Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 1188089, 13 pages
https://doi.org/10.1155/2022/1188089

Review Article

A Systematic Review of Autonomous Emergency Braking System: Impact Factor, Technology, and Performance Evaluation

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Received 13 September 2021; Revised 27 February 2022; Accepted 11 March 2022; Published 18 April 2022

Academic Editor: Francesco Galante

In order to track the research progress of AEB-related technologies, this paper makes a systematic analysis and research on the impact factors, key technologies, and effect evaluation of AEB. First, the paper deeply analyzes the three levels of factors affecting the performance of AEB, which are vehicle factors, driver factors, and environmental factors. Second, the paper deeply studies the technical status of the three subsystems of environment perception, decision-making, and control execution. Particularly, the performance of Mazda, Honda, NHTSA, Berkeley, and Seungwuk Moon are compared and analyzed based on MATLAB. Third, the paper summarizes the current AEB virtual test methods, closed field test methods, and its test sites. Three classic evaluation methods in the world, including the AEB test evaluation standards of ENCAP, IIHS, and i-Vista are analyzed. Finally, the paper prospects the specific research directions, including the protection of vulnerable road users, target detection method, collision avoidance strategy, complex scenarios application, and application of emerging technologies.

1. Introduction

The continuous advancement of the global economy has increased the number of vehicles every year. The World Health Organization (WHO) report shows that more than 50 million people are injured and approximately 2.5% of them die in road traffic accidents every year [1]. According to the statistics, approximately 90% of the total road traffic accidents are caused by drivers' operating errors due to inexperience and irregular driving behaviors (drunk or fatigue driving). In most of the cases, the driver is unaware of the risk of collision, or the reaction time is too short to deal with the imminent collision properly.

As the sensor and control technologies progress continuously, the ADAS allows drivers to identify potential dangers in different scenarios promptly, thereby improving driving safety. As a prominent example, the AEB system leverages on-board sensors (such as millimeter-wave radar and/or camera) to perceive the downstream traffic condition and evaluate the potential collision risk with remote vehicles, pedestrians, or other traffic participants at the front. Then, the system automatically triggers the actuator to implement necessary braking to avoid the collision or mitigate its severity. The working process of the AEB system can be divided into the following three stages. (1) Normal stage: the vehicle will not collide with the vehicle at the front or other obstacles (pedestrians, cyclists, etc.); the AEB system will not intervene in the driving behavior. (2) Early warning stage: the AEB system will alert the driver immediately through visual or audial warning sign, or by tightening the safety belt. (3) Braking stage: the AEB system uses a single-stage or multistage braking strategy (i.e., directly applies the maximum braking pressure or gradually increases the braking pressure) to avoid the collision.

With the advancement in technology, the application scope of AEB systems remains expanding and their effectiveness of collision avoidance keeps improving. In recent years, researchers worldwide have proposed various AEB systems for pedestrians [2], cycles [3, 4], motorcycles [5–9], electric vehicles [10, 11], large buses [12], special vehicles

[13, 14], and other target and application objects and have applied emerging technologies such as machine learning [15–17] and vehicle-to-vehicle (V2V) communications [18] to the latest AEB systems to improve their accuracy. The AEB systems can reduce the number and/or severity of relevant crashes, resulting in reduced number of traffic fatalities. Several existing studies have shown that AEB could reduce rear-end collisions by 25% to 50% [19–22].

In this study, extensive literature on AEB systems is collected and summarized from three aspects: its impact factors, system structure (consisting of environment perception subsystem, decision-making subsystem, and execution subsystem), and its test and evaluation (as shown in Figure 1). The remainder of this paper is organized as follows. Section 2 analyzes the various factors that affect the system performance. The system structure was introduced, and some collision avoidance algorithms were simulated and compared in Section 3. Section 4 describes different AEB test and evaluation methods employed in different countries, and Section 5 concludes this paper and presents future research direction.

2. Impact Factors

The AEB system performance is affected by both the intrinsic and extrinsic factors of the equipped vehicle while driving. The intrinsic factors cover on-board sensing, decision-making as well as actuation, while the extrinsic factors deal with other than the vehicle itself. This study further divides these factors into three categories according to the level of influence: vehicle, driver, and environment factors. These factors may coexist during the AEB working process to affect safety, comfort, and energy consumption as shown in Figure 2.

2.1. Vehicle Factor. While driving, vehicles may encounter complex situations in terms of road environment and traffic conditions, such as (horizontally and vertically) curved roads, intersections, overtaking, and lane changes. At present, AEB system is generally applicable to low- and medium-speed traffic scenes, and high-speed scenes are rarely involved. In the international test standard, the maximum speed of the test vehicle is 80 km/h. Meanwhile, it is important to identify the most dangerous target in the shortest time under complex road conditions. The basic function of the AEB is that the object in front can be recognized by the camera and radar. However, as the main sensing equipment of vehicle, cameras and radars are less effective in bad weather and poor light conditions, such as sandstorms, fog, snow, and darkness. The field-of-view (FoV) angle of the sensor has a significant effect on avoiding collisions, particularly for collisions between vehicles and pedestrians (or bicyclists). Studies have shown that when the detection angle of the AEB system is set to 30° to 50°, more than 95.3% of severe injury and death accidents and 78.5% to 92.2% of minor injury accidents can be detected [23]. With an increase in the detection angle, more targets (specifically pedestrians and bicyclists) can be detected [24], avoiding more accidents [25].

