Adaptive Interaction Field Framework for Risk-Aware Navigation of Driverless Minibus in Pedestrian Zones

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Abstract: In complex pedestrian zones, the navigation of driverless minibuses faces significant challenges due to varying environmental structures and pedestrian behavior. These zones range from organized pathways to open, unstructured spaces with minimal navigational cues. To address this, dynamic interaction fields are developed around the driverless minibus, adapting in size and shape to real-time movements. To achieve a similar representation as vehicle, interaction fields are developed that incorporate pedestrian unawareness. These virtual fields facilitate safer and more intuitive interactions between vehicles and pedestrians by incorporating real-time pedestrian awareness and activity data. The proposed model assesses risk by aggregating grid values from overlapping zones between pedestrians and driverless minibus, computing potential encounters based on spatial positions and awareness levels. A gradient-based heat map visualizes risk, highlighting areas where interaction with pedestrians is needed. This adaptive approach enables the decision-making module to initiate appropriate responses, such as escape maneuvers or interaction mode activation, based on risk thresholds. The interaction field further classifies risk into ambient, direct, or critical levels, guiding the system's reactions. This framework enhances safety protocols and situational awareness in diverse urban environments. The vehicle was able to drive and interaction in a better way with enabled interaction fields. Based on these risk values, various interaction modules were activated, facilitating meaningful and context-aware interactions with pedestrians.

1 INTRODUCTION

The inclusion of driverless minibuses in pedestrian zones is becoming an exciting area for the automotive industry and researchers (Jan and Berns, 2023),(Nesheli et al., 2021),(Milanés et al., 2020). With the expansion of pedestrian zones and narrow spaces, driverless minibuses offer quick and flexible transport between buildings in shared spaces. Safety becomes a primary concern when navigating through crowds. In one of our previous works (Jan and Berns, 2021), a hardwired safety system was configured to prevent collisions. This fail-safe system directly enabled emergency braking in case of routine malfunctions. To ensure smooth navigation and avoid abrupt safety braking due to pedestrians' presence within the field, risky pedestrians need to be informed about the vehicle and give way in advance.

Risky pedestrians are defined by their unawareness of the driverless minibus. This unawareness could stem from several reasons, such as being engaged in conversation, talking/texting on the phone, or walking in the same direction ahead of the vehicle. In such cases, it is necessary to interact with pedestrians to alert them using various interaction modules (Jan et al., 2023), (Rasouli and Tsotsos, 2019).

There exists a spectrum of structural variation in pedestrian zones based on the intended use and level of pedestrian and vehicle integration. This enforces different walking and driving behaviors in pedestrians and vehicle, respectively. To understand the riskiness of pedestrians around the vehicle, we introduce a novel method of understanding riskiness of pedestrians in maps by creating virtual dynamic fields around the vehicle. Such dynamic fields, also known as vehicle interaction fields serve dual purpose, to improve safety and enable useful interaction between vehicle and pedestrians. This helped in better driving and efficient interaction. To understand the riskiness of pedestrians in the map, their riskiness is presented as dynamic fields. Next section presents the inspiration and concept of interaction field for driverless mini. Section 3 provides the implementation of the concept. Integrated results from vehicle-pedestrian interaction

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Table 1: Translation of four interaction phases to three zones for driverless minibus. Implicit and subtle interactions from the phased interaction (Vogel and Balakrishnan, 2004) are combined into direct interaction within the smart interaction zone in this work.

Phased Interaction	Smart Interaction Zones	Purpose in Vehicle for Interaction
Ambient Display	Ambient	General awareness, signals vehicle presence passively to pedestrians
Implicit Interaction Subtle Interaction	Direct	Overt communication with pedestrians
Personal Interaction	Risk	Critical response measures for pedestrian safety

field are shown in Section 5.

