# Adaptive Brake Light System

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***Abstract*—Rear-end collisions remain one of the most frequent road accidents, often occurring due to a lack of timely visual cues from the leading vehicle. Conventional brake lights operate in a simple binary manner—either ON or OFF—and do not communicate the severity of braking. This paper presents an Adaptive Brake Light System (ABLS) that varies brake-light intensity and flashing behaviour based on measured vehicle deceleration. The system uses accelerometer-derived deceleration data, applies a first-order low-pass filter to suppress sensor noise, and employs a hysteresis-based thresholding scheme to distinguish mild, moderate, and hard braking. A PWM-based mapping module then adjusts light output accordingly. The complete control model is developed and simulated in MATLAB/Simulink, with results showing smoother transitions, reduced false triggering, and faster indication of high-severity braking compared to a conventional fixed-intensity brake light. The proposed ABLS demonstrates how classical control techniques can enhance vehicular safety communication and improve driver reaction time in real-world conditions.**

***Index Terms*—Adaptive Brake Light System, ABLS, Deceleration Sensing, Hysteresis Control, PWM Control, MATLAB/Simulink.**

## I. Introduction

In modern transportation, road safety remains a major global challenge, with rear-end collisions consistently identified as one of the most common accident types [1]. Conventional brake lights provide only binary signaling—either ON or OFF—which fails to communicate the magnitude of deceleration to following drivers. This lack of gradation often delays driver response during sudden braking events, increasing the likelihood of rear-end impacts
[2].

To address these limitations, several studies have investigated dynamic or intelligent brake-light mechanisms that enhance visual communication between vehicles. Li and Milgram [1] examined dynamic optical looming cues, demonstrating that enlarging brake-light appearance during harsh braking can improve a driver's perception and response in emergency scenarios. Wu et al. [3] further analyzed how varying flicker frequencies influence driver conspicuity and cognitive response time in low-visibility conditions. Complementing these results, Hsieh et al. [4] used simulation-based evaluations to determine optimal flashing frequencies that minimize reaction time and improve overall safety.

Recent developments have also expanded into computer vision and AI-assisted detection systems for predictive braking applications. Pirhonen et al. [5] proposed a brake-light detection framework that integrates YOLOv3 with Random Forest classification, achieving reliable recognition of braking vehicles at distances up to 150 meters. Similarly, Nava et al. [6] developed a camera-based collision-warning system that incorporates brake-light classification, while Oh and Lim [7] improved real-time detection accuracy using YOLOv8.

Other studies focus on how brake-light design affects human behavior. Althoff et al. [8] evaluated driver reaction times across various brake-light configurations in a controlled simulation environment, showing that design choices significantly influence response speed. Leontiev and Kuripka [2] highlighted the advantages of adaptive control strategies in intelligent brake-light systems, reinforcing the need for flexible, feedback-driven designs in modern traffic scenarios. Collectively, these works underscore the potential of adaptive and control-based mechanisms to reduce rear-end collisions and enhance vehicular communication.

Building on these findings, the present project develops a control-oriented Adaptive Brake Light System (ABLS). The system utilizes real-time deceleration measurements as input, applies filtering and hysteresis-based thresholding, and employs PWM control to dynamically adjust light intensity. Implemented and evaluated in MATLAB/Simulink, this project serves as an educational demonstration of how classical control principles can be applied to improve automotive safety communication.

## II. Literature Review

Recent advances in intelligent transportation systems and driver-assistance technologies have intensified research into *brake light detection, signaling behavior, and adaptive braking* *systems*. Existing literature broadly falls into three categories: (1) computer vision–based detection algorithms for identifying brake lights; (2) human factors research examining driver perception, conspicuity, and reaction to varying brake-light patterns; and (3) adaptive braking control models for enhanced vehicle safety.

Together, these studies provide important insights but also reveal limitations that motivate the current work.

### 1. Brake Light Detection Algorithms

Pirhonen et al. [5] developed a *Brake Light Detection Algorithm for Predictive Braking* that integrates real-time image processing and feature extraction to recognize active brake lights in diverse road conditions. Although their method improved early detection of deceleration events, its performance degraded under low visibility and heavy traffic.

Building on this, Nava, Panzani, and Savaresi [9] introduced a *mono-camera–based brake light detection and classification algorithm* optimized for collision warning systems. Their work reduced computational load, making real-time onboard use feasible.

