# An Illumination-Robust Road Edge Detection Algorithm Postprint

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## Abstract

To address the problem of road edge detection under illumination variation and strong shadow interference, an illumination-robust road edge detection algorithm is proposed. The algorithm integrates guided filtering and a shadow-resistant feature extractor. First, guided filtering is employed to enhance image edges and reduce background noise interference. Second, a shadow-resistant road feature extractor is utilized to extract coarse road edge contours. Finally, fuzzy connectivity analysis is adopted, which combines global road edge information to segment the road edge into far and near regions, refine the extracted edge points, and perform fitting using RANSAC. The experimental section validates the algorithm on the ROMA dataset, and the experimental results demonstrate that the proposed edge detection algorithm achieves a comprehensive performance metric of 83.67%, exhibiting good robustness and accuracy under various road conditions.

## Full Text

## Preamble

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**An Illumination-Robust Road Edge Detection Algorithm**

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**Abstract:** To address the challenges of road edge detection under varying illumination conditions and strong shadow interference, this paper proposes an illumination-robust road edge detection algorithm. The algorithm combines guided filtering with a shadow-resistant feature extractor. First, guided filtering is employed to enhance image edges while reducing background noise. Second, a shadow-resistant road feature extractor is used to obtain coarse road edge contours. Finally, fuzzy connectivity analysis is applied to incorporate global road edge information, dividing the road edge into far and near regions for point refinement, followed by RANSAC-based fitting. Experiments conducted on the ROMA dataset demonstrate that the proposed algorithm achieves a comprehensive performance index of 83.67%, exhibiting strong robustness and accuracy across various road conditions.

**Keywords:** road detection; guided filtering; fuzzy connectivity; driver assistance systems

## 0 Introduction

In recent years, the increasing number of vehicles has led to a rising frequency of traffic accidents. Investigations indicate that most accidents result from driver fatigue and adverse driving environments. Consequently, driver assistance systems—including lane departure warning, lane keeping assist, obstacle detection, collision warning, and autonomous navigation—have become a key research focus for enhancing driver safety.

Road detection serves as the foundation for various driver assistance systems. Its primary task is to separate the road from the background using images captured by vehicle-mounted cameras, providing essential information such as position, lane boundaries, markings, and road direction to the assistance system. Current road detection methods can be broadly categorized into two approaches: feature-based methods and model-based methods.

Feature-based methods typically extract low-dimensional road features, including gradient, color, brightness, and structural information. While robust to road shape variations, these methods are susceptible to illumination changes, shadows, and occlusions, often yielding poor detection results. Reference [4] proposes a visual feature-based region-of-interest selection method that utilizes vanishing points and line segment positions for road area detection. References [5,6] construct illumination-robust feature extractors for road edge detection. Reference [7] introduces an illumination-invariant PCA spatial transformation to mitigate illumination and shadow interference globally. Reference [8] employs illumination-invariant theory with Chebyshev polynomials to obtain illumination-independent images, separating roads from the background through confidence mapping.

Model-based methods primarily rely on prior knowledge to assume road models, including linear, hyperbolic, and parabolic models. Due to their fixed structure, these approaches require fitting only a limited set of parameters and can effectively handle shadows and occlusions. However, no single model can universally accommodate the diverse road conditions encountered in reality, limiting their flexibility. Reference [9] proposes a structured learning approach that leverages image context and label structure for road marking detection. Reference [10] fuses texture and shape features using a maximally stable extremal region detector and Adaboost training for marking detection. Reference [11] divides the road into near-field and far-field regions, employing an improved river flow method and RANSAC fitting for road marking detection, demonstrating good performance even with vehicle occlusion.

To enhance algorithm generality, this paper adopts a hybrid feature-model approach. On one hand, guided filtering strengthens image edges while suppressing noise, addressing the issue of conventional smoothing filters interfering with road line features. By analyzing road-surrounding environment characteristics, a shadow-resistant grayscale algorithm reduces shadow interference for rapid road contour extraction. On the other hand, the road is segmented into far and near viewing regions: the near-field region employs fuzzy connectivity analysis for adaptive segmentation point selection and RANSAC-based linear fitting, while the far-field region utilizes region growing to select edge points, avoiding complex model fitting.

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## 1.1 Guided Filtering

To reduce image noise, preprocessing typically involves filtering. Common low-pass filters such as simple smoothing or Gaussian smoothing are isotropic. Since noise points exhibit similar gradients in all directions while road edges show maximum variation along the normal direction and minimal variation along the tangential direction, isotropic filters weight and process edges, textures, and gradient features while removing noise, thereby corrupting original features. Consequently, numerous edge-preserving smoothing algorithms have been proposed, including bilateral filtering, adaptive smoothing, anisotropic filtering based on the PM equation, and guided filtering.