2 PEDESTRIAN ENGAGEMENT THROUGH PHASED INTERACTION ZONES

The interaction field is made into different phases, since this allows to have specific interaction for pedestrians with specific risk values and different distance to vehicle. The phase interaction was inspired from Vogel et. al. (Vogel and Balakrishnan, 2004). The authors have shown a fluid interaction strategy from distant to close interaction. In the literature, these phases are Ambient Display, Implicit Interaction, Subtle Interaction, and Personal Interaction. The ambient display initially presents general information passively, shifting to implicit interaction as a user approaches to offer personalized notifications. During this phase, simple gestures enable shared use while maintaining an overview. In the personal interaction phase, users can engage directly via touch for detailed information. To the best of our knowledge, no existing research considers pedestrians' unawareness as a risk factor rather than treating them solely as conventional obstacles.

This paper proposes "Interaction Field Zones" based on (Vogel and Balakrishnan, 2004) phased interaction framework to enhance communication with pedestrians. It translates the four phases into three zones as shown in Table 1. The model transitions from ambient awareness to direct engagement, establishing a natural communication channel. In the basic zone, similar to an "Ambient Display," the vehicle passively signals its presence to ensure pedestrians are aware without direct interaction. As pedestrians approach, entering an "ambient interaction" phase, the vehicle dynamically adjusts its behavior based on their speed and path to convey subtle intentions. In the "direct interaction" phase, it uses visual or auditory cues to communicate actions and prioritize pedestrian safety. In complex scenarios, it switches to a "risk" mode with emergency measures like braking to ensure safety. These interaction zones improve communication, safety, and trust, adapting to varying pedestrian environments and aligning with human interaction paradigms.

3 INTERACTION FIELD DESIGN

Establishing interaction fields for Autobus enables real-time risk assessment, spatial awareness of pedestrian activity, and adaptive responses to different pedestrian behaviors, enhancing safety and traffic flow.

To develop the vehicle interaction field for driverless minibus, it is crucial to understand pedestrian behavior (Jan et al., 2022a), (Jan et al., 2022b), particularly the risks posed by a lack of awareness. These risks often arise when pedestrians are distracted by electronic devices or moving in the same direction as the vehicle, increasing the likelihood of collisions or delays. This work proposes a tailored model of interaction fields for pedestrian-vehicle interaction to enhance vehicle navigation and decision-making. The goal is to reduce risks by enabling more informed and responsive vehicle driving and interaction strategies.

3.1 Vehicle Interaction Field

Not all areas around a vehicle are relevant for pedestrian interaction while driving. Due to open spaces and crowds, interactions should primarily focus on individuals in the vehicle's drivable area, referred to as "interactees," even if they are not actively reacting to

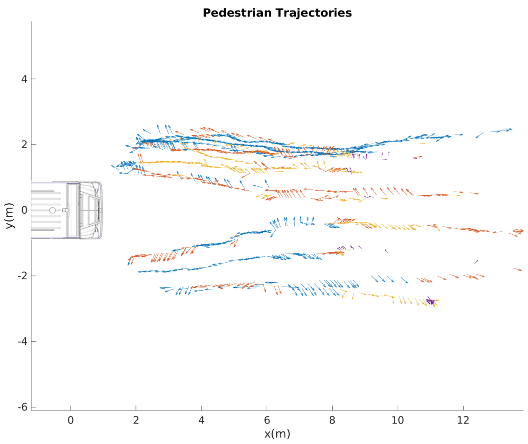


Figure 1: The plot shows top view of pedestrian trajectories and directions during encounters with the driverless minibus during testing in the campus, revealing a consistent pattern of avoidance. This predictable behavior can inform the design of interaction fields that minimize disruptions under normal conditions.

the vehicle. This requires identifying and segmenting regions of interest based on interaction types. To achieve this, interaction fields are created around the vehicle to strategically limit and streamline the activation of interaction modules, enhancing their efficiency.

The interaction field configuration is based on pedestrian trajectories relative to the vehicle. As shown in Figure 1, pedestrians approaching the vehicle often display a clear pattern of yielding, especially in tight spaces. Research by Schneemann et. al. (Schneemann and Gohl, 2016) highlights that pedestrians typically adjust their path to avoid the vehicle, indicating a collective behavior of spatial negotiation and collision avoidance.