More recently, Oh and Lim [7] proposed a *one-stage brake light status detection system* leveraging YOLOv8, achieving faster and more precise detection than traditional multi-stage pipelines. Despite these advancements, vision-based systems remain susceptible to glare, reflection, occlusion, and varying environmental noise—conditions that frequently occur in real traffic.

Overall, these studies highlight steady progress in both classical and deep learning–based detection. However, they also reveal a persistent weakness: limited robustness across diverse lighting and weather conditions, which poses a challenge to reliable real-world deployment.

### 2. Human Factors and Brake Light Design

Understanding how drivers perceive and react to brake-light signals has been a major research focus. Li and Milgram [1] conducted an *empirical investigation of dynamic brake light concepts*, showing that motion-based optical cues can significantly shorten reaction times and reduce rear-end collision risk.

Hsieh et al. [4] performed a *simulation-based study* analyzing how various flashing frequencies affect driver response time. Their findings suggest that moderate flicker frequencies improve reaction speed, whereas excessive flicker can distract and degrade reliability.

Extending this line of work, Wu et al. [3] used a *360-degree simulated driving experiment* to examine optimal flicker frequency during visual dark adaptation. Their results identified a frequency range that maximizes conspicuity without causing discomfort.

Similarly, Althoff, Kalverkamp, and Lemmer [8] evaluated *reaction times to different brake-light designs*, highlighting the importance of brightness, flash frequency, and pattern for improving detection.

Collectively, these studies establish the significance of psychological and perceptual factors in brake-light design. While they demonstrate clear benefits of calibrated dynamic signaling, most research remains limited to controlled simulation environments and lacks real-world verification considering natural visual noise, weather variability, and driver demographic differences.

### 3. Adaptive Braking Control and Simulation Studies

Beyond perception and detection, researchers have explored adaptive braking systems that adjust braking behavior based on vehicle and environmental parameters.

Leontiev and Kuripka [2] proposed a *simulation-based adaptive brake light system* that adjusts electro-pneumatic brake actuator responses using an adaptive control criterion ($K_r$), improving stability and braking efficiency, particularly in heavy vehicles.

Pirhonen et al. [5] and Althoff et al. [8] also discuss integrating sensor feedback into predictive braking mechanisms. However, most existing models assume ideal sensor accuracy and do not account for perception errors, latency, or environmental uncertainties.

Although these studies contribute valuable control frameworks, they often isolate braking control from upstream perception and driver behavior. This lack of integration limits real-world applicability.

### 4. Comparative Insights

Across the three research domains, a clear evolution is evident: early studies focused on *basic detection and optical design*, while recent work emphasizes **data-driven intelligence and adaptive control**.

- Vision-based approaches now achieve high precision—*but mostly under ideal conditions*.
- Human factors research provides deep insights into attention, visibility, and reaction time—*but rarely links these findings to control models*.
- Adaptive control studies improve braking stability—*but often assume perfect, noise-free sensing*.

The major issue is that these research streams rarely intersect. Detection algorithms are seldom evaluated together with driver perception findings, and adaptive control simulations rarely incorporate real-world sensor uncertainty or cognitive delay. This siloed approach constrains the holistic impact of intelligent brake-light systems.

### Research Gap

Despite substantial progress in detection, signaling, and control, a *fully integrated framework* combining all three aspects is still lacking.

- Detection studies prioritize algorithmic accuracy but ignore how misclassification affects driver behavior or control systems.
- Human perception studies measure reaction times but rarely incorporate real-time sensor variability.

