

Human-aware robot navigation in public spaces based on predicting pedestrian reaction patterns

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ABSTRACT

This paper presents a human-aware collision-free navigation system based on long-term motion prediction and a game against nature formulation for modelling uncertainty. The proposed approach explicitly takes into account mutual pedestrian interactions and introduces a method for estimating the confidence of predicted pedestrian reactions through the analysis of anticipated interactions in public spaces. This enables the formulation of a decision-making framework based on the minimisation of the expected value of a cost function. The effectiveness of the method proposed is demonstrated using representative simulation scenarios, showing improved safety and enhanced comfort of navigation behaviour.

Keywords: long-term prediction, uncertainty handling, game against nature, game theory, social navigation.

INTRODUCTION

In recent years, the demand for autonomous vehicles and intelligent transportation systems has increased significantly. This trend is primarily driven by overcrowding in urban areas, resulting in high traffic density and increased safety risks. Consequently, intensive research activities have been undertaken in the fields of autonomous vehicle design, advanced traffic management systems, and intelligent solutions supporting public transportation.

Current trends in development and deployment of autonomous and semi-autonomous mobile robot systems reveal a fundamental shift compared to earlier applications. While initial applications were addressed to structured environments, such as offices or industrial buildings, modern systems are increasingly designed for operation in dynamic, unstructured public spaces. Navigation and control methods originally developed for mobile robotics over several decades are now widely adapted to passenger vehicles in the form of Advanced Driver

Assistance Systems [1]. Ongoing research focuses on fully autonomous platforms, including robotaxis, autonomous buses, and transportation vehicles. In parallel, numerous projects address autonomous or semi-autonomous assistive devices, such as robotic wheelchairs, aimed at enhancing the mobility of people with disabilities.

The increased deployment of autonomous vehicles in public environments inevitably leads to frequent interactions with humans. These interactions may be intentional, arising from the intended functionality of assistive systems, or incidental, resulting from the coexistence of autonomous vehicles and pedestrians within the same operational space. Such interactions pose substantial challenges to safe and efficient vehicle navigation.

As a result, autonomous navigation systems operating in public environments must explicitly take into account human-machine interaction. In many scenarios, these interactions are complex and may negatively affect navigation performance and safety if not properly addressed. This requirement has led to the development of the human-aware navigation (HAN) paradigm,

which encompasses navigation strategies explicitly designed for safe and socially compliant operation of autonomous systems in human-populated environments [2,3].

A couple of challenges are associated with the implementation of HAN [4]. The first one is detecting, understanding, and predicting human behaviour. Navigation systems must reliably identify human presence, estimate motion states, and predict future trajectories to avoid collisions while maintaining smooth and predictable vehicle motion. The second challenge concerns human-machine communication. HAN-compliant systems should convey navigation intentions through explicit or implicit signalling mechanisms and be capable of responding to human cues.

A key challenge, particularly relevant to this study, is compliance with social norms. Beyond ensuring physical safety, human-aware navigation systems must consider psychological factors, such as maintaining appropriate interpersonal distances, avoiding abrupt manoeuvres, and adjusting speed to pedestrian dynamics. Finally, HAN systems must exhibit adaptive behaviour, enabling them to operate robustly under varying environmental conditions and across diverse operational contexts.

Related works

The complexity of HAN and the number of associated challenges have motivated extensive research and development efforts addressing individual aspects of the problem. Due to the breadth of existing studies, only selected representative works are discussed in this section. A common conclusion shared across the literature is that motion planning compliant with the HAN paradigm cannot rely solely on instantaneous observations of the environment. Instead, it must incorporate predictive models, preferably operating over long temporal horizons. As demonstrated in [5], and [6], the integration of long-term environment prediction significantly reduces control variance, resulting in smoother and more human-like navigation behaviour.

In the work [7], an approach to navigating a robot among pedestrians is presented, which takes into account human-related factors. The use of personality theory concepts combined with Bayesian inference enables long-term prediction of pedestrian motion, which is subsequently integrated with a Generalized Velocity Obstacles

(GVO) framework for trajectory planning. In [8], a multi-layer navigation cost map based on pedestrian motion prediction is proposed. Of particular relevance to the work presented is the explicit consideration of potential interactions among agents in the cost modelling process. Both [8] and [9] employ the concept of social forces to determine motion parameters and generate socially acceptable trajectories.

The rapid advancement of AI techniques has also influenced research in HAN. In [10], deep reinforcement learning is applied to generate the navigation strategies that adapt to dynamically changing environments. In contrast, the work presented in [11] utilised a language model trained on real-world scene images and guided by human feedback to generate socially compliant robot navigation strategies. The paper [12] presented a smart combination of two previously discussed approaches: reinforcement learning and the concept of social forces (SFM). Next interesting AI application is presented in [13]. This research showed an application of transformer-based architecture for anticipating pedestrian crossing behaviour in traffic scenarios. Another noteworthy field of research focuses on intention recognition of agents involved in the navigation process. In [14,15], intention detection was successfully employed to derive effective HAN strategies. Similar approaches were reported in [15] and were further developed in the present work.

More recently, game-theoretic formulations have emerged as a principled framework for modelling human-robot interactions, treating navigation as a multi-agent decision process (e.g., [16] and [17]). These approaches enable explicit reasoning about the mutual influence of agents and have been shown to improve both safety and social compliance.

The contribution of this work

The concept of designing a navigation system intended to operate in public spaces, presented in the subsequent part of this paper, is based on the earlier studies. In these works, the theory of game against nature was employed as a means of reducing the uncertainty of forecasts obtained using predictive models. Studies [6,15] present a navigation assistance system for an electric wheelchair designed, in which an adaptive decision-making system based on long-term prediction of the environment state was applied. In the

decision-making layer, a model based on game against nature formalism and its solution according to the Hurwicz criterion were used.

The present work extended this research by redefining the control objective and the decision space of the problem. Moreover, it demonstrated the possibility of estimating the probability of occurrence of specific events based on an analysis of predicted interactions between participants in public-space traffic. This, in turn, enabled the application of a decision criterion focused on minimising the expected value of the cost index. The obtained results are illustrated using appropriately selected simulation scenarios.

THE SYSTEM FRAMEWORK OVERVIEW

A discussion of the proposed robotic vehicle (also referred to as a “robot” for the sake of simplicity) navigation system concept (Figure 1) should begin with the key issue. Namely, it was assumed that the vehicle is equipped with a sensory subsystem sufficiently advanced to enable reliable detection, localisation, and tracking of

pedestrians moving within its navigational space. The problem of object detection and localisation is inherently complex and constitutes the subject of extensive research efforts [19,20]. In this work, however, this issue is not addressed explicitly and is regarded as given.

