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AUTONOMOUS BRAKING SYSTEM FOR MOTORIZED VEHICLES

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Abstract: Assuring the safety of all road users, including non-motorized vehicles, is important in the autonomous driving environment. Autonomous emergency braking (AEB) systems have provided an effective way for automated vehicles to avoid collisions with the less easily detectable non-motorized vehicles. Autonomous and intelligent vehicle systems play a crucial role in transportation by enhancing safety and efficiency. This project focuses on developing a smart vehicle control system that detects and responds to traffic signs using machine learning algorithms and ensures collision avoidance through an ultrasonic sensor. A camera module is integrated to identify traffic signs such as right turn and left turn, enabling the vehicle to take appropriate actions based on the detected sign This system can be applied to autonomous vehicles, driver assistance systems, and robotics to enhance decision-making and accident prevention**.**

Index Terms - Automatic preventive braking, autonomous emergency braking, motorized-to-non-motorized-vehicle-conflict.

I. INTRODUCTION

Automated vehicles, at both partial and high levels of automation, have achieved outstanding performance in controlled environments. Variously known as autonomous and ego vehicles, automated vehicles (AVs; see Appendix TABLE 8 for all abbreviations) will eventually be traveling in much more complex environments, with multiple road users including pedestrians and non-motorized vehicles (NMVs). NMVs such as bicycles and e-bikes (often but not always considered as NMVs), with their various appearances and flexible trajectories, create challenges for the AV's detection, intention prediction, and motion planning systems . In China, bicycles and e-bikes are widely used for commuting and delivering goods. It is estimated that China has the largest number of NMVs in the world (nearly 400 million bicycles and 300 million e-bikes) and they have a high accident rate. In 2015 alone, NMV-related crashes were over represented as 63.9% and 82.3% of fatal and injury crashes, respectively, in Shanghai. The proportion of fatal crashes involving powered two-wheelers, or e-bikes, is also high (60% - 70%), not only in China but in other Asian countries such as Thailand, Cambodia, and Indonesia .Europe, too, is starting to experience increasing fatality rates for e- bikes. For example, Sweden had a 10% increase in powered two-wheeler road fatalities from 2000 to 2018, a period in which the total number of road fatalities decreased significantly . With the current rapid development of automated vehicles and the challenges NMVs pose to them, the NMV road safety issue will persist. It is crucial to explore ways to assure the safety of the non-motorized vehicle in the autonomous driving environment.

The autonomous emergency braking (AEB) system, an essential function of advanced driving assistant systems (ADAS), has been shown to considerably reduce traffic accidents [7], [8]. To adapt AEB to the characteristics of cyclists, an AEB cyclist system was developed by Safety Cube DSS, the European Road Safety Decision Support System, and is currently on the market.

Therefore, in addition to comparing the AEB and APB systems, a primary purpose of this study is to calibrate the parameters of the braking process to be suitable for the SCE; in particular, the proper deceleration rate, jerk, and brake activation time for the SCE should be determined. Calibrate all the systems by testing their driving safety and conservativeness under different parameter combinations and compare their performance in safety and conservativeness; and explore the underlying reasons for crashes in order to improve the autonomous braking systems in future research and development.

II.METHODOLOGY

A. Dataset

Autonomous braking systems (ABS) are designed to automatically apply the brakes to prevent collisions with pedestrians, cyclists, or other vehicles. These systems use sensors and advanced algorithms to make real-time decisions. The APB system uses the same simulation structure, simply replacing the AEB controller with the APB controller.

Table 1. Summary of the 5 one-stage aeb algorithms under study

	d_{one} (m/s^2)	Ego Initial Velocity (m/s)	TTC_b (s)
1-stage AEB 1	4.5	9.0	2.0
1-stage AEB 2	4.5	11.0	2.4
1-stage AEB 3	5.5	9.0	1.6
1-stage AEB 4	5.5	11.0	2.0
1-stage AEB 5	5.5	16.5	3.0

In the AEB with sensor fusion subsystem shown on the left, the tracking and sensor fusion block fuses the data from the sensors and detects the most important object (MIO), as well as its position and velocity. The AEB and speed controller block decides the driving strategy of the next simulation step by analyzing the current safety condition, and outputs the brake pressure or throttle to the vehicle and environment subsystem. The vehicle dynamics and driver steering model block models the dynamics of the simulated subject vehicle, now the ego car, as it drives along the road's various alignments. The motion of the ego car is synchronized in the scenario by the actors and sensor simulation block, after which the sensors output the data for the next step in the simulation.

