A Luminance-Based Lane Marking Candidate Quality Assessment for Autonomous Driving in GIS Contexts

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Keywords: Computer Vision, Geo Information Systems, Image Processing, Lane Detection, Luminance, Lane Marking Quality, Contrast Ratio, Binary Ratio.

Abstract: The detection of lane marking candidates is crucial for autonomous vehicles and advanced driver-assistance systems *ADAS* as they deliver essential information for accurate lane following, localization, and route planning. Detecting these candidates becomes difficult when road conditions deteriorate or the marking paint is faded, sometimes making identification nearly impossible. While deep/machine learning *(DL/ML)* methods perform well in reliable detection, they often come with the need for extensive labeled datasets, substantial computational power, and intricate parameter adjustments. In this research, we present a method purely based on digital image processing to identify and evaluate lane marking candidates, thus avoiding the use of specialized reflectivity equipment (such as luminance meters) and bypassing complex *DL/ML* methodologies. Our pipeline initially identifies lane marking regions using a collection of image-processing techniques. It then subsequently evaluates their quality using two conditional metrics: a luminance-based contrast ratio and a white-to-black pixel ratio. Each candidate is categorized as good, bad, or ambiguous by comparing these metrics to empirically determined thresholds. Evaluations conducted on large sets of road images from conventional and urban highways in South Korea confirm the effectiveness of our proposed method. The system significantly reduces the dependence on time-consuming labor-intensive annotation, high-end hardware, and *DL/ML* expertise. We thus claim that our lightweight, deployable method effectively addresses a significant gap in luminance-centric lane candidate quality evaluation and can serve either as an independent solution or as a supplementary option to more sophisticated *DL/ML* systems in GIS and ADAS applications.

1 INTRODUCTION

Autonomous driving and *ADAS* systems represent the forefront of modern transportation technology. By integrating diverse sensors, powerful computing hardware, and sophisticated algorithms, these systems promise to enhance driver safety, alleviate traffic congestion, and ultimately enable fully self-governing vehicles. Within this ecosystem, lane markings are fundamental; they serve as reliable visual cues for both human drivers and onboard perception systems, facilitating tasks such as lane-keeping, lane-changing, and path planning. Consequently, improvements in detecting and evaluating lane markings directly enhance the accuracy and robustness of vehicular decision-making.

Despite their importance, lane markings are often subject to adverse real-world conditions. Inclement weather (e.g., rain or snow) and prolonged wear due to traffic can degrade markings to the point where detection becomes nearly impossible. Although deep learning models (*DL*), particularly convolutional neural networks (*CNNs*), have shown remarkable performance in lane detection tasks (Aly, 2008), these approaches require substantial annotated data, significant computational resources, and fine-tuning of parameters. Such demands can challenge resource-limited environments, such as small municipal projects or research laboratories with constrained budgets.

In contrast, several luminance-based lane detection strategies have emerged that directly measure visual characteristics such as, brightness, reflectivity, and contrast. While some of these approaches

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Rathnayaka, P., Kim, Y. H., Choi, I. G., Kim, G. C. and Kim, D. J.
A Luminance-Based Lane Marking Candidate Quality Assessment for Autonomous Driving in GIS Contexts.
DOI: 10.5220/0013430400003935

In *Proceedings of the 11th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2025)*, pages 85-94
ISBN: 978-989-758-741-2; ISSN: 2184-500X

use specialized instruments (e.g., luminance meters) or incorporate elements of machine learning (*ML*), fully luminance-driven pipelines remain relatively uncommon despite their potential compatibility with standard RGB cameras. By leveraging fundamental image processing principles and mimicking human brightness perception, luminance-based methods eliminate the need for expensive hardware and large-scale data annotation.

Against this background, this paper introduces a practical and deployable luminance-based solution. We propose a high-quality digital image processing pipeline that first isolates lane marking candidates and then classifies them using two straightforward yet informative metrics: (1) a contrast ratio (*CR*) that compares the mean luminance of the marking with that of its surroundings, and (2) a binary ratio (*BR*) that measures the proportion of white pixels within a thresholded image. This dual-metric approach yields an interpretable quality label—*Good*, *Bad*, or *Ambiguous*—that can be readily integrated into ADAS modules and GIS platforms.

