Research and Optimization of Decision-Making Mechanism for Passenger Vehicle AEB System

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Abstract. As intelligent driving technology continues to advance, Automatic Emergency Braking (AEB) systems increasingly contribute to road safety. The paper investigates the decision-making process for conventional passenger AEB systems, summarizing the mainstream collision judgment techniques based on distribution, including distance-based models and Time-to-Collision (TTC) models, as well as analyzing their adaptability in urban and highway settings. This paper explores both single-stage and multi-stage deceleration approaches and provides a comparative analysis of fixed-threshold decision-making and driver-behavior models. To solve problems like the high rate of misjudgments for AEB systems in complex traffic situations, this paper proposes a refined approach by using multi-sensor fusion, deep learning methods for scene recognition, and human–machine collaboration in braking systems. The findings indicate that the future AEB systems will develop towards “high perception robustness - strong decision-making intelligence - human-machine collaborative integration” as the basis for building safer, more reliable, and personalized intelligent driving systems.

Keywords: AEB, TTC, Safe Distance, Sensor Fusion.

1. Introduction

The increasing number of vehicles on roads results in higher instances of traffic accidents involving rear-end collisions and pedestrian accidents due to inattentive driving, both of which are severe threats to life and property. To minimize collision risks and improve road traffic safety, intelligent vehicle safety systems (including ACC and LKS, among others) have gained expansion. One of such systems is the Automatic Emergency Braking system (AEB) that offers active intervention with automatic braking in crisis situations.

AEB is a sensor-encompassing intelligent system, which can detect obstacles in front through sensors, automatically brake at any moment before colliding, and even if the driver does not apply the braking in time. The algorithm can be subdivided into three stages: target detection, collision forecast, and braking decision-making. The choice the system makes when determining the braking times, braking strength, and driving experience affects the overall system’s performance, calling for further optimization of the system [1]. Despite these developments, AEB decision algorithms available today are not entirely flawless. For instance, the fixed-threshold-based control mechanisms are less flexible and have a low tolerance to complex traffic scenarios, hence the possibility of false triggering, which will substantially affect the user experience [2].

In today’s world, the AEB system has become the focus of many researchers, who, like Iqbal, as well as many others, have proposed various collision judgment mechanisms, like time behavior simulation, adaptive threshold adjustment, and multi-stage braking strategies, gradually gaining acceptance as time passes. Nevertheless, in complex environments such as urban traffic, adverse weather, and mixed traffic conditions, AEB systems still need improvement in accuracy, robustness, and comfort [3].

This paper deals with the decision-making process of AEB systems used in passenger vehicles. Secondly, it details the general composition of AEB systems and mainstream decision-making models. Moreover, it delves into factors that determine the operation of the system, which could be the vehicle parameters, the driver behavior, and the external environment. Subsequently, it encapsulates old-aged optimization techniques, such as context-aware adaptive control, multi-source information fusion, and intelligent decision-making driven by algorithms. This is done by a discussion on current challenges within technological development and trends for the future. The study is anticipated to provide theoretical foundations and methodological support for improving reliability and user experience in real life by AEB systems.

2. Analysis of AEB Decision Mechanism and Mainstream Algorithms

The automatic emergency braking system is a key component of the vehicle safety system as it determines how the system intervenes, when, and at what intensity; this is crucial for response speed and false triggering. For proper system optimization, it is necessary to understand the upstream mainstream decision mechanisms and their effect pathways.

2.1. Overview of Decision Mechanism Workflow

The AEB system functions in three general working steps: firstly, the perception layer, through which the system extracts the vehicle parameters of road contour, relative velocity, and distance using sensor technology like millimeter-wave radar, smartphone cameras, and LiDAR. The second layer is the decision layer. It calculates collision risk by using the pre-defined decision formulas or models and then evaluates whether braking intervention is necessary and decides which intervention level to use. Lastly, the execution layer, which performs the task of applying braking through electronic brake systems (such as brake-by-wire, ECU) to stabilize or suppress the collision. The decision-making layer has the important task of deciding whether to trigger the system, the trigger time, as well as controlling the braking force. Based on behavior modeling, the following methods of decision-making are presented.