The impact of system factors on the collision avoidance effect is reflected in the system error [26], braking delay [27], maximum deceleration, and control strategy [28]. System errors are caused by measurement errors and incomplete environment perception, which leads to uncertainty in system decision-making. Braking delay refers to the time between the driver pressing the brake pedal and the brake system starting to build up pressure, which depends on the ability of the brake execution system. When the vehicle adopts full-braking behavior, greater vehicle deceleration will shorten the braking time and ensure the safety of the vehicle, but too high deceleration will affect the driver's driving experience. With the advancement in sensor and braking technologies, the AEB system's ability to recognize targets, the amount and accuracy of data obtained, and the system delay time are continuously improving. The choice of control strategy directly affects the overall performance of the AEB system, which is the core part of the system. Comparing the current widespread collision avoidance algorithms based on safe distance or time-to-collision (TTC), when the vehicle speed is lower than 60 km/h, the collision avoidance algorithm based on TTC has a better stability and smaller braking force, providing the driver a more comfortable driving experience. When the vehicle speed exceeds 60 km/h, the collision avoidance algorithm based on safe distance can ensure the reliability of vehicle emergency braking [29].

2.2. Driver Factor. The "autonomous" of the AEB system primarily means that the driver's intervention is not required. However, each driver's driving style varies owing to his or her characteristics, such as driver's age, gender, experience, responsiveness, and psychological endurance. Therefore, unified collision avoidance logic and evaluation criteria may not be applicable to different drivers. Therefore, in addition to ensuring safety, the driver's driving comfort should be guaranteed to a certain extent.

To analyze the driving styles of different types of drivers and avoid the dissatisfaction and doubt caused by the control strategies that do not conform to their driving styles, drivers are classified according to the true test data of driving characteristics [30]. This data can be obtained by a driving characteristic identification model based on a hidden Markov chain [31] or a Bayesian filter and support vector machine model [32]. Drivers can be divided into three types: radical, standard, and conservative [33]. After determining the driver style, different control strategies and parameters can be set for different types of drivers to enhance the control accuracy and driving comfort of the system [34].

2.3. Environment Factor. The environment factors that affect the system performance are external factors, including weather, light, and road conditions, in addition to the vehicle itself and driver. Roads can be majorly divided into ordinary road, cross road, and tee sections road. The road conditions, including the road adhesion coefficient, slope, and type, directly influence the efficiency in achieving the expected effect after implementing the braking action.

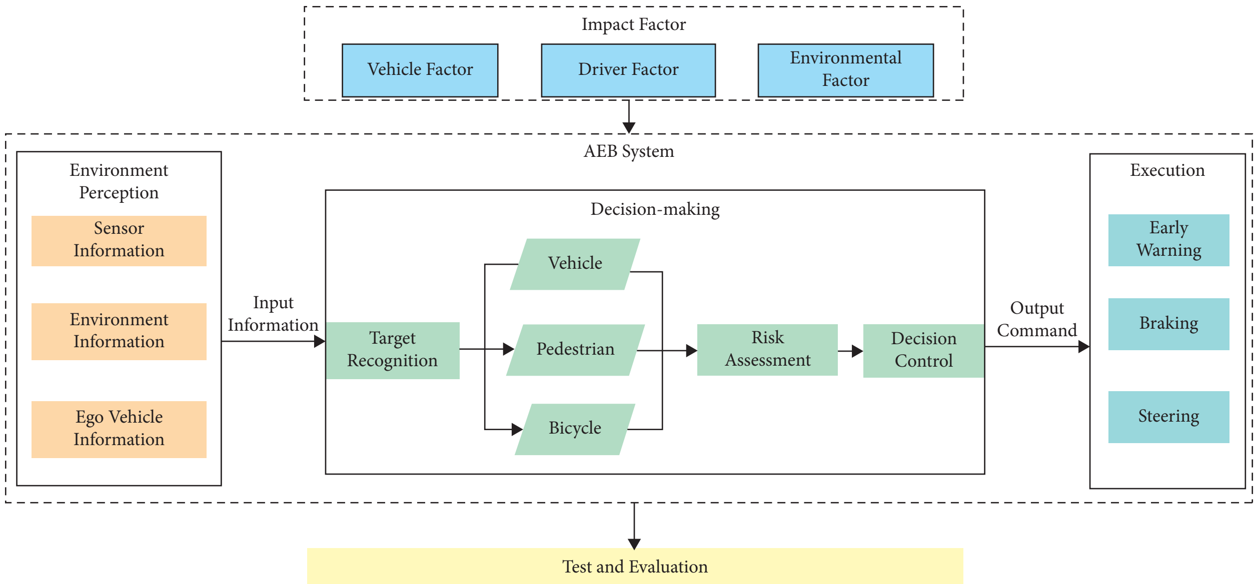

FIGURE 1: AEB system framework.