In regions such as South Korea, official road assessments often rely on reflectivity-based devices or hybrid *DL/ML* approaches to evaluate marking conditions (Lee et al., 2010; Park, 2019). Some other technical materials mostly consider identifying pavement markings and street markings as in (Lee et al., 2024). These methods can be prohibitively expensive and logistically challenging, especially when dealing with diverse road geometries, variable weather conditions, or frequent repainting cycles. Our pipeline addresses these issues by operating with minimal hardware such as a single monocular camera and employing straightforward computer vision techniques. We anticipate that this approach will facilitate large-scale deployment and reduce overall system overhead, ultimately contributing to improved traffic safety and driver comfort.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on lane detection and marking quality assessment, emphasizing gaps in luminance-based approaches and their importance as an adaptable measuring approach. Section 3 details our proposed algorithm. The section is divided into subsections; stating our system architecture and motivation, defining the image processing steps for luminance computation and edge processing for lane marking candidate region extraction, and the luminance-based and binary-based pixel analysis for quality classification criteria. Section 4 presents experimental results obtained under varied illumination conditions, while Section 5 discusses the challenges encountered and potential avenues for future research. Finally, Section 6 summarizes our key findings and their broader implications for GIS and ADAS applications.

2 RELATED WORKS

2.1 Global Overview of Lane Detection Approaches

Lane detection has long been a central topic in computer vision and robotics. Early approaches frequently employed geometric constraints, such as Inverse Perspective Mapping (*IPM*), to project a 2D image onto a top-down view for easier extraction of lane lines (Bertozzi and Broggi, 1998; Yoo et al., 2017; Youjin et al., 2018). Classical techniques relied on methods like the Canny edge detector (Canny, 1986), the Sobel operator (Kanopoulos et al., 1988), and other gradient-based techniques to highlight lane boundaries, with the Hough transform (Kiryati et al., 1991) subsequently grouping these edges into coherent lines or curves. For example, Aly (Aly, 2008) combined intensity thresholding with perspective transformations to achieve real-time lane marker detection under controlled urban conditions.

In recent years, *DL/ML* paradigms, primarily *CNNs*, have become prevalent. Models, such as LaneNet (Garnett et al., 2019), perform lane detection as a pixel-wise segmentation problem (Neven et al., 2018), and architectures like the spatial convolutional neural network (*SCNN*) (Pan et al., 2018) employ specialized layers to capture row-wise dependencies in lane structures. More advanced techniques leverage Transformers (Yang et al., 2024) or generative adversarial networks (*GANs*) to manage occlusions, curves, and lane merges. Although these data-driven approaches often yield superior performance on benchmarks such as TuSimple (TuSimple Inc., 2017), CULane (Pan et al., 2018), and LLAMAS (Garnett et al., 2019), they introduce high requirements for domain-specific training data, GPU processing power, and parameter optimization.

Hybrid methods have also been explored, integrating geometric heuristics with CNN-based feature extraction to reduce computational overhead while enhancing resilience to noise. However, these techniques generally presuppose stable road layouts or favorable lighting conditions. In adverse scenarios, such as nighttime or inclement weather, these hybrid methods may struggle to distinguish lane markings from environmental artifacts.

2.2 Practicality of a Luminance-Based Approach

Luminance-based lane detection offers a simple yet effective alternative by relying on pixel intensity variations. This approach is computationally efficient and circumvents the extensive training datasets and high computational demands associated with *DL/ML* models. Furthermore, because luminance-based methods utilize standard cameras and fundamental image processing techniques, they provide increased interpretability and easier debugging compared to black-box AI methods.

Recent studies, such as those reported in (Lee and Cho, 2023), highlight the importance of retro-reflectivity and luminance in improving lane detection. However, these approaches typically require additional hardware sensors, increasing system complexity and cost. Similarly, LiDAR-based methods (Certad et al., 2022) remove dependencies on ambient lighting but at the expense of high-cost sensors and prolonged data processing times. Also, the channel number of generated LiDAR sensor scans could lead to erroneous qualitative analyses, whereas complicated LiDAR fusion should be implemented to check a particular region as a whole.

On the other hand, luminance-based methods (particularly for mobile platforms like single-board computers with a single camera and simple sensor integrations) enable real-time lane detection with minimal computational demands. Their potential for seamless integration and cost benefits makes these methods highly attractive for use in resource-constrained environments.

2.3 Luminance-Based Quality Estimation

A growing body of literature (Smadi et al., 2008; Burghardt et al., 2021; Zhu et al., 2021; Zhu et al., 2024) emphasizes the role of luminance, or brightness-related metrics, in evaluating road infrastructure quality. Early works as of (Balali et al., 2015) and (Roman et al., 2015) demonstrated the correlation between luminance levels and driver response, while (Zhu et al., 2021) extended these principles to assess nighttime pavement markings, showing that reduced reflectivity directly impacts driver reaction times.