Last but not least, the decision-making models in the current AEB system are classified into traditional basic models and advanced optimization. Supporting the evolution of AEB systems from “scenario-based” to “individual-centric”, driver behavior models emerged as the central topic of research in these models.

2.2. Comparative Analysis of Two Judgment Models

2.2.1. Safe Distance Model

The safe distance model happens to be the most standard and easily substituted model for its simplicity and the fact that it mainly depends on the vehicle dynamics to come up with the minimum safe distance, which is usually at the given speed order. Having engineered it this way ensures that the highway condition is well adhered to. Contrasting with that, this model is adaptable to the target recognition speed and environment changes; what is often lacking is performance in complex cities [4]. In terms of the technical aspects, the safe distance model could be represented in a concise parametric form, which needs only the vehicle and road friction coefficients, resulting in a quick estimation value. The math is so simple that the strategy that fixes the thresholds lacks the adaptive capability to accommodate geometric variations in the dimensions of curves and slopes. The inadequate distinction between longitudinal and lateral movement in this model might severely reduce the utility of this concept in transportation on low-friction surfaces like ice, snow, or wet roads in the process [5].

2.2.2. Time-to-Collision (TTC) Model

By utilizing the TTC model, the system is able to determine collision time by comparing the distance and speed between the vehicle in question with that of the vehicle ahead. Accordingly, a collision is most likely and will initiate brake application when the TTC to the object falls below a threshold (which is typically in the range of 1.5 to 2.5 seconds). In terms of response time, the safe distance model requires a greater or equal degree of distance adjustment in a reverse direction with a decrease in the distance between the target and the host vehicle and vice versa in other scenarios where the target and the host vehicle moved mainly vertically [4]. The downside is its inability to factor in changes in the target's motion state and the vehicle's actual deceleration rate; this might lead to positive triggers in the environments like motionless targets or tiny targets that are treated as obstacles affecting the sensor outputs, as those outputs mostly resort to distance and speed information obtained from the millimeter-wave radar or the vision sensors. In this context, what stands out about the system is the inflexibility in terms of the choice of a well-fitted threshold, which poses a challenge to where the system can guess complex traffic behavior, like cut-in or cut-out. Because of this, frequent positive alarms are likely to occur in dense urban traffic. Another thing to emphasize is that the TTC model also lacks the ability to forecast deceleration targets. More precisely, if the lead vehicle undergoes an intense braking and transmits a delayed braking signal to the host vehicle, the model can be overly optimistic about the remaining time, and thus the braking force is insufficient [6].

2.3. Model Optimization Solutions

Recent studies have suggested that adaptive algorithms for AEB employing strategic distance thresholds see advantages. Such algorithms dynamically adjust the simulation distance threshold according to the estimated mass of the vehicle and the road gradient in real-time. The adaptive algorithm, when compared to the fixed threshold control method, makes its braking initiation 0.2 seconds earlier and the maximum deceleration is reduced by 0.5% in tests including the full load and the low friction coefficient. Ultimately, Zhang et al. extended the model of a safe distance by suggesting a classification methodology taking into account the road curvature as well as a relative spatial location. This method is efficient in addressing the issues of object misidentification along curves. Building a safety robot with a good mix of range and accuracy, Abdullah straightforwardly compared TTC and Artificial Potential Field (APF) and the result showed no less than two meters of stopping distance at static obstacles after the crash, which the reference distance and the dimension of the injury did exceed the threshold distance in reference to the held value of r from the threshold [6].