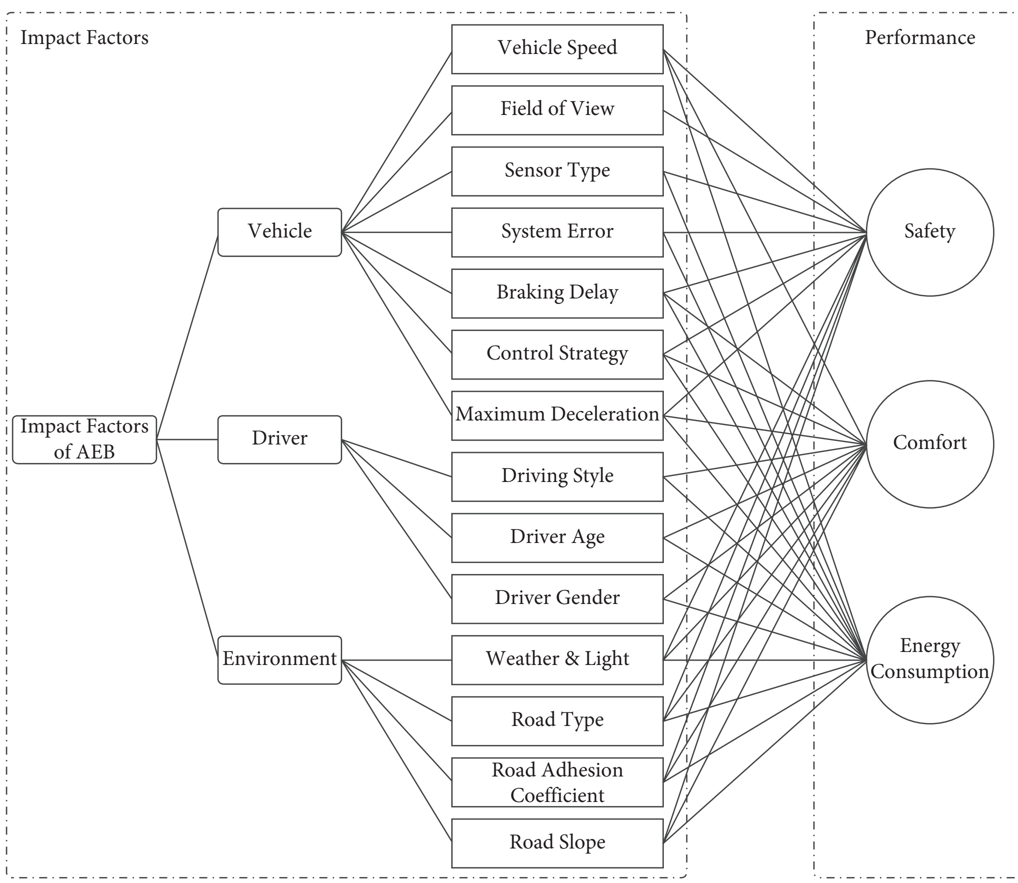

FIGURE 2: Impact factors of AEB performance.

Weather and light are easy to distinguish for drivers, while AEB systems mainly depend on sensors and are susceptible to weather and light. Under special conditions (e.g., rainy, snowy, and fog), the perception ability of the system perception mechanism to the surrounding objects and the deceleration effect of the vehicle after braking will be affected. Weather can be divided into sunny, cloudy, rainy, or severe weather. Light can be divided into daytime and night with and without street lights. The proportions of good light conditions among fatalities and injuries were calculated to be 75.58% and 85.51%, respectively, except for collisions that occur on roads without streetlights. AEB system is assumed to only work effectively in collisions that occur in good weather conditions, including sunny and cloudy days. The proportions of good weather conditions among fatalities and injuries were calculated to be 88.36% and 88.82%, respectively.

The road adhesion coefficient is affected by the road type, wetness, tire property, and air pressure. This can be considered as the static friction coefficient between the tire and pavement. If the AEB system does not consider the effect of pavement adhesion for a vehicle travelling on a road with a small adhesion factor, the braking distance will be larger than expected, and the collision avoidance efficiency of the system will be reduced. Therefore, to enhance the performance of the AEB system for different pavement adhesion coefficients. Rajamani et al. [35] estimated the peak pavement friction based on the longitudinal, transverse, and normal direction tire forces. Hwang and Choi [36] and Sevil et al. [37] employed an adaptive AEB system for different pavement adhesion coefficients. Han et al. [38] and Koglbauer et al. [39] experimentally demonstrated that the adaptive AEB system can alleviate collisions and improve the subjective safety and trust of drivers through the driver's actual driving.

The road slope is mainly divided into uphill and downhill, the AEB system must consider the influence of the vehicle's gravity effect on braking deceleration. The acceleration component of the vehicle gravity on the uphill section increases the maximum deceleration of the vehicle, causing the vehicle to complete braking ahead of time. The gravity component of downhill vehicles offsets part of the braking force, reduces the maximum deceleration and increases the braking time and distance, along with the likelihood of collision. Therefore, while considering the slope, the dynamic characteristics of the vehicle on the uphill and downhill slopes should be analyzed, and the minimum braking distance and braking time should be calculated by estimating the force applied to the vehicle [40]. To ensure that the AEB system can effectively avoid collisions under different road slope conditions, the existing road slope of the vehicle must be determined. To estimate the road slope, Bae et al. [41] proposed two methods based on global positioning system; Kim et al. [42] used a combined extended Kalman filter based on vehicle sensor information and strong nonlinear vehicle dynamics, tire, and inclination angle models; and Vahidi et al. [43] used the recursive least square method with a forgetting factor.

This section summarizes the vehicle-driver-environment factors that can affect the AEB system. At present, there have been a large number of studies on control strategies and road conditions. However, the factors such as system error, braking delay and maximum deceleration have relatively little impact on AEB, and fixed values are adopted in most studies. Which leads to that although AEB system has a mature theoretical basis, these parameters need to be changed when applied to specific models. Considering the driver factor is the focus of current research. On the premise of ensuring the safety of AEB system, improving the driving experience of different drivers can further improve the performance and reliability of AEB system.

3. Subsystems of AEB System

The pipeline of the AEB system primarily includes three components: environment perception subsystem, decision-making subsystem, and execution subsystem. The environment perception subsystem is to obtain the vehicle and surrounding road information through on-board sensors, such as cameras, radars, and thermal sensors, and send the information to the decision-making subsystem. Based on the received information, the decision-making subsystem judges the critical situation of the current road conditions and simultaneously determines whether early warning, braking, and other collision avoidance strategies (e.g., steering) must be implemented. The subsystem then transmits commands to the execution subsystem for executing the collision avoidance operation of the corresponding module.

3.1. Environment Perception Subsystem. The environment perception subsystem primarily comprises various sensors that collect information and identify targets. At present, the most commonly used sensors in AEB systems include 77 GHz millimeter-wave radar, lidar, mono-binocular cameras, and thermal sensors. These mainstream sensors possess different characteristics. For instance, the millimeter-wave radar has a better penetration and large detection range, and is unaffected by light and weather. However, it is expensive, and the target recognition is difficult. Response time of lidar is short with high ranging accuracy, but it is expensive and can be affected by weather. The cost of the monocular camera is low which can effectively identify the target, but the detection range is short.

