# Postprint of Field Road Guidance Technology Based on Graph Inference Model and Intelligent Optimization

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## Abstract

To achieve automatic, universal, and accurate recognition and guidance of unstructured roads for unmanned equipment in off-road environments, this paper proposes an off-road scene road guidance algorithm based on graph inference model and intelligent optimization. Firstly, images are segmented into homogeneous superpixel blocks, and multi-features of these blocks are fused to construct the training set. The traditional Laplacian Support Vector Machine algorithm is improved by dynamically selecting superpixel seed blocks within the road region based on positional information, training both multi-class

## Full Text

## Preamble

### Field Scene Road Guidance Technology Based on Graph Reasoning Model and Intelligent Optimization

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**Abstract:** To achieve automatic, universal, and accurate identification and guidance of unstructured roads for unmanned equipment in field environments, this paper proposes a road guidance algorithm for field scenes based on graph reasoning models and intelligent optimization. First, the image is segmented into homogeneous superpixel blocks, and multi-features of these blocks are fused to construct a training set. The traditional Laplacian Support Vector Machine algorithm is improved by dynamically selecting road region superpixel seed blocks based on position information, which trains both a multi-class classification regressor for superpixel blocks and a consistency regressor for adjacent superpixels. Combining the regression values from both regressors, the energy function of a Markov Random Field is constructed, and standard graph cuts are used to iteratively minimize this energy function for initial road inference segmentation. Based on the initial road segmentation results, constraint conditions are established according to human intuitive perception of roads to construct an objective function, and the Differential Immune Clone Evolution algorithm is employed for intelligent optimization to extract the road guidance line. Testing was conducted on data collected from Zhushan, Nanjing, and the DARPA Grand Challenge database, with qualitative and quantitative comparisons made against classical algorithms. Results demonstrate that the proposed algorithm achieves over 91.79% accuracy in guidance line extraction for unstructured roads in field environments, representing improvements of 48.1% and 35.5% in detection precision compared to classical algorithms, while processing efficiency is enhanced by 98.6% and 97.8%, respectively. The algorithm achieves a balance between real-time performance and detection accuracy, showing strong application prospects.

**Keywords:** Markov Random Field; Laplacian Support Vector Machine; Differential Immune Clone Evolution; Unstructured Road; Superpixel

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## 0 Introduction

Most current vehicle machine vision systems have achieved satisfactory guidance line extraction for structured roads such as highways with clear lane markings. However, in special application domains like military operations and disaster relief, unmanned vehicles must operate on unstructured roads without lane lines or signboards. Therefore, research on guidance line extraction for unstructured roads in complex field environments holds significant practical importance and broad application prospects.

Existing road detection algorithms can be categorized into three main types: feature-based [?, ?, ?], model-based [?], and machine learning-based [?, ?]. Reference [?] proposes a guidance line extraction technique that estimates road edges using double lines, with the fundamental idea that double lines reflect the general road direction while maximizing coverage of the road region. This approach aligns well with human visual perception of roads and provides strong operability with minimal deviation. However, most algorithms rely heavily on texture features and struggle with weak or unclear road textures.

To address these limitations, this paper proposes a field scene road guidance technology based on improved MRF inference segmentation and evolutionary algorithm optimization. First, fused features based on color, texture, and structure are constructed on the foundation of superpixel segmentation, avoiding classification bias caused by limited features while incorporating prior knowledge such as position and shape to enhance the discriminative capability and stability of superpixel blocks. Next, unsupervised MRF inference technology is employed for initial road segmentation in complex field environments, considering both multi-feature fusion information of superpixel blocks and the prior knowledge of neighboring label consistency. This approach helps reduce interference from isolated leaves, shadows, and water stains on classification results, making it more suitable for engineering applications.

Third, in the selection of road cluster centers (superpixel seed blocks), prior knowledge is integrated that within the cross-coverage range of the vehicle' s minimum left and right turning radii, the area must be road. This dynamic selection not only improves the algorithm' s universality for field conditions where "the vehicle moves and the road changes," but also effectively avoids training bias and efficiency reduction caused by random selection of road superpixel seed blocks. Fourth, statistical learning theory and optimization methods are combined with machine learning to improve the accuracy and operational efficiency of the recognition algorithm. To address the issue that Laplacian Support Vector Machine (LapSVM) semi-supervised classification methods cannot effectively handle large-scale image classification problems, a supervised SVM classification method is proposed that dynamically pre-selects road superpixel seed block samples by fusing road models with prior knowledge, effectively improving classifier accuracy while reducing algorithmic time and space complexity. Finally, statistical learning theory and optimization methods are employed to solve machine learning problems, enhancing both precision and operational efficiency.