Guided filtering, introduced by He et al. in 2013, employs a guidance image $I$ to filter the original image $p$, producing a denoised edge-preserving output $q$. The filter formulation is:

$$q_i = \sum_{j \in \omega_i} W_{ij}(I) \cdot p_j$$

where $p_j$ represents pixel values in the image, $W_{ij}(I)$ denotes the weight at corresponding points determined by guidance image $I$, and $q_i$ is the filtered value.

The guided filtering schematic is shown in [Figure 1: see original paper]. A critical assumption underlying guided filtering is the linear relationship between the guidance and output images within a local two-dimensional window: the filter acts as a local linear model between $I$ and $q$. For a window centered at $k$ with linear coefficients $a_k$ and $b_k$:

$$q_i = a_k I_i + b_k, \quad \forall i \in \omega_k$$

Following unconstrained image restoration methods and assuming noise $n$, where $n_i = q_i - p_i$, the linear parameters $a_k$ and $b_k$ are obtained by solving the optimization objective function:

$$\min_{a_k, b_k} \sum_{i \in \omega_k} \left( (a_k I_i + b_k - p_i)^2 + \tau a_k^2 \right)$$

where $\tau$ is a regularization parameter. The optimal solution yields:

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i p_i - \mu_k \bar{p}_k}{\sigma_k^2 + \tau}$$

$$b_k = \bar{p}_k - a_k \mu_k$$

Here, $\mu_k$ and $\sigma_k^2$ represent the mean and variance of $I$ in window $\omega_k$, $|\omega|$ is the number of pixels in the window, and $\bar{p}_k$ is the mean of $p$ in $\omega_k$.

Since obtaining the guidance image $I$ is often difficult, when $I = p$, guided filtering degenerates to edge-preserving filtering. Two scenarios emerge: in high-variance regions where $a_k \approx 1$ and $b_k \approx 0$, edge regions remain unchanged; in smooth regions where $a_k \approx 0$ and $b_k \approx 1$, neighboring pixel averaging reduces noise interference.

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## 1.2 Fuzzy Connectivity

Fuzzy connectivity is widely applied in image segmentation. For adjacent elements in an image, fuzzy connectivity performs similarity measurement by incorporating spatial distance, gradient, and intensity information, assigning appropriate weights to features to determine optimal segmentation points.

We define the fuzzy digital space as $(Z^n, \alpha)$, where $n$ represents spatial dimension (here $n = 2$ for images) and $\alpha$ denotes the adjacency relation between neighboring elements. Let $C$ be a fuzzy relation from $Z^n \times Z^n$ to $[0, 1]$ representing similarity adjacency. For $u, c, d \in Z^n$, the connectivity measure is:

$$\mu_C(u, c, d) = g(\phi(u, c, d), \varphi(u, c, d), \psi(u, c, d), c, d)$$

where $g$ is a metric function mapping to $[0, 1]$, $\varphi$ measures spatial adjacency, $\phi$ measures intensity adjacency of neighboring elements, and $\psi$ measures gradient adjacency.

For a candidate point sequence $P_{cd} = (c = c_1, c_2, ..., c_m = d)$ forming a path of length $m$, each segment's connectivity is enhanced by minimizing the connection function:

$$\rho(c, d) = \min_{1 \leq i < m} \mu_C(c_i, c_{i+1})$$

The strongest connectivity function for the entire road edge is:

$$\xi(c, d) = \max_{P_{cd}} \rho(c, d)$$

We employ gradient and edge intensity as crucial features for road edge detection, using weighted combination for point selection and refinement.

**Intensity similarity measure:** A Gaussian function $g_1$ measures intensity similarity between candidate points based on road edge intensity information:

$$g_1(u, c, d) = \exp\left(-\frac{(S(f(c)) - S(f(d)))^2}{2\sigma_1^2}\right)$$

where $S(f(c))$ and $S(f(d))$ represent intensity information at adjacent road edge points, with mean and variance applied to candidate points.

**Gradient similarity measure:** A Gaussian function $g_2$ measures gradient similarity:

$$g_2(u, c, d) = \exp\left(-\frac{(S(\nabla f(c)) - S(\nabla f(d)))^2}{2\sigma_2^2}\right)$$

where $S(\nabla f(c))$ and $S(\nabla f(d))$ denote gradient information at adjacent road edge points.

