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Research Paper

Biologically Inspired Edge Detection for Autonomous Driving Based on Improved Canny Algorithm and Human Visual Threshold Modeling

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Abstract. In order to increase the precision of lane identification and obstacle avoidance, autonomous driving systems based on computer vision technology must carry out edge detection. Problems like the inadequate flexibility of traditional algorithms to changes in dynamic light settings and environmental noises remain unanswered when the optimised Canny edge-detector is combined with refined human-defined thresholds. For real-time processing capabilities and explainability, local Gaussian filters, gradient-based edge detection, and biologically inspired threshold—which mimics the human visual system—are integrated with robustness enhancement in complicated situations. evaluating this method's performance in real-world scenarios using accuracy, precision, and latency indicators. These results demonstrate that, in comparison to earlier methods, this one typically has superior accuracy and coverage when there is a lack of contrast or bad weather in outside settings. This system satisfies nearly every criterion for autonomous driving systems and can handle high-quality images. In order to establish a foundation for integration into resource-constrained devices and intelligent driving systems, this article combines algorithm performance with biological adaptation. In terms of enhancing the operational stability and safety of an automated vehicle in the near future.

Keywords: *Computer Graphics, Edge Detection, Autonomous Driving, Biologically Inspired Algorithms*

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Introduction

To ensure the good application of modern automatic driving outdoors, there is currently a need for objects near enough to be recognised by cameras. Broadly speaking, in larger scale perception Tasks such as identifying lanes or other objects within a scene such as cars, Pedestrians, and Road Obstacles. After performing edge detection, the following complicated perception and Planning processes will continue to execute [1, 2]. Decision-making and motion planning are directly influenced by the reliability and efficiency of edge detection, especially in dynamic urban environments with varying lighting conditions and cluttered backgrounds [3]. With the widespread adoption of high-performance on-chip computing devices and advanced sensors, there is an urgent need to develop efficient edge detection algorithms to provide reliable real-time performance in various environments for autonomous vehicles [4,5].

Current algorithms perform poorly in complex road environments, despite the existence of many edge detection methods. Traditional methods based on static and global thresholds are prone to errors and perform poorly when lighting or weather conditions change [6,7]. Edge detectors based on hybrid and deep learning can overcome some limitations by learning the features of specific environments. However, due to their computational cost and reliance on large datasets, their application and effectiveness in rare or unusual environments are limited [8,9]. Due to the inability of fixed or preset thresholds to adapt to the varying contrasts

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encountered in autonomous driving environments, both traditional models and deep models find it challenging to determine suitable thresholds. Due to this limitation, there may be errors or missed detections [10,11]. In contrast, the human visual system exhibits better adaptability in edge detection by utilizing physiological mechanisms such as sensitivity to spatial changes, context-regulated perception, and evolutionarily adjusted thresholds, and it can also perform robustly under uncontrolled conditions [12]. By combining perceptual foundations and biologically inspired feature threshold models, the stability of artificial edge detection systems can be improved.

This paper proposes a bio-inspired edge detection method for autonomous vehicles. This method uses an enhanced Canny algorithm and a human visual threshold model. Mathematically describing the laws of human vision, with a focus on adaptive contrast sensitivity. This allows the new detection threshold to vary according to the instantaneous changes in the image state and other environmental factors (such as changes in lighting). Therefore, this paper proposes a new method to address the aforementioned issues. It improves some limitations of traditional algorithms while remaining more practical and interpretable than purely data-driven methods. This section will be organized in the following order: the first section will introduce the relevant literature, including the fundamentals of edge detection and threshold modeling; the second section will present the improved Canny algorithm and bio-inspired fusion methods; the third section will explain the experimental setup, quantitative results, and comparisons; the fourth section will summarize the main scientific achievements and their future research directions.

Background and Related Work

Edge Detection in Autonomous Driving

In order to extract basic road structure information in the early phases of autonomous vehicle detection, edges must be identified in scene image data. Curb stones, cars, and other elements of the roadside environment can all be identified by segmentation. vital to the development of detection algorithms, navigation, and positioning technologies [13,14]. Early detection methods with strong mathematical underpinnings and fast computations, such Sobel, Prewitt, and the Canny Filter, can be widely applied in automobile embedded systems environments. The following algorithms perform better in low light and comparable circumstances.

In actuality, we still don't fully understand driving. The unpredictable nature of human motion and the effects of weather can cause changes in the lighting conditions on urban roads. Shadowy regions, shiny points, glare, and low contrast images are more difficult for traditional edge-detection algorithms to handle. In an effort to address these issues, research on feature learning and building context-aware models has increased recently [15]. In the midst of noise, data-driven approaches can more accurately identify finer details. Since advanced perception modules are directly impacted by their own accuracy, this level of precision is associated with a vehicle that can accurately identify its path and quickly notify when confronted with hazards.