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## 1 Superpixel Label MRF Inference for Scene Segmentation

Unsupervised superpixel MRF inference labeling technology is adopted for initial road segmentation in complex field environments. This approach considers both multi-feature fusion information of superpixel blocks and the prior knowledge of neighboring label consistency. For instance, if certain suspicious superpixel blocks are surrounded by road superpixel blocks, they are more likely to be classified as road; conversely, they are more likely to be classified as non-road. This method helps reduce the impact of interference factors such as isolated leaves, shadows, and water stains on classification results, making it more consistent with practical engineering conditions.

### 1.1 Multi-Feature Fusion of Superpixel Blocks

Superpixels transform images from the pixel level to the region level, and classifying homogeneous regions can improve image segmentation efficiency. The SLIC (Simple Linear Iterative Clustering) algorithm is used for superpixel block segmentation. Compared with traditional superpixel segmentation methods, SLIC offers faster processing speed, smaller memory footprint, and better edge adherence. It can divide images into uniform small blocks where neighborhood features are easily expressed while preserving important information such as object edges and contours [Figure 1: see original paper].

To obtain highly discriminative visual features, multiple features are fused to describe superpixel blocks. Considering the characteristics of unstructured road scene images in field environments, four types of features are extracted to form a visual feature set:

a) **Color Features.** Field road scene images contain rich color information. The sky typically appears sky blue, gray-white, or white, while roads are brown or reddish-brown. Vertical objects exhibit greater color variation, with green being most common. The Lab color model consists of lightness L and color components a and b, aiming for perceptual uniformity. Its L component closely matches human brightness perception, offering strong robustness to shadows and illumination changes. Therefore, color statistical features are extracted in both HSV (Hue, Saturation, Value) and Lab color spaces. Specifically, the mean, variance, and skewness of the two color channels a and b in Lab space are extracted, along with hue and saturation histograms in HSV space [**?**].

b) **Texture Features.** Texture information in unstructured road scenes exhibits characteristics of multiplicity, complexity, and disorder. Traditional statistical, geometric, and model-based methods cannot achieve good discrimination. Local Binary Patterns (LBP) offer excellent representation of local texture features with low computational complexity, grayscale invariance, and easy engineering implementation without requiring trained dictionaries. The MRELBP (Median Robust Extended Local Binary Pattern) method can capture both micro-structures and macro-texture information with low computational complexity and feature dimensionality, while demonstrating high robustness against Gaussian random noise, salt-and-pepper noise, random pixel corruption, and image blur [**?**]. The MRELBP method is employed to extract texture features from superpixel blocks, with the resulting LBP feature spectrum statistical histograms used as feature vectors for classification.

c) **Structure Information.** Structural information offers good stability and is less susceptible to environmental interference, effectively improving the robustness and anti-interference capability of superpixel block classification. Dense SIFT (Scale-Invariant Feature Transform) and HOG (Histogram of Oriented Gradients) features are extracted. Specifically, SIFT and HOG feature vectors are first computed for each pixel within a superpixel, followed by calculating the geometric mean of all SIFT and HOG vectors within the superpixel block as its feature vector [**?**].

d) **Position and Shape Features.** In field unstructured road scenes, the coordinates and shapes of superpixel blocks provide strong geometric layout cues for classification. Shape features are extracted using Hu invariant moments [?], specifically the normalized superpixel invariant moments and eccentricity values. Based on certain models and prior knowledge for unstructured road recognition, when the vision system is fixed and aligned with the vehicle axis during driving, the constant field-of-view area within the lane width is always a reliable road region [?]. Therefore, superpixel block position information also has good discriminative power, with normalized superpixel block center pixel positions used to extract position features [?].

The complete feature vector of a superpixel is denoted as $\langle MATH_1 \rangle$, and the label set is represented as $\langle MATH_2 \rangle$, corresponding to three categories: road, vertical obstacle, and sky. The training set for the multi-class regressor $\langle MATH_3 \rangle$ is composed of $\langle MATH_4 \rangle$ and $\langle MATH_5 \rangle$, as shown in Equation (2).