The interaction fields around the driverless minibus, shown in Figure 2, are designed to enable graduated communication and risk assessment based on pedestrian proximity. Inspired by the behavior observed in Figure 1, these fields extend further in the direction of travel and are shorter in the opposite direction, reflecting the dynamics of pedestrian-vehicle interactions and risk assessment principles. The design of the field was based on the following principles:

- The forward extension of the fields accounts for the vehicle's stopping distance, which varies with speed.
- A longer field in the travel direction provides sufficient space for safe stopping.
- Side fields are shorter since pedestrians in these areas are more likely to have seen the vehicle pass, reducing risk.

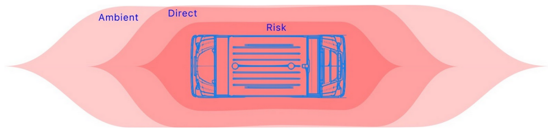


Figure 2: Schematic of the vehicle with interaction fields: the 'Ambient' field (light red) serves as an initial awareness zone, extending forward for early pedestrian detection; the 'Direct' field (darker red) enables active communication, allowing dynamic responses; and the 'Risk' field (darkest red) covers the closest zone for immediate collision prevention. This stratification supports graduated safety measures based on proximity.

According to the zones clarified in Table 1, the three zones of interaction are:

- **Ambient Interaction:** The outermost field provides general awareness by passively signaling the vehicle's presence to distant pedestrians, focusing on those crossing from the front. It aligns with the "Ambient Display" concept and involves no collision risk.
- **Direct Interaction:** This field facilitates active communication, especially with pedestrians who haven't noticed the vehicle. It enables early detection and allows the vehicle to adjust its speed or path, issuing auditory alerts if necessary to enhance safety.
- **Risk Interaction:** The closest zone triggers critical responses when a pedestrian enters, including emergency braking and visual alerts. It is designed for immediate action to prevent collisions in high-risk situations.

3.2 Pedestrian Interaction Field

To integrate pedestrian models into vehicular interaction fields, representing pedestrians as ellipses is effective, as suggested by W. Limprasert et al. (Limprasert et al., 2013). Ellipses capture pedestrian size and direction, simplifying computations and enabling quicker decisions. They adapt to changes in speed and direction, aligning with natural human motion and enhancing pedestrian movement prediction. This approach balances accuracy and computational efficiency, improving safety in pedestrian-vehicle interactions. Figure 3 illustrates this representation.

An ellipse is defined by its geometric parameters, which correlate with pedestrian movement relevant to vehicle interaction fields. The standard equation for an ellipse, centered at the origin and aligned with the coordinate axes, is:

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \quad (1)$$

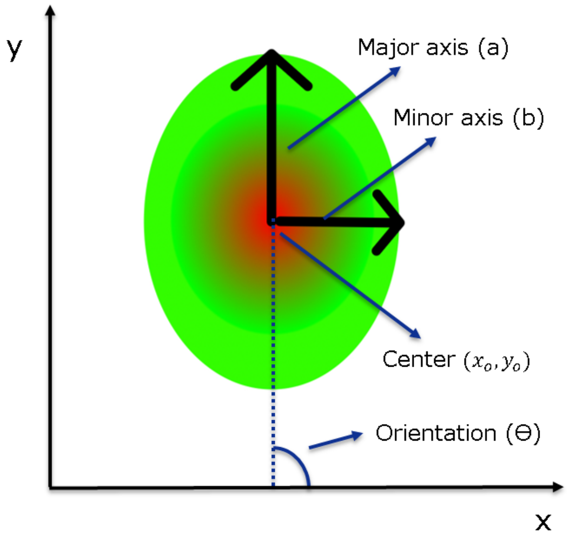


Figure 3: A graphical depiction of a pedestrian interaction field as a gradient-filled ellipse, with 'X' and 'Y' representing horizontal and vertical coordinates. The gradient indicates pedestrian awareness, decreasing from the center outward. Arrows show the major axis (forward movement) and minor axis (lateral space). The unawareness value increases toward the periphery.

where a and b are the semi-major and semi-minor axes. For an ellipse centered at (x_0, y_0) and rotated by an angle θ, this equation is adapted to represent pedestrian positioning and orientation.

