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Retraction

Retracted: Sharpening and Detection of Road Studs for Intelligent Vehicles at Nighttime

Security and Communication Networks

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. H. Siddiqi and I. Alrashdi, "Sharpening and Detection of Road Studs for Intelligent Vehicles at Nighttime," *Security and Communication Networks*, vol. 2022, Article ID 9329715, 10 pages, 2022.

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Research Article

Sharpening and Detection of Road Studs for Intelligent Vehicles at Nighttime

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Intelligent vehicles need to survive against various environments on roads such as sunlit, unclear, showery, shadowy, and inside tunnel conditions. This research designs a robust approach for detecting road studs at nighttime, which is the combination of various statistical methods. This detection approach is a unique approach developed for the detection of road lanes instead of road-painted lanes. Therefore, we detect road studs (cat eyes) instead of the painted lanes on roads at nighttime as the road studs have higher intensities at nighttime. First, we utilized Butterworth low-pass filter in order to sharpen the images. Second, we converted the image to grayscale and extracted the corresponding region of interest (ROI) from it. Then, the Canny edge detection algorithm was applied to create boundary lines in images. Finally, the Hough transform was applied to detect the desired lanes in the images, which are the road studs, and hence we successfully detected the road studs in images. We have used our own dataset for the stud's detection, which considered most of the limitations of the previous datasets. Also, the dataset was collected in naturalistic environments at nighttime. The experimental result presents that the designed approach is accurate and robust for road stud detection against nighttime.

1. Introduction

Vehicles have a vital role in technology development. One of the most advanced technologies is autonomous vehicles that are self-driving vehicles on roads. Mostly autonomous vehicles are driven automatically by Advanced Driver Assistant System (ADAS). Therefore, the intelligent system of autonomous vehicles must improve road safety, traffic problems, and passengers' comfortability [1]. The autonomous vehicles track and detect road-painted lanes, and with the help of those painted lanes (yellow and white), the vehicles keep driving on the road. The vehicles have embedded devices such as cameras, GPS, light detection and ranging (LIDAR), and sensors; through these devices, the autonomous vehicles track and detect road edges and reach the destination. Still, it is a solicitous problem because of different road environments such as sunny, shadowy, nighttime, and inside tunnel conditions. Most of the detection of marker lanes is not

sturdy enough against the natural distinctions in a real scene, like nighttime, changes of light, and shadows [2]. Road lane detection might suffer from various problems such as the nighttime scene, shadows, and lighting fluctuation [3].

Intelligent vehicles cannot easily detect the painted lanes at nighttime because of their low visibility and intensity in the dark. Due to dark lanes, detection is a vast problem for intelligent vehicles and may cause different environmental situations. Due to the short and limited vision of painted lanes at night, for intelligent vehicles, it is difficult to survive at night and cannot drive carefully because of the short vision of the painted lanes. As shown in Figure 1, painted lanes can be seen nearby the vehicles in the dark and are entirely invisible from a long distance. Due to the limited vision of painted lanes in the dark, a big challenge occurs for intelligent vehicles to detect painted lanes at nighttime. Thus, road lane detection is challenging for autonomous vehicles at nighttime.
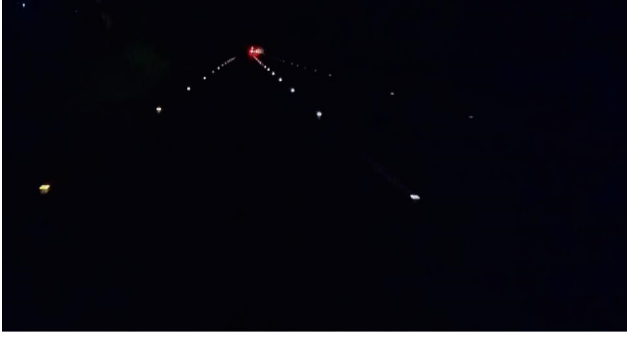
Figure 1: Sample image of road studs at nighttime.