The application of these conclusions has not yet produced the desired outcomes in real-world scenarios. However, the costs and computer resource needs of machine learning algorithms rise in tandem with their increased practical stability. Therefore, there is an urgent need to create strong edge-based algorithms that can operate effectively on embedded devices in order to improve the overall performance of intelligent vehicle vision systems in identifying pedestrians.

Human Visual Threshold Theory

Numerous studies have demonstrated that humans are capable of identifying edges, thus they should improve their capacity to do so in various contexts. this ability's threshold sensitivity base. Humans' eyesight tends to increase or decrease the sensitivity of contrasts and edge differences based on changes in brightness, location relationship within space, surrounds, etc. Through spatial filter structures, the retinal photoreceptors are physically arranged and connected to bipolar cells and retinal ganglion cells. The edges become quieter and more noticeable.

Computational models for human sensitivity thresholds have been established through neurobiological and psychophysical investigations. In addition to adding contrast enhancement and lateral inhibition to a new retinal model, Gaussian difference models can alter their sensitivity with respect to the local scene statistics. These models demonstrate how human perception is influenced by signal intensity, ambient brightness, and spatial frequency range. Both the Mach Band Effect and Weber's Law demonstrate context-dependent perception.

In computer vision research, dynamic thresholding techniques are available to mimic biological processes. Although biomimetic algorithms are not as robust as set parameters, they can adjust to changes in the image's qualities and difficulty. Bio-inspired detectors create multiple-scale dynamic threshold areas to preserve the robustness of the image segmentation process of autonomous vehicles. These threshold ranges have the ability to distinguish between weak features and perceptually significant edges .

Challenges and Limitations of Current Methods

Both learning-based and classical edge detection techniques have demonstrated outstanding results. However, their broad uses in autonomous vehicles are now limited because of certain flaws. The majority of Canny algorithm generalisations employ a constant value for these thresholds because of the threshold issue, which is very severe. Global criteria are insufficient to accurately represent changes in the real driving environment. As a result, these detectors may make errors when identifying significant boundaries in scenes with low contrast. Additionally, regional recognition may fail due to variations in ambient noise or light intensity.

Deep learning techniques make it easier to set parameters than in the past, however similar restrictions might also be present in other environments. These methods struggle to generalise adequately for novel or uncommon circumstances beyond what was learned during training because they require a massive amount of tagged training data. Furthermore, many have longer response times and more processing power than standard automotive micro-controllers, making them inappropriate for safe driving systems. Deep learning networks require stricter supervision because they have issues with explainability and verification during application.

At the edge, greater quality autonomy must replace the conventional division of rigid or opaque models. There is a high likelihood that it will incorporate context awareness, a dynamically modified threshold influenced by human visual physiological mechanisms, and the foundation algorithm (an enhanced implementation of Canny). Enhance its dependability and flexibility and make it possible to enable fundamental interpretations and assessments. The approach used in this study is based on the analysis mentioned above.

Proposed Methodology

Improved Canny Algorithm

Edge detection begins with Gaussian filtering, which serves to remove noise and minor visual perturbations while preserving critical image structure. Crucially, rather than using a globally fixed smoothing parameter, the filter's standard deviation, denoted σ , is computed for each local region by analyzing the underlying contrast and spatial content. The smoothed image $S(x, y)$ is defined by the convolution

$$S(x,y) = G_\sigma(x,y) * I(x,y) \quad \text{Eq. (1)}$$

$G_\sigma(x,y)$ represents the Gaussian kernel and $I(x,y)$ is the observed intensity at each pixel. This adaptive approach effectively suppresses noise in homogeneous regions while minimizing detail loss around genuine edges.

The next stage involves gradient extraction. Local intensity changes are revealed by taking partial derivatives of the smoothed image, generating horizontal and vertical gradient components,

$$G_x = \frac{\partial S}{\partial x}, ?G_y = \frac{\partial S}{\partial y} \quad \text{Eq. (2)}$$

which are then used to compute the gradient magnitude,

$$M(x,y) = \sqrt{G_x^2 + G_y^2}, \quad \text{Eq. (3)}$$

and orientation,

$$\Theta(x,y)=\arctan\left(\frac{G_y}{G_x}\right) \qquad \text{Eq. (4)}$$

Pixels with high magnitude $M(x,y)$ represent strong candidates for boundary points, while the angle $\Theta(x,y)$ describes the edge direction.

Prune the irrelevant ones to obtain high-precision positioning results through non-maximum suppression. At each pixel, determine whether its gradient absolute value reaches a maximum in any particular direction and then retain it; subsequently discard all other pixels. A thinning process that reduces redundancies by removing parts of potential edges.