The combined similarity measure is:

$$\mu_C(u, c, d) = w_1 \cdot g_1(u, c, d) + w_2 \cdot g_2(u, c, d)$$

where $w_1$ and $w_2$ are intensity and gradient weights respectively, with $w_1 + w_2 = 1$. Assuming equal importance, we set $w_1 = w_2 = 0.5$.

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## 2 Road Edge Detection Algorithm Based on Fuzzy Connectivity Analysis

The general road edge detection framework comprises image preprocessing, robust feature extraction, road edge detection, and model fitting. The proposed algorithm flow is illustrated in [Figure 2: see original paper].

### 2.1.1 Guided Filtering

During image filtering, guided filtering requires a guidance image $I$, which is often unavailable as edge gradient information is unknown. Therefore, we apply the filtering using the formulations from Section 1.1 to preserve edge features while removing non-edge clutter. The filtering effect is shown in [Figure 3: see original paper].

### 2.1.2 Region of Interest Selection

Images captured by forward-facing vehicle cameras are analyzed for road regions. With an image size of $r \times c$, road information lies below the horizon line, while the upper portion contains sky. We empirically select the lower 2/3 of the image as the ROI. Subsequently, the detected vanishing point adaptively crops the ROI, enabling efficient road information extraction while reducing redundant data and computational burden.

### 2.1.3 Robust Feature Extraction

Feature extraction is central to feature-based detection methods. Since most road features rely on brightness, shadow effects cannot be ignored. Moreover, the highly correlated R, G, B channels in original images create redundancy and consume system resources. To overcome this, various color space transformations have been investigated to reduce or eliminate shadow impact on brightness features.

Feature extractors can be categorized as illumination-robust or shadow-free. Illumination-robust extractors mitigate shadow interference by isolating brightness channels, such as the H channel in HSI space or Y channel in YUV space. However, single-channel information lacks robustness in complex conditions. Therefore, multi-channel fusion is employed, such as using the S component in HSV space as described in [14], which shows minimal shadow impact in strong shadow scenarios:

$$S' = \frac{\max(R, G, B) - \min(R, G, B)}{\max(R, G, B)}$$

Shadow-free extractors aim to completely remove shadows for road feature selection. Common methods include LCS space transformation and its extensions. Since different colors form parallel lines in LCS space, roads can be fully separated from surrounding vegetation. The transformation is:

$$L = \sin\theta \cdot \log(R/G) + \cos\theta \cdot \log(B/G)$$

where $\theta$ is a camera-dependent parameter.

While shadow-free extractors outperform illumination-robust ones in detection quality, they exhibit significantly higher computational complexity and require known camera parameters, making them environment-dependent.

**Image grayscale conversion:** We adopt the method in Equation (13), which provides better visualization under strong shadows compared to other methods, as shown in [Figure 4: see original paper]:

$$\text{Gray} = \max(R, G, B) - \frac{\min(R, G, B)}{2}$$

### 2.2 Fuzzy Connectivity Analysis

Fuzzy connectivity analysis involves two steps: (a) providing initial search directions through image segmentation, edge point detection, and Hough transform; (b) refining straight edge points and selecting curve edge points based on these directions.

#### 2.2.1 Image Segmentation

Preprocessing yields illumination-robust grayscale images with significantly reduced shadow effects. Fixed thresholding can thus extract road edges. We employ Otsu' s method [15] for binarization, minimizing intra-class variance and maximizing inter-class variance to separate road from background.

As shown in [Figure 5: see original paper], segmentation results still contain interference from road markings, soil, and vehicles. Leveraging the heuristic that the area directly ahead is drivable surface, we construct an isosceles trapezoid centered at the image' s 4/5 height position with width $w$ (single lane width), setting this region' s binary values to 0 to eliminate marking and interference. This substantially reduces road area disturbances.

#### 2.2.2 Edge Candidate Point Extraction

Segmentation separates road from non-road regions, with the middle area primarily road and sides typically vegetation. Extracting boundaries from this binary map provides clear edge annotations for initial direction determination.

Inspired by the "middle-to-sides" search strategy, we employ a "two-step" approach: (1) bottom-to-top scanning extracts candidate edge row coordinates; (2) for the left half, middle-to-left scanning identifies the first pixel value of 1 as a left edge candidate; (3) the same process extracts right edge points. Results are shown in [Figure 6: see original paper].