B. One-Stage AEB System

The one-stage autonomous emergency braking system modeled in this study was chosen for comparison because it is simple and widely used. It is the basic AEB, in which the vehicle brakes with a constant deceleration *done* when the TTC is shorter than the threshold *T TCb* (Fig. 5). The algorithm depends on these two pre-defined parameters, deceleration and TTC, and does not apply any speed dependent parameters.

In the one-stage AEB simulation, the ego car is designed to drive at its initial velocity until it brakes with *done*, so the time that the ego car requires to achieve a full brake is its initial velocity divided by *done*, namely *TTCb*. The values used for *done* and initial velocity are approximations of the 50th, 75th, and 95th percentiles of the subject vehicle's maximum deceleration and initial velocity parameters in TABLE I. Nine one-stage AEB algorithms were initially generated: 3 ×3 combinations of deceleration and TTC threshold values. Four algorithms with *T TCb* larger than 3.0 s were removed to ensure that the system was not activated too early. A total of five one-stage AEB algorithms were thus studied (TABLE II).

C. Three-Stage AEB System

The second system chosen for comparison was a three-stage cascaded AEB with early forward collision warning (FCW). The system is similar to the Audi A7's emergency braking system, which was demonstrated to have good performance by the Allgemeiner Deutscher Automobile-Club (ADAC) comparative test of advanced emergency braking systems . The *vehicle dynamics and driver steering model* block models the dynamics of the simulated subject vehicle, now the ego car, as it drives along the road's various alignments. The motion of the ego car is synchronized in the scenario by the *actors and sensor simulation* block, after which the sensors output the data for the next step in the simulation.

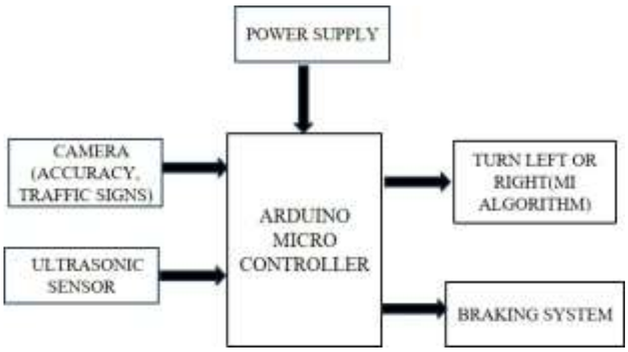
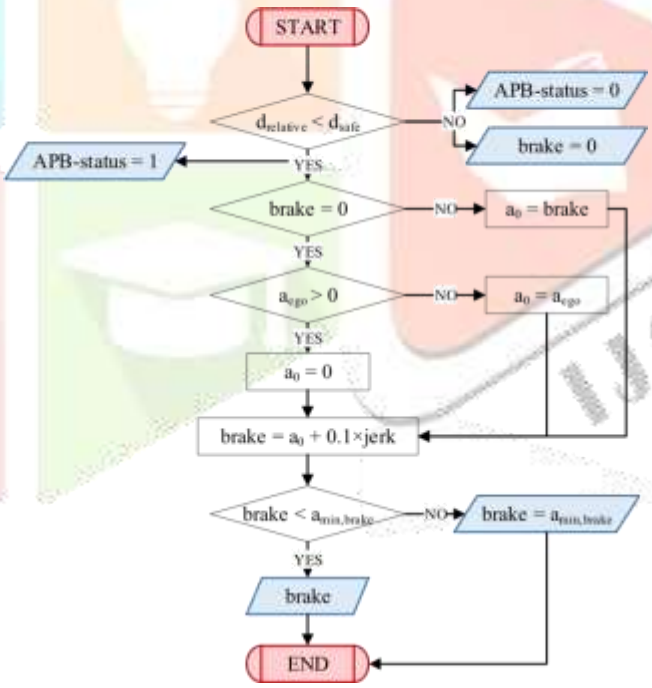