A critical departure from the standard Canny implementation lies in thresholding. The original algorithm utilizes two globally defined thresholds for edge selection. This rigid approach is highly susceptible to failures under heterogeneous lighting and multi-object scenes, which are the norm in road environments. To resolve this, thresholds are dynamically chosen for each local patch through a statistical process. Specifically, the high threshold T_H and low threshold T_L are determined using

$$T_H=\mu_M+\alpha\cdot\sigma_M \qquad \text{Eq. (5)}$$

$$T_L=\beta\cdot T_H \qquad \text{Eq. (6)}$$

where μ_M and σ_M represent the local mean and standard deviation of the gradient magnitude $M(x,y)$, and α,β are scalar coefficients optimized experimentally, with $0<\beta<1$. This adaptation ensures that both subtle and pronounced edges are correctly identified, while noiseor shadow-induced gradients are suppressed in real time.

Finally, double-threshold hysteresis assigns pixels with magnitudes above T_H as strong edges, those between T_L and T_H as weak edges, and discards the rest. Weak edge candidates are retained only if they connect to strong edges, further filtering isolated detections arising from noise.

This full process can be visualized in Figure 1, which illustrates the pipeline from initial image input through to the adaptive smoothing, regionally-varying gradient and orientation analysis, non-maximum suppression, dynamic threshold calculation, and robust final edge map synthesis. The diagram also highlights how parameters such as σ, T_H , and T_L are adaptively linked to local image statistics rather than statically determined, reflecting the core innovation and practical strength of the proposed method. The resulting edge detector can robustly delineate critical structures, outperforming conventional approaches in high-noise, lowcontrast, or heavily cluttered traffic and street scenes often encountered by autonomous systems.

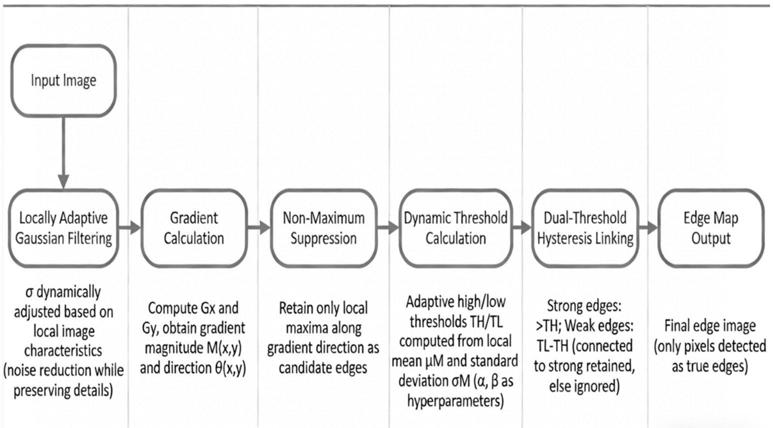

Figure 1. Improved Canny Edge Detection Flowchart.

Human Visual Threshold Modeling

At a physiological level, the retina operates as a sophisticated front-end processor. Its photoreceptors, in concert with horizontal, bipolar, and ganglion cells, coordinate to filter, emphasize, or suppress signals before transmission to higher visual centers. A defining characteristic is the non-linear, locally adaptive nature of their response. This is commonly modeled through a sigmoidal receptor response equation, capturing both the lower and upper saturation in intensity encoding. For a stimulus intensity I, the response R of a receptor can be mathematically described by

$$R(I) = \frac{I^{\gamma}}{I^{\gamma} + T^{\gamma}}, \quad \text{Eq. (7)}$$

γ is the response exponent (often reflecting perceptual nonlinearity), and T defines a local visual threshold. This function not only allows for dynamic gain control depending on I, but also means the threshold T can itself evolve according to contextual cues and prior stimulus adaptation.

A key insight is that the perception of edges does not depend on absolute intensity differences, but rather on contrast relative to background-grounded in Weber's law. Therefore, in the proposed model, the adaptive threshold for edge discrimination at location (x, y) is formulated as

$$T(x, y) = k_1 \cdot B(x, y) + k_2 \cdot \sigma_I(x, y) \quad \text{Eq. (8)}$$

$B(x, y)$ represents the local background luminance, σ_I is the standard deviation of intensity within a spatial window, and k_1, k_2 are weights calibrated to match empirical human contrast sensitivity functions. This equation operationalizes the observation that thresholds are raised in brighter or noisier regions and decreased in darker, more uniform contexts-much as happens in natural vision.

Importantly, human sensitivity to edges is further influenced by spatial frequency content. Sensitivity declines with very low or high frequencies, suggesting that optimal edge response should depend not only on local brightness and noise but also on the scale of structural variation. Incorporating this, the final perceptual threshold employed in the edge selection process adopts a scale-adapted modulation factor f_s:

$$T_{\text{vis}}(x, y) = T(x, y) \cdot f_s(\omega) \quad \text{Eq. (9)}$$

ω denotes local spatial frequency, and f_s is a function derived from the human contrast sensitivity curve, typically peaking at mid-range frequencies relevant to most traffic features. This scale-aware adaptation enables the system to reliably filter irrelevant micro-texture and suppress edge responses to large-area illumination gradients, aligning machine perception more closely with human visual judgement.