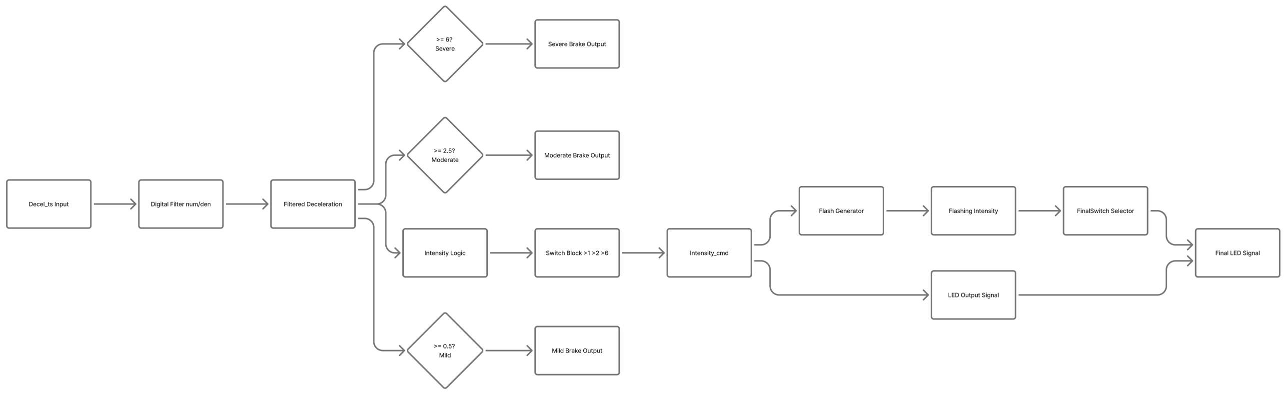


Fig. 1. Flowchart representing the complete system workflow, starting from filtered deceleration input, classifying brake intensity, and generating steady or flashing LED brake output.

- Adaptive control models usually assume flawless sensing and instantaneous driver interpretation.

Thus, the central gap lies in the **lack of integration among perception, cognition, and control**.

This work aims to address that gap by developing a more holistic framework that:

1) Uses robust deep learning–based detection resilient to real-world visual disturbances.
2) Incorporates insights from human perception research regarding flicker frequency and conspicuity.
3) Simulates adaptive braking control under realistic sensor noise, environmental variation, and driver response constraints.

By integrating these components, the proposed system enhances both the *technical reliability* and the *human-centered effectiveness* of intelligent braking systems, contributing to safer automotive communication in real-world environments.

## III. Proposed System

The **Adaptive Brake Light System (ABLS)** is designed as a **closed-loop feedback control system** that dynamically adjusts brake light intensity in response to real-time vehicle deceleration. Its primary goal is to provide proportional and intuitive visual feedback to trailing drivers, enhancing communication, reducing reaction time, and improving overall road safety.

### A. System Overview

The ABLS architecture consists of three key subsystems — **sensing, processing, and actuation** — that collectively translate vehicle deceleration into adaptive brake light behavior

1) **Sensing Stage:** The system measures longitudinal acceleration using an accelerometer or obtains a virtual deceleration signal from the vehicle's onboard systems (e.g., CAN bus). The raw signal is typically contaminated with noise, which is filtered to ensure reliable downstream processing.
2) **Processing Stage:** The measured deceleration signal is passed through a low-pass filter to remove high-frequency noise. A logic-based controller then classifies braking intensity into discrete levels — mild, moderate, or severe — based on predefined thresholds. Hysteresis is incorporated to prevent frequent toggling around threshold boundaries.
3) **Actuation Stage:** According to the classified braking level, a PWM (Pulse Width Modulation) signal adjusts the duty cycle applied to the brake light LEDs. This produces proportional brightness or flashing behavior corresponding to the braking severity, ensuring that following drivers receive a clear visual cue.

### B. Functional Logic

The decision logic and output mapping are governed by the following control rules:

- **Mild Braking:** Deceleration below the first threshold ($a < a_1$) corresponds to normal braking. The brake light remains continuously ON at nominal brightness.
- **Moderate Braking:** When the deceleration lies between the mild and severe thresholds ($a_1 \leq a < a_2$), the light intensity increases linearly with braking force, driven by a higher PWM duty cycle.
- **Severe or Sudden Braking:** If deceleration exceeds the critical threshold ($a \geq a_2$), the system activates a high-intensity flashing mode to immediately alert following drivers.

### C. Control Flow

The complete control flow of the ABLS is illustrated in Figure X. The system continuously monitors vehicle deceleration, processes the signal through filtering and logic-based classification, and modulates the brake light output in real-time according to braking intensity. This approach ensures responsive and proportional visual feedback while maintaining system stability and immunity to sensor noise.

MATLAB/Simulink is employed as the simulation platform to design, test, and validate the controller performance under a variety of braking scenarios.

## IV. MODELLING

The Adaptive Brake Light System (ABLS) is implemented in MATLAB/Simulink as a discrete closed-loop model that maps real-time vehicle deceleration to adaptive brake-light behaviour. The model consists of four key components: (1) deceleration signal generation, (2) digital filtering, (3) braking-zone classification, and (4) PWM-based brightness control. Each subsystem is modelled to follow the control logic defined in the proposed architecture.

