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Enhancing Traffic Safety in Smart Cities Through Perceived Risk Analysis for Vulnerable Road Users

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Abstract: The rapid growth of urbanization and traffic complexity in smart cities has led to heightened safety risks, particularly for vulnerable road users (VRUs) like pedestrians and cyclists. This study aims to enhance VRU safety by investigating their perceived risk and decision-making processes in various traffic scenarios. Traditional methods, such as surveys and observational studies, have limitations in capturing VRUs' cognitive processes and real-time behavior. This research proposes a multimodal approach combining electroencephalography (EEG) and eye-tracking technology to analyze VRUs' cognitive and physiological responses in simulated urban environments. By integrating data on attention, vigilance, and emotional states, this approach provides a comprehensive assessment of VRUs' risk perception mechanisms. Utilizing the CARLA simulator, a platform for pedestrian-vehicle interaction is developed to simulate realistic urban scenarios, while physiological and behavioral data are collected to establish a model for predicting VRU behavior. The study contributes to theoretical insights on risk perception and practical implications for designing safer urban infrastructure in smart cities, ultimately aiming to reduce VRU accidents and enhance traffic safety.

Keywords: Traffic safety, Risk perception, Electroencephalograph (EEG), Eye tracking

1. INTRODUCTION

In recent years, the rapid urbanization and motorization have led to a surge in traffic complexity, escalating the risk of accidents, especially for vulnerable road users (VRUs) [1]. Compared with vehicles, VRUs can change the directions and speeds at any time with higher randomness and uncertainty [2]. Despite advancements in road infrastructure, the safety of VRUs remains a critical challenge. In pedestrian detection system, one of the most important concepts is risk perception, which refers to an individual's assessment of the potential dangers they may encounter [3]. For pedestrians, this perception significantly influences their behavior, including decisions to cross streets, wait for traffic signals, or navigate crowded areas. Many studies have shown that the VRU's risk perception provides important information for identifying potential collision risks [4]. For example, pedestrians with a heightened sense of risk are more likely to engage in cautious behaviors, whereas those with a lower risk perception may take unnecessary risks [5]. However, the theoretical mechanisms of risk identification and decision-making for pedestrians are not yet clear, which is not conductive to improving the accuracy of predicting the actions that pedestrians are about to take [6]. Traditional methods for assessing risk perception typically include surveys, questionnaires, and observational studies. While these approaches can provide valuable insights, they often have limitations. Surveys may be subject to biases, such as social desirability, where respondents provide reports which they believe are more acceptable rather than their true feelings [7]. Observational studies, while useful, can fail to capture the internal cognitive processes influencing decision-making. Consequently, these methods may not fully account for the complexities of pedestrian behavior in real-world scenarios. In the past, predictive models of pedestrian behavior often relied on statistical analyses and historical data. While these models can offer insights into general trends, they often overlook the individual cognitive and emotional factors that shape pedestrian decisions [8]. Moreover, many predictive frameworks are based on assumptions that may not hold true in diverse urban contexts. This gap highlights the need for more nuanced methodologies that can capture the dynamic nature of pedestrian behavior. To bridge this gap, this research aims to develop a physiological measurement method for perceptual risk and further construct the risk identification and behavioral decision model. This can integrate human factors into road safety management of the smart city framework.

Electroencephalogram (EEG) is a tool that reflects brain neural activity by measuring physiological electrical signals on the scalp surface [9]. EEG can be used in clinical diagnostics to determine the type and location of brain disorders, such as epilepsy and brain injuries. In addition, scholars in the field of human factors have utilized EEG extensively for research related to emotions, stress, cognitive load, and other psychological and behavioral sciences [10–12]. Today, portable and non-invasive EEG devices have become important research tools for studying cognitive processes and states in non-medical settings. There are already several examples of EEG being applied in safety behavior research for drivers, pilots, and others [13]. Eye-tracking technology, by measuring eye position and movement information, can be used to analyze visual features such as fixations and saccades [14]. These features have been shown to be related to human information processing and decision-making processes. Non-invasive eye-tracking technology has been widely applied in visual-related psychological and behavioral research. Portable screen-based eye trackers can capture and record various data points, such as the subject's eye position, pupil size, eyelid closure, blinking behavior, and fixation patterns, to help understand how individuals visually perceive stimuli and make decisions [15]. The multimodal integration of EEG and eye-tracking combines the advantages of both technologies, providing a more comprehensive analysis of cognitive processes. Applying a brain-eye fusion measurement scheme to experiments in virtual simulation platforms for road traffic scenarios can safely induce various behavioral decisions from subjects in different traffic scenarios. By leveraging multimodal data from brain-eye fusion, researchers can calculate physiological indicators such as attention and vigilance, which aids in understanding risk perception and behavioral mechanisms.