Since the proposed control system is intended to comply with the human-centered autonomous navigation (HAN) concept outlined in the introduction and is designed for operation in public spaces, the set of potentially detected objects is restricted to pedestrians. Based on pedestrian localisation data provided by the sensory subsystem, a motion model is constructed and used to generate predictions of pedestrian trajectories over a finite time horizon. The resulting forecast of the environment state is the basis for further projection of alternative, hypothetical states of the observed pedestrians.

At this stage of processing the data, a set of motion trajectories alternative to the original prediction is generated. These alternatives represent potential changes in pedestrians’ direction or velocity that may occur as a result of pedestrians’ actions, which are often unpredictable. The subsequent stage, crucial from the perspective

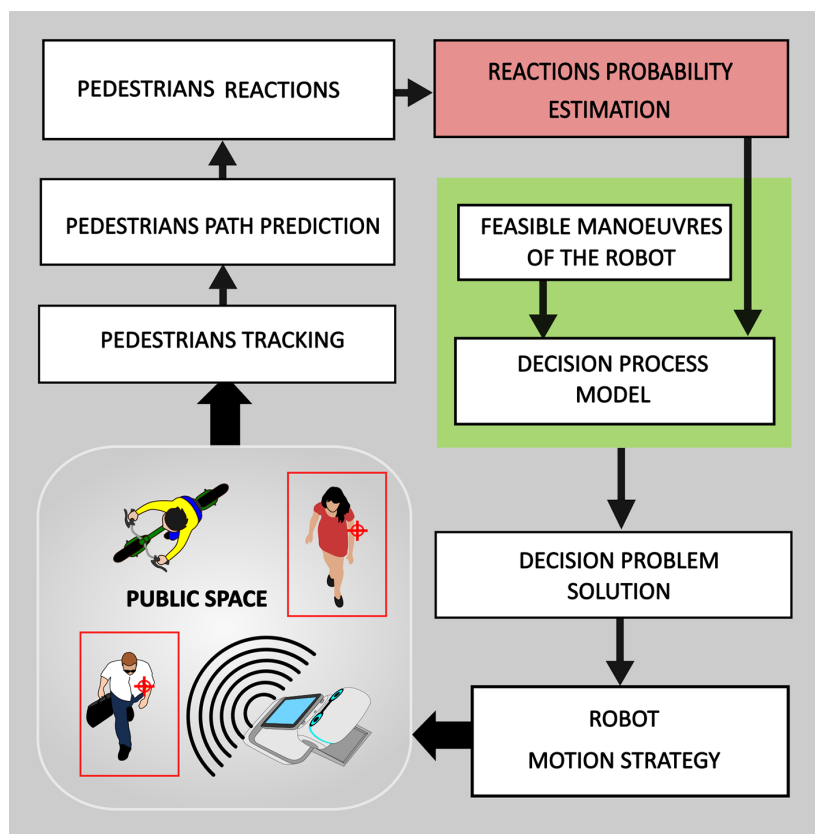


Figure 1. An illustration of the HAN system concept

of this study concerns the predictive analysis of the interactions occurring among the observed pedestrians. This analysis enables the estimation of certainty factors associated with the previously defined alternative environment states. The obtained certainty measures are used further for solving the decision-making problem. The solution obtained determines the robot's motion strategy over the time horizon H . The individual stages of data processing within the navigation system, as well as the methodology used to construct the decision-making model, were described in detail in the remainder of this paper.

PEDESTRIAN REACTIONS MODELS AND VEHICLE MANOEUVRES

Pedestrians' motion style in public spaces differs fundamentally from the behaviour of autonomous vehicles. They typically rely on continuous feedback control, reacting to sensory measurements of obstacle proximity and goal deviation while optimising a cost function that balances collision risk and tracking performance. This results in smooth, reactive manoeuvres that maintain safe distances from obstacles. Pedestrians, in contrast, do not follow such formal optimisation principles. Their movement is driven by perception, anticipation and interaction with other individuals what in turn lead to the behaviours that are rather discrete, intention-based and context-dependent. Consequently, pedestrian motion modelling, particularly in crowded environments, remains an up to date and challenging research topic.

Pedestrians' response models

Except in situations involving perceived danger or loss of comfort, pedestrians moving toward their goals do not continuously maximise their distance from obstacles or other individuals. Instead, they tend to maintain their intended path within spatial channels shaped by long term anticipation of environmental changes. Notably, in most collision-avoidance scenarios, pedestrians preserve the overall direction of motion, adjusting their trajectory primarily through lateral displacement rather than reorientation [21]. These and other behavioural characteristics motivated the definition of a limited set of

pedestrian response patterns, which are used to generate alternative motion hypotheses for the pedestrians observed by the system. Although the spectrum of human reactions is inherently broad, the present study restricts it to a small number of representative classes that commonly occur while walking in shared public spaces. These classes are illustrated in Figure 2 and defined as follows:

- a) Change lane (change lane left/right). A pedestrian response to increased collision risk or reduced walking comfort. That consists in changing the motion lane parallel to the primary direction of travel, either to the left (CLL) or to the right (CLR).
- b) Give way (GW). A response to another traffic participant moving rapidly along a perpendicular direction, manifested as slowing down or a temporary stop until the potential hazard disappears.
- c) Change of direction. A reaction to a sudden event that may lead to a collision, involving a rapid change in walking direction, achieved through changing movement direction to the left (TL) or to the right (TR).
- d) Speed-up (SU). A response to an imminent collision threat originating from behind the pedestrian, consisting of a rapid increase in walking speed without a change in direction.
- e) No reaction (NR). No response, due to either the absence of hazards or complications along the pedestrian's route or failure to notice them (due to various reasons).

The pedestrian responses described above form a set of distinct reactions to potential events occurring in the pedestrian's surroundings:

$$M^p = \{CLR, CLL, GW, TL, TR, SU, NR\} \quad (1)$$

In the remainder of this paper, the following notation is used to denote the i -th pedestrian reaction:

$$m_i^p \in M^p, i = 1, 2, \dots, \overline{M^p} \quad (2)$$

Each pedestrian reaction is represented as a time-parameterised sequence of actions. The model of the selected i -th pedestrian reaction is therefore defined as:

$$m_i^p = \{(\dot{v}_k^p, \dot{\theta}_k^p, t_k)\}, \quad (3)$$

$$k = 1, 2, \dots, \overline{m_i^p}, \sum_k t_k = H$$

where: $\dot{v}_k^p$ and $\dot{\theta}_k^p$ denote the linear acceleration and angular velocity of the pedestrian, respectively, applied over a time interval t_k as a result of executing the k -th action of the i -th reaction. Consequently, the reaction m_i^p , together with the pedestrian's initial state, uniquely determines the pedestrian's motion trajectory over the time horizon H .

