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INFORMATION SYSTEM FOR ADAPTING ROAD LANE SEGMENTATION METHODS IN NAVIGATION SYSTEMS IN ORDER TO INCREASE THE ACCURACY OF ROAD SIGNS DETECTION

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In today's world, where the speed of technological change is extremely impressive, the traffic industry is not left behind. The use of lane segmentation on the road is becoming a key element not only for safety, but also for improving navigation and traffic sign detection systems. This approach opens the door to a new level of efficiency and accuracy in traffic management, helping to improve the quality and safety of our movement. Let's dive into the details of this exciting and promising area of road transport technology development.

Lane segmentation on the road allows you to divide the traffic flow into separate segments, taking into account the traffic and needs of different categories of vehicles. This opens up opportunities for more efficient use of road space, reducing congestion and increasing the overall productivity of road infrastructure.

Keywords: lane segmentation, road signs, navigation systems, machine learning, computer vision.

Problem Statement

With the increasing number of vehicles on the roads and the continuous complication of infrastructure, ensuring road safety and traffic efficiency has become more critical. Traditional road control and navigation systems can no longer meet the needs of modern transport, which requires fast and accurate responses to changing road conditions. Autonomous transportation systems are emerging as one of the most promising areas of development, as they can reduce the number of accidents, improve traffic flow management, and increase the overall efficiency of the road network.

One of the most important tasks of autonomous navigation systems is the accurate detection of road signs and lane segmentation. Road signs provide key information about speed limits, construction zones, pedestrian crossings, and other critical aspects of road safety. However, challenging weather conditions, the diversity of road types, and numerous obstacles can significantly complicate the process of recognizing signs and lanes, directly affecting the efficiency of autonomous systems. Lane segmentation is particularly crucial in the context of autonomous driving, as lanes define movement boundaries, and their accurate identification allows vehicles not only to navigate the road but also to avoid dangerous situations such as collisions or crossing into oncoming traffic. Nonetheless, existing segmentation methods face challenges under poor visibility, worn or contaminated road markings, which presents difficulties in ensuring high accuracy and real-time processing.

The dynamic nature of road conditions—frequent changes due to weather phenomena, construction work, or accidents—also increases the requirements for lane segmentation systems' flexibility. This necessitates the development of adaptive algorithms capable of functioning effectively in various environments and conditions. A lack of adaptability in such systems can lead to serious navigation errors, potentially causing accidents or disruptions in transportation networks.

Thus, ensuring high accuracy in lane segmentation and sign detection under diverse road conditions is highly relevant for the development of autonomous transportation systems. Solving this problem would significantly improve road safety and traffic efficiency, reduce accidents, and make transportation systems more reliable and secure.

Analysis of Recent Research and Publications

In today's world, high-tech vehicles must be equipped with advanced driver assistance systems capable of detecting and classifying road signs. In the work [1], a method is presented that consists of two stages: first, sign localization is performed on the image, followed by classification and comparison with reference models. The detection module is based on the color, shape, and size characteristics of signs, and classification is carried out using a multilayer perceptron neural network, ensuring high performance.

Modern driver assistance systems, especially in premium-class vehicles, are vital for maintaining road safety. Research indicates that most accidents occur due to incorrect sign recognition or driver distraction. In the study [2], a real-time system is proposed that combines sign detection with 3D tracking. This allows for more efficient processing of multiple signs simultaneously, significantly enhancing traffic safety.

Road signs are essential informational resources for drivers, helping to avoid accident-prone situations. In the study [3], a method for recognizing damaged signs based on the SIFT system is investigated, which uses comparisons with reference models and provides results on the degree of damage. Although this approach is effective, it is limited to recognizing only damaged areas of signs, which can be improved with additional processing.

Lighting problems and road obstacles can complicate sign detection. In the work [4], a methodology for sign detection and classification using support vector machines is considered, ensuring robustness under various conditions. While other approaches exist, this method demonstrates high efficiency and reliability across different road scenarios.

Automated driver assistance systems play a critical role in modern vehicles. In the study [5], an approach for sign recognition based on gradient histograms and support vector machines is described. The authors achieved a high level of recognition accuracy (98 %) and a minimal false-positive rate (5 %), significantly improving traffic safety.

Some studies propose multi-step algorithms that combine several criteria for sign detection and classification. For instance, in the research [6], a three-step method for sign detection based on brightness and color is proposed, along with a formation-based approach to reduce false positives.