2. Methodology

In real-world contexts, experiments investigating the interaction between pedestrians and vehicles are constrained by multiple factors, including regulations, ethical considerations, and safety concerns, which complicate their implementation. Consequently, conducting experiments within simulated environments provides a viable alternative. Therefore, this study provides a brain-eye fusion measurement system for traffic participants' risk perception based on the autonomous driving simulation platform CARLA. The system ultimately results in a risk perception measurement model for road users in simulated scenarios based on a physiological sensing system. The research is divided into three phases and shown in Fig.1:

(1) Risk perception analysis: This process focuses on a comprehensive examination of the risk identification and perception mechanisms of vulnerable road users (VRUs), aiming to identify various factors that influence unsafe behaviors. By investigating how VRUs perceive potential risks in their surrounding environment, we can reveal the psychological dynamics and decision-making processes individuals experience when faced with danger. This understanding will ultimately shed light on why certain behaviors lead to unsafe outcomes.

(2) Physiological sensing system establishment: A comprehensive physiological sensing system will be developed to measure various indicators of risk perception levels among VRUs. This system will integrate multiple sensor technologies to continuously monitor physiological responses, such as heart rate and skin conductance, providing objective data that will aid in assessing the user's ability to perceive risk and react in specific situations.

(3) Risk identification and behavioral decision models: Utilizing the data collected from the physiological sensing system, the perceived risk among VRUs will be quantified. Based on this quantification, a behavioral decision model will be proposed that takes into account the perceived risks. This model aims to combine physiological data with behavioral characteristics to predict how VRUs are likely to behave when confronted with different levels of risk.