Vehicle manoeuvres

In accordance with the human-aware navigation strategy adopted in this work, the vehicle's motion characteristics should resemble those of pedestrians interacting within the same environment. The first step toward this objective was to define a set of admissible vehicle manoeuvres that reflects typical human motion patterns. While pedestrian motion is subject to holonomic constraints, vehicle kinematics may not always satisfy the same assumptions. Consequently, the control inputs defining individual vehicle manoeuvres are selected to imitate pedestrian reactions as closely as possible. Let a selected admissible vehicle manoeuvre be denoted as:

$$u_i \in U, i = 1, 2, \dots, \bar{U} \quad (4)$$

where: U represents the set of all feasible vehicle manoeuvres. As in (2), each vehicle manoeuvre is modelled as a sequence of control actions and is described by the following set:

$$u_i = \{(\dot{v}_k^R, \omega_k^R, t_k)\} \\ k = 1, 2, \dots, \bar{u}_i \quad (5)$$

where: $\dot{v}_k^R$ and ω_k^R denote the vehicle's linear acceleration and angular velocity, respectively. It is assumed that, similarly to a pedestrian, the vehicle can execute one manoeuvre from the set (1) within the time horizon H . It should be noted that the actual control variables of the vehicle are typically the accelerations of the propulsion units and/or changes in the configuration of steering-related components. In order to maintain a high level of generality, the control variables defined in (5) are adopted in this work. Depending on the specific kinematic structure and the assumed vehicle model, these variables can be readily transformed into the corresponding actuator control space.

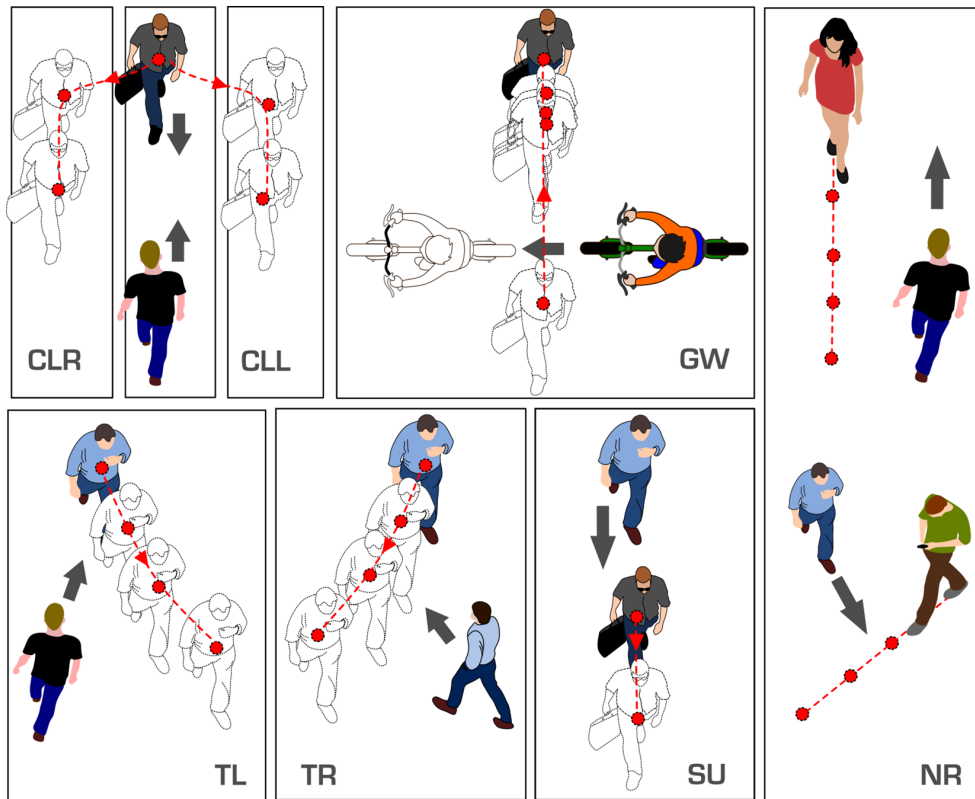


Figure 2. Identified pedestrian reactions to events occurring in public spaces

PROBLEM FORMULATION

To ensure the generality of the proposed approach, no specific vehicle kinematic structure is assumed. For the purpose of the following analysis, it is sufficient to define the vehicle's spatial configuration as a function of time. Let the vehicle state at the n -th time instant be represented by the state vector:

$$R_n = [l_{R,n}, v_{R,n}, \theta_{R,n}]^T \quad (6)$$

where: $l_{R,n} = (x_{R,n}, y_{R,n})$ specifies the vehicle's position in the Cartesian coordinate system of the operational environment, $\theta_{R,n}$ denotes its direction of motion, and $v_{R,n}$ is its linear velocity.

The vehicle operates in a public space shared with pedestrians. It is assumed that the sensory system enables a detection, localisation, and tracking of N pedestrians within the sensor perception range. Although meeting the above requirements is challenging in itself, it is not the focus of the proposed concept. It suffices to note that contemporary sensing technologies allow for the acquisition of such information; representative solutions to this problem can be found in [18]. Let us denote a set containing i -th pedestrian poses, detected and recorded over a time interval of length M :

$$P_i = \{p_{i,k}\}, i = 1, 2, \dots, \quad (7)$$

$$N, k = n, n - 1, \dots, n - M$$

where: $p_{i,k} = [x_{i,k}, y_{i,k}]$ denotes the recorded position of the i -th pedestrian at the k -th discrete time instant, defined by coordinates $x_{i,k}$ and $y_{i,k}$. The current time instant is indexed by n . Based on the data set (6) stored in the buffer, a pedestrian motion model is identified, which is subsequently used to predict the future spatial configuration of pedestrians. Let the predicted spatial configuration of the i -th pedestrian at the h -th future time instant is denoted as:

$$\hat{p}_i^h = [\hat{x}_{i,h}, \hat{y}_{i,h}, \hat{\theta}_{i,h}], \quad (8)$$

$$i = 1, 2, \dots, N, h = n, n + 1, \dots, H$$

where: $\hat{p}_{i,k} = [\hat{x}_{i,k}, \hat{y}_{i,k}, \hat{\theta}_{i,k}]$ denotes the predicted spatial configuration of the i -th

pedestrian at the h -th time instant. The coordinates $\hat{x}_{i,k}$ and $\hat{y}_{i,k}$ represent the predicted pedestrian position obtained using the historical data (6), while $\hat{\theta}_{i,k}$ denotes the pedestrian orientation estimated from the sequence of predicted positions.

The navigation problem is typically formulated by defining a target location to be reached by the vehicle. More complex tasks are represented as a sequence of such subproblems. However, from the perspective of HAN, a formulation inspired by pedestrian navigation models is more appropriate. In this approach, navigation is driven by maintaining a preferred movement direction, rather than reaching the target location. Although the classical goal-based formulation can be transformed into this representation, the direction-based approach better reflects the personal perception of pedestrians and was therefore adopted in this work.