Many studies have been done to detect road lanes, painted lanes (such as yellow and white lanes), orange paint, and pedestrian lanes. The authors of [4] have proposed a method for the detection of road markings under different weather and environmental conditions like daytime, fog, rain, and dryness conditions. Similarly, the authors of [5] have proposed an automatic detection system for road weather and surface conditions under the presence of various pretrained deep learning models. They, respectively, considered six environmental and surface conditions such as clear, dry, snowy, heavy snow, light snow, and wet conditions. On the other hand, a smart road stud detection system was proposed in [6], which focused only on detecting two lanes during traffic surveillance. This system has the ability to collect data from high-resolution traffic and light-based traffic. This system utilizes a three-dimensional sensor on the road lane that is further employed in advanced domains like traffic, guidance of driving, and traffic monitoring. Likewise, the authors of [7] investigated the difference in quality detection in two conditions such as dry daytime and nighttime, respectively. They claimed better classification results against these conditions in four sections of rural roads. A state-of-the-art approach was proposed in [8], which extracts the local features from LIDAR cloud points to identify the global features, through which they detect road lane lines. They utilized a standard dataset of urban lane dataset that has six lanes against different urban road conditions. Moreover, a novel algorithm has been proposed by [9], where the authors employed linear Hough transform to assess the possible observation concerns against challenging situations such as different types of roads, weather conditions, shades, and lighting fluctuations. However, all of these systems were tested and validated mostly in the daytime under the presence of various conditions such as dry, clear, cloudy, snowy, and fog conditions. Also, most of these systems failed to identify the road separating lines against various lighting conditions. No or little work has been done for the detection of studs under the presence of various conditions at nighttime.

Therefore, this research work presents a pioneer road stud detection technique for intelligent vehicles at nighttime. For tracking road studs at night, first, we attached the camera at the front of the vehicle with the resolution of 960×540 and moved the vehicle on Charsadda Road at nighttime. The normal speed of the vehicle was 70 to 100/km per hour. We captured N frames from the moving vehicle of road studs at nighttime. So, for studs' detection, we used our own dataset because we are using an advanced detection approach and the dataset is not available. In our proposed work, we used a conventional Canny edge detector and Hough transform (HT) in order to detect the road studs at night in an image. First, we utilized Butterworth low-pass filter in order to sharpen the image. Then, we converted the image to gray-scale and extracted the corresponding region of interest (ROI) from it. Then, the Canny edge detection algorithm is applied to create boundary lines in the image. Then, the Hough transform is applied in order to detect the desired lanes in the image, which are the road studs, and hence, we successfully detected the road studs in the image. The proposed work has been implemented in Python using the OpenCV library. The results signify that road studs have a higher intensity than road-painted lanes at nighttime and can help to easily recognize the studs. As our new approach states, detection of road studs at nighttime is much easier than painted lanes because studs have more visibility than road-painted lanes lines.

The remaining article is structured as follows: Section 2 elaborates the background of this study. Section 3 presents the detailed concept of the proposed study detection methodology. The implementation followed by experimental results is briefly described in Section 4. Finally, the conclusion has been discussed in Section 5 with some future works.

2. Related Works

Different approaches have been established and developed for road lanes detection; however, these methods are under limited environments. Moreover, most of them have their own limitations.

A robust approach was developed by [10] that has the ability to track the road lanes at nighttime. The authors utilized a layered approach, such as temporal blur, low-resolution Hough transform, and iterated matched filtering. However, this approach failed to detect the painted lanes at nighttime because of shining street lights on the road, which saturate the appearance of painted lanes due to which this approach missed the detection. Similarly, the authors of [11] detected road lanes during the daytime and at nighttime by proposing the Hough transform method. However, still during implementation, this approach used constant parameters, which might only detect road lanes during the daytime but cannot detect at nighttime, as shown in Figure 2.

On the other hand, authors of [12, 13] developed an effective procedure for road lanes detection in low light situations and utilized visible spectrum imaging sensors. These approaches have the ability to accurately determine road lines by employing intensity variations. However, due to the lack of color information (low intensity of marker lanes) and nonuniform brightening, their performances degrade during dark situations. The authors of [14] have described in their study that the detection of nighttime road lanes is a challenging task. Various dynamic and robust techniques were developed; however, there are still some

Figure 2: Algorithm failed at nighttime [3].

limitations in road lanes' detection at nighttime. Most of the works have been done for the detection of road-painted lines against a limited environment. However, there are some environmental factors like sunlit, unclear, showery, shadowy, and inside tunnel conditions, which make the stud detection a challenging task.