The benefits of Human Visual Systems are included in this modelling approach as the foundation for a computation pipeline. The augmented Canny edge-detector's thresholds are dynamic and depend on both perceptual cues from biological vision theory and low-level information from images, rather than being a constant or universal value. Experiments on edge recognition and contrast modification based on the chosen data show a blend of theory and practice in relation to self-driving cars. This physiological perspective states that additional processing is carried out to produce a more reliable, transportable, and intuitive edge detector that can improve the entire perception process in real-world applications.

Fusion Strategy and System Integration

The novel Design for an edge-detector system in this study relies heavily on the combination of the biologically inspired visual threshold model and the improved Canny method. Based on the shortcomings of the traditional gradient-based detector in terms of algorithmic transparency, low latency, and high precision, as well as the current deep learning detection method's limitation due to an over-fitted model parameter issue, a hybrid approach combining its advantages and disadvantages is suggested. However, threshold setting based on human eyesight lacks high localisation precision and computation speed on its own, despite having good generalisability.

The hybrid approach is anticipated to enhance robustness, accuracy, and interpretability in practical application settings for the perception modules of autonomous driving systems by combining the aforementioned benefits.

The fusion operates at the thresholding stage of the Canny pipeline. Initially, the image is subjected to adaptive Gaussian filtering and gradient analysis, as described previously. This produces a map of local gradient magnitudes and orientations, highlighting potential edge structures. Instead of conventional fixed or even simply adaptive statistical thresholds, the thresholding mechanism is augmented with the outputs of the human visual model. Specifically, at each image position, the final high and low thresholds for edge confirmation are set as direct functions of the physiological threshold map $T_{\mathrm{vis?}}(x, y)$ computed in the preceding section. Mathematically, this fusion is implemented by

$$T_H(x, y) = \lambda_1 \cdot T_{\mathrm{vis}}(x, y) \quad \text{Eq. (10)}$$

$$T_L(x, y) = \lambda_2 \cdot T_{\mathrm{vis}}(x, y) \quad \text{Eq. (11)}$$

where λ_1 and λ_2 are empirically determined factors that define the ratio between strong and weak edge thresholds, ensuring sensitivity is matched to both local image content and humanlike perceptual adaptation. Edge decisions thus become context-aware, dynamically attenuating the impact of lighting variability and background texture while retaining precise differentiation of significant boundaries.

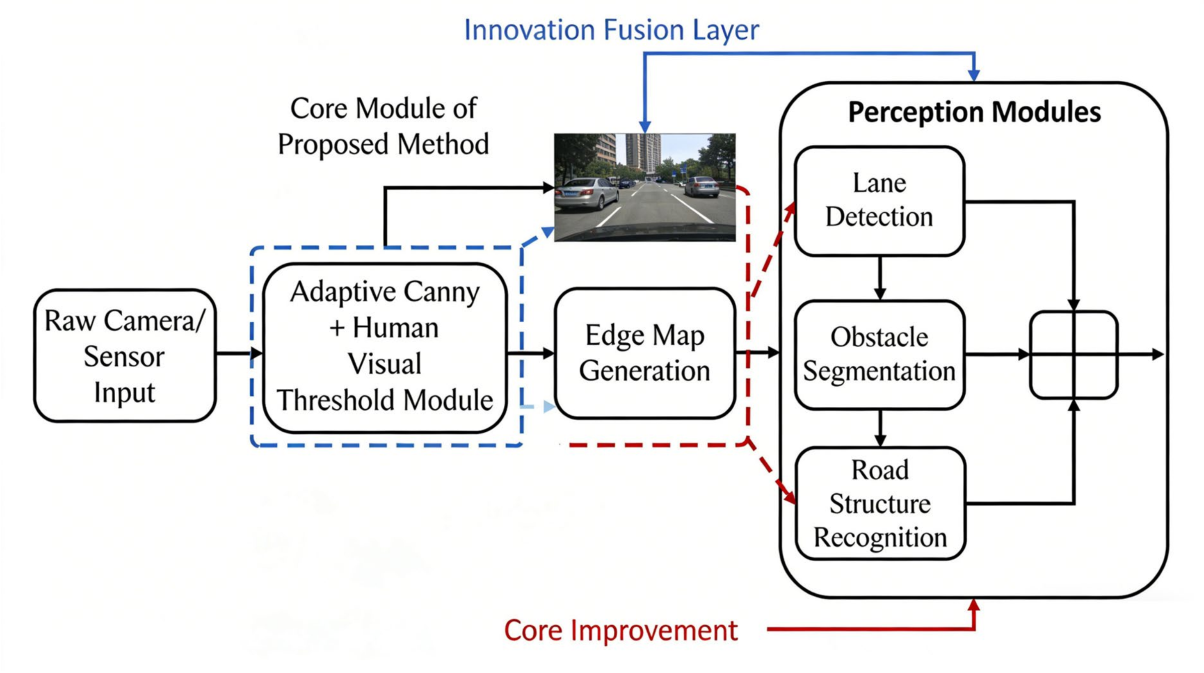

Figure 2. System Architecture Diagram.