- **Center** (x_0, y_0)**:** Indicates the pedestrian's current position, serving as the geometric center of the ellipse.
- **Major axis** $(2a)$**:** The longest axis, aligned with the pedestrian's primary direction of movement, indicating forward motion and intended path length.
- **Minor axis** $(2b)$**:** The shorter axis, perpendicular to the major axis, representing lateral movement and the pedestrian's width in the field.
- **Angle of rotation** (θ)**:** Defines the orientation of the ellipse relative to the coordinate frame, aligning the major axis with the pedestrian's movement direction for accurate path projection.
- **Color Gradient:** The gradient within the ellipse represents the pedestrian's level of awareness, decreasing from the center to the edge, with unawareness increasing outward. These parameters help autonomous vehicles dynamically adjust navigation for pedestrian safety.

4 INTEGRATING INTERACTION FIELDS AS AN ENTITY OF ASPECT MAPS

The design of interaction fields uses aspect maps, a framework developed by (Zolynski, 2018) that applies cognitive processes in robotics. Unlike traditional object-oriented methods, it employs parallel data flow networks inspired by biological visual systems. Aspect maps are modular structures that represent specific aspects of the environment, integrating data from sources like sensors, storage, and expert knowledge. They unify and abstract data, enabling question-solving, information extrapolation, and contradiction detection. This approach emphasizes modular, reusable solutions with multilevel abstractions and supports early data unification, improving processing, transparency, and reliability. Interaction fields for vehicles and pedestrians are represented within this framework for seamless correlation and integration.

4.1 Vehicle Interaction Field Mapping

The interaction field around the vehicle is shaped using Bézier curves, as shown in Figure 4, offering an efficient design. The cubic Bézier curve with four control points is expressed as:

$$B(t) = (1-t)^3 P_0 + 3(1-t)^2 t P_1 + 3(1-t) t^2 P_2 + t^3 P_3 \tag{2}$$

where:

- $B(t)$ denotes a point on the curve.
- P_0, P_1, P_2, and P_3 are the control points.
- t ranges from 0 to 1.

At $t = 0$, the curve starts at P_0, and at $t = 1$, it ends at P_3, passing smoothly through intermediate control points.

The construction of interaction fields around the vehicle involves a multi-step process using Bézier curves and gradient maps to define and refine spatial boundaries. Each step progressively shapes the interaction zones, ensuring efficient vehicle navigation and pedestrian safety. Figure 4 illustrates the steps involved in creating the interaction field, as detailed below:

1. **Bézier Curves (Step 1):** The interaction field is generated by extending two Bézier curves from the vehicle's front to its left and right sides. These curves shape the interaction boundaries on both sides of the vehicle, as illustrated in the top left and bottom left insets. The Bézier curves act

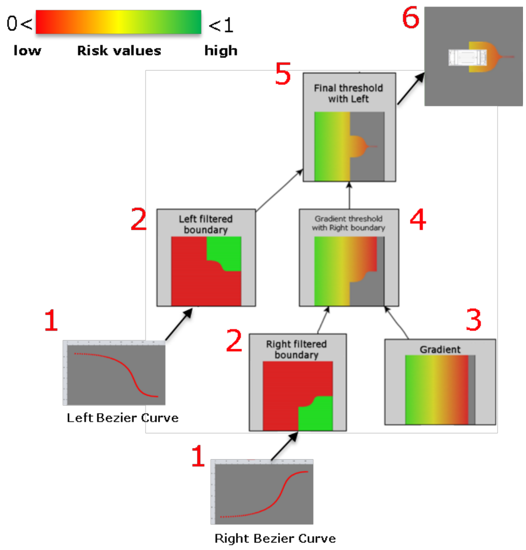


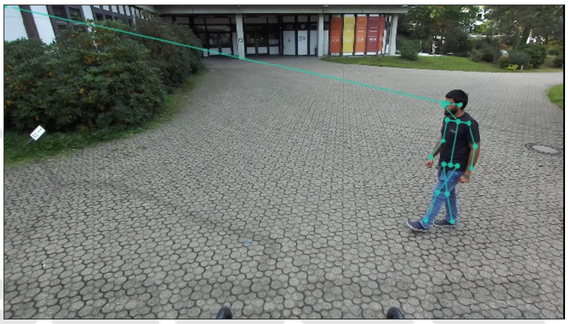
Figure 4: The figure illustrates the step-by-step process for creating a vehicle interaction field design.

as flexible boundaries that are created on a grid, defining the field's spatial extent.