Fig. Block diagram for motorized vehicles

D. APB System

As mentioned earlier, the decision making and control procedures of the automatic preventative braking (APB) algorithm, having originated in the RSS model, are similar to those of the RSS: in a car-following situation, the following vehicle continuously compares its relative distance to the lead vehicle with the safe distance, which is the difference in distance that each of the two vehicles require to reach a full stop. When the car enters an unsafe driving condition it will decelerate until it stops or the distance becomes safe. To make the braking gentler, APB redefined the longitudinal safe distance between the lead and following vehicles by substituting the original braking profile of the following vehicle with a jerk-bounded profile . the car will decelerate.



E. Evaluation Indicators

Evaluation of the autonomous braking algorithms considers both safety and conservativeness. Three indicators were used to evaluate driving safety: number of crashes, time-integrated time-to-collision (TIT), and driving volatility. Two indicators were used to evaluate conservativeness: TTC and relative distance at the time of brake activation.

1) Number of Crashes: Safety Indicator: Although no crashes actually occurred in the NDS safety critical events before extraction, the crashes were avoided because the drivers were successful at performing the evasive maneuvers that identified the events as SCEs. When an event was simulated and the autonomous braking algorithms, with their varying parameters, took control of the evasive maneuvers, avoidance of the crash in the simulation was not predetermined. An autonomous braking algorithm would still cause a crash if the brake was not applied in time or with sufficient strength.

2) Time-Integrated Time-to-Collision (TIT): Safety Indicator: Time-to-collision (TTC) is a widely used indicator of crash risk; however, the TTC is only measured at a given instant, so it cannot show how long the risky event lasts nor its severity within a given trip. The TIT indicator, in contrast, uses the integral of the time-to-collision profile of a trip to express the level of safety (in s^2) over a certain time period].

III. RESEARCH METHODOLOGY

The research methodology for this project follows a structured approach to developing a smart vehicle control system that integrates machine learning-based traffic sign recognition and ultrasonic sensor-based collision avoidance. Initially, the problem identification phase highlights the increasing number of road accidents involving both motorized and non-motorized vehicles, emphasizing the need for intelligent vehicle systems to enhance road safety. The proposed system is designed with a camera module to capture traffic signs, an ultrasonic sensor for obstacle detection, and a microcontroller for decision-making and vehicle control. The system architecture ensures that the machine learning model processes traffic sign images while the microcontroller executes necessary maneuvers to prevent collisions.
For hardware implementation, key components such as a camera module, microcontroller (e.g., Raspberry Pi or Arduino), ultrasonic sensor, and motor driver circuit are integrated to enable real-time traffic sign detection and vehicle control. The software implementation involves training a machine learning model using a dataset of traffic signs, employing Convolutional Neural Networks (CNNs) for classification, and utilizing OpenCV and TensorFlow for image processing. The microcontroller is programmed in Python or C++ to interface with sensors and execute control actions based on detected traffic signs and obstacles.

A decision-making algorithm is implemented to determine appropriate vehicle maneuvers such as turning left, right, or stopping based on real-time inputs.

The testing and validation phase involves evaluating the system in both simulated and real-world environments to ensure accuracy and reliability. The machine learning model's performance is assessed using accuracy metrics, while the ultrasonic sensor's obstacle detection sensitivity is analyzed under varying conditions. Additionally, system response time is measured to determine the efficiency of real-time decision-making. Performance evaluation is conducted based on key metrics such as traffic sign recognition accuracy, obstacle detection precision, reaction time, and system reliability under different environmental conditions. This structured methodology ensures that the developed system is robust, efficient, and capable of enhancing autonomous vehicle safety by integrating machine learning and sensor-based collision avoidance technologies.