For that reason, the goal of the automatic control system was to maintain a desired movement direction over a prediction time horizon H . The vehicle's navigation goal was thus defined as a traffic corridor described by the pair:

$$\vartheta^n = (\beta_{0,n}, \delta) \quad (9)$$

where: β_0 denotes the desired direction of motion of the vehicle, defined as the angle of a ray originating at point (5), while δ specifies the permissible distance between the vehicle centre defined in (5) and the previously defined motion axis. During the execution of the navigation task, traffic corridors were generated by a higher-level planning system.

The problem of synthesising a control law that accomplishes the navigation task (8) was defined as follows. At a given time instant n , based on the predicted pedestrian motion (7), one admissible manoeuvre was selected from the set (3):

$$u_{i_0}(n), i_0 \in \{1, 2, \dots, \bar{U}\} \quad (10)$$

such that its application over the time instants $n, n + 1, \dots, H$ ensures:

- Collision-free motion path,
- minimal deviation from the desired motion corridor,
- the best possible adaptation to the characteristics of pedestrians movement.

CONTROL UNDER UNCERTAINTY AS A GAME AGAINST NATURE

The HAN control strategy for vehicle motion in the presence of pedestrians is largely based on the predicted state of the environment. However, it must be noted that any prediction is inherently burdened with uncertainty. The sources of this uncertainty are manifold, one of the most significant is the unpredictability of pedestrian behaviour or its imperfect representation within the control model. Sudden changes in pedestrian motion may result either from individual intentions (unpredictable events) or from reactions to variations in the surrounding dynamics. For instance, a pedestrian following a given motion lane may decide to change direction or stop after observing a rapidly approaching vehicle. Such behaviour, however, can often be anticipated through the analysis of predicted pedestrian trajectories. The remainder of this paper was focused on this class of scenarios.

The vehicle control problem based on the prediction of changes in the environmental state can be regarded as a decision-making problem under uncertainty. In this context, potential events involving significant deviations of the actual environmental state from its predicted one may be considered as alternative scenarios of the future course of events. A well-established framework for modelling decision-making under uncertainty, understood as a set of competing scenarios in the operational space, is the theory of games against nature [22]. Accordingly, the vehicle control problem under uncertainty considered in this work can be formulated as a single-player strategic game. Consequently, for each discrete time instant n , the control problem can be stated as follows:

$$G_{MS}(n) = (E, J(n)) \quad (11)$$

where: E denotes the event space, and the function $J(n)$ defines the cost associated, for a given time instant n , with the occurrence of a particular event contained in E .

Event space

The event space of the game (10) is defined as the Cartesian product:

$$E = U \times S \quad (12)$$

where: U denotes the set of admissible vehicle manoeuvres (4), and S is the set of all scenarios of pedestrian reactions considered. Consequently, a single element of the set (11) corresponds to an event in which the vehicle executes a particular manoeuvre under a specific pedestrian reaction scenario. Let the selection of the k -th reaction from the set (2) made by the i -th pedestrian be denoted as:

$$m_{i,k}^p \in M^p$$

Within this single scenario, each traffic participant responds to the current situation by selecting one reaction from the set (2). Such a scenario is represented by the set:

$$s_k = \{m_{i,j}^p\}, i = 1, 2, \dots, N, j \in \{1, \dots, M^p\} \quad (13)$$

Finally, the set of all possible pedestrian reaction scenarios, representing all considered cases of environmental changes in the vehicle surroundings, is defined as:

$$S = \{s_1, s_2, \dots, s_{\bar{S}}\},$$

$$Ss_k = \{m_{i,j}^p\}, i = 1, 2, \dots, N, j = 1, 2, \dots, \bar{M}^p \quad (14)$$

Derivation of the cost function

A cost associated with selecting a particular manoeuvre reflects two fundamental aspects of the navigation process. First, the vehicle must maintain a sufficiently large and safe distance from nearby pedestrians, ensuring collision-free motion under varying environmental conditions. Second, it should follow the prescribed reference path as accurately as possible, minimising deviations in position and orientation. Although these objectives may be in conflict (strict path tracking can reduce available clearance) the optimisation framework prioritises safety. Consequently, the overall cost function is formulated as a combination of a pedestrian-proximity penalty and a path-tracking error term, with weighting factors chosen to enforce collision avoidance as the dominant requirement:

$$J^n(u_i, s_j) = J_{saf}^n(u_i, s_j) + J_{acu}^n(u_i) \quad (15)$$

The first component reflects motion safety, and its value should decrease as the vehicle–pedestrian distance increases. This term is defined using the following relation:

$$J_{saf}^n(u_i, s_j) = \alpha_{saf} \left(\sum_{h=n+1}^{n+H} \min_{k=1..N} \left(\hat{d}_{k,h}^R(u_i, s_j) \right)^2 \right) \quad (16)$$

where:

$$\begin{cases} \hat{d}_{k,h}^R(u_i, s_j) = |\hat{l}_{R,h}(u_i) - \hat{p}_{k,h}(s_j)| \\ \hat{d}_{k,h}^R(u_i, s_j) = D_s \\ \text{for } \hat{d}_{k,h}^R(u_i, s_j) \leq D_s \\ \text{otherwise} \end{cases}$$

In the above relation, $\hat{d}_{k,h}^R(u_i, s_j)$ denotes the predicted distance (evaluated at future time h) between the vehicle and the k -th pedestrian after executing manoeuvre u_i under scenario s_j . The term $\hat{l}_{R,h}(u_i)$ represents the estimated vehicle position at time step h resulting from manoeuvre u_i , whereas $\hat{p}_{k,h}(s_j)$ denotes the predicted location of the k -th pedestrian at the same future instant under scenario s_j . The threshold parameter D_s defines the comfort-zone distance. During navigation, the vehicle is required to remain within a prescribed motion lane. Therefore, the second component of the cost function evaluates the planned trajectory with respect to task-execution accuracy. The chosen performance measure is the degree to which the vehicle deviates from the corridor, quantified by its lateral distance from the reference path and its heading error. Consequently, the second cost component is expressed as the following sum:

$$J_{acu}^n(u_i) = w_d \sum_{h=n+1}^{n+H} d_{h,\vartheta_0}^R(u_i)^2 + w_{\vartheta} (\theta_{R,n+H} - \vartheta_{0,n})^2 \quad (17)$$

where: quantity $d_{h,\vartheta_0}^R(u_i)$ represents the predicted distance between the vehicle and the centerline of the motion corridor at future time h . It is obtained as:

$$d_{h,\vartheta_0}^R(u_i) = \begin{cases} d_{h,\vartheta_0}^R & \text{for } d_{h,\vartheta_0}^R \geq \delta \\ 0 & \text{otherwise} \end{cases}$$

On the other hand, $\theta_{R,n+H}$ in (16) denotes the vehicle's orientation at the end of the manoeuvre, while $\vartheta_{0,n}$ represents the prescribed heading. The weighting coefficients α_{saf} , w_d and w_{ϑ} balance the influence of the individual criteria on the overall cost and are selected heuristically.