The difficulty of research on environment sensing subsystems of AEB system is the identification and selection of targets, including the accuracy of recognition, radar and camera data fusion, and the selection of the most dangerous targets. The false positive of the environment perception subsystem will cause the false triggering of AEB. Therefore, in order to reduce the false positive, OEM (original equipment manufacturer) will generally carry out a large number of performance tests and field operation test (FOT). According to previous research [44–47], sensor fusion technology can improve target perception ability in AEB system. With the research development, the AEB system will face more complex traffic environments (curves, intersections, overtaking, lane changes, etc.); therefore, the most dangerous targets in the current and complex road conditions must be analyzed. At present, the most dangerous target selection strategy includes three methods: the target closest to the vehicle in the current lane, judging the driver's intention to identify the most dangerous target, and selecting the most dangerous target according to the driver's behavior.

In addition to the use of physical sensors, the rapid development of wireless communication technology (e.g., vehicle-to-vehicle communication, V2V) and high-performance computing can improve the AEB's target detection capability. The fundamental benefit of V2V lies in its ability to exchange vehicles' information, which enables the system to make better decisions in terms of safety. At present, some studies have proved the effectiveness of V2V technology in vehicle collision avoidance [48], particularly in pedestrian target recognition [49]. The problems that limit the development of this technology are the long-term coexistence of vehicles with V2V and without V2V on the road.

3.2. Decision-Making Subsystem. Decision-making subsystem, the core part of the AEB system, is also the focus of most existing research. It includes three main parts: target recognition, risk assessment, and decision-making control strategy.

3.2.1. Target Recognition Strategy. According to different collision avoidance targets, the AEB system recognizes objects into three categories: vehicles, pedestrians, and bicyclists. Pedestrian and bicyclist are mainly focused for target recognition. Owing to the different conditions of pedestrian clothing, age, and gender, and difficulty in predicting the trajectory, the requirement for accurate target recognition is significantly high. Generally, the speed of bicyclist is higher than that of pedestrians, and 50% of severe and fatal injuries in bicyclist accidents are observed at the speed range of 12 to 15 km/h [50].

If the pedestrian is considered as a stationary target and there is a possibility of collision, the longitudinal collision avoidance will be considered only. However, to the moving target, the possibility of collision is calculated. Therefore, to enhance the detection and tracking ability of AEB system for moving targets, ensuring the optimum effect and cost, ultrasonic array sensor is generally selected [51], which can achieve 86% detection accuracy, with a detection time of 0.8 s [52]. In addition, Lee et al. [44] proposed a robust pedestrian tracking method based on a multisensor fusion strategy and designed the activation area by predicting the possible distance of pedestrian collision through the braking model, which proved to be advantageous. Song et al. [53] proposed a new theory and algorithm to predict the position of pedestrians and determine accurate warning and braking times. This algorithm can effectively avoid or mitigate pedestrian collision accidents when the vehicle speed is below 40 km/h. Park et al. [54] proposed a pedestrian target selection method based on a funnel graph structure. By comparing the predicted position of the pedestrian target with the current position, the probability of collision was estimated, and the effectiveness of the method was verified through simulation and real vehicle tests.

3.2.2. Risk Assessment Strategy. Risk assessment strategy is the judgment of the AEB system on the possibility of collision and severity of the accident under the current working condition, which provides a reference for the system to perform corresponding collision avoidance operations. First, the evaluation parameters should be set and the widely used evaluation parameters are the safe distance and TTC. In addition, the predicted minimum distance [55], time to brake [56, 57], time to act, time difference to collision [58], and critical speed for decision-making [59] can be used as evaluation parameters.

Subsequently, based on the collected information and predicted trajectory, the parameter threshold of the risk scenario is calculated by collision avoidance algorithm. Owing to the algorithm is directly related to the execution time of braking, it has a great impact on the collision avoidance ability of the AEB system. In section 3.2.4, several common collision avoidance algorithms are simulated and compared, which take the safety distance as the evaluation parameter. Finally, a risk assessment is performed and defined quantitatively. Risk quantification is an intuitive expression of the degree of risk. Shimizu et al. [60] developed a risk quantification model based on collision speed in a dangerous scene. The effectiveness of the model in predicting collision risk was proved by comparing the simulation results with the actual driving data. Cafiso et al. [61] used the pedestrian risk index to assess the potential severity of danger and duration. For instance, the risk coefficient ε is defined numerically based on the current car spacing d and safety distance (including warning distance d_w and braking distance d_{br}).

$$\varepsilon = \frac{d - d_{br}}{d_w - d_{br}}. \tag{1}$$

When $\varepsilon > 1$ and $d > d_w$, the vehicle is in a safe state, and the AEB system does not intervene. When $0 < \varepsilon < 1$ and $d < d_{br}$, the vehicle may collide, and the driver needs to be reminded to perform collision avoidance operations. Furthermore, when $\varepsilon < 0$ and $d_{br} > d$, the vehicle needs to apply emergency braking for avoiding a collision.

3.2.3. Decision-Making Control Strategy. The decision-making control strategy determines the corresponding collision avoidance operation according to the dangerous extent based on existing road conditions. The vehicle is considered as the control target. The existing decision control models include the hierarchical control, brake steering control, acceleration control [62], and brake pressure adaptive models [63].

The hierarchical control model was designed to deal with complex scenarios such as pedestrian collision accidents. To estimate the danger more accurately, the upper-level evaluation and control part usually adopt new technologies, such as fuzzy neural networks. Yang et al. [2] used the hierarchical control model for upper fuzzy neural network and lower proportion-integration-differentiation (PID) control, and introduced a genetic algorithm to train the fuzzy neural network. Based on the theoretical basis of TTC and braking safety distance, AEB-pedestrian system early warning model was established, and the credibility of the control strategy was proved through experiments. The radial basis function neural network (RBFNN)-based variable structure control (VSC) [16] was used to optimize the AEB system to achieve higher deceleration. Christopoulos et al. [64] proposed a rear-end collision avoidance control strategy using hierarchical control. The upper risk assessment layer continuously calculated the threat parameters related to braking control to avoid collisions, and the lower tire slip control layer used RBFNN and VSC. The results showed that the proposed control scheme can effectively achieve collision avoidance.