Therefore, the authors of [15] have used a data mining technique that initially categorized the visual presence of road lanes under various lighting environments, which was based on the physical and optical assets. Then, the data mining technique was employed on driving dataset containing different videos under natural conditions. This approach was validated against various environmental conditions such as sunny, fogy, shadow cloudy, and rainy conditions. However, this approach did not consider the tracking of road lanes at nighttime because the road lanes are not visible while snowing and at nighttime. Likewise, the authors of [16] have presented a novel painted lane detection approach at nighttime. This technique utilized an 8-directional Sobel operator and thresholding division dependent on OTSU in order to deal with crude path pictures taken from an advanced CCD camera. They utilized Hough transform to get the highlight boundaries. However, the performance of this work fails against the detection of road lanes at nighttime. Moreover, at nighttime, street lights are required for the visibility of road lanes; however, this method also misses painted lanes because of the dark.

On the other hand, Shenoy and Sonkusle [17] have utilized four various techniques against different scenarios for the detection of lanes. In this approach, they employed the correction of adaptive gamma using dark images, while inverse perspective mapping is utilized coupled with the calibration of the camera. Moreover, they used the Kalman operator, which plays a significant role in lane detection against the dark condition. However, the detection of road lanes is missed in the dark time because the street lights on the road are required for the visibility of road lanes in the dark. A vision-based approach was proposed by [18] for lane detection against daytime and nighttime, respectively. For lane detection, the flow of traffic and situations of the road surface against urban and highways are assessed. They utilized Hough transform in order to detect the lanes. However, they did not achieve the best performance against daytime and nighttime because of limited resources' utilization.

A state-of-the-art method was developed by [19] for lane detection against a fog environment. They utilized various images captured via a vehicle-fixed colorless polarization camera under dense fog, dark, and bright conditions. Hough transform and Canny edge operators are employed for lane detection. However, they utilized a lighting resource in order to enhance the dark images, which is one of the heuristic techniques that might not be utilized in the real domain. Similarly, the authors of [8] proposed a network for lane mixer for six lanes detection, respectively. They extracted local features from the LIDAR point cloud and categorized global features to detect the lanes. They utilized publicly available datasets which were recorded against various environmental conditions. However, this system cannot be used in real domains due to the usage of a fixed camera. Also, this approach cannot detect the studs, which is one of the main limitations of this work. On the other hand, an end-to-end framework based on deep learning and rowwise recognition was designed by [20] for efficient lane detection. This framework is accompanied by a false positive suppression technique and a curve fitting method in order to improve the accuracy, which also showed a significant efficiency against the existing works. However, this framework did not consider real-world domain and stud detection in their study.

A fast framework was proposed by [21] for lane detection, which was working under the speed of 50 frames per second. This framework has the ability to tackle a variable number of lanes and manage lane variations. However, the performance of this framework degrades under dynamic domains and also does not consider stud detection. Furthermore, an adaptive learning technique was developed by [22], which automatically learns the features from various lanes against different scenarios. Also, they developed a technique for the automatic generation of lane label frames in a simple setting to expand the training efficacy, which delivers label information for the training of the first-step network. Furthermore, an adaptive Canny operator-based method was used to locate the detected lane detected at the first stage of the model. However, most of these systems did not consider stud detection in their respective approaches, which is one of the major shortcomings of the existing works.

Therefore, this research work presents a pioneer road stud detection technique for intelligent vehicles at nighttime. For tracking road studs at nighttime, we attached the camera at the front of the vehicle with a resolution of 960×540 and moved the vehicle at nighttime. The normal speed of the vehicle was 70 to 100/km per hour, and we captured N frames from the moving vehicle of road studs at nighttime. So, for stud detection, we used our own dataset because we are using an advanced detection approach and the dataset is not available.

3. Stud Detection Concept

Image processing methods have been used for road stud detection at nighttime. The proposed work consists of five steps, Input Image, ROI, Canny Edge Detection, Hough Transform, and reconversion to the original image. The procedure of the road stud detection process is shown in

Figure 3. The diagram block has been exclusively described in the following.

3.1. Input Image.

In the first step, we take the original RGB-based image as an input frame from our own dataset as shown in Figure 4.