3.1 Theoretical framework

The foundation of this project is built upon principles from machine learning, sensor-based collision avoidance, and intelligent vehicle systems. As autonomous and driver-assist technologies continue to evolve, integrating these concepts into smart vehicle control becomes essential for improving road safety and efficiency. This theoretical framework explores the key components and underlying theories that guide the development of this system.At the heart of traffic sign recognition lies computer vision and machine learning.
The system utilizes Convolutional Neural Networks (CNNs)—a deep learning algorithm known for its effectiveness in image classification. CNNs mimic the way the human brain processes visual information, enabling the system to accurately identify traffic signs such as right turn, left turn, and stop signs. By training the model with a diverse dataset of traffic signs, the system learns to recognize patterns and make quick decisions in real-world driving scenarios. Image processing techniques, such as edge detection and color filtering (using OpenCV), further enhance the model’s ability to differentiate traffic signs from surrounding objects.
For collision avoidance, the system relies on ultrasonic sensor technology, which operates based on the principles of sonar. By emitting high-frequency sound waves and measuring the time taken for the waves to bounce back after hitting an obstacle, the system determines the distance to potential hazards. This principle is widely used in robotics and autonomous vehicles for real-time navigation, ensuring that the vehicle can stop or adjust its path when an obstacle is detected. The integration of sensor fusion allows the system to combine data from multiple sensors, improving the accuracy and reliability of obstacle detection.

The control mechanism of the vehicle follows the sense-think-act paradigm, a fundamental concept in artificial intelligence and robotics. The "sense" phase involves data collection from the camera and ultrasonic sensor, the "think" phase processes this data through machine learning algorithms and predefined rules, and the "act" phase translates the processed data into vehicle movements such as turning, stopping, or braking. This structured approach ensures a real-time response, reducing the likelihood of accidents.

From a broader perspective, this project aligns with the principles of intelligent transportation systems (ITS), which aim to enhance traffic management, reduce congestion, and improve road safety using smart technologies. The fusion of machine learning, sensor-based decision-making, and embedded systems contributes to the advancement of autonomous vehicles and driver-assist applications. By leveraging these theoretical foundations, the smart vehicle control system provides a reliable solution for traffic sign recognition and collision avoidance, ultimately making roads safer for all users.

3.1.1. Image Processing and Machine Learning (Traffic Sign Recognition)

Traffic sign recognition is a crucial component in autonomous driving, enabling vehicles to interpret road signs and respond accordingly. This process involves image acquisition, preprocessing, feature extraction, and classification. A camera module captures real-time images of traffic signs, which are then processed using edge detection, noise reduction, and color segmentation techniques.

To accurately classify traffic signs, Convolutional Neural Networks (CNNs) are employed. CNNs extract important visual features such as edges, shapes, and patterns, allowing the system to distinguish between different traffic signs. The classified traffic signs provide input for decision-making in autonomous vehicle control.

3.1.2 Softmax Function for Traffic Sign Classification

In machine learning, classification tasks require a probability-based approach to determine the most likely category for an input image. The Softmax function is used in the final layer of a CNN model to convert raw model outputs into probability distributions across multiple traffic sign classes. The traffic sign with the highest probability is selected as the recognized sign.

This classification approach ensures high accuracy and robustness, even in varying lighting and environmental conditions. By integrating a well-trained model, the system enhances real-time recognition and decision-making capabilities.

3.1.3 Ultrasonic Sensor-Based Obstacle Detection

Obstacle detection is essential for ensuring the safety of autonomous vehicles. Ultrasonic sensors play a key role in detecting nearby objects by sending out high-frequency sound waves and measuring their reflection time. The system uses Time- of-Flight (ToF) principles, where the sensor determines the distance of an object based on the time taken for the wave to travel to the obstacle and return.

This detection method allows the vehicle to react dynamically by slowing down or stopping when an obstacle is too close. The system is highly effective in low-visibility conditions such as fog, rain, or darkness, where traditional cameras may struggle.

3.1.4 Vehicle Control Dynamics

The vehicle’s response to detected traffic signs and obstacles requires efficient control dynamics. Several factors, such as braking distance, speed regulation, and steering adjustments, play a significant role in ensuring smooth and safe navigation.