### 1.2 Dynamic Selection of Road Superpixel Seed Blocks

For unstructured road recognition, when the vision system is fixed and aligned with the vehicle axis during driving, the constant field-of-view area within the lane width is always a reliable road region. The selection of road cluster centers (superpixel seed blocks) integrates prior knowledge that within the cross-coverage range of the vehicle' s minimum left and right turning radii, the area must be road. This approach enhances adaptability to field conditions where "the vehicle moves and the road changes" while avoiding training bias and efficiency reduction from random seed selection. A schematic diagram of the image road region is shown in [Figure 2: see original paper].

In road images, the optimal region for selecting road superpixel seed blocks is an isosceles triangle with base length slightly larger than the vehicle width $\langle MATH_6 \rangle$ and height $\langle MATH_7 \rangle$. Based on geometric principles, the height $\langle MATH_8 \rangle$ can be calculated using Equation (1), where $\langle MATH_9 \rangle$ represents the vehicle width in image coordinates and $\langle MATH_10 \rangle$ represents the vehicle' s minimum turning radius in image coordinates.

### 1.3 LapSVM Superpixel Block Regressor Training

Superpixel neighborhood information can assist in attribute discrimination, so a regressor is trained to estimate the consistency of adjacent superpixel categories. The consistency regressor is trained using differences between superpixel pairs. The consistency label for a superpixel pair is denoted as $\langle MATH_11 \rangle$, where -1 and 1 represent different and identical classification results for adjacent superpixels, respectively. The training set for the consistency regressor $\langle MATH_12 \rangle$ is shown in Equation (3), where $\langle MATH_13 \rangle$ represents the feature difference between two adjacent superpixels.

Laplacian Support Vector Machine (LapSVM) is a semi-supervised classification algorithm based on manifold regularization that studies how to simultaneously utilize a small number of labeled samples and a large number of unlabeled samples for training and classification [?]. By introducing a sample manifold regularization term, LapSVM incorporates the intrinsic geometric structure information of the sample distribution into the learning model. The parameter $\langle MATH_14\rangle$ controls the weight of the function in the Reproducing Kernel Hilbert Space (RKHS), while $\langle MATH_15\rangle$ is the intrinsic regularizer that preserves the manifold structure of the sample distribution. The parameter $\langle MATH_16\rangle$ controls the complexity of the intrinsic geometric structure function in the low-dimensional manifold.

The LapSVM model is defined as $\langle MATH_17\rangle$, where $\langle MATH_18\rangle$ is the ambient norm defined in RKHS, and $\langle MATH_19\rangle$ is the RKHS associated with the kernel function. By calculating Lagrange multipliers, the classifier is obtained as $\langle MATH_20\rangle$, where $\langle MATH_21\rangle$ are Lagrange multipliers and $\langle MATH_22\rangle$ is the kernel matrix. The Lagrange multipliers are solved using $\langle MATH_23\rangle$, where $\langle MATH_24\rangle$ is the identity matrix and $\langle MATH_25\rangle$ is the Laplacian matrix.

The LapSVM algorithm involves numerous matrix operations and transformations. When unlabeled samples are abundant, large memory space and long CPU time are required, potentially causing memory overflow. The training process can be accelerated through primal optimization by redefining the LapSVM model as $\langle MATH_26\rangle$, where $\langle MATH_27\rangle$ is the threshold defined in SVM, $\langle MATH_28\rangle$ are labeled samples, $\langle MATH_29\rangle$ is the weight parameter, $\langle MATH_30\rangle$ is the kernel matrix, and $\langle MATH_31\rangle$ are Lagrange multipliers.

Fewer labeled samples in LapSVM classification may lead to larger classification errors. This paper dynamically selects road region labeled samples by choosing superpixel block samples within or near the determined road region that may belong to the road area, while discarding unlabeled samples far from the determined road region or at the image corners. This ensures that the unlabeled samples participating in training provide richer heuristic information.