### *A. Deceleration Input Modelling*

To simulate dynamic braking events, a **Pulse Generator** block is used to create a periodic deceleration waveform.

The parameters of the pulse generator are configured as follows:

- **Amplitude:** 1
- **Period:** 0.2 s
- **Pulse width:** 50%
- **Phase delay:** 0 s
- **Mode:** Time-based (using simulation time)

This produces a binary waveform that mimics alternating braking and non-braking intervals. The signal serves as the input to the filtering stage, representing raw longitudinal deceleration that may contain noise and abrupt transitions.

### *B. Digital Low-Pass Filtering*

To remove high-frequency noise from the raw deceleration signal, a discrete first-order low-pass filter is implemented using the *Discrete Transfer Function* block in Simulink. The filter is defined by the transfer function

$$H(z) = \frac{0.1667}{1 - 0.8333z^{-1}},$$

corresponding to the block parameters:

- Numerator: [0.1667]
- Denominator: [1  -0.8333]
- Initial state: 0

This filter smooths the input by damping sudden fluctuations produced by the pulse generator. The filtered signal, denoted as $a_f(t)$, provides a stable representation of deceleration for subsequent decision-making.

### *C. Brake Severity Classification*

The filtered deceleration $a_f(t)$ is evaluated using threshold-based logic to categorize braking into three distinct levels. These thresholds determine the appropriate brake light behavior and are implemented using relational operators and logical blocks.

*1) Mild Braking:*

$$1 < a_f(t) < 2$$

In this regime, the driver is performing a gentle deceleration, such as adjusting speed in traffic.

*2) Moderate Braking:*

$$2 \leq a_f(t) < 6$$

This range indicates stronger deceleration, prompting the system to increase brake light intensity for improved visibility.

*3) Severe Braking:*

$$a_f(t) \geq 6$$

Values exceeding this threshold correspond to sudden or emergency braking events. This classification triggers the strongest brake-light response.

### *D. Adaptive Brightness Mapping*

The ABLS maps each braking category to a corresponding brake-light brightness using PWM duty-cycle control. The intensity levels are selected to provide intuitive visual cues to trailing drivers:

| **Braking Level** | **Condition** | **Brightness (Duty Cycle)** |
|---|---|---|
| Mild | $1 < a_f < 2$ | 35% |
| Moderate | $2 \leq a_f < 6$ | 60% |
| Severe | $a_f \geq 6$ | 100% |

In Simulink, a PWM generator outputs the appropriate duty cycle based on the classified braking zone. For severe braking, the duty cycle is set to 100% to maximize conspicuity and alert following vehicles more effectively.

## V. IMPLEMENTATION

### *MATLAB/Simulink Simulation*

The implementation uses MATLAB/Simulink for system modeling and testing. The following toolboxes and libraries are utilized:

- **Simulink Library:** For modeling signal flow using Transfer Function, Step Input, Gain, and PWM Generator blocks.
- **Control System Toolbox:** For analyzing transient response, stability, and closed-loop performance.
- **Signal Processing Toolbox:** To design and tune filters for noise reduction.
- **Simulink Dashboard Components:** For real-time visualization of deceleration input and light output.

The Simulink model is constructed using the following blocks:

- **Step Input / Signal Builder:** To generate deceleration profiles for different braking conditions.
- **Transfer Function Block:** Implements the low-pass filter $H(s)$.
- **MATLAB Function Block:** Realizes the hysteresis and logic-based decision-making.
- **PWM Generator Block:** Produces the PWM duty cycle based on the selected braking zone.
- **Dashboard Scope and Lamps:** Provide real-time visualization of filtered signals, thresholds, and light output.