When the safety distance is short, the vehicle may change its lane to avoid collisions quickly; according to this, several studies have been conducted on automatic emergency braking systems. Llorca et al. [65] used a stereo vision detection module to calculate the collision time between the vehicle and target. A simulation controller was used to simulate the human behavior and reaction. The collision avoidance system was primarily based on automatic steering. The results showed that the system could effectively avoid pedestrian collisions at a speed up to 30 km/h. To solve the problem of over-steering and instability when the vehicle speed is high, Choi et al. [66] proposed a collision avoidance strategy of simultaneous steering and braking using the nonlinear model predictive control method, and proposed a constraint on the wheel steering angle considering the predicted lateral acceleration of the vehicle.

3.2.4. Comparative Analysis of Different Collision Avoidance Algorithms. The collision avoidance algorithm is an important part of the AEB risk assessment strategy. The judgment of the dangerous state and collision possibility is obtained by comparing with the actual data, and the evaluation results directly affect the control behavior of the system. At present, several algorithms for estimating the severity of vehicle rear-end accident safety assessment models exist. The specific evaluation parameters can be divided into safety distance, TTC [67], time headway [68], minimum deceleration [69], and driver perception models [70]. Currently, there are several applications of AEB products based on the safety distance and TTC models.

The safety distance model considers the real-time headway as the safety evaluation parameter and provides the judgment basis for further warning and braking by calculating the safety critical value of the relative distance between the ego and front vehicles. The threshold algorithm includes five main algorithms: Mazda, Honda, NHTSA, Berkeley, and Seungwuk Moon (Table 1).This type of algorithm is based on the speed and acceleration of two vehicles, considering the driver reaction time, braking system delay, and other factors. The calculation method of this critical value is constantly improving. At present, the safety distance model is widely used in the safety assessment of AEB systems.

According to the basic threshold calculation method of the proposed safety distance model, four algorithms other than the NHTSA algorithm with complex parameters were simulated (as shown in Figure 3). To compare the algorithm characteristics under the same working conditions, uniform parameters were used: the maximum acceleration of the ego and target vehicles was 6.5 m/s^2, driver's reaction and system delay times were 0.5 and 1 s, respectively.

The results show that under the same conditions, the braking distance obtained by the Seungwuk Moon algorithm was the most reasonable and the effect was optimum. In Berkeley algorithm, braking distance distribution was reasonable and simple, when considering fewer factors. The Mazda algorithm was too conservative because its calculated braking distance is clearly large, which leads to a high alarm rate and reduces user's trust. The Honda algorithm was relatively too radical because its calculated braking distance is clearly small, and the system intervention time was delayed.

3.3. Execution Subsystem. When the AEB decision-making subsystem judges that the vehicle is about to collide, the actuator receives the command to remind and protect the driver through warning and braking. In the early warning stage, the execution subsystem can form different early warning strategies through a combination of visual, auditory, and tactile means. The specific forms are buzzer alarm, human-computer interface image alarm, and tightening or retracting seat belts. In the braking stage, the current braking pressure building methods can be divided into three types: the active pressure building of motor piston pump based on electronic stability control (ESC), active pressure building of high-pressure energy storage based on electronic hydraulic braking, and active pressure building of master cylinder power-assisted motor based on electronic power-assisted braking [76].

Owing to the disadvantages of high-pressure accumulators, such as sensitivity to vibration, low safety and reliability, large volume, and high cost, auto parts manufacturers select motor piston pump, master cylinder power motor, or a combination of motor piston pump and master cylinder power motor as the active pressure building scheme. At present, the active pressure building of motor piston pump is widely used as an actuator in AEB systems. However, the hardware and performance require further strengthening owing to limited precision and time. Therefore, a brake-by-wire technology can be employed to resolve previously mentioned issues. The brake-by-wire technology has the advantages of fast braking response, high braking energy, simple structure, and easy expansion. This is a major development direction of the future brake system. To further reduce the response time of active braking, shorten the braking distance and simplify the braking system, the research and development of new generation braking systems, such as electro-mechanical and electromagnetic braking, are also important directions for the braking scheme selection of AEB system in the future.

This section summarizes the three subsystems included in a complete AEB system. The environmental perception subsystem has the problem of false positives based on the existing vehicle sensors. Reducing false positives and improving the perception ability are the problems to be solved by AEB system and other vehicle active safety technologies. With the development of V2V technology, the vehicle perception ability will be further improved. The key of the decision-making subsystem is the collision avoidance

Table 1: Existing algorithms for the safety distance model.

Research	Organization	Algorithm	Character
Doi [71]	Japan Mazda corporation	Mazda	More scenarios covered
Fujita [72]	Honda corporation	Honda	Two level early warning structure
Burgett et al. [73]	NHTSA	NHTSA	High accuracy of early warning
Seiler et al. [74]	University of Berkeley	Berkeley	Adapting to different road conditions
Moon and Yi [75]	Han Yang university	Seungwuk Moon	Estimation of pavement adhesion coefficient