2.4. Comparative Analysis of Braking Strategies

A single-stage braking mechanism here means the system would instantaneously apply the maximum brake force (generally above 0.7g), preferably upon the formation of collision risk for a superior avoidance outcome. Such a strategy is rather easy to vary among the play environment and the hardware standpoint, making it easier to implement, and it has a faster response time to the environment. What, at the same time highlights its weaknesses: even though the braking increases tension in emergency situations, it can be more detrimental to the driver's comfort and increase the chances of rear-end collisions if they occur. Another issue is that the single-stage system may be unsuitable for complex traffic environments. In areas where many traffic situations occur, such as school zones, this single-stage AEB system will experience problems, as its algorithms cannot discriminate between different levels of consolidation in the field of hazards. In order to enhance the system with more than just a single stage of an event, the stage of multiple events is the current approach, which is implemented with the following three stages: Stage 1: Visual/Auditory/Tactile warning; Stage 2: Partial braking (deceleration approx. 0.3g); Stage 3: Full braking (deceleration approx. 0.6g or above). The multi-stage strategies have a much calmer flow than a single-stage approach [7-9]. Furthermore, multi-stage strategies could also involve varying height and timing thresholds for slippery areas, as well as a higher friction coefficient to brake to slow down.

2.5. Comparative Analysis of Decision Logic

Systems with fixed thresholds lead to the use of specified parameters like TTC, safe distance, and speed limits as conditions for rules, which is a great advantage of this system because of the clear and simple structures and easy-to-adjust parameters during calibration and making the system practically convenient and ready for widespread use. On the other hand, fixed-threshold systems have their downsides: because of the use of a uniform approach for the so-called drivers, the car is deficient in adaptive ability. For example, it may use unnecessary braking interventions in cautious drivers, and this also contrasts with the potential hazards for aggressive drivers. Vehicles that exceed or fail to reach certain thresholds, according to statistics, may compromise safety in traffic because of the issues they may cause in this circumstance [4].

Perspective-wise, this strategy has an advantage because of its structural simplicity and the need to adapt to the driver situation, but it lacks flexibility in terms of the diversity of driving demands. On the other hand, adaptive systems integrated with the driver behavior ensure the precise adaptation of braking methods, leading to greatly improved system usability as well as user satisfaction, consequently. Instantly, further innovations of the AEB technology allow us to project them in a more personalized and informed way in the future.

3. Factors Influencing System Performance and Optimization Directions

3.1. Factors Influencing System Performance

Vehicle physical parameters and braking reaction times have a great impacts on this system's performance. The vehicle's weight or mass affects inertia and causes a longer reaction distance based on the speed of the vehicle. In traffic safety, SUVs and bigger pickup trucks require more room for their small safe distance, while low-speed vehicles such as motorcycles can afford to have more sensitive trigger zones. The electronic braking system units, including the e-Booster or the e-Pedal, have such benefits as quick reaction time as well as superb accuracy.

Not only sensor layout but also perception capability can be affected by certain configurations. Cameras can be specified as the primary sensors due to their strongest recognition ability and resolution under low light levels. However, the performance can be greatly impaired if the light conditions are poor. Millimeter-wave radar, on the other hand, has characteristics of strong anti-jamming ability and high detection accuracy, but the resolution is low, and the identification ability of small targets is insufficient. The pluses in the case of LiDAR include accurate 3-dimensional measurement and detection; unlike other sensors, it can be more costly, but it's known to be susceptible to weather conditions. There is a need for a serious consideration of these sensors regarding the advantages and disadvantages, and only then can be made regarding configuration in order to achieve the right level of performance and reliability from these systems. Like most widely used architectures of Advanced Emergency Braking System (AEB), protected by a camera + millimeter-wave radar dual-channel, and high-grade LiDAR, used in addition to have the improved perception ability under complex conditions [5].

Complexity of the environment is one of the most important factors in system performance. The AEB system becomes less accurate under the environmental conditions of nighttime, rain, snow, fog, glare, when road markings are unclear, and the terrain is not structured. This is a challenge that starts with improving the adaptability and adding a more specific threshold control system in the perception module [10].