Solution of the decision-making problem

The objective of the decision problem (10) is to determine the action u_0 which minimises the cost index (14). The difficulty arises from the fact that the decision maker has no control over the state of nature, which determines the realisation of one of the $\bar{M}^p$ possible event scenarios. Within this class of problems, two general situations are typically distinguished.

The first corresponds to the case in which no information is available regarding the likelihood of individual scenarios. Under such conditions, subjective criteria reflecting the decision maker's attitude toward risk and sensitivity to potential losses are employed. Commonly used approaches include the Wald, Savage, and Hurwicz criteria. The latter has been applied in [6][15] to a similarly formulated navigation problem for a semi-autonomous wheelchair drive assistant.

The second situation arises when information is available about the factors leading to particular events, enabling the assignment of weights that express the certainty of each scenario. In this context, it is natural to seek a decision that minimises the expected value of the adopted performance index. Let the resulting decision be denoted as:

$$u_{i_0} = \min_{u_i} \sum_{j=1}^{\bar{M}^p} c_j J^n(u_i, s_j) \quad (18)$$

$$\sum_{j=1}^{\bar{M}^p} c_j = 1$$

where: c_j denotes the weighting coefficient that specifies the degree of certainty associated with the occurrence of the j -th event from the set of scenarios defined in (13).

Determination of scenarios certainty levels

A method for estimating the weighting coefficients that define the certainty levels of individual events is presented in this section. To determine these coefficients, the authors drew on a concept adapted from the artificial potential field (APF) method. Specifically, the notion of repulsive forces generated by objects moving within an artificial potential field was exploited. Figure 3a illustrates the directional zones associated with the i -th pedestrian, corresponding to the potential reactions triggered by a given environmental

configuration. By performing a predictive analysis from the perspective of each pedestrian, the aim was to estimate the likelihood of every possible reaction of the i -th pedestrian (as defined in (1)) to potential intrusions of other pedestrians into his reaction zones. Let us first define the set of indices of people located within the perception range $D_{range,i}$ of the i -th pedestrian:

$$O_i = \{j\} \in \{1 \dots N\} \setminus i \quad (19)$$

Next, the resultant repulsive force vector generated by each pedestrian from the set (18), acting on the i -th pedestrian at prediction step h was determined:

$$\vec{F}_i^h = \sum_{j \in O_i} \vec{F}_{i,j}^h \quad (20)$$

The direction the virtual force vector $\vec{F}_{i,j}^h$ is determined by the positions of the i -th and j -th pedestrians (Figure 3), while its magnitude is given by the following relation:

$$\begin{cases} \vec{F}_{i,j}^h = v_{apr,i,j} (\hat{d}_{i,j}^h)^{-2} \\ 0 \end{cases} \quad (21)$$

for $\hat{d}_{i,j}^h \leq D_{range,i}$
otherwise

where: $\hat{d}_{i,j}^h$ denotes the predicted distance between the i -th and j -th pedestrians at the future time instant h , while $v_{apr,i,j}$ is the relative approaching velocity of pedestrians i and j , defined as follows:

$$\begin{cases} v_{apr,i,j} = \frac{\hat{d}_{i,j}^{h-1} - \hat{d}_{i,j}^h}{\Delta t} \\ 0 \end{cases} \quad (22)$$

for $\hat{d}_{i,j}^{h-1} - \hat{d}_{i,j}^h > 0$
otherwise

The velocity (21) serves as a scaling factor that determines the possible collision risk. As a basis for determining the confidence coefficients of occurrence of specific events from the perspective of the i -th pedestrian, the maximum value of the repulsive force vector computed at time instant n over the prediction horizon H was adopted:

$$\vec{F}_i^n = \max_{h=n+1 \dots n+H} (\vec{F}_i^h) \quad (23)$$

Vector (22) determines the direction in which the motion of the i -th pedestrian entails the highest collision risk. Therefore, the projection of vector (22) onto the vectors associated with the reaction zones of the i -th pedestrian (Figure 3b) was employed to estimate the confidence coefficients of their occurrence.

As an example, let us consider the situation shown in Figure 3b, in which the highest collision risk with the k -th pedestrian is theoretically observed. This assessment is based on the maximum magnitude of the projection of vector (22) onto the CLL/CLR zone. Accordingly, this reaction was expected to be the most probable one for the i -th pedestrian. Let us therefore denote by the magnitude of the projection of vector (22) onto the vector associated with the k -th ($k \in M^p$) pedestrian reaction, defined by set (2):

$$\begin{cases} F_{i,k}^{proj} = \frac{|\vec{F}_{i,k}^{proj}|}{|\vec{F}_{max}|} & \text{for } |\vec{F}_{i,k}^{proj}| > \\ 0 & \text{otherwise} \end{cases} \quad (24)$$

$> F_{min}^{proj} \quad k = 1 \dots 6$

where: $|\vec{F}_{min}^{proj}|$ denotes the minimum value of the magnitude of the considered vector projection, while $|\vec{F}_{max}| = v_{apr}^{max} D_{risk}^{-2}$ represents the maximum possible value of the repulsive force vector.

The coefficient v_{apr}^{max} is the maximum approaching velocity assumed, and D_{risk} is the minimum acceptable distance between two pedestrians. The confidence coefficients of the i -th pedestrian's reactions are proportional to the magnitudes of the projections of vector (23) onto the directions associated with the first six reactions from set (2). Note that two zones (2 and 3) are associated with the yielding reaction; therefore, the confidence coefficient of this event is given by the sum of the corresponding projections. In contrast, the vector representing the absence of a pedestrian reaction is defined as a nonlinear function of the elements of set (2), according to the following relation:

$$F_{i,k=7}^{proj} = e^{-\beta F_{max}^{proj}}, F_{max}^{proj} = \max_{k=1 \dots 6} \frac{|\vec{F}_{i,k}^{proj}|}{|\vec{F}_{max}|} \quad (25)$$

Let us determine the values of the confidence coefficients for the occurrence of individual reactions of the i -th pedestrian, as defined in (2), in