The algorithm flow is as follows: a) Input the labeled sample set $\langle MATH_32\rangle$ and unlabeled sample set $\langle MATH_33\rangle$; b) Pre-select $m$ unlabeled samples with richer heuristic information from $u$ unlabeled samples; c) Compute the kernel matrix using the Gaussian kernel function; d) Calculate the graph Laplacian matrix $\langle MATH_34\rangle$, where $D$ is a diagonal matrix and $W$ is the edge weight matrix; e) Select appropriate weights $\langle MATH_35\rangle$ and $\langle MATH_36\rangle$; f) Solve the optimization problem to obtain the classification function $\langle MATH_37\rangle$; g) Output the classification function.

Through training on feature vectors of labeled and unlabeled superpixel blocks, the LapSVM classifier can be obtained for detecting and recognizing road regions in complex unstructured road images. The multi-class regressor $\langle MATH_38\rangle$ is obtained through training. During testing, for an input feature, the output of the multi-class regressor $\langle MATH_39\rangle$ is 1, 2, or 3, corresponding to road, vertical obstacle, and sky categories, respectively. The regression values from the consistency regressor $\langle MATH_40\rangle$ serve as the membership degree of two superpixel blocks belonging to the same category, with outputs being continuous values between -1 and 1.

### 1.4 Superpixel Label MRF Inference Segmentation

The Markov Random Field (MRF) model offers the advantage of providing a simple method to model prior knowledge. Compared with other pixel-based or local methods, it can consider the influence of environmental knowledge, potentially obtaining a globally optimal solution more consistent with human vision when the graph model is properly constructed [**?**]. After superpixel classification, MRF inference is used to determine superpixel labels.

For an input image, assuming $\langle MATH_41\rangle$ is the set of superpixels, the corresponding pairwise MRF energy function is shown in Equation (11), where $i$ and $j$ are superpixel indices, $\langle MATH_42\rangle$ and $\langle MATH_43\rangle$ are candidate labels for superpixels $i$ and $j$, $\langle MATH_44\rangle$ is the weight for pairwise energy terms, and $\langle MATH_45\rangle$ and $\langle MATH_46\rangle$ represent data term and smoothness term potential functions, respectively, calculated from superpixel regression results.

The data term $\langle MATH_47\rangle$ represents the cost of assigning label $\langle MATH_48\rangle$ to superpixel block $\langle MATH_49\rangle$, defined as the absolute difference between the category regression value and label value, as shown in Equation (12).

The pairwise potential $\langle MATH_50\rangle$ penalizes adjacent superpixels $\langle MATH_51\rangle$ and $\langle MATH_52\rangle$ for taking different labels. The Potts model is used to represent the pairwise cost function, as shown in Equations (13) and (14), where $\beta$ is the weight between adjacent superpixels calculated from the category consistency regressor output, as shown in Equation (15).

Graph cuts are powerful tools for optimizing discrete equations. This paper minimizes MRF energy functions through graph cuts to complete image scene segmentation [**?**, **?**].

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## 2 Intelligent Optimization for Road Guidance Line Extraction

Road segmentation yields complex and irregular road regions. Guiding the vehicle' s next movement direction becomes another critical challenge for autonomous driving. Guidance line estimation based on texture vanishing points produces large errors for irregular road boundaries, while road model-based estimation faces difficulties in selecting fitting points in complex field environments, resulting in large fitting deviations. Double line road boundaries can reflect the general road direction while maximizing road region coverage, offering strong operability with minimal deviation.

### 2.1 Unstructured Road Double Line Boundary and Guidance Line Model

Most field unstructured roads are not straight but typically have small curvature. Assuming both left and right boundaries of unstructured roads are straight lines allows constraining road boundaries in images using linear road boundaries, as shown in [Figure 3: see original paper]. This significantly reduces computational complexity and improves program efficiency.

Based on prior knowledge, the vehicle' s current position is assumed to be point $F$. The left road edge is represented by linear function $\langle MATH_53\rangle$ as shown in Equation (16), and the right edge by line $\langle MATH_54\rangle$ as shown in Equation (17). With image dimensions $m \times n$, the intersection points with axes can be solved from the equation system (18): intersection $C$ with the x-axis and intersection $B$ with the y-axis for line $\langle MATH_55\rangle$; intersection $D$ with the x-axis and intersection $A$ with the y-axis for line $\langle MATH_56\rangle$; and intersection $E$ of $\langle MATH_57\rangle$ and $\langle MATH_58\rangle$ serves as the vanishing point for unstructured roads.