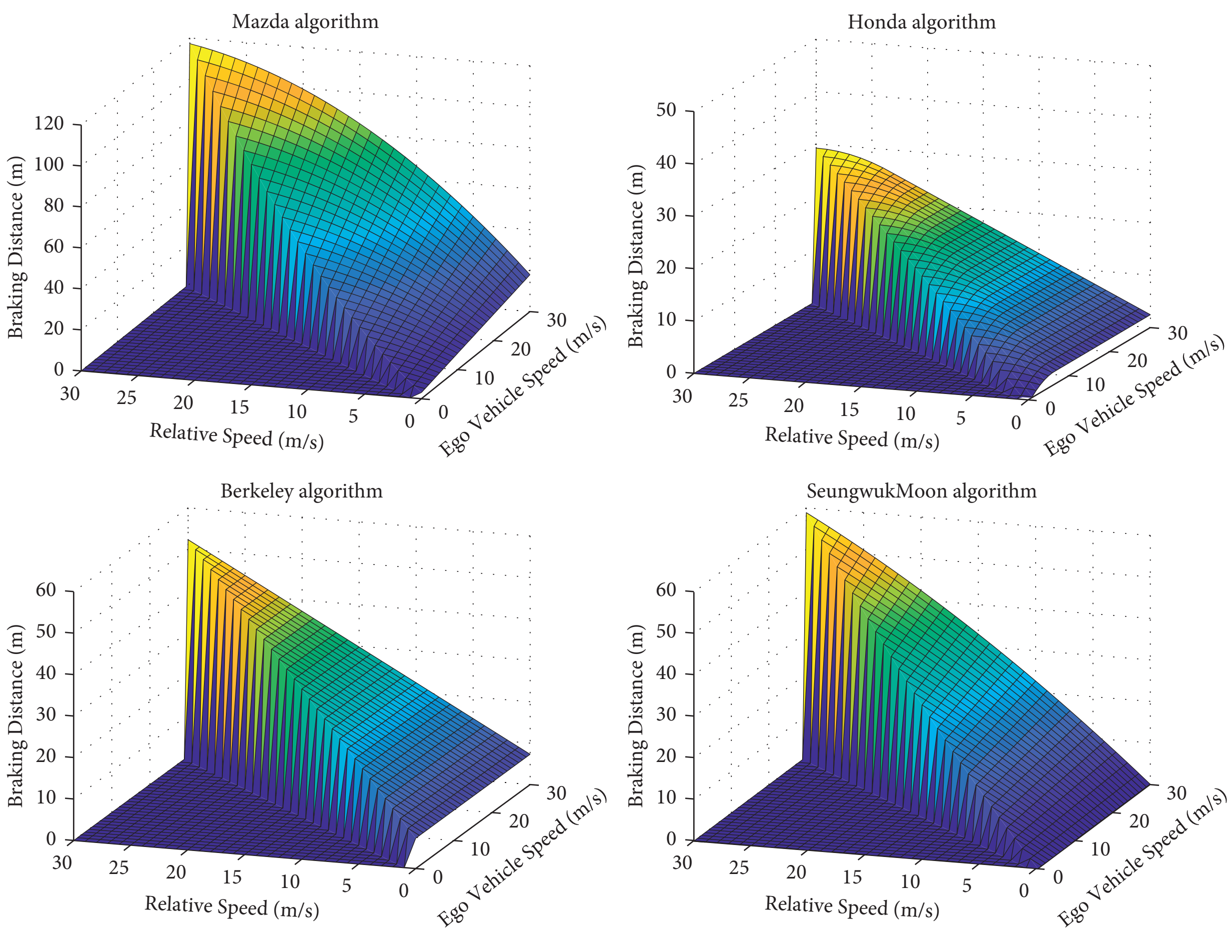

Figure 3: Simulation results of the four algorithms.

algorithm. The experimental results show that different algorithms have great differences in safety and comfort. The optimization of the algorithm has always been the focus of AEB research. When braking, the execution subsystem mostly adopts multilevel braking strategy to improve the driver's comfort. At present, research has added steering operation on the basis of traditional vehicle braking to avoid the collision with short vehicle spacing.

4. Test and Evaluation

At present, test and evaluation procedures for AEB systems are well established all over the world. Since 2013, automobile safety certification authorities, such as Euro-NCAP, NHTSA, IIHS, CNCAP, and i-Vista, have included AEB test and evaluation procedures (Table 2).

4.1. Test Methods. Currently, the AEB system is a relatively mature active safety system. The specific tests are aimed at existing or improved sensors, collision avoidance algorithms, actuators, and human-machine interfaces to verify their performance, stability, robustness, and safety. First, based on real road data, a relationship between driving behavior, road, environment, and other traffic participants is analyzed, and the test scenario is constructed. Subsequently, the test evaluation method is designed. At present, two methods are used to test AEB systems: virtual and closed field test. Table 3 presents the comparison results of the two methods.

4.1.1. Virtual Test. Virtual test usually uses various simulation software tools to restore, track, and collect data for specific test scenarios. Vehicle sensors, dynamics model,

Table 2: International standards and test report.

Organization	Country/ Region	Standard name	Year	Document name
ISO	International	ISO-22839	2013	Intelligent transport system-forward vehicle collision migration system ——operation, performance, and verification requirement
IIHS	American	Front crash prevention testing	2013	Autonomous emergency braking test protocol (version 1)
NHTSA	American	—	2014	Objective tests for automatic crash imminent braking (CIB) systems final report
ECE	United nations	ECE131	2014	Uniform provisions concerning the approval of motor vehicles with regard to the advanced emergency braking systems (AEBS)
SAE	American	SAE-J3087	2017	Automatic emergency braking (AEB) system performance testing
i-Vista	China	i-Vista SM-ADAS-AEBR-A0-2018	2018	Autonomous emergency braking rating protocol
Euro-NCAP	European union	ENCAP-2020	2020	European new car assessment programme (test protocol-AEB system)
CNCAP	China	CNCAP-2021	2021	Test method of active safety ADAS system

Table 3: Comparison of test methods.

	Virtual test	Closed field test
Scene construction capability	Controllable scene, low cost, fast speed	Controllable scene, high cost, low speed
Scene coverage	Define test scene independently, high coverage	Restricted by the site facilities, low coverage
Data	Extract holographic test data, comprehensive data, high precision	Extract testing facility data, comprehensive data
Efficiency	Support multivehicle collaborative testing, high efficiency	Restricted test objects number, low efficiency

controller and driver, as well as traffic environment, are simulated by simulation software, and dangerous scenarios are considered to simulate the AEB system. Currently, numerous virtual simulation tools are available. The benefits of this method include: simplicity, safety, low cost, ease of repetition, and enabling of detailed analysis. With these existing advantages, virtual tests can be adopted in rare and hazardous conditions and/or used to traverse critical values of key system parameters through repeated tests. However, the reliability of the test results depends on the selection of test scenarios and accuracy of the simulated vehicles and environment.