3.2. Sharpening via Butterworth Low-Pass Filter.

Butterworth low-pass filter [23] is one of the famous sharpening methods, which is known as filter order. For high parameter values, the Butterworth algorithms are the ideal operators, while for lower parameter values, it has a smoothing capability, the same as the Gaussian operator. Hence, the Butterworth might be observed as a conversion amongst the two extremes. Moreover, this approach does not have a sharp disjointedness creating a clear cutoff amongst passed and processed frequencies. The transition function of this approach against a low-pass filter having γ orders and cutoff frequency at a distance D_{ist} from the origin is given as

$$B(i, j) = \frac{1}{1 + [D_{ist}(i, j)/D_{ist}]^{2c}}, \tag{1}$$

where $D_{ist}(i, j)$ is explained as follows:

$$D_{ist}(i, j) = \left[\left(i - \frac{C}{2} \right)^2 + \left(i - \frac{\gamma}{2} \right)^{2c} \right]. \tag{2}$$

3.3. Region of Interest.

In this step, the region of interest (ROI) has been extracted from the original image, which is based on the combination of similar pixels in the image. The pixels are indicated in the form of rows and columns that are further described in array form, where the rows are represented by m, while columns are present by n, respectively. In this step, we are dealing with the two-dimensional array of an image as shown in Figure 5.

To traverse the ROI in the image, we executed the frame in a graph, which contains the x-axis and y-axis that are accordingly represented by n and m. In our experiments, for left lanes studs traversing, we set $n = 700$ and $m = 350$, and for right lanes traversing, we set $n = 700$ and $m = 350$. By this way, the vanishing point of the road studs has been traversed with the help of left and right lanes of studs at the end of the images that looks like a triangle in the corresponding image. For such a vanishing point, we set the $n = 230$ and $m = 650$, respectively. The resultant ROI on the road studs at nighttime is shown in Figure 6.

3.4. Canny Edge Detection.

For edge detection, many scholars have used the ideal edge detector known as the Canny algorithm [24]. The goal of the Canny edge detector is to identify the boundaries of objects in an image.

In this step, the Canny edge detection has been employed on the corresponding ROI. We utilized the Canny edge detector technique in order to find out the variations in intensities and colors in the ROIs in the form of finding the edges. Moreover, we extracted the entire information of the frame in lines and circles due to which the desired ROI (like road studs) detection becomes easy as shown in Figure 7.

Moreover, the Canny algorithm is very significant and does not miss the borders of the image made by small points. It also has a decent localization nature of boundary points. This algorithm tracks down the image gradient to enlighten the domain along with high spatial derivatives. Then, the Canny procedure is applied to these areas and smoothes the entire pixels, which are not at the most extreme (nonmaximal destruction). The gradient array is additionally decreased by hysteresis. Hysteresis is utilized to follow the leftover points that are not repressed. Hysteresis utilized two values, low threshold and high threshold, which are, respectively, 50 and 150 for our experiments.

3.5. Hough Transform.

The Hough transform is one of the foremost methods for lane detection due to its robustness to noise and obstruction in lines. For stud detection, we utilized this algorithm with a limited search space that looks for lines involving the following equation:

$$p = x\cos\theta + y\sin\theta. \tag{3}$$

In Hough's transform, the line is transformed from its traditional formula such as

$$y = mx + b. \tag{4}$$

The transformed formula is

$$\rho = x\cos(\vartheta) + y\sin(\vartheta), \tag{5}$$

where ρ is the perpendicular distance from the origin to the line and ϑ is the respective angle between the perpendicular line and horizontal axis as shown in Figure 8.

By utilizing the previous equations, we can terminate any external and unwanted line. For instance, a horizontal line is presumably not the lane border of the stud that might be terminated. For every side, the constrained Hough transform was altered to restrict the find the space till 45° angle. Similarly, the input frame is separated in half, yielding a left and right half of the image. The left and right sides are seen independently returning the most prevailing line in the half image that falls within the angle of 45° window. The skyline is essentially determined, utilizing the right and left Hough lines and extending them to their convergence. The horizontal line at this union is introduced as the skyline.

3.6. Stud Detection.

When we utilize the Hough transform, we are capable of successfully detecting the road studs at nighttime as shown in Figure 9.