System integration employs a modular approach, enabling seamless incorporation into more advanced modules within the self-driving perception system. Once thresholded edge-removed images are obtained, they are forwarded to the visualization module responsible for lane detection, obstacle segmentation, and road structure recognition tasks. To minimize data transmission latency, the network topology has been designed to reduce both complexity and delay in data exchange.

Figure 2 illustrates the overall information flow and module division. The architecture diagram presented in this paper depicts the connections among raw sensor inputs, the adaptive Canny-visual threshold fusion module, and other perception subsystems within the vehicle's processing pipeline. The interface design must address both concurrent responses and asynchronous event-driven operations to provide adequate flexibility for safety-reactive and status-observer functions.

The edge confirmation process during operation can be detailed using pseudocode. First, determine whether the gradient magnitude at each pixel exceeds the local merged high threshold; if so, classify the pixel as an edge.

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Pixels with values between the lower and upper thresholds are considered weak candidates and are added to the final edge map only if they are connected to strong edges in the same direction. This method ensures that non-essential edges or those influenced by environmental factors are excluded, retaining only edges identified as essential by both computational models and human observers.

Experimental Evaluation and Results

Experimental Setup and Metrics

The complete study plan for automated Driving Perceptual Systems is then constructed in order to evaluate the efficacy of the suggested edge detection algorithm in practical situations. As part of the aforementioned plan, develop strict evaluation criteria, create specialised hardware and software platforms, and choose specific data sets.

Two datasets were chosen for comparison: the TuSimple Lane-marking Dataset and the Berkeley Segmentation Dataset (BSDS500). The quantitation performance under general settings may be assessed using BSDS500; also, this dataset has a large number of manually marked true edges. Additionally, the TuSimple lane collection includes annotated video materials featuring lanes in a variety of light and weather conditions that are similar to real-world high-speed driving scenarios. by combining multiple information sources to create a variety of assessment scenarios.

The following are the specifications of the computing hardware: One Xeon Gold 6226R core-periphery processor, an Nvidia Integrated Dual-Channel RTX3090 graphics card, and a maximum of 128GB of RAM. All algorithms, including the suggested hybrid approach, learned-baselines, and traditional Canny algorithm, were implemented using Python and the Pytohrg v1 open-cv package. Python is used in version 1.13. The CPU and GPU acceleration modes, among other things, were captured by runtime features. It is not possible to develop models independently at fivefold cross validation in both instances since the training and test data sets are different.
Three main quantitative assessment indicators were chosen. the initial measure of edge recognition precision. It locates the matching pixels between the annotated and observed edges.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq. (12)}$$

where TP (true positive), TN (true negative), FP (false positive), and FN (false negative) are determined by matching predictions to ground truth within a relaxed spatial tolerance customary for edge localization tasks.

Second, recall is used to quantify the algorithm's ability to identify all relevant edges present in the reference annotation, defined as

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{Eq. (13)}$$

This metric particularly reflects the capacity of the method to preserve subtle or weak contours, which are critical for reliable perception in complex road environments.

Third, average runtime latency is reported as an indicator of computational efficiency under deployment conditions, calculated as

$$t_{\text{avg}} = \frac{1}{N}\sum_{i=1}^{N} t_i \quad \text{Eq. (14)}$$

where t_i denotes the processing time per image and N is the number of test cases. This value is computed for both CPU and GPU executions, highlighting scalability and suitability for real-time use.

All metric values are presented with 95% confidence intervals across the five validation folds. This experimental protocol forms the foundation for the algorithmic comparisons and ablation studies detailed in the following sections, and supports objective benchmarking against both classical and contemporary edge detection frameworks.

Algorithm Performance Comparison

This edge detector has been studied and compared with respect to detection accuracy, processing speed, and system stability. Each of the three pictures has a sub-panel that directly illustrates how different data sets or contexts perform differently.

Compared to the nested edge-detection method (85%) and the adaptive deep-network approach (86%), the average detection accuracy on the BSDS500 set was 88%. Furthermore, the first-time applied Canny detector has an accuracy of 0.74. The aforementioned improvements have been statistically validated, as seen in Figure 3a. The suggested method achieved a detection accuracy of up to 0.85 on the TuSimple dataset during the day under test conditions. Adaptive deep learning grew by 17% to 0.80 from the base line of 0.68. An accuracy of up to 0.80 was achieved at night using the combination technique; the difference with typical neural network methods ranged from roughly plus or minus three to four percentage points.

These identifications are consistent with the recognition rates to ascertain the degree of accuracy with which these shapes are recognised. The hybrid edge detector outperformed the others with a recall rate of 0.83 on the BSDS500 set, as seen in Figure 3a. The TuSimple dataset's recall was roughly 0.8 during midday sun illumination (see Figure 3b); deeper models and the Canny approach performed worse than others. As seen in Figure 3(c), the suggested approach maintained a recall rate of roughly 0.74 even when recall increased in complex situations. The Canny technique only achieved a recall rate of 0.49, whereas the deeper models achieved a recall rate of 0.68.