Braking distance is a key parameter that determines how quickly a vehicle can come to a stop after detecting an obstacle. It depends on factors like the vehicle’s speed, road conditions, and tire grip. A well-calibrated braking system ensures the vehicle responds appropriately to obstacles, preventing accidents and maintaining smooth traffic flow.

3.1.5 PID Control for Vehicle Steering

A Proportional-Integral-Derivative (PID) controller is widely used in autonomous vehicles for smooth steering and trajectory correction. The system continuously monitors the vehicle’s position and compares it with the desired path. Based on the deviation (error), the PID controller adjusts the vehicle’s steering angle, braking force, and acceleration.

The proportional component ensures immediate correction, the integral component accounts for past deviations, and the derivative component predicts future errors to prevent overshooting. This combination allows for precise navigation, reducing sudden jerks and ensuring a comfortable ride.

IV. RESULTS AND DISCUSSION

The comparison revealed that the APB system's safety performance was inferior to that of the two AEB systems in that it caused a greater number of crashes and also had higher TIT. However, APB's jerk-bounded braking profile did reduce braking intensity, and thereby generated low driving volatility. An autonomous braking system with lower volatility will cause less impact to the vehicle following it, and less fluctuation in the traffic flow. As has been claimed , one of the aims of APB is to not compromise the traffic throughput, which this study has demonstrated to be achievable.
One-stage AEB was shown to be the least conservative system, braking latest, while three-stage AEB brakes earliest, and thus may lead to frequent false alarms. This study demonstrated that for safety-critical events, one-stage AEB can prevent crashes by applying a moderate deceleration with a relatively small TTC threshold. The APB system, while somewhat less conservative, is not as safe as Shalev-Shwartz supposed it to be vehicle. As was shown in Fig. 9(d), by the increases in the brake is activated late and is more likely to cause a crash.

The safe distance in the APB model was defined as the difference in distance that the lead and following vehicles each require to reach a full stop. For the subject following vehicle, the larger its minimum reasonable brake and maximum jerk the better is its braking ability and thus the shorter distance it needs to reach a full stop. A larger for the lead NMV indicates that the event is more critical and the lead vehicle will reach a full stop sooner, which leads to a shorter full brake distance for the NMV. Consequently, the increase of the subject vehicle's will decrease the safe distance while the increase of the NMV's will increase safe distance. In Section V.B, results showed that crashes occurred more frequently when the ego vehicle had better braking ability and less frequently when the event was more critical both of which are contrary to our expectations. In Fig. 11, the safe distance and actual headway of two randomly selected events are plotted using the baseline APB algorithm (APB 1) and two other algorithms, one with larger (APB 19) and one with larger (APB 3). The solid lines represent the safe distance, the dashed line the actual headway, and the dots represent the brake activation time.
In both events, APB 19, the APB algorithm with larger brakes later than the APB 1 baseline algorithm, as APB 19 provides the vehicle with stronger brake ability, while APB 3, the algorithm with larger brakes earlier as it supposes the events to be more critical.
It should also be noticed in Fig. 11 that the safe distance is not a smooth line, but fluctuates across the headway from time to time. The fluctuation is mainly caused by changes in velocity and acceleration: 1) the vehicle decelerates when the headway is smaller than the safe distance; 2) this decrease of velocity and acceleration makes it easier for the following vehicle to reach a full stop, thereby reducing the safe distance; 3) once the safe distance drops below headway, the vehicle will stop the braking process and start to accelerate; however, little difference between headway and safe distance is evident at that point; 4) headway soon becomes smaller again than safe distance, and the vehicle again begins to decelerate. This fluctuation interrupts the continuous deceleration process and raises another problem. The safe distance is calculated under the assumption that the vehicle will continue decelerating until the distance becomes totally safe, but instead, the vehicle starts to accelerate as soon as the safe distance exceeds headway.

In summary, the deceleration process of the time-triggered AEB systems is more consistent and reliable, while the APB deceleration process triggered by safe distance is more unpredictable due to the change of the three parameters and real-time kinetic parameter values.