In the context of lane markings, Sultana et al. (Sultana et al., 2022) have addressed all kind of real-life environmental challenges to detect road lane markings and categorized them into four types. Munir et al. (Munir et al., 2021) proposed an encoder-decoder architecture for lane marking detection using event camera images, which they tend to extract higher-dimensional features from images, robust to illumination variations. Huang et al. (Huang and Liu, 2021) further illustrated illumination invariant Hough-based technique, evaluating the robustness of brightness comparisons as cues for road network extraction.

However, one major research gap that persists in most of these researches is the application of luminance-based algorithms is only limited to lane marking candidate detection. The approach is not only for detection but also for the quantitative assessment of marking quality. Road maintenance agencies require objective metrics to flag deteriorated markings for repainting or to assess safety risks. While specialized reflectivity meters exist (for Testing and Materials., 2005; Commission Internationale de l'Eclairage, 2001), their high cost and labor-intensive operation limit their scalability. Our approach addresses this by using contrast ratio *(CR)* and binary ratio *(BR)* metrics—correlating closely with human perception of clarity—to provide an interpretable and efficient quality assessment for lane markings.

3 ALGORITHM PIPELINE

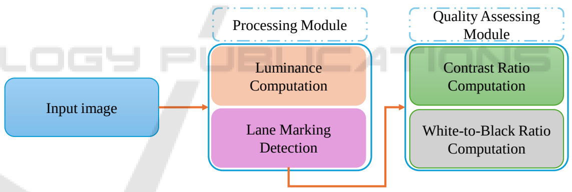

Figure 1: Overview of our proposed algorithm. The input image is processed in the first module–*Processing Module*– and it extracts all the lane marking candidates using advanced image processing techniques. All these candidates are then passed to and processed in the second module–*Quality Assessing Module*–to evaluate their quality.

3.1 Motivation and System Architecture

The proposed pipeline, illustrated in Figure 1, comprises two primary modules. The first module employs advanced image processing techniques to detect potential lane marking candidates, while the second module assigns quality labels based on combined luminance contrast and binary ratio evaluations. This dual-layer approach not only identifies lane markings but also quantitatively measures their clarity in real-world conditions.

Our rationale for adopting an exclusively luminance-based approach is twofold:

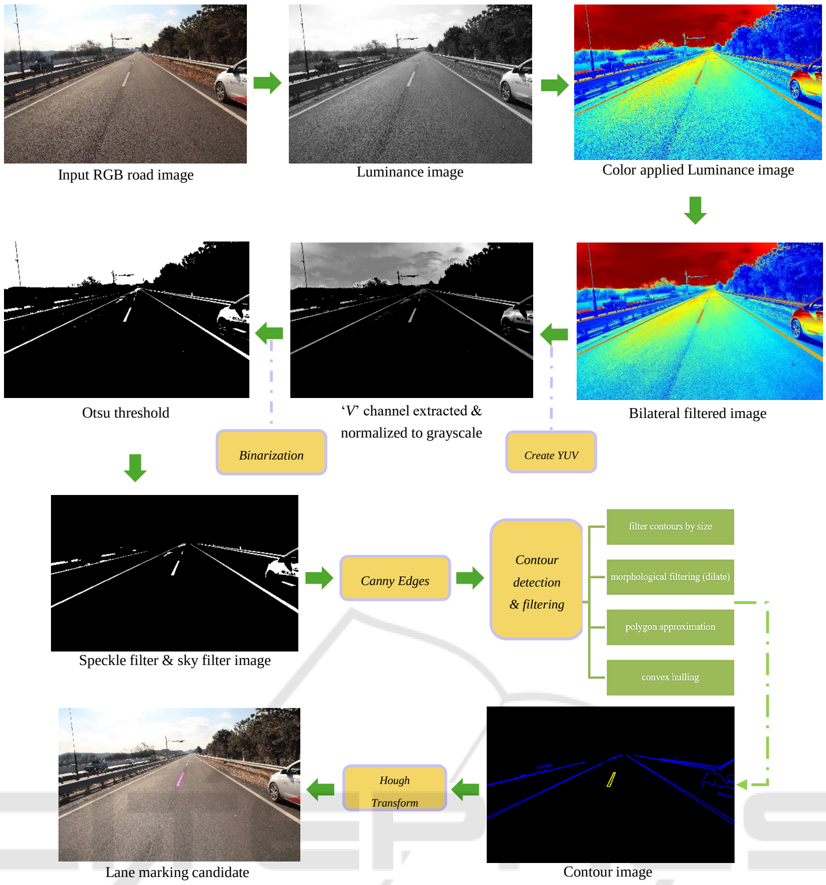

Figure 2: Overview of the first module: lane marking candidates are detected using image processing techniques. The luminance image is created and new color values are applied as a LUT and normalized to make marking candidates more distinguishable. The 'V' channel is extracted from the normalized image, where binarization, edge detection, n, and contour extraction methods are applied to identify the proper candidate region. Hough transformation is next applied to identify the lane marking as the final output of the first module.

- **Hardware Minimization:** The method avoids the need for specialized reflectivity meters, facilitating widespread adoption in standard camera-based ADAS or onboard vehicle systems. This makes this method a suitable approach, even if additional equipment, such as LiDARisre required to be integrated for further intensity-based processing.
- **Algorithmic Simplicity:** By relying on established computer vision operations, such as filtering, thresholding, and morphological analysis, we eliminate the requirement for large annotated datasets, extensive GPU training, and complex optimization procedures/parameter tuning required in many *AI* approaches.

The subsequent briefly explains our proposed method w.r.t two processing modules described in Figure 1.

3.2 Detecting Lane Marking Candidates

The process of lane marking candidate detection is depicted in Figure 2 (*First Module* in Figure 1). In this, we prefer generating a luminance image to detect lane marking candidates, instead of using raw RGB camera images directly. Luminance images are preferred over RGB images as they leverage inconsistencies that could hinder the detection of lane marking candidates where clear distinctions should be made between lane surfaces and road surfaces at varying lighting conditions.

The luminance L can be computed as:

$$L = sB \times 0.0722 + sG \times 0.7152 + sR \times 0.2126, \quad (1)$$

This enables us to have a clear idea of the perceptual relativity of the human non-linear response curve. Thus, a more suitable luminance calculation suffice for the requirements of this research can then be derived by

1. normalizing *sRGB* values into decimal within the range of 0.0 ∼1.0,

$$\mathrm{Norm}_{(R,G,B)} = \frac{\mathrm{sChannel}}{255} \tag{2}$$

eliminating the limitations of 8-bit quantization.

2. computing gamma-encoded RGB values from normalized sRGB values,

$$= \begin{cases} \frac{\mathrm{Norm}_{(R,G,B)}}{12.92} & \text{if Norm} \leq 0.03928 \\ \left(\frac{\mathrm{Norm}_{(R,G,B)}+0.055}{1.055}\right)^{2.4} & \text{otherwise} \end{cases} \tag{3}$$

following established sRGB protocols (Poynton, 2012).

3. And using gamma-encoded values to compute luminance values which align with human visual sensitivity as of:

$$L = 0.2126R' + 0.7152G' + 0.0722B'. \tag{4}$$

Once the luminance for every pixel is computed, the image is recolored as a look-up table (*LUT*) to identify the regions of our interest. Once recolored, it was witnessed that the imagecontainedin unnecessary noise; which could degrade our image processing pipeline. A bilateral filter (Tomasi and Manduchi, 1998) is applied to suppress these high-frequency noise data while preserving important boundaries of lane lines. The image is converted to the *YUV* color space, and the *V* channel is extracted to isolate brightness or chrominance data useful in identifying reflective or bright candidate's paint information.

A *min-max* normalization is applied to standardize *V* channel intensities to $[0, 255]$, followed by a gamma correction (Poynton, 2012) to align the brightness perception more closely with human vision. The Otsu's thresholding (Otsu et al., 1975; Otsu, 1979) is used to segregate brighter lane markings from the darker road surface. Small noise artifacts are further eliminated using morphological opening and speckle filtering.

The Canny edge detector (Canny, 1986) is used to identify the edge boundaries of lane candidates. A morphological dilation is applied to connect all the disjoint dashed candidates. By this, we managed to minimize the effect of mildly faded lane markings. Edge contours are approximated using the Ramer–Douglas–Peucker (RDP) algorithm (Douglas and Peucker, 1973; Ramer, 1972) to reduce polygon complexity, and convex hulls are computed to ensure continuous bounding while eliminating irregular clusters. Contours failing to meet minimum area or width criteria are discarded.