3.2. Optimization Directions

The optimization of decision making and perception could be accomplished by using CNNs to classify and learn the traffic-friendly patterns, thus increasing the system's capability of spotting the generalized scenes like bicycle lane changes and demonstrating more adaptability in almost any scene. Use needs detection to understand situations, either where the driver is engaged in driving behaviors (wrong-way driving and crossing pedestrians) or on the contrary, where the driver is not engaged. Under such circumstances, it is crucial to put the system instantly into high-sensitivity mode, interrupting earlier with the braking response [6].

Having achieved the ability to integrate human-machine cooperation decision optimization, the next step is to make it really work. In this mechanism, it is possible to assess many factors in such a way that throttle, brake, steering inputs, as well as eye gaze or head posture, may be able to speak about the driver’s behavior. If there is an active avoidance reaction, then the AEB system will be hidden in an instinct and lower its intervention level to avoid this. So that combining the driver's intention with the automatic judgment results and using a denormalizing fusion method, such as fuzzy control to obtain driver-machine cooperation control, the conflict between the driver control and the machine's effect can be reduced [11].

Another component in V2X technology is the opportunity for optimization. V2X integration into a vehicle involves different levels of operation: In Vehicle-to-Vehicle (V2V), as a result of the invention, vehicles trailing or preceding the lead vehicle in front are able to receive brake intention of the lead vehicle in a transposed manner, which allows AEB to activate timely and cut own action round-down toward rear-end collision probability. In the case of the Vehicle-to-Infrastructure (V2I), it will utilize the V2I communication systems and sensors distributed in road signals and sensors to collect warning information about hazards like accidents, slippery roads, etc. With this proactive information, the system can adjust proactively and improve its performance. Not only can cooperative vehicle avoidance and optimal paths be designed based on the V2X network, but system strategies can also be continuously updated using cloud big data analysis, making it dynamically activated, thus response becomes more efficient and adaptive in traffic environments [12].

4. Challenges Facing the System and Future Development Trends

4.1. Challenges

One of the major challenges facing the AEB system is its depletion of effectiveness within complex traffic. The AEB system is effective in structured road environments like straight highways, but there are issues of incorrect judgments and missed detections for complex traffic environments that contain multiple targets or become usually unstructured, where there are prolonged uncertain scenarios such as intersections, pedestrians dash out, and nighttime bicyclists [13]. In addition, a darkness, torrential rain, etc., of these elements could deteriorate the effectiveness of this system, especially if nighttime rain or fog, for example, reduces the camera-based target detection ability and raises the chance of false alarm [10]. Moreover, under the “gravity curve” or “motion curve”, along the route within the scenes changing quickly (for example, mixed urban traffic), validity is reduced significantly due to low sensing level.

The problem of the AEB system getting an acceptable threshold can also stem from the other side: that is, conflict between the false trigger rates and the trust of people. The limitation of current AEB systems is finding, even in a notion, a reasonable kind of balance between "the proper moment to intervene" and "the false triggers". In some systems, where false triggers often send signals for such targets as slower ones or light/shadow interference, those systems might get in the way of user's driving experience and subsequently, the user does not trust such systems any longer. When systems are too conservative, then they can lose their functionality, for example, by missing the right time for braking. The problem, however, is especially prevalent for aggressive drivers, whose approach rarely leaves room for flexibility of the system. The driver may receive cold signs of frequent false triggers aside, which can greatly impair the acceptance of the system [13].

Moreover, weak recognition capabilities for vulnerable road users (VRUs) also prove to be a technical challenge. The AEB systems have some weaknesses in detecting complex vehicle passengers, such as pedestrians, riders of a variety of motorcycles, and especially light-emitting scooters at night or in inclement weather conditions, reducing the ability of recognition of small target size or poor visibility of the road surface [10].