Our proposed approach justifies that the stud detection is better than road-painted lanes at nighttime because studs have higher intensities in the dark environment, which can easily be detected in a long distance compared to road-painted lanes.
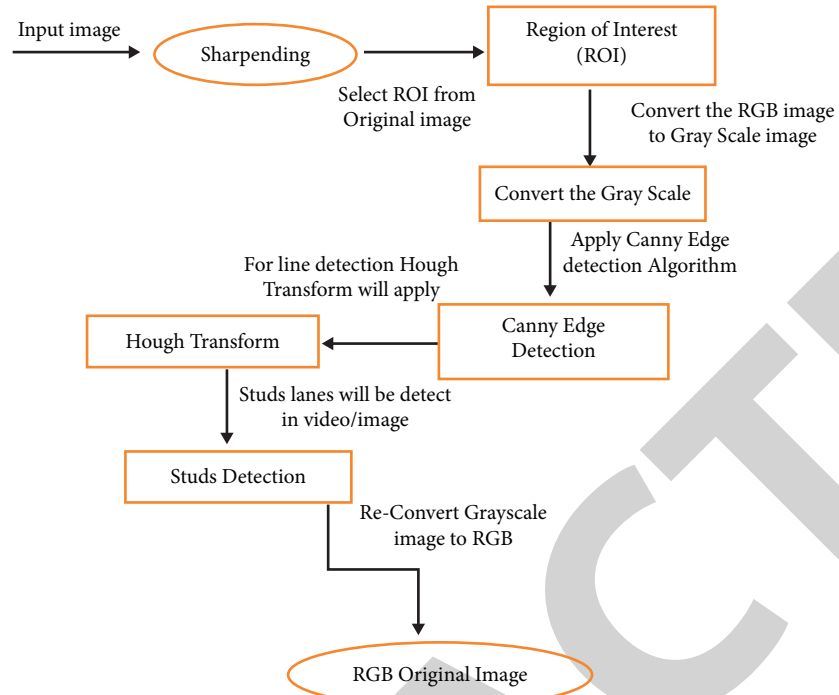
FIGURE 3: The flow of road stud detection method.

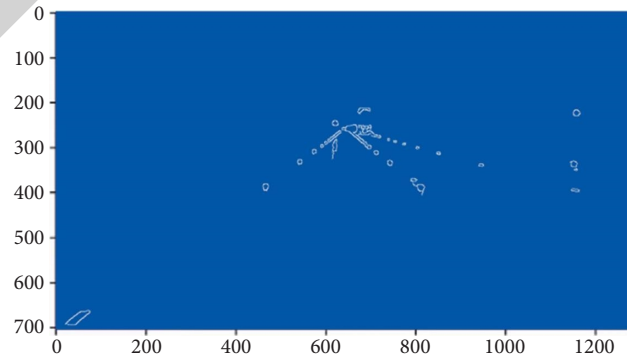FIGURE 4: The flow of road stud detection method.

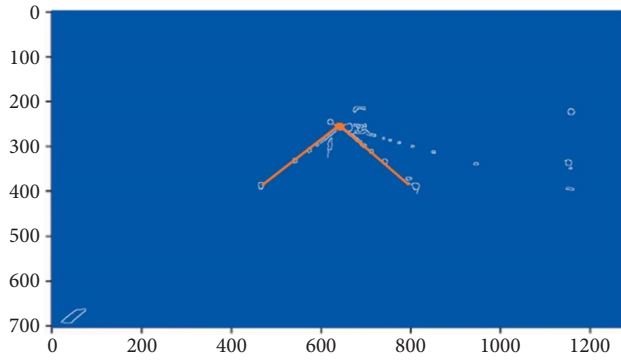FIGURE 5: Selection of ROI from the original image.
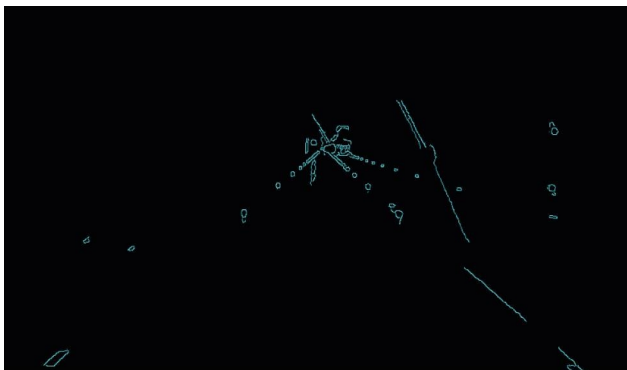
Figure 6: Left and right lanes of studs.