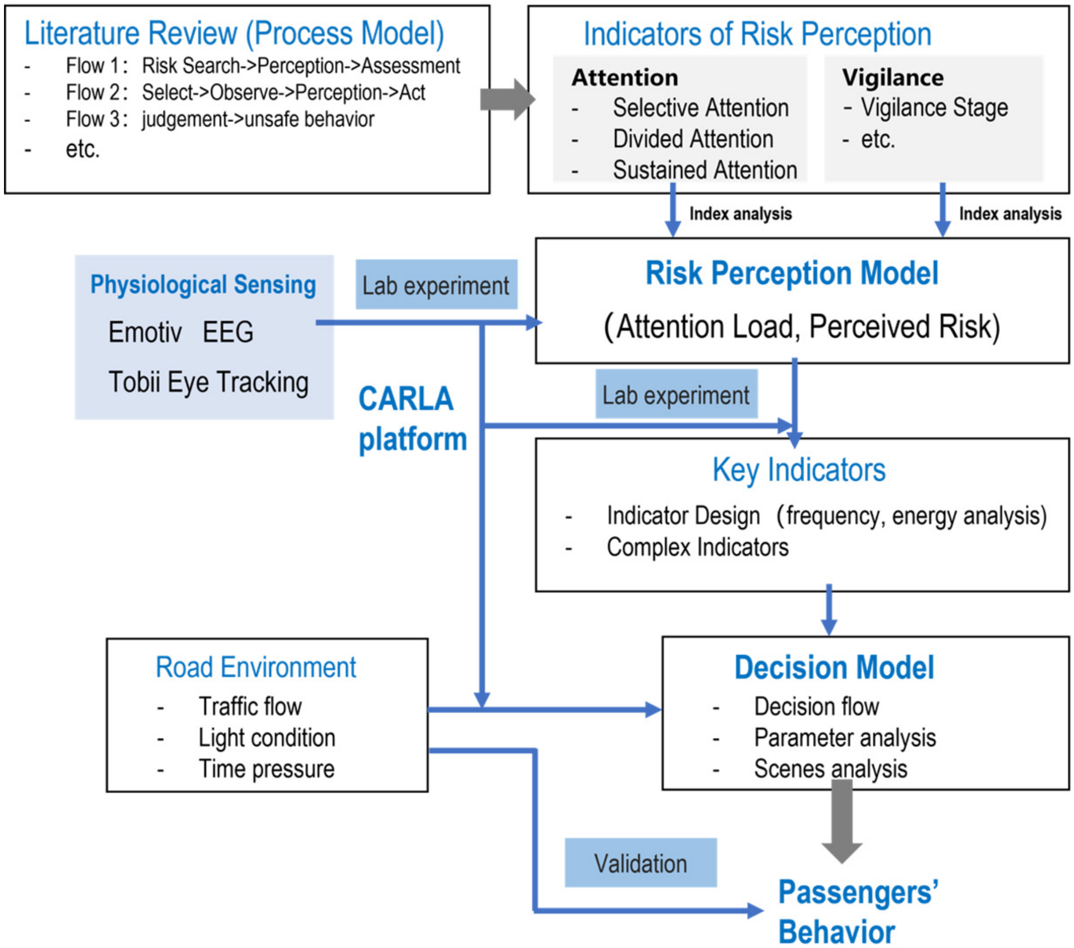

Figure 1. Workflow of the study

2.1 Pedestrian-vehicle Interaction Platform

In this research, we utilize the Python API authorized by CARLA Simulator to develop various intersection traffic scenarios, with visual representation based on Unreal Engine 4. These scenarios are built based on the digital resource of CARLA, including buildings, vehicles, and other infrastructure that closely resemble the real-world conditions expected in research. The implementation of the scenarios is divided into the server (Service Module) and the client (Agent Module). The sever, built on the Ureal Engine, is responsible for presenting the simulation, including the streets, buildings, traffic light changes, sensor computation principles, and more, thus providing a complete simulated world. The client is responsible for inputting Python commands into the Application Programming Interface (API) to update the world provided by the server, including changes in weather, vehicle speeds, and the number of pedestrians. To provide interaction functionalities for the experimenters, the invention calls the Pygame toolkit within the API, designing movement control components for pedestrians and vehicles. Before the simulated scenario is finally presented on the screen, the experimental subjects first receive verbal task instructions through listening, then observe the scene visually, and further use their own judgment and decision-making to determine the necessary actions. They then use the keyboard to perform basic operations such as dragging to adjust the view, controlling the direction and speed of movement, and emergency braking to complete the tasks.