Next, a probabilistic Hough transform (Kiryati et al., 1991) is applied to refine lines that approximate typical lane geometry (straight and gently curved), adhering to parallel or near-parallel constraints. The surviving polygons, which are lane marking candidates, are superimposed on the original RGB image for real-time validation. These lane marking candidates are subsequently assessed for quality, as discussed next.

3.3 Lane Marking Quality Assessment

After extracting lane marking candidates, their quality is quantified using two conditional metrics:

1. *mean luminance comparison (contrast ratio : **CR**)*
2. *white-to-black pixel comparison (binary ratio : **BR**)*.

By integrating these measures, we obtain a holistic assessment of how distinct or faded each marking is relative to its background.

The first criterion is inspired by human visual perception of brightness differences and obviates specialized reflectivity measurements, whereas the latter is a justification of white pixel count w.r.t black pixel count inside the detected lane marking. To assess the visual distinctiveness of a candidate lane marking region, we compute the contrast ratio between the average luminance inside the region and the average luminance of the surrounding background. The process proceeds as follows:

1. Region Isolation
   - A binary mask is created from the polygon that bounds the candidate lane region. Pixels within this polygon are set to white (255), and all other pixels remain black (0).
   - We apply this mask to the luminance image and crops the resulting masked region using the polygon's bounding rectangle, ensuring that only relevant pixels (i.e., those within the polygon) are retained.
2. Lane vs. Background Accumulation
   - Within the bounding rectangle, each pixel's value is added to a *lane* or *background* sum depending on whether it lies inside (> 0) or outside ($= 0$) the polygon. The total luminance for each category is tracked, along with the number of pixels in each category.
3. Mean Luminance Computation
   - After processing all pixels, the total luminance of the lane region is divided by the lane-pixel count to obtain the *average lane luminance* ($\bar{L}_{\text{lane}}$).

$$L_{\text{lane}} = \frac{\sum(\text{lane intensities})}{\text{lane pixel count}} + 0.05 \tag{5}$$

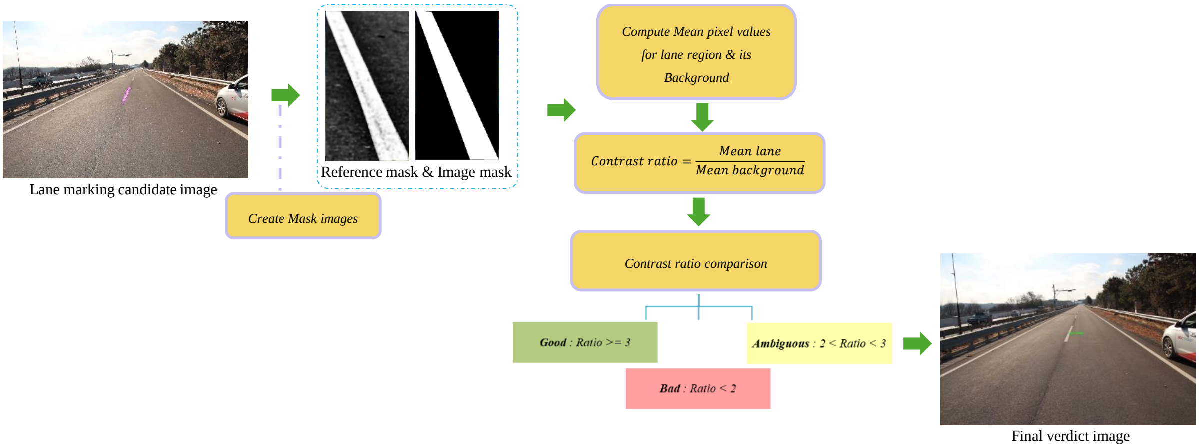

Figure 3: Overview of the second module: evaluating the contrast ratio *(CR)* for each candidate. An ROI from the lane candidate found at the first module is extracted and a simulated pure black-and-white region (0s and 255s only) is created to distinguish pixel values above the lane marking from its surrounding road surface. Mean values are used to compute the contrast ratio and the outcome is compared with pre-determined threshold values. This is the first qualitative conditional metric of our proposed quality evaluation.