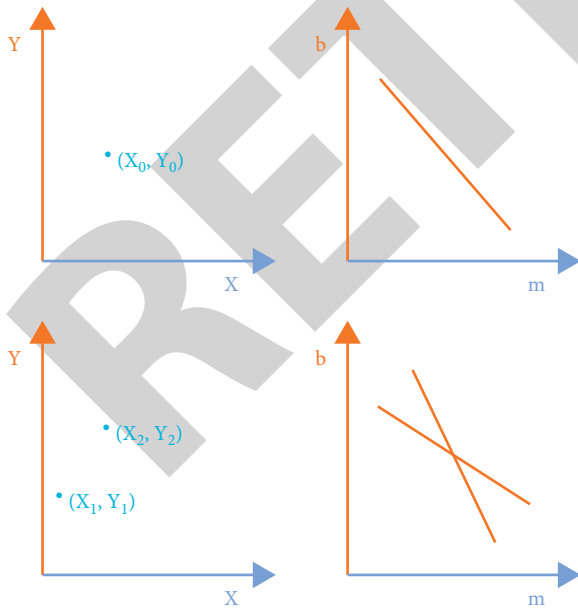Figure 7: Left and right lanes of studs.

Figure 8: Selection of the lines using line equation as in equation (4).

Figure 9: The detected studs.

4. Algorithm Evaluation

The proposed algorithm has been evaluated in the following way.

4.1. Dataset Preparation. For stud detection, we have built our own dataset rather than collecting it from the Internet in order to present the significant performance of the proposed algorithm in real scenarios. A detailed description of the utilized dataset is given as follows:

(i) To record the data, we have fixed the Canon camera with the specification of 60D Mark II at the front of the Vitz Car 2010. In the initial step, we have recorded the videos against moving vehicle scenarios on the road at nighttime.

(ii) During the data collection, the vehicle was moving, which traveled approximately 6 to 7 kilometers under the speed of 70 to 100 kph.

(iii) The average length for the recorded videos was 5 minutes and 23 seconds, and we considered the comprehensive number of frames for the detection of road studs.

(iv) All the dataset was collected at nighttime which is one of the major shortcomings of the previous works.

(v) In the recorded dataset, every frame was of size 960 × 540.

4.2. Experiments Arrangements. The proposed stud's detection algorithm is implemented in Python with OpenCV library [25] on Window 10 operating system, using hardware of Core i3 system, Processor 1.8 GHz, and 6 GB RAM. The processing time of stud detection is 0.0233 per second. The entire experiments are performed in the following order to show the efficacy of the proposed algorithm:

(i) First, we took an RGB-based input image from the collected dataset

FIGURE 10: Conversion of RGB image to grayscale: (a) original image and (b) converted grayscale image.

(ii) In the second step, we converted the original RGB image to a grayscale image

(iii) In the third step, the Canny edge detection algorithm has been employed on the grayscale image to get the image boundaries, through which we can extract the entire information of the image

(iv) Finally, in the fourth step, we selected ROI in the image using the Hough transform algorithm

4.3. Results. In the first step, we took the original RGB images and then converted them into grayscale levels. The reason for conversion is to improve the efficiency of the proposed approach. The sample images are represented in Figure 10.

In the next step, the noise has been removed from the grayscale image. We blurred the image using Gaussian Blur. Image blurring is done by convolving the image with a low-pass filter kernel. It is useful for removing noises. We selected the value 5 for the kernel size. The sample image is presented in Figure 11.

In the third step, we utilized the Canny edge detection. First, the original image was, respectively, processed in horizontal and vertical directions in order to determine every pixel's gradient. Once we achieve both magnitude and directions, unnecessary pixels are diminished by employing a complete scanning on the corresponding image that might not establish the edges. For such a scenario, the pixel has been checked at every location, whether it is a local maximum in its surrounding. Therefore, after various experiments, we kept the low threshold value 30 and high threshold value 170 for the Canny edge detection. The sample image is shown in Figure 12.

As we already described before, the road studs are marked as the region of interest, which can be seen as road lanes in the image and selected as the edge detected in the image. Initially, we took the resolution of the image, and then we generated corners of the trapezoid that have four corners. In the next step, we produced the trapezoid by the above vertices, and lastly, the bitwise operation has employed. Therefore, the individual pixels that are inside the ROI are categorized as edge and marked as one. The sample result is presented in Figure 13.