The test of the AEB system is functional in nature and scenario-based. It can be specifically described as a sequence of events occurring in chronological order [77]. The generation of accident scenarios is mostly based on local accident depth investigation data (GIDAS, CIDAS, etc.) and real natural driving data. The rapid generation of virtual test scenarios is the focus of research in the fields of driving assistance systems and automatic driving (as shown in Table 4). Currently, the methods available are as follows:

(1) Test Matrix: The test dimension matrix is constructed based on key parameters (each point of the matrix corresponds to a scene). The test scenarios are sorted and tested accordingly.

(2) Worst-Case Scenario Evaluation [78]: On the basis of monotonic change feature extraction of system function, boundary conditions are set and effect function is optimized to test the most challenging scenario.

(3) Monte Carlo Simulation: Based on the data collected from the real vehicle, a random test was conducted through the scene generated by the Monte Carlo simulation.

(4) Accelerated Evaluation [79–81]: Importance sampling theory and the cross-entropy method are used to identify key test scenarios with high precision and speed, to achieve accelerated simulation and evaluation.

4.1.2. Closed Field Test. Closed field test is used to conduct real vehicle test on real roads without excessive external interference, resulting in high controllability, reliability, and repeatability. However, owing to its high cost, closed field testing is widely used in new car assessment program (NCAP) institutions and existing vehicle testbeds in various countries.

In closed field test, it is equally important to select representative test scenarios. Appropriate test scenarios can produce reliable test results and reduce testing costs. At present, the most commonly used closed field test scenarios are those defined in the NCAP regulations of various countries where Euro-NCAP provides the basis for the test and evaluation regulations. Based on the actual road traffic accident databases of the United States, China, and other countries, AEB test procedures have been issued for their own countries. According to the evaluation procedures and related test scenarios, the AEB test scenarios are divided into rear-end collisions, pedestrian accidents, and bicyclist accidents.

Table 4: Partly researches on AEB test scenarios.

Researchers	Test scenarios	Scenario source	Test method
Fleury and Brenac [82]	Rear-end	French accident data	Similar accidents generate typical accident scenarios
Huang et al. [83]	Pedestrian and vehicle collision at intersections	STRADA	All pedestrians can be detected when FoV is greater than 60°
Niewöhner et al. [84]	Pedestrian and vehicle collision	GIDAS, UDV	Propose an improved AEB-pedestrian test method
Lenard and Danton [85]	Pedestrians collide with the front and rear ends of vehicle	STATS 19, OTS	Typical pedestrian accident scenes are obtained by comparison
Camp and Lubbe [50]	Bicyclist and vehicle collision	Accident data of five European countries	Provide theoretical support for the development of AEB-bicyclist test scenarios
Sander [86]	Collision at intersection	GIDAS	Cluster analysis of AEB test scenarios and established evaluation method
Chen et al. [87]	Pedestrian and vehicle collision	CIDAS	Summarized three dangerous scenes of pedestrian vehicle collision
Xu et al. [88]	Collision at intersection	NAIS	Eight typical dangerous scenes are obtained by hierarchical clustering algorithm

A vehicle comprehensive test site is an indispensable practical condition for closed road tests. Various countries have actively invested in construction and have achieved remarkable results. Table 5 summarizes a list of existing test sites for automobiles that have the ability to test the automobile ADAS system. These test sites cover various road types, such as highways, urban roads, and rural roads, and a few of them can even emulate rain, fog, and other weather conditions.

Intelligent and connected vehicle has become the development trend of the industry. As an important link, the construction of automobile closed test site plays a key role in accelerating the upgrading of the industry. By learning from the successful experience at home and abroad and allocating resources reasonably, the automobile test and evaluation system can be further improved.

4.2. AEB System Evaluation Standard. The complete evaluation method comprises three parts: identification of evaluation metrics, determination of index weights, and selection of evaluation methods. The test data are collected, processed, and analyzed for evaluating the test process. The vehicle systems, modules, or algorithms are then evaluated using the evaluation method. The key performance index of the AEB system is the successful rate (i.e., whether the system can avoid the collision). If the collision cannot be avoided, then the speed reduction during braking will be considered as the major evaluation metrics. The evaluation results are quantified and summarized based on the score sheet under different test conditions, which represent the overall performance of the AEB system in terms of collision avoidance. Nowadays, different evaluation methods for the AEB system have been proposed and actively used by major institutions, such as ENCAP, IIHS, and CNCAP.

4.2.1. ENCAP Evaluation Standard. The AEB evaluation standard of ENCAP includes functional tests and human-machine interface tests. For functional tests, the relative impact velocity is considered as the key parameter. For test speed less than 40 km/h, the score weight of each test velocity is determined according to the actual reduction in relative velocity. In the case of incomplete collision avoidance, the linear interpolation method is used to calculate the score of a single test velocity. For each test speed above 40 km/h, score will only be awarded when the actual measured test speed is reduced by at least 20 km/h.

The score formula for each test speed is as follows:

$$\text{Score}_{\text{test\_speed}} = \left(\frac{V_{\text{rel\_test}} - V_{\text{rel\_impact}}}{V_{\text{rel\_test}}}\right) \times \text{points}_{\text{test\_speed}}, \quad (2)$$

where, $V_{\text{rel\_test}}$ and $V_{\text{rel\_impact}}$ represent the theoretical relative test speed and actual relative collision speed, respectively.

The AEB-VRU (vulnerable road user, including pedestrian and cyclist) score is determined by the total score of the three test systems (head, upper limb, and lower limb). The AEB-VRU part can only be scored if the total score is at least 18 points. The total score of the pedestrian and bicyclist AEB systems is 9 points, respectively. The standard scores of test speed for each test scenario are calculated by multiplying the score rate by the scenario score.

