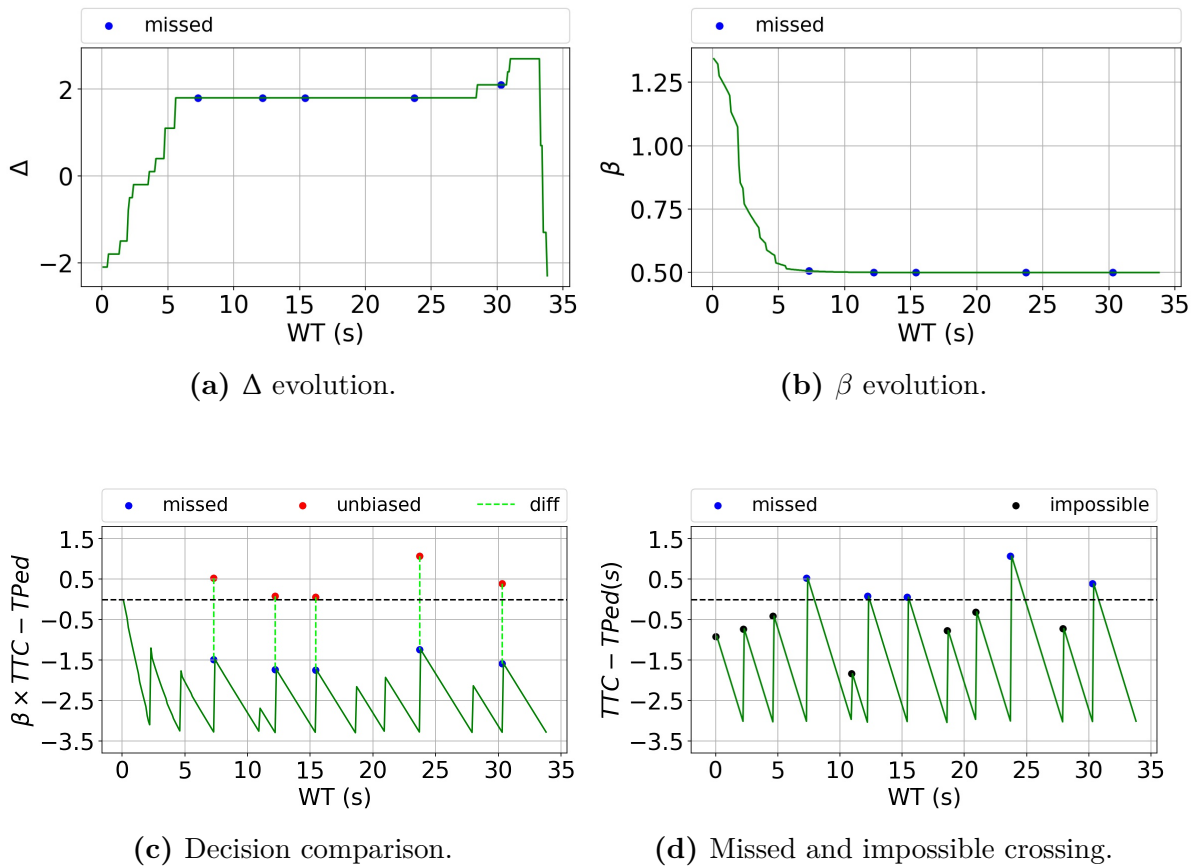
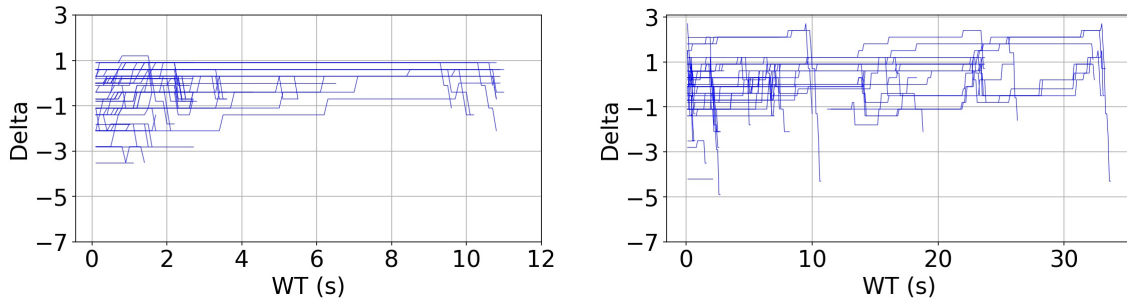


Figure 7.14: An illustration of missed and impossible crossing by one pedestrian waiting for 33.8 seconds.