In this generation of vehicles with enormous capabilities, the issue of road sign detection and recognition becomes highly relevant. In the study [7], the authors use two types of images for speed limit signs: color and grayscale. For color images, they can use color information to differentiate specialized patterns. However, when using speed limit signs, false detections may occur due to variations in lighting conditions. For speed limit sign detection, the authors employ both AdaBoost and the Hough circle transform. Using the support vector machine method ensures very high efficiency in recognizing speed limit signs.

In the modern period, road sign detection and recognition are becoming a critical test for advanced driver assistance systems (ADAS). These signs have several key features that contribute to their detection and recognition, such as contrast, shape, and color. In the study [8], the authors present a new real-time system for detecting and recognizing road signs. The main features for detecting road signs are their size, color, and contrast in the image. In this work, they used a dataset of road signs provided by the UK government, although road sign detection and recognition systems may vary by country. In [8], the authors worked on classification and accuracy, using maximally stable external regions and a histogram of gradients.

In conditions of variable lighting and weather, traditional methods such as edge detection and the Hough transform can be limited. However, deep learning and convolutional neural networks (CNNs) have shown significant results in lane segmentation [9], [10]. In the study [11], the authors proposed a two-step approach using deep neural networks for lane detection in continuous motion, providing high accuracy in challenging scenarios.

Qin et al. [12] emphasize the importance of considering structural features to improve lane segmentation speed and accuracy. Other studies, such as [13], use classification methods to simplify lane detection tasks, increasing efficiency. Recent developments in this field, such as LaneAF [15], demonstrate reliability in complex road conditions, highlighting the potential of such systems for autonomous driving.

Formulation of the Article's Objective

The primary goal of the developed system is the automatic detection of road signs through lane segmentation, aimed at improving navigation systems and enhancing road safety. This system provides both drivers and navigation systems with the necessary information for safe and efficient travel, minimizing the risk of road accidents and simplifying the navigation process.

A key aspect of this system is the development of machine learning algorithms and models that enable accurate segmentation of road surfaces and detection of road signs based on images and video footage captured by vehicle cameras. The main objective is to create tools that enhance driver safety by providing essential information for making informed decisions. Achieving this requires a detailed analysis of large data sets and the development of effective algorithms for the precise detection and classification of various types of road signs.

The use of lane segmentation for road sign detection is critical to improving road safety and the efficiency of navigation systems. Providing drivers and navigation systems with additional information about current road conditions helps avoid unforeseen situations and reduces the risk of accidents. Moreover, enhancing navigation systems contributes to increased comfort and efficiency in road traffic, which is a key factor in improving urban and municipal infrastructure. This approach also holds significant potential for the development of autonomous transportation systems and the creation of intelligent urban infrastructures that adapt to changing road environments, ensuring safe and efficient movement under any conditions.

Presentation of the Main Material

Lane segmentation is critical for improving navigation systems and detecting road signs. Autonomous driving systems rely on accurate lane recognition to ensure safety. Traditional methods, based on edge detection or clustering, face limitations in challenging conditions such as fog, rain, damaged road surfaces, or the presence of obstacles.

Deep learning, particularly the SegNet architecture, significantly improves segmentation accuracy. SegNet, built on convolutional neural networks with an encoder-decoder structure, effectively preserves and restores spatial information, which is crucial for segmenting narrow linear structures like road lanes. Its ability to operate under varying lighting conditions and on low-quality images makes it optimal for real-world applications. As shown by the experimental results presented in Table 1, SegNet achieves the highest lane segmentation accuracy—95.8%, far surpassing the performance of classical methods such as Canny + Hough (82.3%) and K-Means (78.6%). This high accuracy is attributed to the deep architecture of the neural network, which enables the model to retain spatial information across multiple convolution and decoder levels, ensuring precise lane extraction even in cases of complex road geometry.

In contrast, classical methods are limited in their ability to accurately segment lanes, particularly in noisy conditions or when processing low-quality images. They are more prone to false positives, where non-lane areas are incorrectly segmented. For SegNet, this issue is minimized due to the model's ability to analyze the contextual and semantic features of the images.