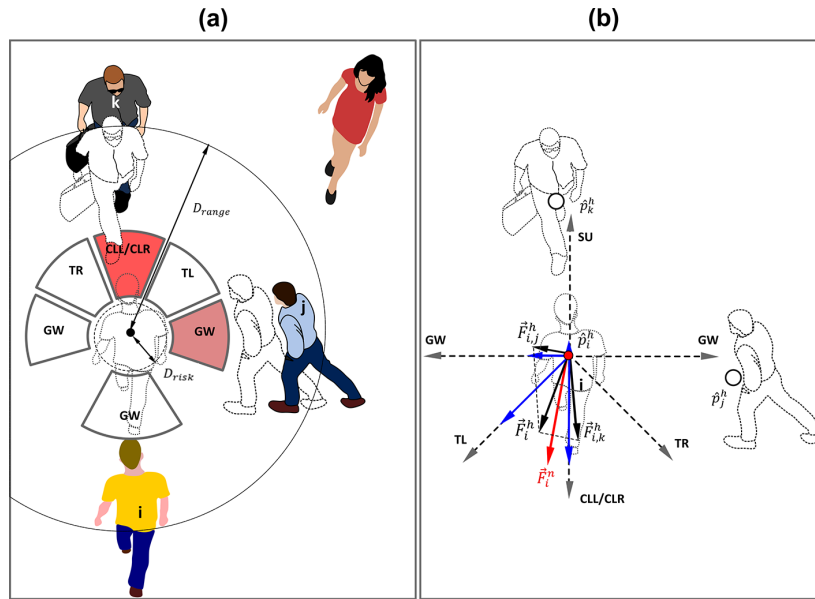


Figure 3. Illustration of an arrangement of reaction zones (a) and a projection of virtual repulsive force vectors onto the vectors associated with these zones (b)

response to predicted changes in the environmental configuration:

$$c_{i,k} = \frac{F_{i,k}^{proj}}{\sum_{k=1..7} F_{i,k}^{proj}} \quad (26)$$

The confidence coefficient c_j of the scenario defined in (13), which consists in the simultaneous occurrence of reactions of all N traffic participants within the prediction horizon H can now be computed.

$$c_j = \prod_{i=1}^N c_{i,k} \quad k \in \{1.. \bar{M}^p\}, j = 1, 2, \dots, \bar{S} \quad (27)$$

SIMULATION RESULTS

This section presents the evaluation of the proposed human-aware navigation framework based on simulation studies. The primary objective of these simulations is to analyse the decision-making process under controlled and reproducible conditions across diverse pedestrians' motion scenarios. The considered variants include varying pedestrian densities, interaction patterns, and uncertainty levels, enabling a systematic assessment of the impact of individual components of the proposed method. The use of simulation allows precise control over scenario parameters and ensures repeatability of experiments. However, it should be noted that the

adopted validation approach has certain limitations. In particular, simplified perception models, idealised representations of pedestrian behaviour, and the absence of sensing uncertainties may not fully reflect real-world conditions. Therefore, the presented results should be interpreted as a proof of concept demonstrating the effectiveness and internal consistency of the proposed framework.

Before illustrating the operation of the complete HAN navigation system, let us consider three representative two-pedestrian interaction scenarios in order to assess the confidence levels of individual reactions. These scenarios are shown in Figure 4. In all illustrations, the following notation is adopted. The pedestrian silhouette indicates the pedestrian's position at the current time instant n . Black circles denote pedestrian positions in the past M time instants, while colored circles represent the H predicted pedestrian locations. Reaction zones associated with possible pedestrian responses are depicted around each silhouette. Green shading indicates a zero value of the confidence coefficient for the reaction associated with a given zone, whereas shades of red correspond to nonzero values. Let us consider the first scenario (Figure 4a). It simulates one of the typical situations in which the trajectory of pedestrian $p1$ is gently crossed by pedestrian $p2$, who moves faster than $p1$. The pedestrians' velocities are $v_1 = 1.1$ m/s and $v_2 = 1.3$ m/s, respectively. After applying the methodology described above (20–26), the confidence coefficients for the

occurrence of specific reactions are determined from the perspective of each pedestrian. In this case, the following is obtained:

$$c_{1,k} = [0,0,1,0,0,0,0],$$

$$c_{2,k} = [0,0,0.43,0.57,0,0], k=1,2,\dots,7$$

Finally, by applying (26) to the above data, we obtain the confidence coefficients for the occurrence of all 49 possible events. From these, the most probable event can be identified from set (12), corresponding to the simultaneous occurrence of the pedestrian reactions $\{GW, TR\}$, i.e., pedestrian p_1 slows down and yields to p_2 , while p_2 slightly changes the direction of motion. Considering the characteristics of pedestrian traffic, such behaviour appears both feasible and probable, although any other scenario remains possible. For the remaining two scenarios, the following most probable events are obtained: $\{CLR, CLL\}$ for scenario (b) and $\{CLL, GW\}$ for scenario (c). Figure 5 presents the actual pedestrian trajectories in the simulated process. As can be observed, in this case they are consistent with the predicted reactions.

As in Figure 4, the predicted motion trajectories are indicated by coloured circles. The actual trajectories, resulting from the pedestrians' reactions, are shown in black. Figure 6 presents the evolution of the minimum distance between pedestrians for the three scenarios discussed above.

The predicted distance between pedestrians over the prediction horizon H is marked in red, while the actual distance measured along the trajectories resulting from the considered reactions is shown in green. As can be observed, in each case this variant leads to an improvement in traffic safety.

This section presents a simulation of the proposed navigation system in a scenario typical of public areas. The notation adopted is consistent with that used in previous experiments. The robot's initial and final positions are marked with pictograms, while its trajectory is indicated by black dots. The green band denotes the reference motion corridor of the vehicle. Red segments represent the distance between the robot and the nearest pedestrian.

The prediction horizon is set to $H = 8$ with a sampling period of $\Delta T = 0.5$ s. The total simulation time is 12 s and comprises three decision-making stages. The robot moves parallel to a stream of pedestrians labelled $P1 - P4$. Based on the mechanism for evaluating predicted pedestrian interactions, a high probability of pedestrian reactions is determined as $[NR, NR, CLR, CLL]$. Relying on this forecast, the navigation system generates a sequence of manoeuvres: $[GW, NR, NR]$. The robot trajectory and the actual pedestrian behaviour are shown in Figure 7a. Figure 8a presents the time histories of the robot velocity and the minimum robot–pedestrian distance.

For the same scenario, a simulation was also run in a variant without evaluating the effects of interactions between pedestrians. Navigation is performed based on pedestrian motion prediction and in accordance with the Hurwicz decision strategy [15].

By predicting pedestrian motion solely on the basis of previously collected data, the system fails to detect a collision risk and generates the sequence $[NR, NR, NR]$, which implies that no manoeuvres altering the current direction or speed of motion are executed.

