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A Narrative Review: V2X-based Artificial Intelligence for Vulnerable Road User Protection of Urban Autonomous Vehicles

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Abstract

Since vulnerable road user protection is a critical challenge for vehicles operating in urban areas, Artificial intelligence (AI) and vehicle-to-everything (V2X) communication is becoming one of core enabling technologies in the development of intelligent transportation systems. In automated vehicle control, traditional onboard sensing is generally limited by occlusion, sensing range, and the complexity of dynamic traffic environments. V2X communication can provide additional information from surrounding vehicles, roadside infrastructure, and traffic systems, which creates new opportunities for improving vehicle perception, decision-making, and motion control. However, existing reviews rarely focus on the systematic integration of V2X communication and AI algorithms for VRU protection in urban autonomous driving scenarios, especially the coordination mechanism between multi-source data fusion and trajectory prediction. This review focuses on the application of V2X-based artificial intelligence in automated vehicle control in the awareness of road user movement. It summarises the key technologies of V2X communication, cooperative perception, multi-source data fusion, vulnerable road user trajectory prediction, collision risk assessment, and decision-making control. The main objective is to investigate how V2X information can enhance environmental awareness and support safer and more efficient control strategies for automated vehicles.

Keywords

vehicle-to-everything (V2X), vehicle-to-pedestrian (V2P), vulnerable road users (VRU), autonomous vehicles, collision-risk assessment

1. Introduction

Road injury is one of the major global concerns. According to the World Health Organization, approximately 1.19 million people die each year as a result of road traffic crashes, and more than half of road traffic deaths are among vulnerable road users [1]. Vulnerable road users, including pedestrians, cyclists, and users of micromobility devices, are exposed to higher accident risks in urban traffic environments because they lack physical protection and often interact directly with motorized vehicles.

Traditional perception devices such as cameras, radar and lidar may suffer from limited visibility, occlusion and performance degradation in adverse weather [2, 3]. As a result, artificial intelligence has become increasingly important for traffic risk prevention and VRU protection. Under these circumstances, vulnerable road user protection has become an important research topic in autonomous vehicles and intelligent transportation systems.

Vehicle-to-everything (V2X) can help overcome limitations of onboard sensors by providing information beyond the line of sight [2, 3]. In combination with artificial intelligence (AI), V2X can support earlier and more cooperative road-user protection [4]. The integration of AI and V2X has therefore become an important trend in cooperative perception and intersection control.

In recent years, the combination of AI and V2X has become an important trend in cooperative perception, trajectory prediction, and intersection management. Existing studies show that V2X cooperative perception can improve detection and perception performance [5], while V2X-based machine learning can support earlier VRU collision warning.

The main topics include V2X communication, VRU behavior characteristics, cooperative perception, multi-source data fusion, intention prediction, risk assessment, decision-making, motion control, simulation platforms, and performance evaluation. In addition, this paper discusses current technical challenges and future research directions for safer and more reliable autonomous vehicle deployment.

2. Preliminary Key Technologies

Cooperative perception is one of the most important applications of V2X-based artificial intelligence. Unlike traditional perception methods that rely only on onboard sensors, cooperative perception allows autonomous vehicles to receive information from other vehicles, roadside infrastructure, traffic signals, and pedestrian devices [6]. Before discussing cooperative perception and control strategies, it is necessary to introduce the fundamental technologies related to V2X communication, vulnerable road user characteristics, and AI-enabled V2X frameworks.

2.1 V2X Communication Technology

Vehicle-to-everything (V2X) systems refer to the exchange between vehicles and other traffic entities. V2X mainly includes four communication modes: V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), V2P (Vehicle-to-Pedestrian), and V2N (Vehicle-to-Network) [3]. Mainstream technical solutions include cellular V2X (C-V2X) and dedicated short-range communication (DSRC). In comparison to traditional onboard sensing, V2X communication provides extended perception capability and enables vehicles to detect potential risks beyond the line of sight. This is especially important in urban environments where occlusion and mixed traffic are common. Current V2X technologies mainly include Dedicated Short-Range Communication and Cellular Vehicle-to-Everything, both of which provide important technical support for connected and automated driving [4].

2.2 VRU Characteristics

Vulnerable road users have no fixed trajectories; they may cross suddenly, be hidden by occlusions, or interact unpredictably with surrounding traffic [7, 8]. High accident risks occur frequently at urban intersections and in mixed traffic scenarios. In these situations, over-the-horizon perception and advanced prediction are required. Urban intersections are high-risk areas for vulnerable road users because traffic participants interact frequently and visibility is often limited. Therefore, advanced perception, early prediction, and active safety control are required to improve VRU protection.