V. CONCLUSION

To explore ways to ensure the traffic safety of nonmotorized vehicles in an autonomous driving environment, this study calibrated and compared three autonomous braking systems: one-stage AEB, three-stage AEB, and APB. A total of 108 longitudinal safety-critical events between motorized and non-motorized vehicles were extracted from the Shanghai Naturalistic Driving Study and recreated in the MATLAB simulation platform. One three-stage AEB algorithm, five one-stage AEB algorithms, and twenty- seven APB algorithms with different combinations of parameter values were tested on the safety-critical events. The algorithms were evaluated for safety performance (indicators: number of crashes, TIT, driving volatility) and conservativeness (indicators: TTC and relative distance when brake is activated) in order to identify the optimal parameter combinations in each system.

The comparison between the above three calibrated systems demonstrated that one-stage AEB has the best safety performance and is the least conservative. Although the APB system has the best driving stability and therefore causes less fluctuation in the traffic flow, it was shown to cause the most crashes. Further analysis of the APB brake pattern revealed that the crashes were likely the result of fluctuating safe distance combined with the fact that larger $a_{min,brake}$ and j_{max} postpone brake activation time. Comparison of the triggering criteria suggested that the time-triggered brake process of the AEB systems may be more consistent and reliable than the distance-triggered process of the APB system.

Two main contributions have been made by this study. First, by calibrating the parameters of the autonomous braking systems with SCEs between motorized and non-motorized vehicles, it was shown that a one-stage AEB with low deceleration is the best of the tested systems at defusing the danger of SCEs. Second, the APB system was calibrated for the first time with naturalistic driving data and its effectiveness was evaluated. The APB's safety performance was not as good as expected, as the trigger time and safe distance criteria are easily affected by the pre-defined parameters and changing kinetic parameters. This study has some limitations. Only 108 SCEs were tested, and only longitudinal scenarios, that is, no crossing or turning scenarios, were considered. Future research should investigate and analyze a greater number of events with various types of scenarios. Although it was demonstrated that smoother deceleration would be preferable in the safety critical event, a method to distinguish the events' severity level in real-life driving was not, in the current study, given attention. Similarly, the identification of APB modeling issues that may cause crashes was merely speculation. It will be left to future studies to consider how to improve the system to take advantage of the APB's driving stability benefit. Similarly, future research can use our results of longitudinal SCEs to investigate their disproportion in the Shanghai study area.

VI. FUTURE WORK

Despite advancements, there are still challenges with detection accuracy, especially in low-visibility conditions. Additionally, the systems need to make quick, accurate decisions in unpredictable scenarios. Future developments are focused on improving sensor fusion, AI algorithms, and testing methods to enhance reliability and performance. The proposed system aims to improve the accuracy and reliability of autonomous braking in situations where motorized vehicles encounters the object detection and the traffic signs. The combination of machine learning-based sign recognition and real-time obstacle detection enhances autonomous navigation and ensures improved road safety.

The data from the ultrasonic sensor will be processed using arduino microcontroller. If a danger is detected, the system will automatically activate the brakes to prevent or reduce the impact of a crash, improving overall road safety. Additionally, an ultrasonic sensor is employed to detect obstacles in the vehicle's path, triggering an automatic braking mechanism using an Arduino microcontroller.

This project focuses on developing an advanced driver-assistance system (ADAS) that detects traffic signs and responds accordingly. A camera module, integrated with machine learning algorithms, recognizes road signs such as left turn and right turn, enabling the vehicle to take appropriate actions advancement of autonomous vehicle technology promises. In addition, an ultrasonic sensor is incorporated to detect obstacles in the vehicle's path, ensuring real-time collision prevention. When an object is detected, the system automatically applies brakes using an Arduino microcontroller, enhancing safety and reducing accidents.This system merges computer vision, embedded systems, and sensor-based technology to improve autonomous vehicle navigation. It is designed for applications in self-driving cars, robotics, and intelligent transport solutions. The project aims to reduce human intervention, minimize road accidents, and create a safer and smarter driving experience.

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