7.2.5 Evolution of social influence during the waiting phase

Figure 7.15 shows two illustrations of the evolution of Δ for some pedestrians during the waiting phase. The first illustration is on the left; some pedestrians are waiting for a shorter waiting time, reaching approximately 12 seconds. The second illustration is on the right; some pedestrians are waiting for a longer waiting time, reaching about 32 seconds. Each plot represents the Δ of one pedestrian, starting from $WT = 0$ until the decision to cross. The figure shows that Δ can have positive and negative

values during the waiting phase, meaning that the social influence can evolve during the waiting phase.



(a) Shorter waiting time before crossing.

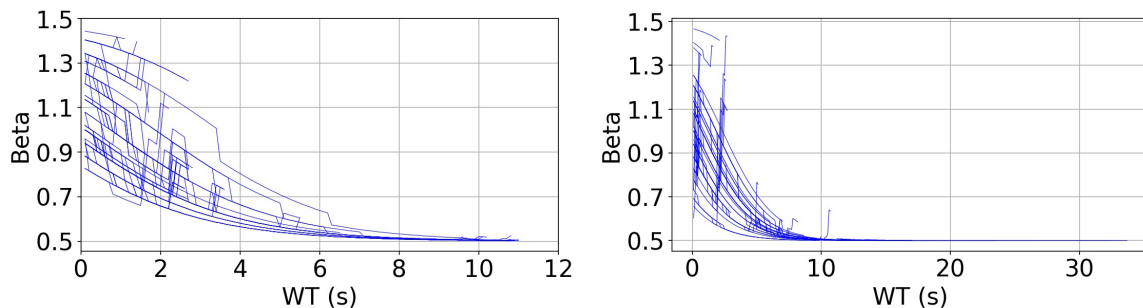
(b) Longer waiting time before crossing.

Figure 7.15: Two illustrations of the evolution of the Δ of several waiting pedestrians. Each plot represents the situation of one pedestrian, and at the end of each line, that pedestrian crosses the street.

7.2.6 Evolution of the bias before crossing

The bias β is computed from Δ and WT . Figure 7.16 illustrates the β values obtained from the previous illustration Δ , in figure 7.15. Each plot represents a β for one waiting pedestrian, every time-step until the pedestrian crosses. The β parameters used for all simulations are $a = 0.8$, $b = -0.5$, and $c = 0.5$.

The illustrations show some variability in β , during the first 6 seconds, then the β stabilized later until the crossing. This illustrates that Δ has less impact on β after the first 6 seconds, and WT has a stronger influence over Δ after this stabilization because after 6 seconds Δ still have variability in figure 7.15, but does not impact much β .



(a) Shorter waiting time before crossing.

(b) Longer waiting time before crossing.

Figure 7.16: Two illustrations from the results of the evolution of β of several waiting pedestrians, using Δ from figure 7.15. Each plot represents one pedestrian, until he crosses the street.

To understand why after 6 seconds, β becomes relatively constant, even if Δ changes, I illustrate two situations with two extreme values of Δ . I select a low value $\Delta_{low} = -6$, and a high value $\Delta_{high} = 1$. Then, I use the two values of Δ with $WT = 10$ seconds (greater than 6 seconds) to compute β . I found similar values of β in the two situations:

$$X \begin{cases} X & = b \times \Delta - a \times WT \\ X_{(\Delta_{low})} & = -1.8 \\ X_{(\Delta_{high})} & = -5.3 \end{cases} \quad (7.4) \quad \beta \begin{cases} \beta & = \frac{2 \times (1-c)}{1+e^{-X}} + c \\ \beta_{(\Delta_{low})} & = 0.51 \\ \beta_{(\Delta_{high})} & = 0.5 \end{cases} \quad (7.5)$$

7.2.7 Conclusion from the scenario with road traffic

In this second scenario, the pedestrians cross a street with road traffic and a without a pedestrian light. The vehicles follow the same itinerary, do not interact with pedestrians, and have a constant speed.

The pedestrians base their crossing decision on comparing the time-to-contact and the crossing time if an oncoming vehicle is perceived. Pedestrians can have an inaccurate estimation of the time to cross. Experimental work finds that some pedestrians have inadequate crossing decisions [Oxl+05; LCO9]. I suppose it can be caused by a bias in the perception of the time-to-contact, and the bias is based on the social influence from neighbors and on the waiting time.