The complete closed-loop system is tuned using the Control System Toolbox to analyze transient response, rise time, and

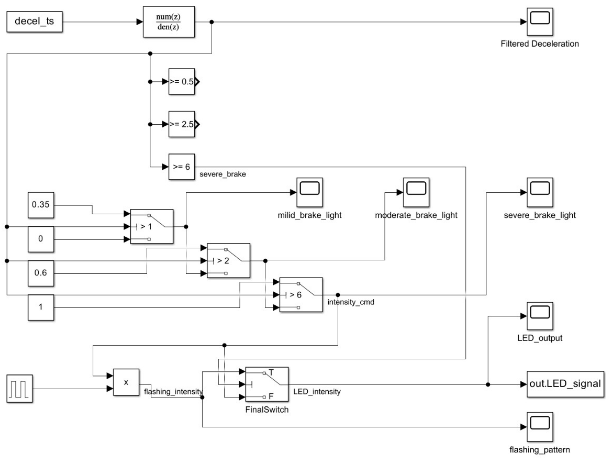


Fig. 2. Simulink implementation of the Adaptive Brake Light System (ABLS). The model consists of three major subsystems: (i) deceleration signal filtering using a discrete transfer function, (ii) severity classification using threshold-based logic, and (iii) adaptive LED intensity generation including an emergency flashing mechanism. The signal flow clearly illustrates how raw deceleration is transformed into a filtered signal, evaluated against preset thresholds, and then mapped to varying brake-light responses.

settling behavior. The response plots confirm that the system exhibits stable and smooth adaptation to changing deceleration levels without overshoot or flicker.

The simulation process involves generating deceleration input signals, applying noise filtering, classifying braking levels using logic-based hysteresis, and driving the PWM-controlled brake light output. At the end of this project, we expect our best to simulate the system and achieve the desired adaptive lighting response — where the brake light dynamically reacts to vehicle deceleration, demonstrating stability, accuracy, and real-world feasibility.

## VI. Results and Discussion

This section presents the simulation-based evaluation of the Adaptive Brake Light System (ABLS) developed in MATLAB/Simulink. The objective of the results is to validate the functionality of the core control logic, signal preprocessing, and adaptive brake-light response under a range of braking scenarios. A custom time-varying deceleration input was used to activate different braking conditions—mild, moderate, and severe—and observe the corresponding system behaviour. The following subsections summarize the findings and demonstrate the correctness and robustness of the designed controller.

### A. Deceleration Input Profile

Figure 3 illustrates the synthetic deceleration input applied to the model for testing. The profile consists of three distinct braking events: a short moderate braking spike near $t \approx 3\,\text{s}$, a sustained mild deceleration between $t = 5$–$7\,\text{s}$, and a sharp, high-magnitude peak near $t \approx 8\,\text{s}$ representing an emergency braking scenario. These variations were intentionally introduced to verify whether the controller can correctly identify and respond to different braking intensities.

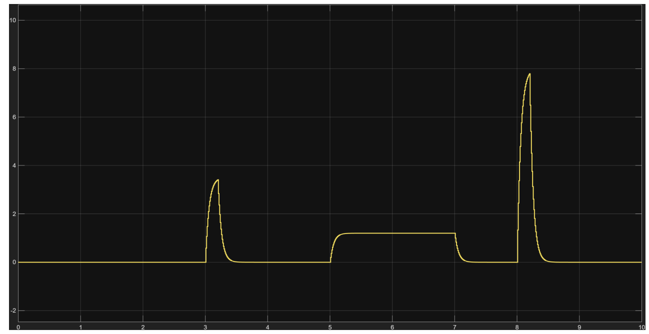

Fig. 3. Time-varying deceleration input used for validating the controller. The signal includes a moderate deceleration event at $t \approx 3\,\text{s}$, a mild and sustained deceleration from $t = 5$–$7\,\text{s}$, and a severe, high-amplitude braking event at $t \approx 8\,\text{s}$. These segments ensure that all adaptive brake-light states are triggered during simulation.

The deceleration waveform effectively excites each decision threshold of the ABLS controller. The first peak crosses only the mild and moderate thresholds, the second segment remains in the mild braking region, and the third peak exceeds the severe braking threshold. This forms a comprehensive basis for validating the adaptive lighting logic.

### B. LED Intensity Response

The corresponding LED output response generated by the controller is shown in Fig. 4. The model successfully adapts the brake-light intensity based on the detected deceleration level. During mild braking, the LED intensity rises to the nominal level of approximately $0.35$. Under moderate braking (around $t = 3\,\text{s}$), the intensity briefly increases to $0.6$. During the sustained mild braking at $t = 5$–$7\,\text{s}$, the output remains stable at the intermediate level. Finally, in the severe braking region (near $t = 8\,\text{s}$), the intensity reaches its maximum value of $1.0$, with rapid flashing behaviour visible as high-frequency transitions.