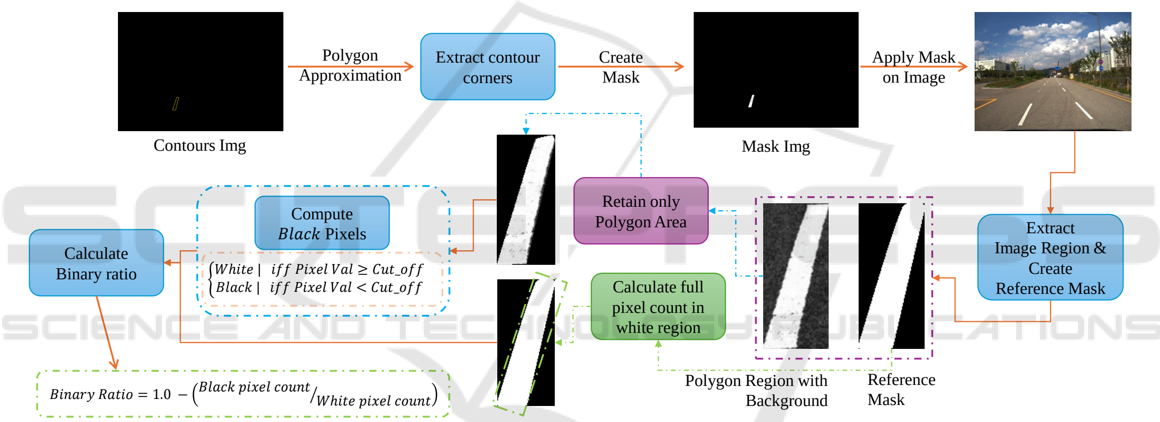

Figure 4: Overview of the second module: assessing the binary ratio *(BR)* for additional clarity analysis. The candidate region with the surrounding road surface area is extracted. A simulated ROI of the same size with only having 0s and 255s is created as a reference mask, and the total number of white pixels is calculated. The total white and black pixels from the real candidate polygon area is estimated by comparing them g with a pre-assigned threshold value. The final white-to-black ratio is computed using these two values.

- Likewise, the total luminance of the background region is divided by the background-pixel count to obtain the *average background luminance* ($\bar{L}_{bg}$).

$$L_{bg} = \frac{\sum(\text{ground intensities})}{\text{ground pixel count}} + 0.05 \quad (6)$$

- A small offset (e.g., 0.05) is added to both values to avoid division by zero and to mitigate extremely low pixel intensities.

4. Contrast Ratio

- We define the *contrast ratio*, CR, as the ratio of the average lane luminance, $\bar{L}_{lane}$, to the average background luminance, $\bar{L}_{bg}$:

$$CR = \frac{\bar{L}_{lane}}{\bar{L}_{bg}} \quad (7)$$

- A larger contrast ratio implies that the lane region is significantly brighter than its surroundings, enhancing its detectability. Conversely, values below a chosen threshold (e.g., 2.0) suggest that the lane may be difficult to discern from the background.

5. Binary Ratio

- To further assess the region's distinctiveness, the cropped mask is thresholded via Otsu's method to produce a binarized mask.

- The number of white pixels ($whiteCount$) and black pixels ($blackCount$) are then computed.
- The *binary ratio*, *BR* is determined by:

$$BR = 1.0 - \frac{\text{blackCount}}{\text{whiteCount}} \tag{8}$$

- This ratio captures how many pixels remain bright (white) relative to dark (black) pixels within the thresholded candidate region. Values closer to 1.0 indicate a more clearly distinguished (i.e., whiter) region after thresholding.

6. Quality Verdict Classification
   - Equations $1 \sim 8$ ensure that intensity values within the candidate lane region and the local background context are accounted for, yielding a robust measure of how clearly the lane markings stand out from their surrounding background. This combination provides a good conditional criterion to make a distinct verdict whether the candidate is of good condition, bad condition, or in a state in between.
   - Experimenting with a multiple of input images, and with thorough condition evaluations by naked human eye, a *cut-off* value range suitable for making verdicts of lane markings is determined for both *CR* and *BR*.
   - If $CR < 2.0$; the region is deemed to exhibit insufficient contrast and thus, assessed as of *Bad CR*.
   - If $2.0 \leq CR < 3.0$; the region possesses borderline contrast and thus, assessed as of *Ambiguous CR*.
   - If $CR \geq 3.0$; the region is considered to have sufficiently high contrast and thus, assessed as of *Good CR*.
   - After the *CR* evaluation, then it is checked against the *BR* condition. If $BR < 0.17$; the region is assessed as of *Bad BR*.
   - If $0.17 \leq BR < 0.49$; the region is assessed as of *Ambiguous BR*.
   - If $BR \geq 0.5$; the region is assessed as of *Good BR*.
   - A candidate is classified as **Good Quality** only if both CR and BR meet the "good" thresholds, **Bad Quality** if both fail, and **Ambiguous Quality** in all other cases. These thresholds were established after extensive pilot testing and visual inspections across a diverse set of road images.