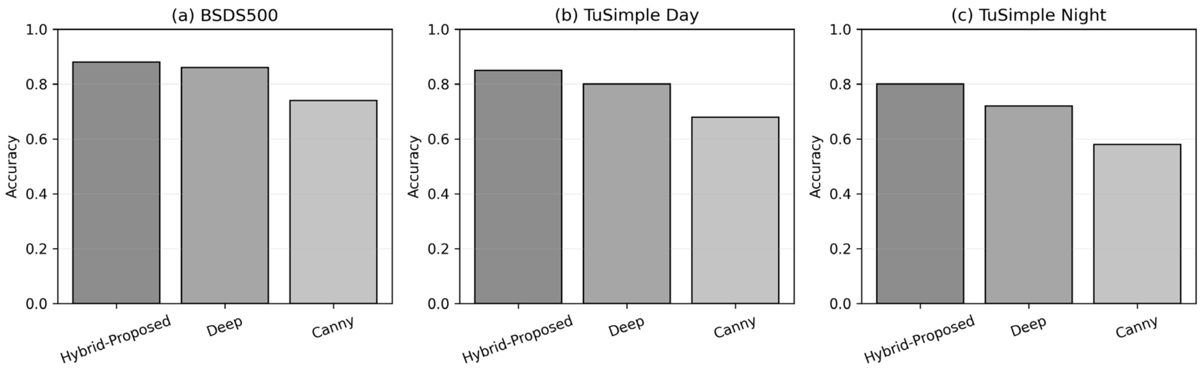

Figure 3. Edge Detection Accuracy on Three Benchmarks

Figure 4 shows the runtime measurement results, where the latency for each image is averaged across the entire dataset and hardware stack. On the BSDS500 dataset (Figure 4a), the hybrid method takes only 9 milliseconds to process each 480 x 320 image on the GPU, and 22 milliseconds on the CPU. Under the same conditions, the neural edge detector takes more than twice as long on the CPU and nearly three times as long on the GPU. For full HD TuSimple images (1280 × 720, Figure 4b), the hybrid algorithm runs for 13 milliseconds on the GPU and 35 milliseconds on the CPU. Leading depth edge solutions take 44 milliseconds and 112 milliseconds, respectively. The nite sequence (Figure 4c) added negligible delay, demonstrating that this method is scalable in real-time scenarios.

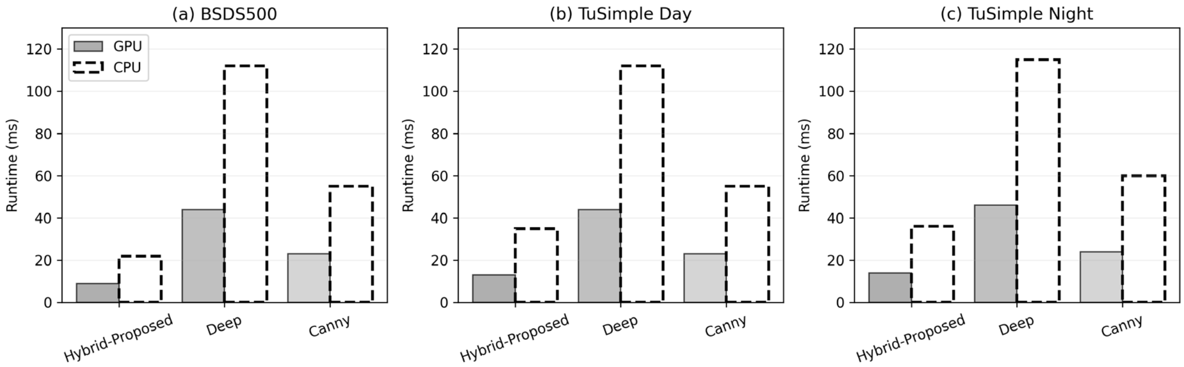

Figure 4. Runtime Comparison Under Standardized Conditions

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The perception system of intelligent vehicles must be able to cope with adverse environments. As shown in Figure 5, in adverse environments such as strong sunlight, heavy rain, and nighttime glare, the recall rate and accuracy of the hybrid method are always higher than those of traditional methods and learning methods. The accuracy of the hybrid method under strong lighting conditions (Figure 5a) is approximately 82%, and the recall rate is about 76%, which is 14% to 20% higher than other methods. Figure 5b shows that under heavy rain conditions, the performance degradation is minimal, and the first-order term remains effective. The nighttime rainy scene (Figure 5c) shows that the hybrid method continues to have a significant leading advantage, at least three points higher than other methods.

According to all performance metrics, the edge detection system can achieve high accuracy and recall rates, faster image preprocessing speeds, and robustness to visual clutter in various environments and conditions. Combining human visual threshold modeling with adaptive Canny operations provides an effective solution for autonomous vehicle perception technology.