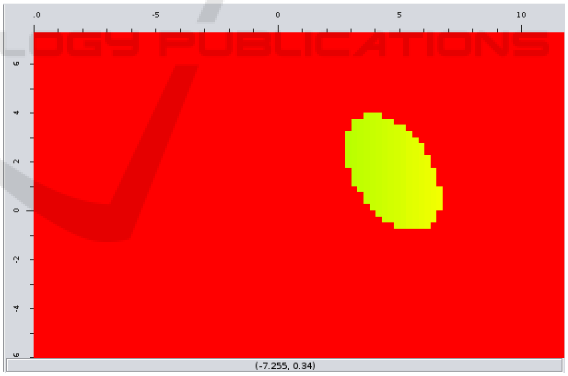
2. **Filtered Boundaries (Step 2):** The left and right filtered boundaries are determined on a grid, with specific regions designated as null (indicated in red). These boundaries establish the limits of interaction fields, separating null zones (zero interaction) from active zones (one interaction).
3. **Gradient Map Creation (Step 3):** A gradient map is created, as shown in the middle of the image, indicating different zones of pedestrian interaction with varying intensities. The gradient progresses from red (low risk) near the vehicle to green (high risk) at the periphery, representing awareness levels within the interaction field.
4. **Thresholding and Composite Maps (Step 4 and 5):** The gradient map undergoes a thresholding process using the right and left filtered boundaries sequentially. During each thresholding step, red zones (zero values) are assigned gradient values, while non-colored zones are marked as NaN, denoting inactive areas. The sequential filtering refines the map, ultimately leading to a composite map representing finalized interaction boundaries.
5. **Final Interaction Field (Step 6):** The uppermost image shows the culmination of this process, presenting the final interaction field map around the vehicle. This map indicates varying interaction zones based on proximity and provides the necessary spatial structure for the vehicle's navigation system.

4.2 Pedestrian Interaction Field Mapping

The vehicle interaction field concept requires an analogous representation of pedestrians to understand their unawareness and associated risks. Unlike the vehicle interaction field, this method uses ellipses, as shown in Figure 3, to model pedestrian dimensions and movement dynamics accurately. In Figure 5, pedestrian is depicted as yellow-green ellipse centered based on their actual position relative to the vehicle, which is positioned at the origin (0,0). This alignment ensures precise spatial representation and enhances the model's ability to assess interactions and collision risks. The ellipses' orientation further indicates pedestrian movement direction.



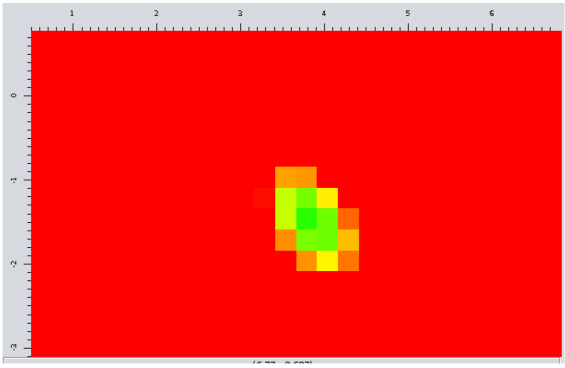
(a) Pedestrian walking in front of the vehicle.



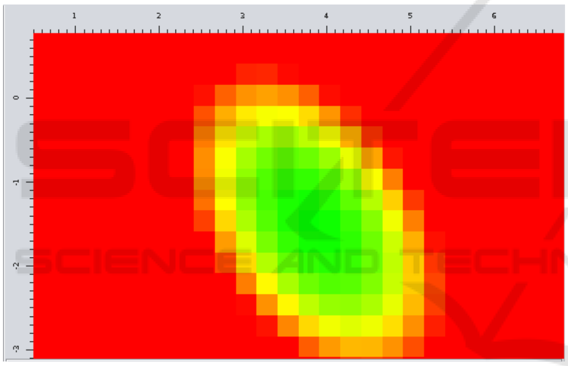
(b) Aspect map representation of pedestrian awareness in grip map (top view), where the minibus center is located at (0, 0).