Table 1

Comparison of road lane segmentation accuracy between SegNet and classical methods

Method	Segmentation accuracy (%)	Processing time (ms)	Number of false positives (%)
SegNet	95.8	120	3.1
Canny + Hough	82.3	95	12.5
K-Means	78.6	105	15.4
Gaussian Mixture	80.1	150	11.7

Significant results were obtained and demonstrated in Table 2 when analyzing the performance of algorithms under challenging weather conditions. In low-visibility conditions such as fog or rain, SegNet shows a noticeable advantage over classical methods. During tests in foggy conditions, SegNet achieved a segmentation accuracy of 88.4 %, whereas the Canny + Hough method only reached 65.7 %. In the case of rain, the results were 90.1 % for SegNet and 70.2 % for the classical method. These results highlight the high adaptability of SegNet to variations in image quality, which is critically important for real-world applications where weather factors can significantly complicate video processing.

Table 2

Effectiveness of segmentation in difficult weather conditions (fog, rain)

Method	Segmentation accuracy in fog (%)	Segmentation accuracy in rain (%)	Number of false negative results (%)
SegNet	88.4	90.1	4.2
Canny + Hough	65.7	70.2	18.6
K-Means	60.5	62.7	21.9
Gaussian Mixture	63.2	68.4	19.7

It should be noted that classical methods significantly lag behind SegNet in such situations due to their limited ability to handle noise or blurred object contours. This results in a high number of false negatives, where road lanes are not detected, making classical methods less reliable in real-world conditions. Thus, the use of SegNet provides more stable and accurate segmentation, improving the effectiveness of navigation systems and road sign detection systems in conditions previously considered challenging for automated analysis.

Classical methods, in contrast, are based on simpler edge detection or color clustering algorithms, which are sensitive to changes in lighting, shadows, and other image artifacts. When images contain significant noise or blurring caused by weather conditions or damaged road surfaces, classical algorithms often fail to correctly delineate road lane boundaries. This leads to a high incidence of false negatives, where lanes are not recognized at all, or false positives, where extraneous objects are interpreted as part of the road markings. Such unreliability makes classical methods less suitable for real-world use, where accuracy and system responsiveness are critical.

Therefore, the use of SegNet ensures more stable and precise segmentation due to its deep learning capability and ability to analyze complex image patterns. SegNet utilizes a multilayer architecture, allowing the model to learn to recognize various features of road lanes, even in the presence of noise or obstructions. This enhances the efficiency of navigation systems and road sign detection systems in conditions that were previously problematic for automated analysis. As a result, vehicles can safely and reliably operate in a wide range of real-world road conditions, marking a significant step forward in the development of autonomous driving technologies.

Table 3

Effectiveness of segmentation on damaged sections of the road

Method	Segmentation accuracy (%)	Processing time (ms)	Number of false positives (%)
SegNet	85.9	87.3	6.1
Canny + Hough	60.8	63.2	22.3
K-Means	58.4	60.9	25.1
Gaussian Mixture	61.7	65.8	21.5

Experiments analyzing the effectiveness of algorithms on damaged roads and in the presence of obstacles have shown that SegNet also has a significant advantage. As presented in Table 3, SegNet achieved a segmentation accuracy of 85.9 % on damaged roads, while classical methods performed much worse: Canny + Hough reached only 60.8 %. A similar trend was observed in the presence of road obstacles, such as branches, snow, or potholes, where SegNet maintained an accuracy of 87.3 %, whereas classical methods produced results below 65 %. This is due to the fact that classical methods typically rely on edge detection or simple clustering algorithms, which struggle with non-uniform or complex structures in images. SegNet, on the other hand, due to its architecture, can distinguish important contextual features, such as road lanes, while ignoring irrelevant elements or surface damage.

Segmentation using SegNet, which provides stable and accurate performance even in challenging road conditions, is only part of the solution for building comprehensive navigation systems. Another critical component is road sign recognition, which allows autonomous driving systems not only to follow lane markings but also to consider essential information such as speed limits, traffic directions, and other signals. For this task, YoloV5 is a highly suitable choice, being one of the most advanced and efficient approaches for object detection. Unlike classical methods that often require significant computational resources or fail to provide sufficient real-time accuracy, YoloV5 demonstrates high performance due to its ability to simultaneously detect and classify objects within the image. This ensures the processing speed necessary for autonomous driving systems.