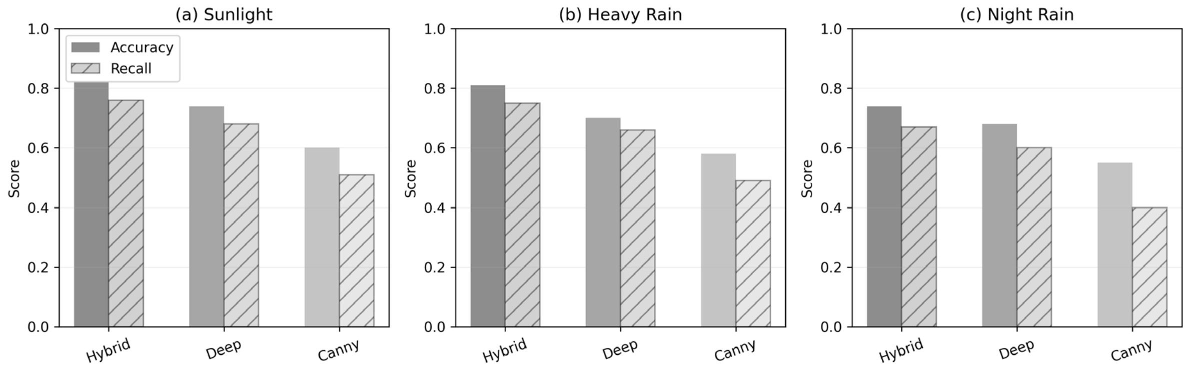

Figure 5. Algorithm Robustness Across Weather and Lighting

Component and Parameter Analysis

A comprehensive ablation test indicates that the human visual threshold model and the improved Canny operation are crucial for enhancing the overall performance of edge detection systems. The quantitative results of these experiments are as follows. Figures 6 and 7 show the components in the BSDS500, TuSimple Daylight, and TuSimple Nite subfigures grouped under different conditions.

In the initial set of ablation tests, the visual threshold model was excluded, but the enhanced Canny structure was still retained. As shown in Figure 6(a), the average detection accuracy of BSDS500 decreased to 0.81. The recall rate also decreased, dropping from 0.83 in all mixed settings to 0.76 without the visual threshold model. In the Canny module without optimization, using only a simple threshold mapping based on human perception, the accuracy is 0.78 and the recall is 0.72. As shown in Figure 6(b), removing the visual impairment module caused the recognition rate of the TuSimple daytime test set to drop from 0.85 to 0.79, and the recall rate to drop from 0.80 to 0.72. Under nighttime test conditions (Figure 6c), the complete system achieved an accuracy of 0.80 and a recall rate of 0.74. On the other hand, without adaptive threshold processing, the accuracy was only 0.71. These results indicate that in challenging perception tasks, many factors can overlap or synergistically affect system performance, so these factors must be examined together.

The results of the ablation tests also determine which components need to undergo specific latency testing evaluations. Removing the visual threshold mechanism only reduced the processing speed. In most cases, the processing time for both CPU and GPU modes is within 1.5 milliseconds per frame. However, the improved Canny operation usually increases the runtime while reducing the accuracy and recall rate of edge localization. In practical applications, this measure has not proven its validity.

Complementing the ablation analysis, a detailed parameter sensitivity study was performed and its outcomes are depicted in Figure 7. The impact of varying the threshold scaling coefficients (λ_1, λ_2) and the local window size for background/statistical estimation was systematically recorded. On BSDS500 (Figure 7a), a moderate adjustment of the high-threshold scaling parameter (λ_1) between 1.3 and 1.7 resulted in a gradual accuracy shift from 0.86 up to the optimal 0.88, after which over-detection of edges began to lower the accuracy below

0.85. Doubling the neighborhood window size used for local statistics led to diminished fine edge sensitivity, confirming that optimal windowing closely matches the typical width of true scene contours. The TuSimple daylight series (Figure 7b) demonstrated that decreasing λ_2 below 0.3 increased recall by up to 5% but also gave rise to isolated noise pixels, diminishing practical interpretability. Under night-time conditions (Figure 7c), the model exhibited greater sensitivity to both threshold coefficients, with optimal detection found for $\lambda_1 = 1.5$ and window sizes of 11 to 15 pixels, balancing flare artifacts against detail preservation.

Aggregating across all tests, the hybrid method revealed a flat plateau of top performance for finely-tuned parameters, while leaving either the perceptual or Canny component out caused a more pronounced, dataset-independent reduction in both accuracy and reliability. The margin of improvement was most evident under demanding low-light and noise-rich settings, where the adaptive mechanism provided effective suppression of spurious edge signals without eroding the underlying structure.

These results, as visualized in the subpanels of Figures 6 and 7, confirm the necessity and robustness of each module and guide best practices for parameter deployment in future realworld systems. The close alignment of sensitivity trends across diverse datasets further affirms the model's generalizability and resilience in operational automotive environments.