4 EXPERIMENTS AND RESULTS

To rigorously assess the performance of our pipeline, we compiled a dataset of approximately 5,000+ images captured under varying traffic and illumination conditions in South Korea. Images were recorded using a standard monocular camera mounted on a test vehicle at three distinct times: 10 a.m., 1 p.m., and 5 p.m. This sampling strategy covers scenarios with high sun angles, partially overcast skies, and early-evening shadows. All experiments were conducted on a standard desktop (Intel(R) Core(TM) i7-9700 CPU @ 3.00GHz, 32GB RAM), demonstrating that the proposed method is computationally feasible without dedicated GPU infrastructure.

4.1 Implementation Details and Parameters

Key parameters of the pipeline include:

- **Bilateral Filter Kernel Size:** Selected between 5 and 9 pixels to balance noise reduction with edge preservation.
- **Morphological Dilation Size:** Typically set between 3×3 and 5×5, ensuring that dashed or slightly faded markings merge into continuous contours.
- **Minimum Polygon Area:** Set to 100 pixels to filter out minor noise or artifacts.
- **Probabilistic Hough Transform Settings:** A minimum line length of 30 pixels and a gap threshold of 5 pixels facilitate the detection of partial or dashed lines.

4.2 Quantitative Evaluation

Manual annotation was performed on a subset of 1,000 images to validate detection and quality labeling. Human evaluators rated each detected marking as *visually good*, *borderline*, or *visually poor* and used as ground truth evaluations in our work.

Throughout the experiments, it was observed that the proposed bilateral filtering plus morphological approach was able to effectively isolate lane edges in the presence of moderate wear or dashed patterns, even when shaded occlusion was available. The contrast ratio reliably distinguished freshly painted ("Good") markings from heavily faded or unclear ("Bad") ones, with borderline scenarios marked as "Ambiguous" for further inspection. Unlike ML-based approaches, extensive annotated data sets or specialized reflectometry equipment were not needed.

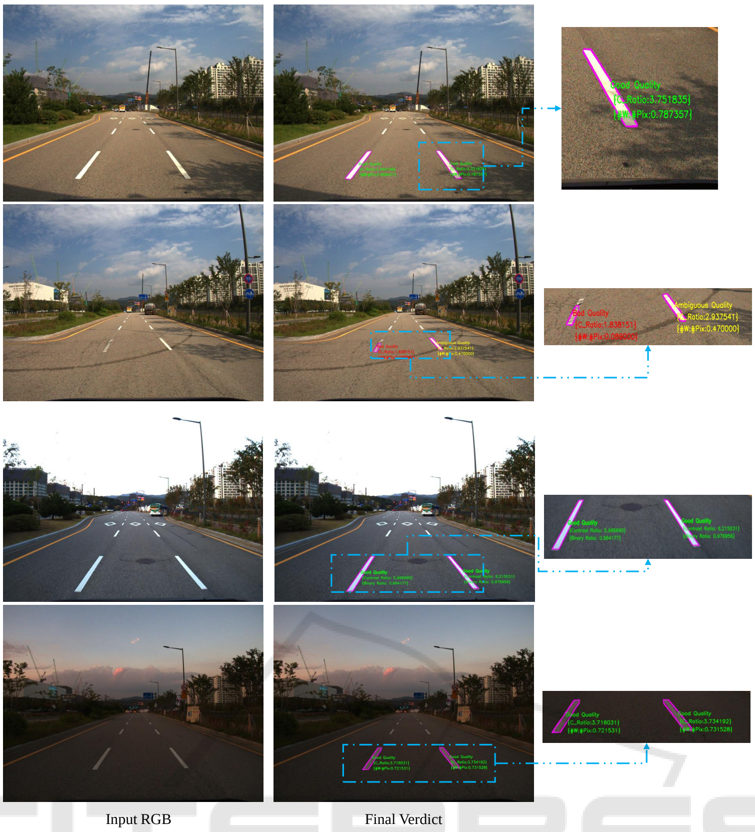

Figure 5: Some of the representative results of our proposed lane marking detection and quality assessment algorithm. The top row shows the correct detection and analysis of road markings even when partially shadowed regions exist; the second row depicts the distinction between "Bad" and "Ambiguous" quality assessment; the third row shows the successful detection under overcast/evening conditions; the bottom row depicts the robust performance of our method even in bad and dim lighting conditions.