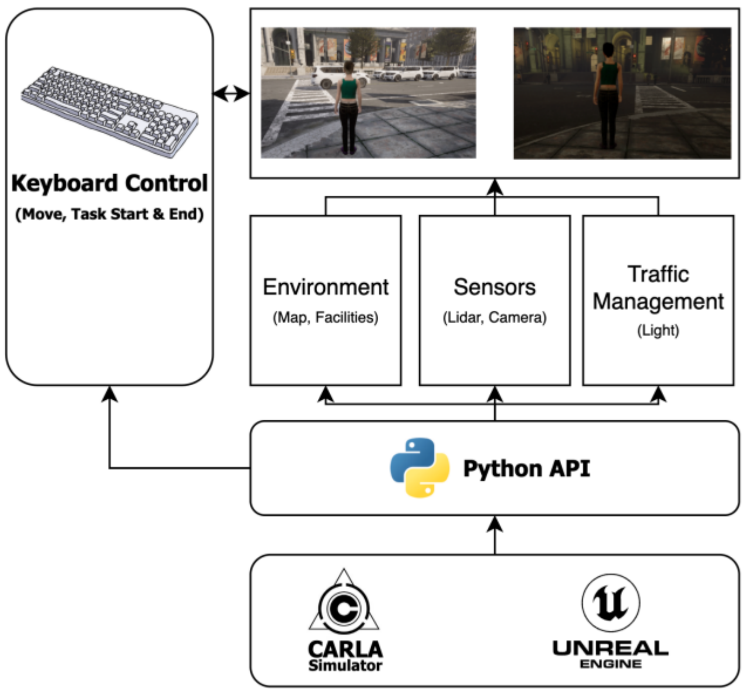

Figure 2. General structure of the interaction platform

2.2 Physiological Data Collection

For EEG collection module, a portable EEG device, the Emotiv Flex Saline with 32 channels, is used with a sampling rate of 120Hz. These data are then transmitted to EmotivPro via Bluetooth in real-time. For eye-tracking collection module, the Tobii Pro Fusion screen-based eye tracker is used, with a sampling rate of 120 Hz. The Tobii Pro Lab is utilized to record corneal infrared reflection information during the subject's screen observation, labeled as visual tracking type. In addition, a 1080P resolution, 30Hz frame rate camera is placed above the display monitor, directly facing the subject's face, and records the subject's facial expressions in real-time during the experiment. To ensure the completeness of the behavior data, a Python logging tool is deployed to record keyboard operations during the simulation scene at a 30Hz sampling rate. In addition, a 1080P resolution, 30Hz frame rate camera is placed above the display monitor, directly facing the subject's face, and records the subject's facial expressions in real-time during the experiment. Before the experimental tasks, the basic information of the subjects is collected, such as traffic experience, personality, and risk tendency. For each task, the subject's cognitive load and the immediate and retrospective safety self-assessment are assessed by questionaries.

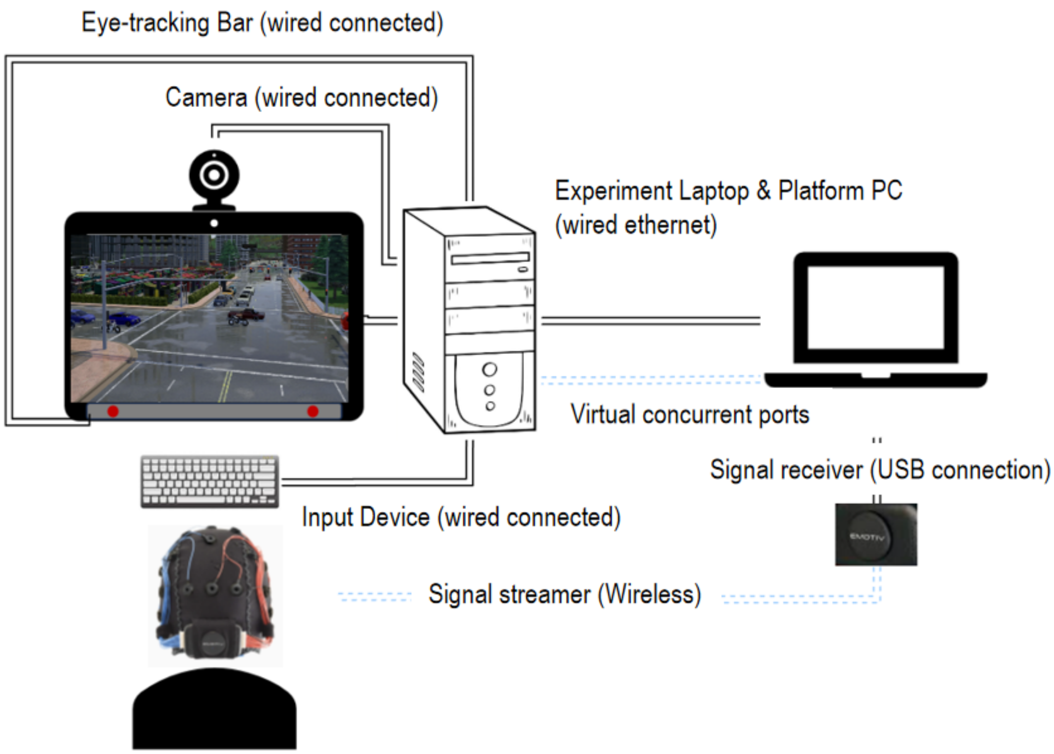

Figure 3. Setup for data collection

2.3 Data Analysis

The final establishment of the risk perception measurement model in this study employs EEG, eye movement, and emotional indicators as features. The specific feature extraction steps include:

(1) EEG indicators: the artifact removal and feature extraction are performed based on band-pass filtering, re-referencing, independent component analysis (ICA) and time-frequency transformation through wavelet packet transform (WPT). The indicators value then can be calculated by the frequency domain energy during each task period. These indicators are related one's attention, vigilance, mental fatigue and other aspects associated with cognitive state.