The bias produces several crossing behaviors (safe, unsafe, missed, or impossible). A pedestrian can only have safe or impossible behaviors with a standard time-to-contact model. Pedestrians adapt their behavior according to the situation. Pedestrians can decide to cross, even if they do not have the speed to cross safely because the situation influences them to cross. Conversely, pedestrians can decide to wait, even if they have the speed to cross safely because the situation influences their decision to wait. Thus, a pedestrian would have different behavior if he is alone or in the presence of neighbors. Moreover, a pedestrian would not behave the same regardless of the time. A pedestrian would have different behavior after waiting some time on the sidewalk.

To estimate to the consistency of the simulations, I compared the gap_{obs} observed by simulated pedestrians during their street crossing with the gap_{select} selected by pedestrians during an experiment realized by [LCO9]. The gap_{select} and the gap_{obs} have the same tendency. I also compare the unsafe decision with another experimental work [Oxl+05]. They found a negative margin between $[-2, 0]$ seconds for young and

adult pedestrians, while in the simulations, the margin is between $[-1.25, 0]$ seconds. I have also compared the percentage of hesitation during the street crossing. [Jay+20] found some pedestrians miscalculate their timing and cross, and during the crossing they realize their miscalculation. In their results, [Jay+20] found about 5 and 10 % of pedestrians have hesitation behaviors. I compared these hesitations to unsafe decisions, and my percentage of unsafe decisions is about 11.03% for all simulations.

7.3 Conclusion

To improve the heterogeneity of behaviors during street crossings, I hypothesized that the patience value can evolve based on social influence such that a pedestrian decides to violate the pedestrian light, if the patience runs out during a red light. This modification of patience allows a pedestrian to violate or to comply with the traffic law, depending on to the social influence. These hypotheses are observed in the behaviors of pedestrians, in the simulations. Then, I made another hypotheses that pedestrians could have a bias on the perception of oncoming vehicles during street crossings, leading to inaccurate decisions. The simulations show that some simulated pedestrians have inaccurate decisions, and these inaccurate decisions are consistent with several observations of pedestrian behavior during experimental works and field observations. Thus, the two hypotheses are observed in the behaviors of pedestrians during the street crossing simulations.

Chapter 8

Conclusion and perspectives

Section 8.1 summarizes the contributions realized during this thesis. Section 8.2 develops the contributions realized. Section 8.3 presents some limitations, and section 8.4 presents the long-term and short-term perspectives.

8.1 Summary

Pedestrian simulations would be more realistic if their behaviors were similar to those observed in real-life situations. However, many of these simulations lack behavioral heterogeneity due to the simplifications of models, diminishing their realism. This thesis aims to increase the heterogeneity of the interactions between pedestrians during collision avoidance and street crossing decisions. My first contribution consists in adapting collision avoidance to the situation perceived by pedestrians. My second contribution combines collision avoidance with a queuing model by considering a leader in front of a pedestrian who constrains the pedestrian more than the rest of the neighbors. These contributions are based on the perceived physical characteristics of pedestrians (size, position, speed). However, temporal situation (how long the agent has been in a situation) and social information (actions of perceived neighbors) can impact the behaviors of pedestrians. A pedestrian agent with the same physical characteristics but different temporal situations or social influences may decide differently. My main contributions consist in developing a street crossing model that considers the waiting time and social influence from perceived neighbors. The model is assessed under two scenarios: 1) a street crossing with a traffic light without road traffic, and 2) a street crossing with only road traffic. The results show behaviors that are not frequent in the context of pedestrian simulations but are often observed in real-life situations, such as decisions to violate or comply with the traffic rules or an inadequate crossing decisions with oncoming vehicles. These decisions would be different if the pedestrians arrived

differently on the sidewalk or received different social influence. I have proposed four contributions to increase the heterogeneity of pedestrians. The contributions presented several activities of pedestrians: avoiding collisions, following someone, and crossing a street with a pedestrian light or with road traffic. The results show a consistency of the simulated behaviors with behaviors observed in the literature.

8.2 Major contributions

Work 1 gives to pedestrians the possibility to adapt collision avoidance based on the perception of neighbors. Related to this topic, [Der+19] was interested in face-to-face collision avoidance interactions. They found that the one with higher attention avoids the collision. I, therefore, assume that higher attention means greater anticipation of the collision avoidance. Reciprocally, lower attention means lower anticipation. [Cur+13] was interested in breaking the symmetry during collision avoidance interactions. They give priority to pedestrians, and the one with lower priority avoids more than the one with higher priority. My contribution is the combination of the collision avoidance effort and the anticipation of pedestrians. Thus, each agent can have different anticipation and collision avoidance, leading to asymmetric interactions. I have implemented the model by simulating two pedestrians moving toward each other in a corridor and avoiding when they meet. The result shows that pedestrian agents can adapt to the situation. A pedestrian agent can avoid another agent more than its capacity if the other agent does not avoid enough. Conversely, a pedestrian agent can avoid another agent below its capacity if the other agent avoids enough. The ORCA model is used for collision avoidance in this work.