4.2. Future Development Trends

The succeeding AEB systems will become more intelligent in decision-making systems. Deep neural networks, with the help of Machine Learning, will drive this change to new intelligent decision systems, where the embrace of technology means they can learn over time, adapt, and make more complex judgments. For example, ML techniques are used in Classification models—the collision prediction probability balancing results are balanced across performance metrics. Additionally, reinforcement learning applications can help the systems continually adjust brake preferences in the repeated environments (simulated) that are improving the decision efficiency and precision.

There is also an upgraded multi-sensor approach with an integrated redundancy feature in sensors. The system of AEB in the future innovations will include multimodal perception through the combination of appropriately camera, millimeter-wave radar, LiDAR, ultrasonic sensors as well as Inertial sensors and map data that will compose an intelligent sensing system with features like perspective redundancy due to timestamp merging and the ability to remotely understand the world changes with high categorization performance, both spatial and temporal components are intended [5].

AEB System Fintech personalization and an integrated human-machine hybrid decision-making, too, will be of great interest. The upcoming AEB system in the future will definitely make it impossible to apply the same methods of the system to different drivers. What the system would begin to do is to create user profiles based on behavioral habits, risk tolerance, as well as attention, and more that enable real-time adjustment of the system's braking strategy. Another way that this could happen is by creating a shared control system where the system can make a required intervention when complying with the driver's subjective will and therefore allow both human and machine to work cooperatively. Elaborately, for highly experienced drivers, the system shall be built to hold the implementation for an even longer time. In the case of distracted drivers or drivers in the state of fault, the warning shall be faster, and proactive braking shall be longer [11].

The AEB system now stands before the threshold of moving from only "passive judgment" to "active learning." Its further development will have three further areas of focus in making systems. The first aspect that is covered is the "Generalization" capability; therefore, the system needs to provide not only more traffic participants, but also more states and scenarios as the traffic evolves. The second aspect is focused on the "Adaptation" capability, and it means that it will be able to take into account the individual driver behavior, such as threshold tolerance or alertness level, to apply a customized level of intervention. Finally, this aspect is covered on the "Collaboration", which means to achieve multi-collisions, systems, and vehicles, as well as the level of cooperation [12].

As a conclusion, the AEB system will not just work as an "emergency prevent" device, but it will become a most crucial, complex, and integrated accident prevention feature of the intelligent traffic care system.

5. Conclusion

Considering such factors as false triggers, failure to adapt to real-life scenarios, and compound difficulties in integrating individual preferences, if one pays close attention to the applied research on passenger vehicle AEB systems, we seek to fill the gaps mentioned. In this paper, as an example of a decision-making mechanism in the AEB system, firstly, the classification and fusion in order to increase the accuracy, put the system into a stage, and secondly, the system will be comfortable and adaptable to the driver. The methods used in the paper are also multi-modal sensor fusion, human-machine co-working, and V2X technology, which means that the hardness of driving experience in any traffic scenario will be improved remarkably. Based on the research, multi-dimensional coordination and transition in the pattern of performance is the key to AEB systems to achieve a "perception-decision-control." Such an exposed issue applies not only to shared information but also to components of speeding up the development. Self-learning capability, shared human-machine knowledge as well as perception are the main factors for future AEB system development. This paper also shows that it could be of interest to the autonomous-driving industry developers, vehicle manufacturers and government safety regulators as it stands for L2+ and higher autonomous driving, that proven to indicate trust naturally to a driver inside a vehicle. Not only a safety technology, but a major challenge for intelligent driving technology to maintain public trust, this breakthrough also marks the most critical point for whether it could be accepted by the users or not, and when it is widely launched by automakers. Failure to keep progressing the gears of intelligence, response, robustness of perception, adaptability, and tailor it to users will mean that, unfortunately, the idea of "technology-driven safety" as a passport helper will be in vain.

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