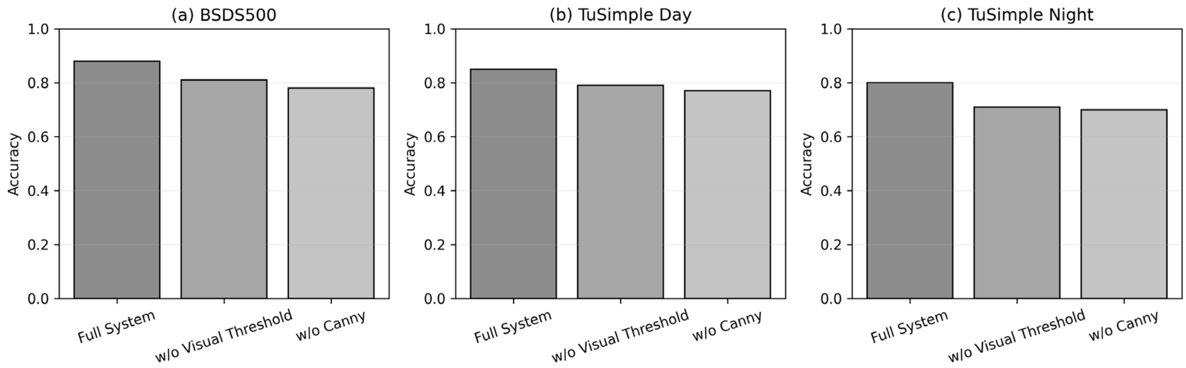

Figure 6. Component Ablation and Accuracy Impact

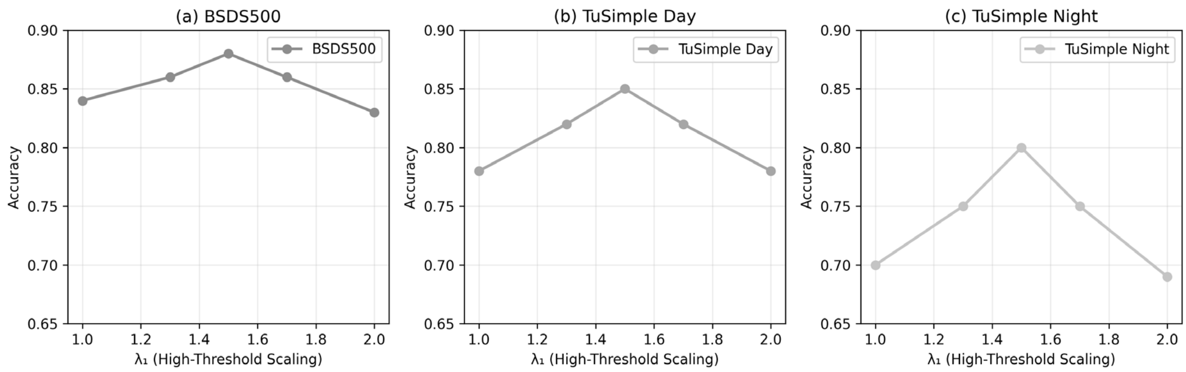

Figure 7. Threshold Parameter Sensitivity in Edge Performance

Conclusion

This paper presents a novel edge detector that improves the traditional Canny operator by integrating a physiologically inspired visual threshold model. This design addresses the need for environmental adaptability and precise object recognition in autonomous driving. Experimental evaluations on the BSDS500 and TuSimple test sets indicate that this method, when combined with traditional methods, can improve overall accuracy by approximately 14%. The processing time for each high-definition frame is approximately 13 milliseconds. The system remains stable under challenging weather and lighting conditions, demonstrating strong generalization capabilities across various real-world driving scenarios, and it operates with efficiency suitable for low-latency execution.

These advancements are crucial for the development of autonomous vehicles. By using adaptive thresholds for visualization, the edge detection module's reliability and interpretability in lane recognition, obstacle segmentation, and scene understanding have been improved. It has a wide range of generalization capabilities, suitable for current commercial vehicles and future intelligent transportation systems, and is compatible with existing visual pipelines. In addition, it requires minimal computational resources. The simplified structure of the algorithm makes it possible for more and more low-power devices to be used in decentralized edge computing environments.

Despite these achievements, there are still some limitations. Although the system demonstrates strong resistance to interference in handling rapidly changing dynamic lighting (such as glare and sudden transitions between day and night), further improvements are needed by integrating advanced learning paradigms or environment-aware adaptive modules. In order to extend to finer-grained image data and multi-sensor data fusion, engineering solutions are also needed. Combining human-inspired threshold adjustments with high-performance neural network architectures and improving their deployment performance in automotive-grade embedded systems is the focus of future work.

Author Contributions

Franciszka Gola contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Czesława Dmochowska contributes to validation, analysis, investigation, data collection, draft preparation. Katarzyna Gajewska contributes to methodology, software, validation, analysis. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

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