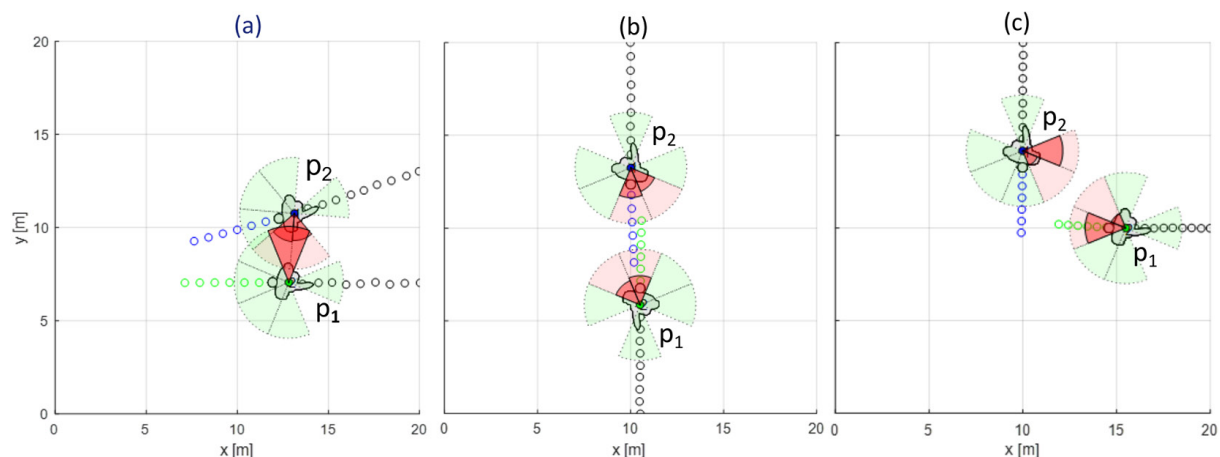


Figure 4. Illustration of two-pedestrian interaction scenarios

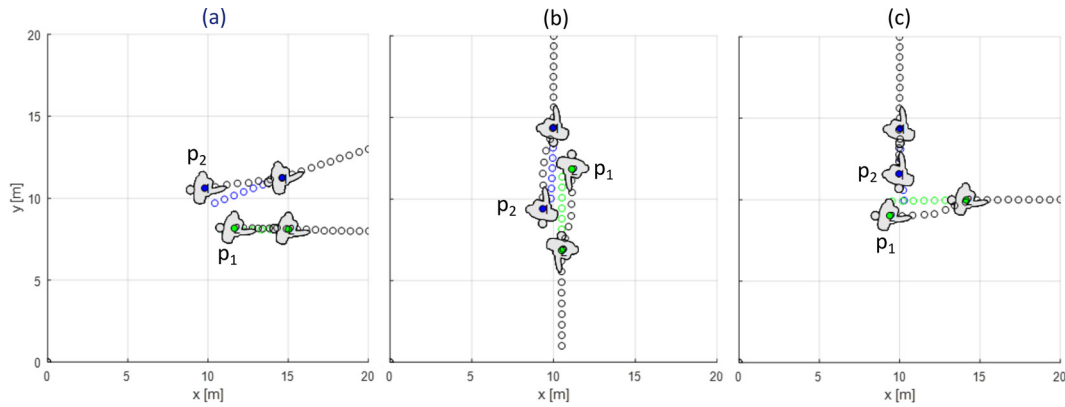


Figure 5. Actual motion trajectories resulting from the interactions between the pedestrians identified above for the three scenarios shown in Figure 4

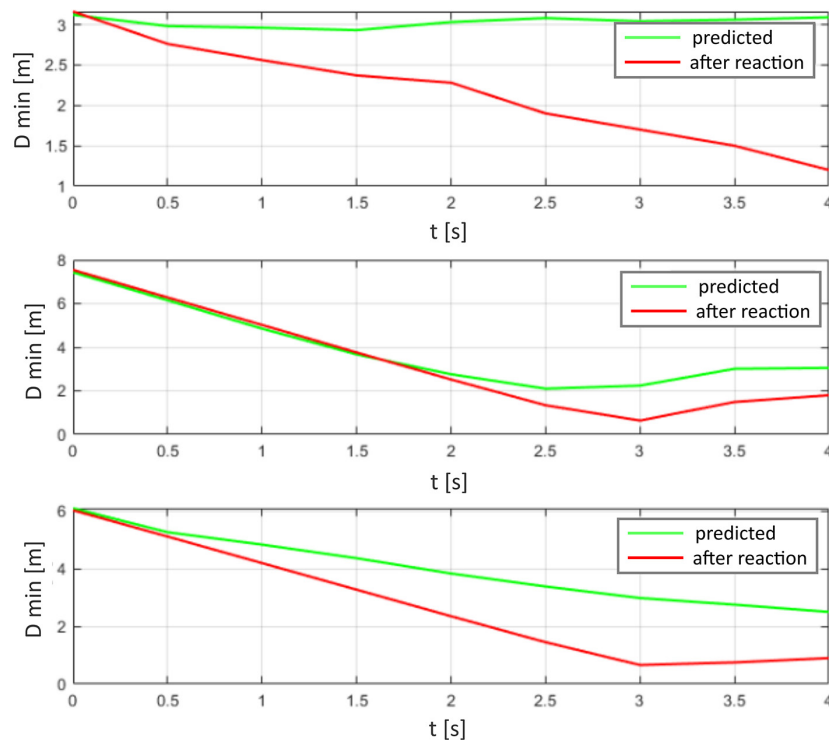


Figure 6. Time plot of the predicted and actual minimum distance between pedestrians for the motion scenarios described above

As shown in Figures 7b and 8b, this results in a potentially hazardous, collision prone situation.

SUMMARY

This article introduced a human-aware navigation framework for autonomous vehicles/robots navigating in populated public areas. The proposed approach departs from conventional reactive navigation methods by explicitly accounting for mutual interactions between pedestrians and

their influence on future environment configurations. Central to the framework is a long term prediction mechanism combined with a decision-making model under uncertainty, formulated as a game against nature. Pedestrian behaviour was modelled using a discrete set of representative reaction patterns, such as lane or direction changes, speed adjustments etc. For each pedestrian, alternative future motion hypotheses were generated over a finite prediction horizon. Possible interactions among pedestrians were then analysed using a concept inspired by artificial