Work 2 combines a collision avoidance and a queuing model. [LA16] was interested in diversifying the collision avoidance by extending the ORCA model with a queuing model. The ORCA and the queuing model are used to compute pedestrians' acceleration in their model if the pedestrian finds a neighbor (leader) who constrains the pedestrian the more. The acceleration is the minimum computed by the two models. If no leader is found, then the ORCA model is used. My contribution consists in enriching this model by defining three different interactions between the pedestrian, the leader, and the rest of neighbors. Instead of using only the minimum acceleration from the ORCA and the queuing model, I defined: (1) the maximal, (2) the smallest, (3) or pure queuing. The simulations show that pedestrians adapt their behaviors according to neighbors' situations. I computed fundamental diagrams to see if the simulated crowds follow the property of standard crowds, consisting of higher average

speed at lower pedestrian density and lower average speed at higher pedestrian density. The fundamental diagrams show that increasing the heterogeneity does not modify the propriety of the simulated crowd.

Work 3 uses the patience of the agent and social influence from the behaviors of perceived neighbors to modulate crossing decisions at a street with a pedestrian red light without traffic. [KO03] found that some pedestrians begin to violate the traffic signal after waiting about 20 seconds, which can be assimilated to the fact that pedestrians have limited patience for waiting at a red light and violate the pedestrian light if they lose patience. [Ros09] found that crossing decisions may be related to social influence. The author hypothesized that seeing someone crossing influences a pedestrian to cross (H_1), and seeing someone waiting influences a pedestrian to wait (H_2). My contribution consists of computing a social influence factor consistent with H_1 and H_2 , using a linear combination of the number of crossing and waiting neighbors, and using the social influence to modify the patience at each time step. Then, the social influence can increase patience, and pedestrians may wait longer than if they had been alone in this situation. Conversely, the social influence can decrease patience, and pedestrians may wait longer than if they had been alone in this situation. The violation rate produced with the model is consistent with those observed in the literature. This model is pretty simple regarding the formulation. I use a linear combination to combine two hypotheses, and the model can produce heterogeneous crossing behaviors, which can be observed and compared to real behaviors. This model also is modular regarding the implementation. I developed the crossing decision model at the tactical level using ORCA at the operational level. I expect to have a similar result with another operational model, such as SFM. Nevertheless, the first formulation of patience cannot be used for a real-time simulation. Therefore, I developed another formulation of patience used to simulate a group of non-player-character (NPC) pedestrians influenced by a bot controlled by an experimenter. This new formulation allows the model to be scalable and reproducible under different time-steps, including real-time, which can be considered as a criterion of the robustness of the model according to [Don+08].

Work 4 uses the waiting time of the pedestrian agent and social influence from the behaviors of neighbors to modulate crossing decisions with road traffic without a pedestrian light. [Oxl+05; LC09] found that pedestrians can have inadequate decisions; some pedestrians have unsafe crossings and others have missed. I hypothesized that the inadequate decisions could be caused by a bias in estimating the time-to-contact (TTC) of oncoming vehicles. My contribution is the development of the bias, using the waiting time and social influence from the perceived neighbors. This bias leads to an

inaccurate estimation of the TTC , and then to an inadequate decision. The pedestrian agent may thus decide to wait when he can cross, missing an opportunity; he also may decide to cross when the situation does not allow it. The results are consistent with the behaviors observed by [Oxl+05; LC09] when comparing the negative margin during unsafe decisions and the gaps between vehicles observed during crossings. The percentages of unsafe decisions are consistent with those observed by [Jay+20]. Thus, the model can produce inadequate decisions consistent with the behavior of real pedestrians.