The road guidance line $\langle MATH_59\rangle$ can be obtained through points $E$ and $F$, with its equation derived using the point-slope formula as shown in Equation (22). The angle adjustment required for the vehicle to continue forward is $\langle MATH_60\rangle$, as shown in Equation (23).

### 2.2 Constrained Road Boundary Double Line Estimation Objective Function Construction

Based on the unstructured road double line model and prior knowledge, constrained boundary conditions for the optimization objective function can be obtained: (a) To improve efficiency and convergence speed, the road vanishing point (intersection of two boundaries) is assumed to be within the image: $\langle MATH_61\rangle$; (b) The slope intervals are $\langle MATH_62\rangle$ and $\langle MATH_63\rangle$, with slope intervals $\langle MATH_64\rangle$.

Reasonable road boundary double lines should comprehensively contain the road region, meaning the proportion of road portion within the boundary relative to the total road region should be maximized. Simultaneously, within the optimal road boundary region, the road should occupy the maximum possible proportion. Two objective sub-functions are constructed: the proportion of road portion within the boundary region $\langle MATH_65\rangle$, and the proportion of road within the boundary relative to the overall road $\langle MATH_66\rangle$.

Based on the constructed double line model, the area of the region contained by the double line model road boundary is $\langle MATH_67\rangle$. Since road regions are generally irregular shapes, the edge pixel positions obtained from initial segmentation can be transformed into the double line model coordinate system as coordinates $\langle MATH_68\rangle$, and Newton integration can be used to calculate the area $\sigma$ of the irregular road region within the boundary.

The overall road region area from initial segmentation is $\langle MATH_69\rangle$, so $\langle MATH_70\rangle$.

The objective function $F$ for the DICCA algorithm is constructed through linear weighting of $\langle MATH_71\rangle$ and $\langle MATH_72\rangle$, as shown in Equation (28), where

$\langle MATH_7 3\rangle$ and $\langle MATH_7 4\rangle$ represent the weight coefficients for constraint subfunctions $\langle MATH_7 5\rangle$ and $\langle MATH_7 6\rangle$ in the overall optimization objective function. The minimum value of the optimized objective function $F$ corresponds to the optimal road boundary detection result.

### 2.3 Swarm Intelligence Boundary Optimization Estimation

The Differential Immune Clone Clustering Algorithm (DICCA) is primarily based on differential evolution and immune cloning. It evolves the population through cloning reproduction, differential mutation, crossover, and clone selection operations, incorporating local search mechanisms during evolution to improve convergence. DICCA offers good universality, is not prone to falling into local optima, and demonstrates strong global convergence and robustness, making it highly suitable for solving various numerical optimization problems.

By properly constructing constraint conditions and objective functions, the optimal parameters $\langle MATH_7 7\rangle$, $\langle MATH_7 8\rangle$, $\langle MATH_7 9\rangle$, and $\langle MATH_8 0\rangle$ for road boundaries can be obtained through DICCA iterative optimization. The DICCA algorithm first initializes parameters: population size of 30, crossover probability of 0.85, mutation probability of 0.05, and maximum iteration count of 100. The algorithmic operators include differential mutation, differential crossover, clone proliferation, uniform mutation, and clone selection [**?**].

Through clone selection operations, the next generation population is obtained. The algorithm terminates when the maximum iteration count is reached or when the fitness values of four consecutive generations are all below the minimum iteration precision. The entire DICCA algorithm flow is shown in [Figure 4: see original paper], and the overall algorithm flow is presented in [Figure 5: see original paper].

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## 3 Experimental Results and Analysis

### 3.1 Experimental Design and Database

Experiments were conducted on a PC with a quad-core Intel i7 processor and 8.0 GB RAM, using MATLAB R2014a as the development platform under Windows 7. The unstructured road image data used in experiments were sourced from the DGC (DARPA Grand Challenge) scene segmentation database, a non-structured road database collected in Zhushan, Nanjing, and typical complex unstructured road images screened from the Internet. All experimental images were normalized to 640×480 pixels.