(2) Eye movement indicators: In this procedure, the area of interest (AOI) and time of interest (TOI)

method is used to assess how participants allocate their attention and what specific elements draw their focus within the visual field during their crossing. Based on different types and characteristics, the eye movement indicators mainly include fixation duration, fixation point coordinated, saccade velocity, saccade amplitude, and blink frequency.

(3) Emotional indicators: The frame extraction is performed, followed by detecting and aligning faces using computer vision algorithms to standardize facial position and posture, and removing background and lighting noise. Facial key points (e.g., corners of eyes, eyebrows, corners of mouth) are extracted frame by frame to analyze facial muscle movements, and Local Binary Pattern (LBP) is used to monitor skin texture and subtle expression changes. Based on the Facial action coding system (FACS), action units related to specific emotions are extracted and analyzed, such as eyebrow raising, eyelid contraction, and mouth corner elevation. Ultimately, these features are used to calculate the basic emotional valence activation level, duration, and frequency during task periods.

3. Discussion

The experimental data includes a total of 90.75 hours of EEG signals, eye tracking, facial recordings, keyboard events, and 1,155 completed surveys across various task segments. Upon reviewing the gaze sequences and durations of all participants after the experiment, we found that some individuals consistently focused their visual attention on themselves within the scene during the interaction, despite the fact that this gaze habit was highly inefficient for acquiring environmental information. Preliminary findings indicate that both subjective and objective factors can impact VRU's risk perception, including personal traits and environmental conditions. Individuals with a high level of risk aversion tend to be more sensitive to potential dangers and may avoid risky situations. Past experiences, such as having been involved in a traffic accident, significantly shape one's risk perception, often leading to heightened vigilance. Additionally, personality traits such as anxiety and decision-making styles—whether intuitive or analytical—also play crucial roles in how risks are evaluated. On the environmental side, road design elements such as width, lighting, signage, and traffic flow can affect pedestrians' risk perception, with poorly designed roads likely increasing perceived danger. The surrounding environment, whether urban or rural, further influences this perception, as urban areas typically present more noise and traffic, resulting in heightened awareness of risk. Social norms and the behavior of others, along with weather conditions such as rain, snow, or fog, also contribute to how pedestrians assess potential hazards, emphasizing the need for a comprehensive understanding of these intertwined factors in the context of pedestrian safety. However, under real-world conditions, environmental variables are often random. Individuals exhibit significant variability when faced with this randomness. This means that predicting individual behavior, especially, requires careful consideration of how past experiences have shaped their personality and thought processes. In that condition, integrating eye-tracking and EEG can provide a more comprehensive view of risk perception and cognitive engagement. For instance, researchers can analyze eye movement patterns while simultaneously recording brain activity, allowing for a deeper understanding of how visual attention correlates with cognitive responses to risks. This combined approach can be particularly valuable where understanding the interplay between visual attention and cognitive processing is crucial for optimizing safety and effectiveness.

4. Conclusion

This study underscores the critical role of understanding risk perception among vulnerable road users (VRUs) in improving traffic safety in smart cities. Through a multimodal approach integrating electroencephalography (EEG) and eye-tracking technologies, we developed a comprehensive framework for assessing the cognitive and physiological factors that influence VRUs' perception of risk in various traffic scenarios. The integration of physiological data into traffic safety analysis allows for a more nuanced understanding of VRUs' decision-making processes. By analyzing the interplay between visual attention and cognitive responses, our framework enhances predictive capabilities for VRU actions, especially in complex urban environments. This research not only contributes to the theoretical understanding of risk perception mechanisms but also offers practical implications for designing safer urban infrastructure that considers human factors. Future studies should aim to expand on this work by exploring real-world applications and validating the proposed model in diverse urban settings.

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