The pipeline's classifications were compared with these ground-truth labels:

- **Detection Rate:** Over 90% of clearly visible lane markings were successfully localized, with most missed cases occurring under severe occlusions or extreme fading (since lane marking candidate detection was extremely difficult in such regions).
- **Quality Label Accuracy:** Approximately 86% of the classifications matched the human-labeled categories (i.e., `Good`, `Ambiguous`, `Bad`), indicating a strong correlation between our luminance-based metrics and human perception.

Figure 5 illustrates some of the representative outcomes. In many cases, even faint or partially occluded markings were detected due to the effective use of bilateral filtering and morphological operations. The contrast ratio (CR) reliably differentiated between newly painted and heavily worn markings, while the binary ratio (BR) validated the overall whiteness of the candidate regions. Markings labeled as "Ambiguous" typically exhibited moderate wear or incomplete paint coverage, reflecting the inherent challenges in achieving consistent classification.

4.3 Performance and Timing

On our CPU-based system, the pipeline processed 1936×1464 resolution images at an average rate of $8 \sim 12$ frames per second (fps). While further optimization (e.g., code-level improvements, vectorization, or parallelization using OpenMP) could enhance this performance, the current throughput indicates that near-real-time operation is feasible on standard hardware.

5 CHALLENGES AND FUTURE DIRECTIONS

Despite promising results, the proposed pipeline faces several limitations and opportunities for further improvement:

1. **Nighttime Glare and Harsh Lighting:** Although the system performs well under partially shadowed and overcast conditions, nighttime scenes with strong headlight glare or streetlight reflections can introduce artifacts that impair thresholding. As for future work, we are planning to incorporate adaptive exposure techniques and specialized nighttime preprocessing.
2. **Curved Lane Detection:** The current approach primarily handles relatively straight lane segments. Incorporating polynomial and spline-fitting methods is under development to enhance detection on winding roads or at highway interchanges.
3. **Detection of Crosswalks and Road Symbols:** Road markings are not limited to lane lines; features such as crosswalks, directional arrows, and textual signs also influence safe navigation. We are currently extending the morphological and shape approximation modules to enable effective detection and classification of these additional elements.
4. **Harsh Shadows and Occlusion Robustness:** Severe shadows, such as those cast by bridges, tunnels, or dense foliage can distort CR and BR metrics by darkening both the lane markings and the background. We are developing to implement local region-based thresholding with multi-frame data fusion to improve robustness in these challenging scenarios.
5. **Temporal Smoothing and Tracking:** Processing each frame independently may result in occasional flickering detections. Incorporating temporal smoothing or short-term tracking across consecutive frames could enhance detection stability and reduce transient artifacts.

Addressing these challenges will further improve the reliability and extend the applicability of our pipeline, from rural two-lane roads to complex urban highways.

6 CONCLUSION

This paper presents a comprehensive digital image processing and luminance-based pipeline for detecting lane marking candidates and assessing their quality, which avoids the complexities associated with deep/machine learning models and the necessity for specialized reflectivity sensors. By using advanced image processing techniques such as bilateral filtering, thresholding, morphological filtering, and Hough-based line refinement, the system manages to effectively identify the regions of lane marking candidates. It then employs a dual-metric approach, utilizing contrast ratio (*CR*) and binary ratio (*BR*), to categorize each candidate as ”Good,” ”Bad,” or ”Ambiguous.”

Experimental evaluations conducted on a diverse dataset from South Korea demonstrate that the proposed method aligns well with human assessments of lane marking quality and performs efficiently on standard computing hardware. This solution offers a cost-effective alternative to sophisticated deep/machine learning methods and experiments that depend on using expensive reflectometers, making it particularly suitable for resource-constrained environments.

From the perspective of *GIS* systems, integrating techniques that detect and assess lane markings based on luminance allows to evolve from traditional static mapping frameworks to advanced, real-time monitoring systems. This advancement enhances the precision and reliability of road network databases, supports proactive road maintenance strategies, boosts the effectiveness of navigation systems, and lays a solid foundation for more informed and strategic urban planning decisions.

In future work, we plan to address nighttime-specific challenges, improve curved lane detection, and incorporate advanced shadow compensation strategies, thereby broadening the system's applicability in many *GIS* and *ADAS* contexts.

ACKNOWLEDGMENTS

This study was conducted with the support of the “Road Traffic Infrastructure Monitoring and Emergency Recovery Support Service Technology Development (RS-2021-KA160853)” project of the Ministry of Land, Infrastructure and Transport.

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