#### 2.2.3 Search Direction Determination

Based on coarse edge points, linear fitting determines the search direction. In the near-field region, road edges can be approximated as straight lines, and linear models require fewer parameters than curves, significantly reducing computation. Since threshold-derived edge points contain large errors unsuitable for curve fitting, we first use linear models to establish initial directions for fuzzy connectivity analysis.

Hough transform converts Cartesian to polar coordinates, selecting lines through curve intersection detection. Leveraging prior knowledge that road edges from forward-facing cameras fall within $[-45°, -75°]$ and $[45°, 75°]$, we constrain the angle range to accelerate detection, as shown in [Figure 7: see original paper].

### 2.2.4 Fuzzy Connectivity Analysis for Road Edges

Building on Hough transform' s initial directions, we analyze road edge points separately for straight and curve sections from bottom to top.

**Straight Section:** Using the linear model, we sample candidate points at equal intervals along the Hough-fitted line. Fuzzy connectivity analysis is performed within a neighborhood of size $2w$ (where $w$ is normal road marking spacing). The optimal segmentation objective function is:

$$\arg \max_{x\in[x_l,x_r],y\in[y_i-w,y_i+w]} f(y) = \sum_{j\in\mathcal{N}(x)} \mu_C(u_j, u_k)$$

This optimizes candidate edge point selection within a limited neighborhood for rapid refinement.

**Curve Section:** Curve analysis employs region growing to avoid complex geometric model assumptions and parameter estimation. The starting point connects to the straight section' s endpoint to prevent discontinuities, while the termination point is set where road edges converge.

As shown in [Figure 9: see original paper], region growing performs bottom-up fuzzy connectivity analysis between adjacent pixels. After each update, the corrected point becomes the new center, and the next candidate is selected along the gradient direction. Due to perspective effects causing convergence at distance, growth stops when left and right edge points fall below a threshold distance.

### 2.3 Model Fitting

Following fuzzy connectivity analysis, edge points are processed in segments. To avoid insufficient expressive power from single models, we fit straight and curve sections separately.

For straight sections, RANSAC fitting on refined edge points effectively eliminates outliers, ensuring optimal linear fitting as shown in [FIGURE:10(a)]. For curve sections, candidate points are analyzed from the straight segment endpoint toward the vanishing point. Linear constraints are applied: candidates within the maximum linear extension range are accepted, while outliers are discarded until reaching the vanishing point, as shown in [FIGURE:10(b)].

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## 3 Experimental Results Analysis

Performance evaluation was conducted on the ROMA dataset [16] and KITTI dataset [17], which contain structured and unstructured roads with challenging scenarios including shadows from buildings, vehicles, and trees. Experiments were simulated and tested in MATLAB 2014a with images normalized to $480 \times 640$.

[Figure 11: see original paper] demonstrates that the fuzzy connectivity-based method effectively extracts both straight and curve road edges. Subfigures (a) and (b) show successful edge extraction and lane marking detection under strong shadows, verifying robust shadow resistance. Subfigures (c)-(f) confirm consistent performance across various roads, times, and lighting conditions.

Error cases occur due to marking types, vehicle occlusion, and shadows. In [Figure 12: see original paper], (a) shows false detection from sparse markings and vehicle interference; (b) demonstrates confusion between strong shadows and lane markings where shadow edges dominate; (c) and (d) exhibit extraction difficulties from excessive markings.

For quantitative analysis, we manually annotated 116 road images from ROMA, evaluating performance via precision ($P$), recall ($R$), and F-measure ($F$):

$$P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN}, \quad F = \frac{(1+\beta^2)PR}{\beta^2 P + R}$$

where $TP$, $FP$, and $FN$ represent true positive, false positive, and false negative areas respectively. $\beta$ balances precision and recall (here $\beta = 1$).

compares our algorithm with [2], showing our F-measure improves by 3.86%, demonstrating superior comprehensive performance. [Figure 14: see original paper] presents qualitative comparisons: [2]' s linear model assumption detects straight edges well but suffers interference, while our method shows better overall performance. [Figure 15: see original paper] shows sample results on KITTI.

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## 4 Conclusion

This paper' s contributions are twofold: (1) Guided filtering enhances edge features while suppressing noise in smooth regions; (2) Fuzzy connectivity analysis enables piecewise road model fitting. By segmenting the scene into far/near fields and employing neighborhood analysis, we reduce parameter estimation complexity and computational requirements. Dataset testing confirms the proposed algorithm' s robustness against illumination and strong shadows, delivering effective road edge detection across diverse conditions.

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*Note: Figure translations are in progress. See original paper for figures.*