2.3 AI-Enabled V2X Framework

AI plays an important role in transforming V2X data into useful driving decisions. Data from onboard sensors, roadside units, pedestrian devices, traffic signals, and cloud systems can be collected and fused. AI algorithms can support VRU detection, intention recognition, and intelligent decision-making. In this way, V2X supports a perception-decision-control loop for cooperative autonomous driving [9]. A typical V2X-AI framework follows a perception-decision-control structure. In the perception stage, multi-source traffic information is integrated to build a more complete representation of the surrounding environment. In the decision-making stage, AI models evaluate potential risks and generate safe driving strategies. In the control stage, the vehicle adjusts its speed, trajectory, and braking behavior based on the decision results [10]. This framework provides the foundation for active and cooperative vulnerable road user protection.

3. V2X + AI Cooperative Perception and Data Fusion

Cooperative perception is one of the most important applications of V2X-based artificial intelligence. Unlike traditional perception methods that rely only on onboard sensors, cooperative perception allows autonomous vehicles to receive information from other vehicles, roadside infrastructure, traffic signals, and pedestrian devices. This extended information can improve perception range and reduce the impact of occlusion [9].

3.1 Multi Sources Data Input and Open-source Cooperative Perception

In urban autonomous driving scenarios, V2X systems can collect data from multiple sources, including vehicle-mounted sensors, roadside units, VRU terminals, traffic signals, and high-definition map input. The integration of these data sources forms a heterogeneous multi-input system. This system enables autonomous vehicles to obtain more complete traffic information, especially in complex intersections and non-line-of-sight scenarios. For vulnerable road users, multi-source data input can improve early detection and provide more time for risk assessment and vehicle control. Open-source cooperative perception platforms, such as AutoC2X, provide a basis for the verification and optimization of multi-source data fusion algorithms, which can promote the application of V2X-based cooperative perception in VRU protection [11].

3.2 Multi-level Data Fusion

Data-level, feature-level, and decision-level fusion can be applied to improve VRU tracking accuracy in occluded and complex scenarios. Data-level fusion directly combines raw sensor or communication data. Feature-level fusion integrates extracted features from different sources. Decision-level fusion combines independent perception or prediction results to support final decision-making.

For vulnerable road user protection, multi-level fusion can improve detection accuracy, tracking stability, and prediction reliability. For example, when a pedestrian is occluded from the vehicle's onboard sensors, information from roadside units or nearby vehicles can help maintain tracking continuity [2, 9]. AI-based fusion methods can further enhance the robustness of perception systems in complex urban environments.

3.3 Open-source Cooperative Perception

Data fusion is essential for processing heterogeneous V2X information. In general, V2X data fusion can be divided into data-level fusion, feature-level fusion, and decision-level fusion. Data-level fusion directly combines raw sensor or communication data. Feature-level fusion integrates extracted features from different sources. Decision-level fusion combines independent perception or prediction results to support final decision-making. For vulnerable road user protection, multi-level fusion can improve detection accuracy, tracking stability, and prediction reliability. For example, when a pedestrian is occluded from the vehicle's onboard sensors, information from roadside units or nearby vehicles can help maintain tracking continuity. AI-based fusion methods can further enhance the robustness of perception systems in complex urban environments [10, 11].

4. VRU Intention Prediction & Risk Assessment

After detection, autonomous vehicles need to predict future VRU movements and evaluate possible collision risks [4]. This is particularly important in urban scenarios because randomness of vulnerable road users may contribute to sudden movement into vehicle paths.

4.1 VRU Trajectory and Intention Prediction

Trajectory prediction aims to estimate the future positions of vulnerable road users based on their historical movements and surroundings. Commonly used models include recurrent neural networks, long short-term memory networks, gated recurrent units, graph neural networks, and Transformer-based models. These models can learn temporal and spatial relationships from traffic data and predict possible future trajectories. V2X information can improve trajectory prediction by providing additional context beyond onboard sensors. For example, information from roadside units can help identify pedestrians approaching a crosswalk, while traffic signal data can indicate whether a pedestrian is likely to cross. In combination with V2X data and AI models, autonomous vehicles can achieve earlier and more accurate prediction of vulnerable road user behaviour [12].