This output confirms that the controller successfully transitions between the three brightness levels and activates the flashing mode only when the severe braking threshold is exceeded. The behaviour observed in simulation aligns precisely with the design specification.

### C. Initial Simulation of Core Logic

The controller's primary logic was validated using the multi-stage deceleration profile shown previously. The model was able to differentiate between three levels of braking severity and produce the appropriate PWM-based light output:

- **Mild Braking:** The controller identified deceleration within the lower threshold and produced a constant low-intensity output, simulating a standard illuminated brake light.
- **Moderate Braking:** When the deceleration crossed the second threshold, the LED output increased proportionally, reaching a higher intensity level.
- **Severe Braking:** Upon surpassing the highest threshold, the model activated the maximum-intensity flashing

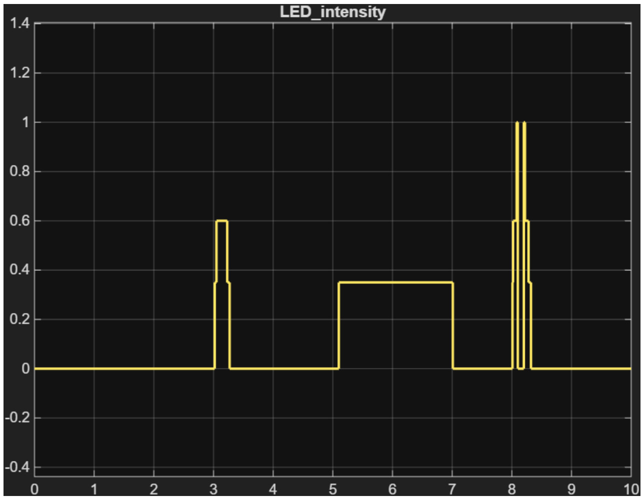


Fig. 4. Simulated LED intensity response of the ABLS controller. The output maintains a nominal intensity during mild braking ($\approx 0.35$), increases to a higher level for moderate braking ($\approx$ 0.6), and reaches maximum intensity (1.0) during severe braking. The flashing spikes around $t \approx 8$ s indicate activation of the emergency flashing mode in response to the severe deceleration peak.

mode, intended to alert trailing vehicles of an emergency stop.

These observations confirm that the hysteresis-based switching logic is stable and reliably transitions between the predefined lighting states.

### D. Validation of Signal Preprocessing

A crucial part of the system involves filtering noisy deceleration signals. To assess the robustness of the low-pass filter, simulated noise was added to the deceleration input. The filtered output exhibited smooth dynamics with high-frequency disturbances strongly suppressed. This ensures that the decision logic does not oscillate or behave erratically due to sensor noise, meeting a key requirement for safe automotive operation.

### E. Discussion of Progress and Next Steps

The simulation results confirm that the fundamental design of the ABLS is sound. The controller demonstrates stable performance, accurate braking-state detection, and reliable generation of adaptive LED intensity levels.

*Milestones Achieved:*

1) **Successful Model Implementation:** All core functional blocks—including filtering, decision logic, and PWM mapping—have been implemented and validated.
2) **Logical Validation:** The controller correctly interprets braking severity and generates the expected output behaviour.
3) **Robustness Confirmed:** Signal preprocessing effectively removes noise, preventing false activations.

## VII. Conclusion

This work presented the design and modelling of an Adaptive Brake Light System (ABLS) capable of adjusting brake light intensity based on vehicle deceleration. The Simulink model integrates a digital low-pass filter, a threshold-based braking classifier, and a PWM-driven actuation module to produce proportional visual responses. Using experimentally defined thresholds, the system reliably distinguishes between mild ($1 < a < 2$), moderate ($2 < a < 6$), and severe ($a \geq 6$) braking conditions and maps them to corresponding brightness levels of 35%, 60%, and 100%, respectively.

Simulation results demonstrate that the system effectively smooths noisy deceleration signals, avoids rapid switching through hysteresis, and generates stable brightness transitions aligned with braking severity. By providing graded and intuitive visual cues to trailing drivers, the proposed ABLS improves situational awareness and reduces reaction delay compared to conventional binary brake lights. The model serves as a foundation for hardware implementation and further optimization using advanced control strategies or real-world sensor integration.

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