8.3 Limits

1. The adaptation behavior is based only on physical information (velocity, position, and size) in work 1 and 2, meaning that two different agents with the same perceived physical characteristics will be processed the same.
2. I have only launched three distributions for setting the pedestrian speed and the gap between vehicles because the model does not have any randomness (work 1 and 2). To have a better statistical power, more distributions should be performed.
3. I have set the number of neighbors perceived by an agent pedestrian to ten neighbors because of human limitation to process several items simultaneously [SO03] (work 1, 2, 3, and 4). The selection of the neighbors perceived is based on their nearest positions. If more neighbors are waiting on the sidewalk and the waiting neighbors are closer than the crossing neighbors, a pedestrian may not see crossing neighbors.
4. I empirically configured the weight parameters p_C and p_W used to compute the social influence Δ (work 3). The same is true for the parameters a , b , c for the calculation of the bias β (work 4). A sensitivity analysis of these parameters would be useful.
5. Street crossing could be roughly classified in four configurations (Figure 8.1). The first is with a pedestrian light without road traffic (A), the second situation is with a pedestrian light with road traffic (B), the third situation is without a pedestrian light with road traffic (C), and the last situation is without a pedestrian light without road traffic (D). The model should be assessed for the configuration (B).

<p>With pedestrian light Without road traffic A</p>	<p>Without pedestrian light With road traffic C</p>
<p>With pedestrian light With road traffic B</p>	<p>Without pedestrian light Without road traffic D</p>

Figure 8.1: Crossing situations for a global street crossing model.

8.4 Perspectives

8.4.1 Short-term

Regarding limit 3, a perspective is to build a meta-agent, similar to one developed by [LA16], during group collision avoidance. Several pedestrians would be considered as one group in this situation, allowing perceiving more than ten neighbors and respecting the human limitation.

Regarding limit 5, my objective is to have a general street crossing model with the four situations in figure 8.1. The perspective is to implement (B) situation. (B) situation combines (A) and (C). Another perspective is to allow a pedestrian to define the crossing location. For example, a pedestrian walking on the sidewalk toward the crossing location, may find an opportunity to cross, and cross before arriving, at the crossing location. This crossing behavior also known as jaywalking. [Wan+10] modeled pedestrian's gap acceptance during jaywalking. They use three factors in their model: the gap time, age of the crossing pedestrian, and the number of crossing pedestrians.

I compared the results of the simulations from experimental and observation work. Another way to evaluate the reliability of simulated NPC pedestrians is to develop a virtual experiment using videos and a questionnaire. One way to realize that is to develop a video of several scenarios and use a questionnaire to ask participants whether the street crossing made by the NPCs are plausible or not, compare their own experience, for example. [Der+19] developed videos of two pedestrians moving toward each other in a narrow sidewalk. The size of the sidewalk is only large for one

pedestrian, and one of them has to step down when they meet. Then they developed a questionnaire asking participants which one of the pedestrians would step down.

An unsafe decision in this model would lead to a collision after they decide to cross because the pedestrians and the oncoming vehicle has a constant speed. However, the driver may have different behaviors (to accelerate, to decelerate, or stop). I would consider the interaction between the driver and pedestrian as a perspective of this model. For example, [Zhu+22a] developed a game theory model between the decision of the driver to yield and the pedestrian to cross. Moreover, this model is developed to decide to cross, and agents do not change their decision when they start crossing. But in many situations, the crossing is a continuous process. Pedestrians adjust their speed according to the reaction of the oncoming vehicle. For example, [Jay+20] found some pedestrians running to finish their crossing to compensate for an unsafe decision.

8.4.2 Long-term

An agent pedestrian can be influenced by his neighbors in his decision to cross. To simplify my model, I have limited the influence to pedestrian behavior (crossing/waiting). To enrich the model, different other factors could be considered. [LBM55; GP01] found that the status of the neighbors can have different influences on the agent pedestrian. A high-status pedestrian can influence more than a low-status one. The distance between the neighbors and the agent pedestrian also could impact the influence [FKK10]. Moreover, in most situations, the crosswalk is bidirectional, and pedestrians can cross from both sides of the street. In this work, I have only considered the influence of neighbors on one side, while the presence of other pedestrians on the opposite side can reduce the cautiousness of pedestrians, according to [Harg91].

I developed a social influence model for street crossings, but the concept could be implemented in different situations, such as a leader following. Instead of selecting a leader only based on physical characteristics, one could use social status or social influence.

Regarding street crossing with a pedestrian light, pedestrians cross immediately when the light turns green, which is impossible for real pedestrians. [Fug+00] finds that pedestrians have a reaction time of around one second when the pedestrian light changes color, and the reaction time is longer for older pedestrians than for younger ones. Thus, the perspective is to include this reaction time in the model.

The street crossing model can be used to experiment with street crossings in VR environment. I have already used this model to implement a scenario of a group of NPC pedestrians influenced by a bot [RAB21]. It would be interesting to see if NPCs can influence humans, or if human players can influence NPCs.

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