Figure 5: Grid representation of pedestrian space: Pedestrian occupancy as unawareness is shown as a yellow-green ellipsoid, while unoccupied areas are marked in red. This visualization quantifies pedestrian dynamics and spatial interaction on the grid.

Figure 6 presents a zoomed-in view of the pedestrian representation on the grid map, comparing awareness levels between zero and one. The grid cells transition from green (indicating higher awareness) to red (indicating lower awareness) based on grid values. This color scheme not only aids visualization but also enhances the model's ability to quantitatively assess and represent pedestrian awareness, highlighting areas of potential vulnerability and improving safety insights in vehicle-pedestrian interactions.



(a) Pedestrian awareness with unawareness value 0, shown as an isolated high-intensity area on a red background indicating maximum awareness.

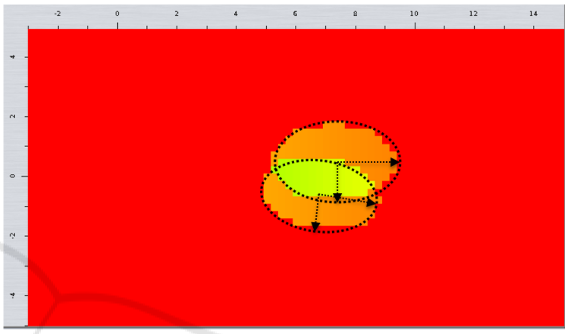


(b) Pedestrian awareness with unawareness value 1, showing a gradient from green (low awareness) to red within the ellipsoid on the grid map.

Figure 6: (a) Unawareness value of 0 shows a localized high-awareness area in green, surrounded by a red background indicating maximum awareness. (b) Unawareness value of 1 demonstrates a gradient from red (lower awareness) to green (higher awareness) within the ellipsoid on the grid.

To represent the collective awareness of multiple pedestrians, their respective values are aggregated. Figure 7 illustrates two pedestrians with reduced awareness near the vehicle, indicated by areas of higher intensity. When pedestrians' unawareness regions overlap, the values are summed, resulting in more saturated colors that reflect increased risk. This approach captures and emphasizes heightened risks from reduced awareness in overlapping pedestrian groups.

(a) Front camera image showing two pedestrians walking ahead of the Autobus.



(b) Top view grid map showing the spatial occupancy of both pedestrians.

Figure 7: The grid map visualizes two overlapping pedestrian spaces as ellipses on a red background. The intersection creates a value gradient, with the central yellow region indicating the highest overlap. This composite view is essential for analyzing pedestrian density, movements, and interactions.

5 INTEGRATED VEHICLE-PEDESTRIAN INTERACTION FIELD

The analysis of merged values within interaction fields is essential for understanding pedestrian-vehicle dynamics, particularly with a driverless minibus. In Figure 8, a pedestrian's entry into the interaction field is depicted, marked by a black elliptical outline on the grid map, while the vehicle's field is shown with a gray dotted line. A schematic of driverless minibus is overlaid for orientation, indicating its position and direction.

The grid map uses a color gradient from red to yellow to represent increasing perceived risk, with yellow highlighting areas of higher merged awareness values. As the pedestrian enters the interaction field, the model assesses their location and corresponding awareness levels to compute the likelihood and severity of a potential encounter with the vehicle. This