The score formula for each test scenario is as follows:

$$\text{Score}_{\text{scenario}} = \frac{\sum \text{Score}_{\text{test\_speed}}}{\text{Score}_{\text{total}}} \times \text{points}_{\text{scenario}}, \quad (3)$$

where, $\text{Score}_{\text{total}}$ represent the total points in each specific scenario and $\text{points}_{\text{scenario}}$ represent the score for each scenario.

4.2.2. IIHS Evaluation Standard. Since 2013, the American Insurance Institute for Highway Safety (IIHS) has included the evaluation of front crash prevention in the new car evaluation procedures, and the evaluation level is divided into three levels: excellent, advanced, and primary, with a total score of six points. The function of the front crash prevention system is the same as that of the AEB system, including the front collision warning and active braking systems. It is mainly evaluated according to the test vehicle equipment and test results.

Table 5: Partly test sites for vehicles in the world.

Location	Name	Area (km^2)	Road type	Road length (km)	Function
USA	M-city	0.129	High/low speed test area	8	Auto-driving and V2X
	Go Mentum Station	8.498	Highway, real hill, viaduct, tunnels, etc.	32.1869	Expressway test area and urban test area
Sweden	Asta-zero	2	Multilane highways, four-street urban areas, expressway areas, rural and suburban roads	5.7	V2X, driver behavior, vehicle dynamics
UK	City circuit	3.04	24 loops	95	Auto-driving, ITS, V2X
Japan	Toyota ITS test site	0.035	Intersection	—	V2V, V2I ICV test
China	Shanghai demonstration zone	150	Intersection, tunnels, avenues, gas stations and indoor parking lots	500	Auto-driving, V2X
	i-Vista	2.51	Various special roads, high-speed loop roads and simulated town roads	The first phase is 6 km	Road traffic, efficiency, information services
	CAVTEST	0.28	Urban area road, highway	3.5	Intelligent vehicle test, C–V2X test

The front crash prevention system has only 1 point (primary evaluation) when the test is effective and a higher evaluation level can be obtained only when the active braking system is equipped and proved to be effective during the test. The reduction in vehicle speed during the test process is considered as an evaluation parameter. The IIHS stipulates that the test vehicles need to be tested at different speeds (19.3 and 40.2 km/h). The score is determined according to the vehicle speed reduction under the action of the system. The more the vehicle speed decreases, the better would be the performance of the front crash prevention system, resulting in lower risk or severity of the collision.

4.2.3. i-Vista Evaluation Standard. The Intelligent Vehicle Integrated Systems Test Area (i-Vista) has proposed an overall evaluation procedure for intelligent vehicle safety since 2018. The AEB-C2C and AEB-VRU standards are included in the latest 2020 edition of the regulation. According to the scoring rate, the intelligent safety grade is divided into four evaluation grades: excellent, good, general, and poor.

The evaluation standard of the AEB-C2C system can be applied to the forward collision warning (FCW), AEB, and advanced assistance function tests. The main test scenarios include static, deceleration, and low-speed conditions of the target vehicle. Each FCW scenario will be scored if five out of seven tests meet the conditions. Otherwise, no points will be scored. In the AEB test scenario where five tests are performed at the same speed, braking deceleration is used as the evaluation parameter. Advanced assistance functions include the FCW assistance alarm, active safety belt warning function, and emergency steering collision avoidance function. One point for each function is awarded if the function is effective.

This section summarizes the test and evaluation methods and related research of AEB system. At present, various countries and standards organizations are actively promoting the popularization of AEB system and constantly improving the test and evaluation system. Researchers continue to improve and optimize testing methods and speed up the process of testing and evaluation. However, there are still some problems in the test of AEB system. Although closed field test can effectively test the performance of AEB system, it takes a lot of time and cost and is not suitable for testing a large number of scenarios. There are few test scenarios specified in international standards, so it is impossible to popularize the test to a wider range of road real conditions. In the future, with the continuous improvement of AEB technology, pedestrian AEB, cyclist AEB test, and false response test will be gradually studied and standardized.

5. Future Work

A significant amount of effort has been devoted by industry, academia, and government to advance AEB over the past decade. With the breakthrough of hardware technology such as sensor and brake, the collision avoidance ability of AEB system will be further improved. It is also recommended to further explore the following directions in the future:

(1) The effectiveness of the AEB function depends on the appropriate selection of potential targets at risk and timely feedback for execution. Therefore, the perception ability of driving environment information is an important factor restricting the development of automatic emergency braking systems. The combination of sensor fusion and vehicle-to-everything (V2X) communications can improve the application and sensing range of AEB systems.

(2) At present, the AEB is aimed at the front target when the vehicle is running longitudinally, and only few studies exist related to collision avoidance strategy under the test scenarios of sudden insertion of a side vehicle, vehicle turning, multivehicle environment, multipedestrian or riding environment, and limited driver vision. Therefore, the AEB collision avoidance strategy in complex multitraffic scenarios should be studied to optimize its comprehensive performance.

(3) To better cover various test scenarios in a cost-effective manner, augmented reality or mixed reality methods should be used to reconstruct, configure,

and enhance the test scenarios. Meanwhile, the current evaluation parameters are independent, and only the speed reduction is considered as the evaluation index. The system can be comprehensively evaluated using the TTC, peak value of braking deceleration, distance after braking, relative distance between braking and stopping, success rate of sensor recognition, and success rate of collision avoidance.

(4) Currently, the research is only restricted to the performance of safety from the individual vehicle perspective, without considering other performance metrics (e.g., environmental footprint) and the impact of the AEB system at the system level. The change and impact on vehicle stability, energy consumption, and overall traffic efficiency after equipping AEB system (to some extent) would become a research direction in the future.

Data Availability

No data were used in this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research has been supported by the National Key Research and Development Program of China (No. 2021YFB2501200), the National Natural Science Foundation of China (No. 61703053), the Shaanxi Province Key Research and Development Program (2022GY-300), the Shaanxi Province Postdoctoral Science Foundation (No. 2018BSHYDZZ64), and Chang'an University Graduate Student Innovation Ability Cultivation Project (No. 300203211242).

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