4.2 Collision Risk Assessment

Collision risk assessment evaluates the possibility and severity of potential conflicts between autonomous vehicles and vulnerable road users. Conduct V2X + AI early warning model, using indicators including TTC (Time-to-Collision), collision probability and dangerous area, to support active safety intervention. These indicators can help autonomous vehicles to make adequate decisions to slow down, brake, or adjust their trajectory. V2X-based AI can support early warning by analysing real-time information from multiple sources. Compared with traditional onboard risk assessment, V2X-based methods can detect potential conflicts earlier, especially when vulnerable road users are hidden or located outbound the vehicle's detection. Therefore, collision risk assessment is an important component of active safety protection for vulnerable road users [8].

5. Decision Making & Optimised Control at Urban Intersections

5.1 Decision-Making Framework

Urban intersections are complex traffic environments where vehicles, pedestrians, cyclists, and traffic signals interact frequently. For autonomous vehicles, safe and efficient decision-making at intersections requires accurate perception, reliable prediction, and real-time control. V2X-based artificial intelligence can provide a global traffic view and support optimised driving strategies [3, 13].

5.2 Motion Control Algorithms

In a V2X-based decision-making framework, autonomous vehicles can receive information from nearby vehicles, roadside units, traffic lights, and vulnerable road user devices. AI algorithms may use this information to determine right-of-way, identify potential conflicts, and select safe driving actions. For example, when a pedestrian is predicted to cross the road, the vehicle can slow down in advance instead of performing sudden braking. Decision-making should consider both safety and efficiency. A conservative strategy may improve safety but reduce traffic efficiency, while an aggressive strategy may increase risk. Therefore, AI-based decision-making models need to balance collision avoidance, travel efficiency, passenger comfort, and compliance with traffic rules [10].

5.3 Improvement of Control

The integration of V2X and AI can improve both safety and driving performance. In terms of safety, V2X-based decision-making and control can help reduce emergency braking and sharp steering while improving riding comfort and traffic efficiency [14, 15]. Therefore, V2X-based decision-making and control are important for the practical deployment of autonomous vehicles in urban areas. Future research should further improve real-time performance, communication reliability, and the robustness of control algorithms under complex traffic conditions. For example, random pedestrian movements in dense traffic may increase detection and prediction difficulty, while AI can help analyze V2X information for earlier prediction and safer control.

6. Challenges and Future Trends

Although V2X-based artificial intelligence provides significant advantages for vulnerable road user protection, several challenges remain. First, multi-source V2X data may have different formats, update rates, and timestamps, making data synchronization and fusion difficult. Second, vulnerable road user behavior is highly uncertain, and AI models may not perform well in rare or extreme scenarios [12]. Third, communication latency, packet loss, and network congestion may affect the reliability of safety-critical applications. Fourth, real-time computing is still challenging because perception, prediction, decision-making, and control must be completed within a very short time. Finally, the lack of unified standards, open datasets, and standardized testing methods limits the large-scale deployment of V2X-based autonomous driving systems.

Future research on V2X-based artificial intelligence for vulnerable road user protection is expected to focus on several directions. First, collaborative AI, end-to-end cooperative models, and learning-based prediction methods may improve the generalization ability of VRU prediction and planning models. These methods can help autonomous vehicles better understand rare and complex traffic scenarios. Second, vehicle-road-cloud collaboration will become an important development direction. By combining onboard computing, roadside edge computing, and cloud intelligence, autonomous vehicles can achieve more efficient cooperative perception, decision-making, and control. This integrated framework can improve both real-time performance and global traffic coordination [16]. Third, digital twin technology can provide high-fidelity virtual environments for testing and validation. Digital twins can reproduce complex urban traffic scenarios and support the evaluation of V2X-based safety functions under different conditions [17, 18]. Fourth, robust AI and secure communication will become increasingly important. Since V2X systems depend on data exchange, they must be protected against communication failure, interference, cyberattacks, and unreliable information. Robust and explainable AI methods can also improve the trustworthiness of autonomous driving systems. Finally, future research should promote open datasets, unified evaluation metrics, and standardized testing frameworks. These efforts are necessary for comparing different methods and supporting the large-scale deployment of V2X-based vulnerable road user protection systems.

7. Conclusion

The integration of V2X and AI breaks through the limitations of standalone vehicle perception, achieving over-the-horizon and active safety protection for VRU in urban areas, with significant improvements in complex intersections. This review summarises key technologies, including cooperative perception, data fusion, intention prediction and decision-making control, identifies current challenges, and prospects future trends. Vehicle-road-cloud integration will be a core shift of the next-gen VRU protection systems for autonomous driving.

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