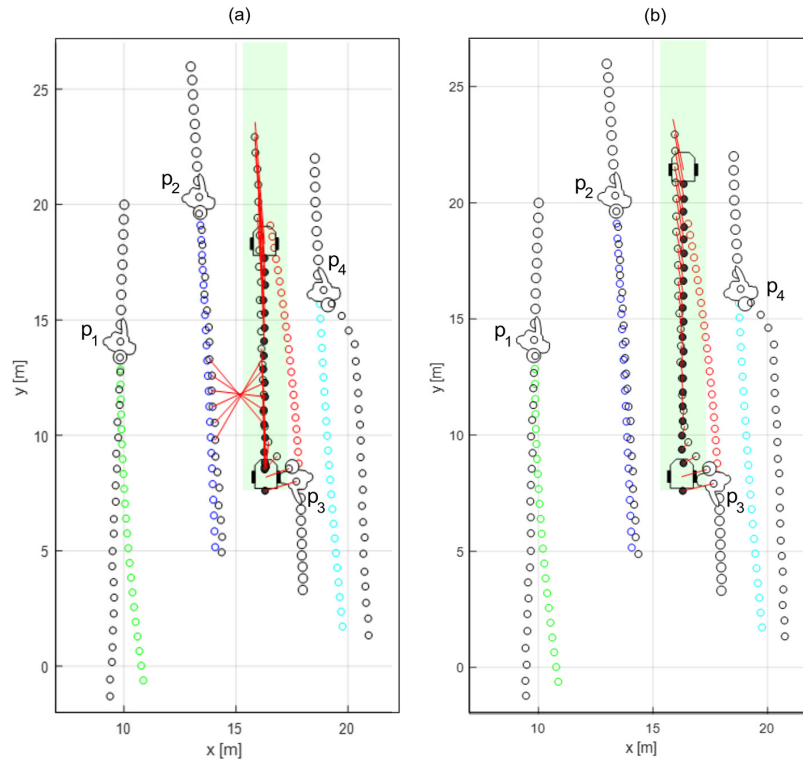


Figure 7. Robot navigation scenario arranged for comparing two approaches: With (a) and without (b) taking into account interactions between pedestrians

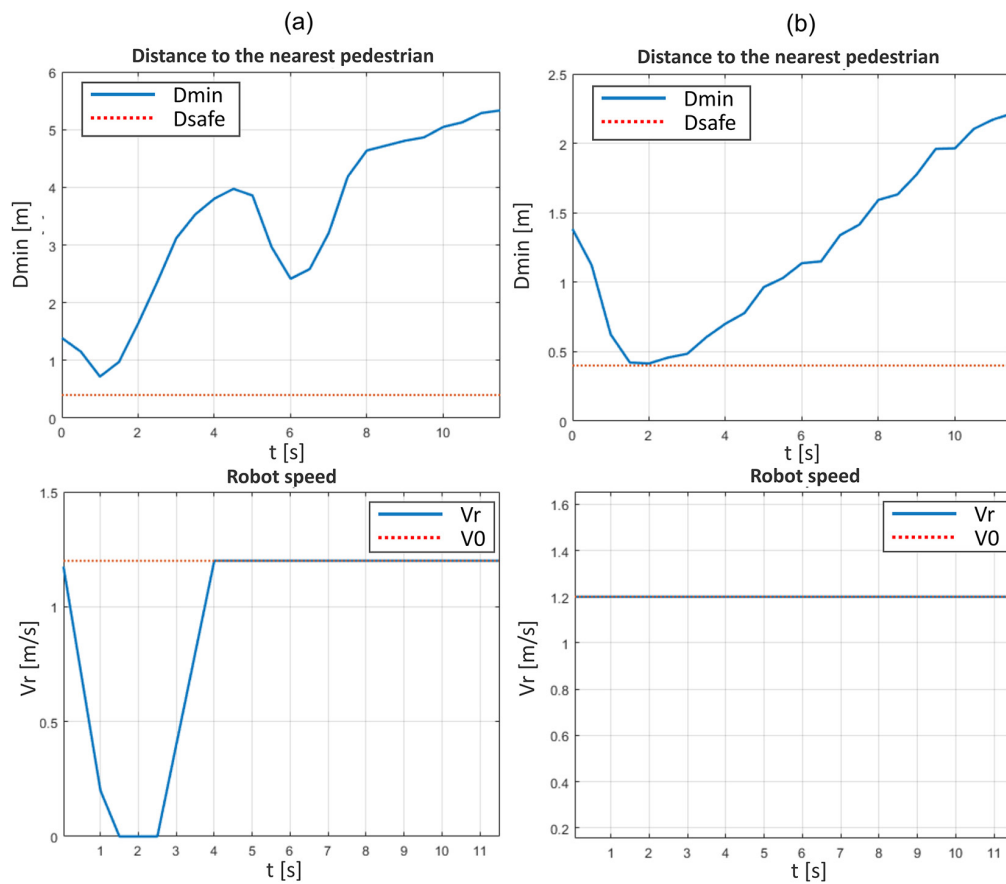


Figure 8. Time plots of the robot velocity and the minimum robot–pedestrian distance for scenarios presented in Figure 7 respectively (a) and (b)

potential fields, allowing the estimation of confidence coefficients associated with pedestrians' reaction scenarios.

These confidence levels were incorporated into a decision-making process that minimises the expected value of a composite cost function, balancing safety-related criteria and navigation accuracy. This represents a methodological extension beyond earlier work based on pessimistic/personal decision criteria, enabling probability-weighted evaluation of future scenarios. The effectiveness of the proposed framework was demonstrated through simulation studies. First, representative two-pedestrian interaction scenarios validated the consistency of the predicted reaction confidence levels with realistic pedestrian behaviours. Subsequently, a navigation scenario involving a robot moving in parallel with pedestrian flow illustrates the benefits of explicitly considering pedestrian interactions. Compared to a baseline approach relying solely on trajectory prediction and the Hurwicz criterion, the proposed method successfully anticipated collision risks and generates adaptive, socially compliant manoeuvres that improve safety.

CONCLUSIONS

The presented work demonstrated that explicit modelling of pedestrian–pedestrian interactions significantly enhances the quality of human-aware navigation in public spaces. By coupling long term pedestrian motion prediction with interaction-based estimation of scenario confidence levels, the proposed framework enables anticipatory decision-making rather than purely reactive behaviour. Formulating the navigation problem as a game against nature with weighted scenarios allows uncertainty inherent to pedestrian behaviour to be addressed in a structured manner. The methodology for deriving scenario confidence coefficients based on predictive analysis of virtual repulsive forces was presented. This provides an intuitive and computationally efficient mechanism for approximating the likelihood of complex multi-agent interactions without requiring fully probabilistic models. Simulation results confirmed that such approach leads to safer and more socially acceptable robot motion, particularly in the situations where pedestrian interactions significantly alter future trajectories. In contrast, the navigation strategies that neglect

these interactions may underestimate collision risk and produce potentially hazardous behaviour. Although the study was limited to simulated environments and a constrained set of pedestrian reaction patterns, the results are promising. Future work are going to be focused on extending the reaction models and refining interaction analysis in denser crowds. To enhance the validity and applicability of the results, the validation of the proposed approach using publicly available datasets is planned. It will enable direct comparison with state-of-the-art methods under standardised experimental conditions. Furthermore, real-world experiments are planned with the use of a holo-nomic mobile platform currently being developed at our research centre. This will allow assessing the proposed solutions under realistic operating conditions, taking into account hardware constraints, measurement noise, and interactions with humans.

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