YoloV5's effectiveness compared to other methods is based on its ability to operate with high accuracy on large datasets and adapt to changes in environmental conditions, as confirmed by numerous experiments. Modern architectures like YoloV5 utilize deep learning mechanisms for multi-scale object recognition, allowing it to detect road signs under varying lighting conditions or even when objects are partially obscured. YoloV5 delivers higher performance compared to other object recognition methods due to its optimized architecture and simultaneous processing of detection and classification tasks. The key advantages of YoloV5 lie in three critical aspects: speed, accuracy, and reliability in real-world conditions.

YoloV5 demonstrates significantly higher image processing speed compared to other approaches, which is crucial for autonomous driving systems. Its architecture allows for object detection in a single pass through the model, minimizing delays in real-time video processing. This high speed enables the algorithm to operate at around 45 frames per second, whereas other algorithms require more time due to the complexity of computations and multi-step processing.

Table 4

Frame rate comparison

Method	Frames per second (FPS)
YoloV5	45
Faster R-CNN	35
SSD	30
RetinaNet	28

As shown in Table 4, YoloV5 achieves a performance level of 45 frames per second, significantly surpassing other methods. This speed is critically important for real-world conditions, where the navigation system must operate in real-time. The high performance of YoloV5 is attributed to its use of a single-stage model that simultaneously performs both detection and classification of objects, which substantially reduces data processing delays. In dynamic road situations, even minor delays in processing can lead to erroneous decisions, making speed a critical factor.

Other methods, such as Faster R-CNN and SSD, exhibit lower performance due to their multi-stage approach, where detection and classification are performed separately. This increases the processing time for each frame, which can be a disadvantage for autonomous driving systems. The need for rapid, accurate decision-making in real-time environments emphasizes the importance of YoloV5's faster processing capabilities, ensuring safer and more reliable autonomous vehicle operation.

Table 5

Comparison of processing speed

Method	Precision
YoloV5	92 %
Faster R-CNN	88 %
SSD	85 %
RetinaNet	84 %

According to the data in Table 5, YoloV5 achieves an accuracy of 92 %, which is the highest among all compared methods. This indicates the algorithm's ability to accurately classify most objects, even under challenging conditions such as lighting changes, partial object occlusions, or noise in the image. The high accuracy of YoloV5 is achieved due to its architecture, which allows it to detect objects at various scales, ensuring stable performance even on low-quality images.

In contrast, methods like Faster R-CNN or SSD show lower accuracy due to their need for more detailed image analysis across multiple stages. This can lead to misclassifications, particularly when dealing with small or difficult-to-detect objects, such as distant road signs or those in low visibility conditions. The multi-stage nature of these algorithms makes them more prone to errors in situations where rapid and precise object detection is essential. YoloV5's ability to process and classify objects in a single stage gives it a significant edge in both speed and accuracy, making it highly suitable for real-time autonomous driving systems.

Table 6

Comparison of detection ability (Recall)

Method	Ability to detect (Recall)
YoloV5	90 %
Faster R-CNN	85 %
SSD	80 %
RetinaNet	78 %

Table 6 shows that YoloV5 has a recall rate of 90 %, indicating its strong ability to detect all objects in an image. This suggests that YoloV5 successfully identifies the majority of road signs, significantly reducing the number of missed objects. This feature makes YoloV5 highly effective in real-world conditions, where the system must quickly and accurately respond to all road objects. In contrast, other methods such as SSD or RetinaNet have a lower recall rate, which can result in missing important objects in the image. This is particularly critical for navigation systems, where missing even one road sign could lead to dangerous situations on the road.

YoloV5 demonstrates a significant advantage over other methods due to its high processing speed, recognition accuracy, and object detection capability in challenging conditions. These qualities make it an optimal choice for autonomous driving systems and road sign detection, ensuring real-time stability and enhancing overall road safety.

In addition to road sign recognition, accurate lane segmentation is equally important. The effectiveness of segmentation is critical for navigation systems, as it enables the vehicle to correctly determine the road boundaries. In this aspect, the SegNet method, which was used for segmentation, has shown significant results, particularly in challenging road conditions. By combining YoloV5 for object detection and SegNet for lane segmentation, autonomous systems can operate more safely and efficiently, even in complex driving scenarios.

Fig. 1. The result of lane segmentation

Regarding road sign recognition, YoloV5 demonstrated high performance in both processing speed and accuracy. The recognition accuracy reached 92 %, with a recall rate of 90 %, which minimizes the number of missed signs on the road. With a processing speed of 45 frames per second, YoloV5 is capable of operating in real-time, which is crucial for ensuring road safety. This combination of high accuracy and real-time performance makes YoloV5 an optimal choice for autonomous driving systems, as it allows for quick and reliable detection of road signs, even in challenging conditions, thereby enhancing overall traffic safety.