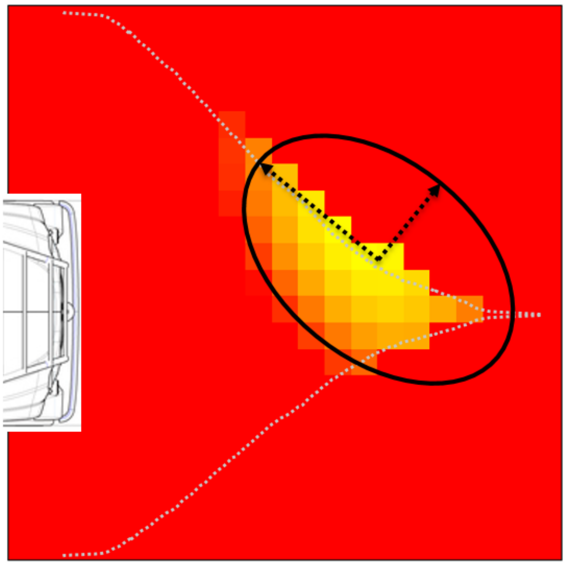


Figure 8: The grid map illustrates the spatial risk assessment between a pedestrian and the vehicle. The pedestrian's position is outlined in black, while the vehicle's interaction field is marked with a gray dotted line. A schematic of the vehicle provides orientation. The heat map, with a red-to-yellow gradient, indicates increasing perceived risk, with yellow denoting higher merged awareness values. These values help evaluate the likelihood and severity of a potential encounter, enhancing understanding of how the pedestrian's location influences the system's risk assessment.

visualization allows the system to quantify and evaluate how the pedestrian's spatial positioning affects the system's risk assessment, thereby enhancing the understanding of dynamic pedestrian-vehicle interactions.

Associated pedestrian risk is quantified by summing the grid values of the pedestrian's ellipsoid and the vehicle's interaction field. The grid is modeled as a two-dimensional matrix, where each entry represents a specific position. The overlapping area, denoted as E for the pedestrian's ellipsoid and V for the vehicle's interaction field, is used to calculate the total risk. The formula sums the values within this overlap, capturing the combined effect of both entities on the grid.

Let E be the set of grid positions occupied by the pedestrian's ellipsoid and V be the set of grid positions occupied by the vehicle's interaction field.

$$S = \sum_{(i,j)\in E\cap V} (E_{ij} + V_{ij}) \quad (3)$$

Where:

- S is the total sum of the overlapped grid values.
- E_{ij} is the grid value at position (i, j) due to the pedestrian's ellipsoid.
- V_{ij} is the grid value at position (i, j) due to the vehicle's interaction field.
- $E \cap V$ represents the set of grid positions where the ellipsoid and interaction field overlap.

The ellipsoid grid values represent pedestrian unawareness, while the vehicle interaction field values signify potential risk. The combined sum of these values at overlapping positions provides a composite metric to assess risk in the interaction zone based on predetermined thresholds for various fields.

These aggregated grid values are then sent to the decision-making process, which evaluates the data to determine if escape maneuvers are possible or if activating the interaction module is necessary. This decision-making phase integrates risk assessments to enhance safety measures in scenarios requiring active intervention.

Additionally, the calculated risk is utilized by the interaction module, which classifies it into three types of interactions—ambient, direct, or risk-based—using a threshold mechanism. This classification guides the module's response to different levels of pedestrian-vehicle interactions, ensuring an adaptive approach to managing potential hazards.

6 CONCLUSION

In conclusion, the concept of this work prioritizes effective risk assessment through adaptive interaction fields aligned with the vehicle's direction of travel. This strategic alignment minimizes inappropriate interactions, especially in less critical peripheral zones. The pedestrian interaction area is oriented based on the pedestrian's walking path, establishing a dynamic safety buffer that provides the driverless minibus with ample time to respond to pedestrian movements.

The design's flexibility is emphasized by its customizable features, allowing the size and intensity of the interaction fields to be adjusted for various environmental conditions. The driverless minibus improved its navigation by evading pedestrians when possible and efficiently interacting with them based on their assessed risk level. This adaptability ensures optimal configuration across diverse scenarios, enhancing safety in both crowded urban streets and quieter suburban areas. The integration of these technical elements optimizes pedestrian-vehicle interactions, promoting proactive risk management and situational awareness.

Future work can focus on enhancing interaction fields by integrating advanced perception systems like gaze tracking, adapting to diverse urban and environmental contexts, and addressing the needs of vulnerable pedestrian groups. Real-world validation through longitudinal studies in complex urban environments and multi-vehicle scenarios can refine the framework, while incorporating cultural factors and smart infrastructure (e.g., V2X communication) can improve contextual awareness. Exploring energy-efficient interaction designs and conducting user acceptance studies will further optimize the system for usability, trust, and sustainability. These advancements aim to create safer, adaptive, and globally effective autonomous pedestrian-vehicle interaction strategies.

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