### 3.2 Experimental Evaluation Metrics

To quantitatively compare the road edge detection quality of various algorithms, the precision metric $\tau$ from reference [**?**] is adopted to evaluate road region segmentation accuracy, where smaller $\tau$ indicates lower detection precision and vice versa:

$$\tau = \frac{|B_o \cap B_t|}{|B_o \cup B_t|}$$

where $B_o$ is the manually labeled road region pixel set, $B_t$ is the algorithm-detected road region pixel set, $B_o \cap B_t$ represents their intersection (common portion), and $B_o \cup B_t$ represents their union [?].

To quantitatively evaluate guidance line extraction accuracy, the guidance precision $\tau_3$ is defined as shown in Equation (33), where $k_3$ is the manually annotated guidance line slope and $k_3'$ is the algorithm-extracted guidance line slope. Larger $\tau_3$ values indicate higher guidance line extraction accuracy. To make the results more consistent with human cognition, $\tau_3$ is transformed via numerical conversion as shown in Equation (34).

### 3.3 Experimental Results

The rationality of weight coefficients directly affects the accuracy of multi-attribute evaluation results. To properly select optimal weights $\lambda_1$ and $\lambda_2$ for improved road edge detection accuracy, numerical constraints are applied. Twenty images were randomly selected from the database, with road regions and road boundary lines manually labeled to obtain $\mu_1$ and $\mu_2$. By iterating $\lambda_1$ over interval (0,1) with step 0.001 and setting $\lambda_2 = 1 - \lambda_1$, the values of $\lambda_1$ and $\lambda_2$ that minimize objective function $F$ were recorded to construct weight samples. Through averaging, universally applicable optimal weights were obtained: $\lambda_1 = 0.645$, $\lambda_2 = 0.355$ [Figure 6: see original paper].

Qualitative and quantitative comparisons were made between the proposed algorithm and algorithms from references [?], [?], and [?], with detection results shown in [Figure 7: see original paper] and Tables 1-3. The first column in [Figure 7: see original paper] shows original images with manually annotated vanishing points, while subsequent columns show detection results from references [?], [?], [?], and the proposed algorithm, respectively.

Since references [?] and [?] are both based on pixel texture vanishing point detection, they perform poorly when road texture is weak or unclear (images 4, 10 in [Figure 6: see original paper]) or chaotic (images 3, 5, 7, 9). Reference [?] shows good robustness to illumination and texture interference after training on unstructured road datasets but performs poorly on irregularly shaped and chaotic scenes (images 5, 8, 9). The proposed algorithm performs initial segmentation before road edge detection, effectively removing irrelevant interference, improving operational efficiency, and achieving significantly better road boundary detection results than other methods. It effectively overcomes interference from strong light, shadows, water stains, rain, snow, fog, and fallen leaves. However, limitations remain for irregularly shaped and curved roads (images 4, 9, 10, 5).

To reduce the impact of randomness on segmentation performance evaluation, 100 unstructured road images were selected from databases and the Internet. Each algorithm was applied for road edge detection and guidance line extraction, with road region segmentation precision $\tau$ and guidance precision $\tau_3$ calculated. The results are shown in Tables 1-3.

**Table 1** shows that the proposed algorithm achieves 28.1% and 45.1% higher road region segmentation precision than references [**?**] and [**?**], respectively, slightly lower than reference [**?**]. **Table 2** demonstrates that guidance precision is 35.5% and 48.1% higher than references [**?**] and [**?**], respectively, and 15.5% higher than reference [**?**]. **Table 3** reveals that the proposed algorithm achieves 97.8% and 98.6% higher real-time performance than references [**?**] and [**?**], respectively, enabling rapid road processing.

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## 4 Conclusion

This paper proposes a field scene adaptive road guidance algorithm based on graph reasoning models and intelligent optimization. Experimental results demonstrate that the algorithm achieves 89.9% road region segmentation precision and 91.8% guidance precision overall for unstructured roads in complex field environments, with processing efficiency improvements of 97.8% and 98.6% compared to classical algorithms. The algorithm balances real-time performance and detection accuracy, providing higher road detection precision and better real-time capability. Road region determination and road contour estimation better align with human intuitive perception of roads, enabling accurate and rapid detection of field unstructured roads with strong application prospects.

However, the double line road boundary estimation model is relatively simple, yielding average performance on complex curved roads, and the algorithm’ s real-time performance still needs improvement. Future work will focus on more complex road models and further efficiency optimization.

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