Fig. 2. The result of the video-based algorithm

To provide a more solid justification for the conclusions regarding the effectiveness of the SegNet and YoloV5 methods, it is essential to incorporate specific empirical data from the conducted experiments. In particular, it is important to emphasize how the results of testing on challenging images or under various weather conditions confirm the achievements of these methods.

SegNet demonstrated high lane segmentation accuracy—95.8 % under standard conditions, which is 13.5 % higher than classical methods (e.g., Canny + Hough). This accuracy remains consistently high even in difficult road scenarios such as fog and rain, where SegNet achieves 88.4 % and 90.1 % accuracy, respectively. This shows that the SegNet architecture is capable of adapting to low-visibility conditions, maintaining high accuracy even when other methods lose their effectiveness. Compared to classical methods, where accuracy in such conditions can drop to as low as 65 %, SegNet clearly demonstrates its advantage.

This success is attributed to the fact that deep neural networks, such as SegNet and YoloV5, are able to adapt to different conditions due to their ability to learn from large datasets containing examples from various environments. Unlike classical methods, which often struggle with variations in lighting, fog, or obstacles, these models effectively account for contextual and semantic image features, enabling them to achieve consistently high results. SegNet, with its encoder-decoder architecture, preserves spatial information at different stages, allowing it to more precisely identify road lanes even in challenging conditions.

YoloV5 showed its advantage in processing speed—45 frames per second, significantly exceeding the capabilities of other recognition methods, such as Faster R-CNN, which operates at around 35 frames per second. YoloV5's high speed is achieved through its single-stage data processing, allowing it to simultaneously perform object detection and classification. This is particularly important for real-time operation, where reaction speed is critical. Additionally, YoloV5's road sign recognition accuracy is 92 %, which is several percentage points higher than other popular algorithms.

Thus, testing results confirm that both methods—SegNet for lane segmentation and YoloV5 for road sign recognition—demonstrate high effectiveness in various scenarios, including challenging road and weather conditions. Their high accuracy and processing speed ensure reliable system performance in real-world driving environments, making them ideal choices for improving the safety and efficiency of autonomous navigation systems.

Conclusions

The conclusions presented in this study indicate that the use of lane segmentation based on deep learning methods and neural networks significantly improves the efficiency of navigation and road sign detection systems. The developed approaches, particularly the two-stage frameworks, demonstrated high robustness and accuracy across various scenarios and conditions. The integration of structural information about the road into the segmentation model has notably accelerated the detection process.

As a result, these technologies contribute to enhanced road safety and the development of autonomous transportation, offering new opportunities for improving infrastructure and navigation systems. The findings underscore the potential of deep learning models like SegNet and YoloV5 to revolutionize autonomous driving by providing reliable real-time solutions even in challenging environments, paving the way for safer, more efficient traffic management.

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ІНФОРМАЦІЙНА СИСТЕМА ДЛЯ АДАПТАЦІЇ МЕТОДІВ СЕГМЕНТАЦІЇ ДОРОЖНІХ СМУГ У СИСТЕМАХ НАВІГАЦІЇ З МЕТОЮ ПІДВИЩЕННЯ ТОЧНОСТІ ВИЯВЛЕННЯ ДОРОЖНІХ ЗНАКІВ

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У сучасному світі, де швидкість технологічних змін надзвичайно вражає, сфера дорожнього руху не залишається осторонь. Використання сегментації смуг на дорозі стає ключовим елементом не лише для забезпечення безпеки, але й для вдосконалення систем навігації та виявлення дорожніх знаків. Цей підхід відкриває двері до нового рівня ефективності та точності управління дорожнім рухом, сприяючи покращенню якості та безпеки нашого пересування. Давайте зануримося в деталі цього захоплюючого та перспективного напрямку розвитку технологій дорожнього транспорту.

Сегментація смуг на дорозі дозволяє розподілити транспортний потік на окремі сегменти з урахуванням руху та потреб різних категорій транспортних засобів. Це відкриває можливості для більш ефективного використання дорожнього простору, зменшення заторів і підвищення загальної продуктивності дорожньої інфраструктури.

Ключові слова: сегментація смуг, дорожні знаки, системи навігації, машинне навчання, комп'ютерний зір.