Finally, in the last step, we used the Hough line transform in order to detect the studs line in the image. A road stud edges might be of a circular shape, but in our case, we

FIGURE 11: Noise removal from the grayscale image.

FIGURE 12: Sample image for the Canny edge detection algorithm.

are considering the detection of road studs. The Hough transform technique produces a line from its traditional $y = mx + b$ method to $\rho = x * \cos(\theta) + y * \sin(\theta)$, where ρ is the perpendicular distance from the origin to the line and θ is the angle formed by this perpendicular line and horizontal axis. The sample result is presented in Figure 14.

4.4. Discussion. Besides our experimental result, road studs have more visibility and intensity during the dark time or at nighttime, which can be easily detected compared to road-painted or marker lane lines. The road studs can be seen in the structure of road lanes such as lines on the road, and tracking of studs is better in the dark as well as in the far distance. Our testing result shows that at nighttime road stud tracking is accurate for intelligent vehicles as compared to
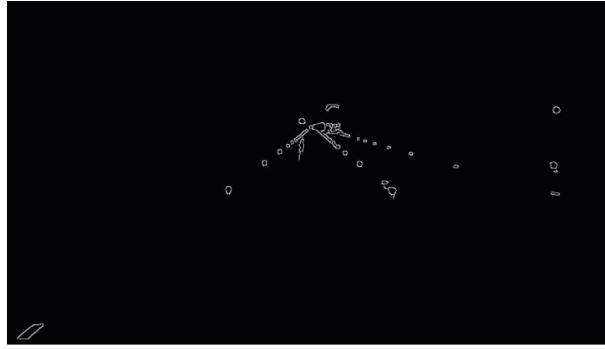
Figure 13: Canny edge detection with the threshold value.

Figure 14: The stud detection result of the proposed approach after employing the Hough transform.

Figure 15: Sample results of the proposed stud detection algorithm before and after preprocessing.

road-painted lanes because of their higher intensity and visibility in the dark time. As the front headlight of the vehicle lays on the studs, the studs become more relaxed with extreme focus and can be effectively followed in the far distance in the evening. For stud detection, our collected dataset was utilized, which was recorded from the moving vehicle on the real domain at nighttime. To show the performance and ability of the proposed approach, we execute some sample images of the experimental results in Figure 15.

Moreover, we also generated the histogram for testing the stud intensity. First, we took the original image as an input image and then converted it to grayscale. The grayscale
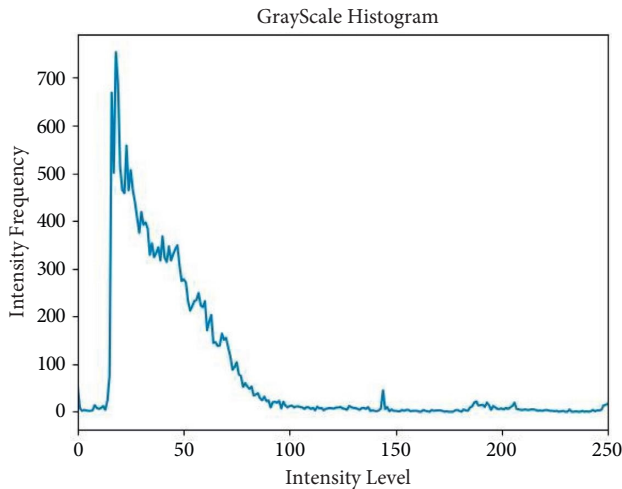
FIGURE 16: Stud intensities presented in the form of histogram.

image has been processed for the generation of histogram as shown in Figure 16.

5. Conclusion

For smart vehicles, the detection of road studs is a fascinating and challenging research against nighttime because of less visibility of lanes marker on roads. In this work, we have proposed a robust method for the detection of studs against nighttime. First, we utilized the Butterworth low-pass filter in order to sharpen the images. Then, the conventional Canny edge detector and Hough transform (HT) were employed in order to detect the road studs at nighttime in an image. This research designs a robust approach for the detection of road studs at nighttime, which is the combination of various statistical methods. We successfully detected the road studs in images. The proposed work has been implemented in Python using the OpenCV library. The results signify that the road studs have a higher intensity than road-painted lanes at nighttime and can help to easily recognize the studs.

The proposed research work is missing the detection of stud lanes in the presence of front headlights of the vehicles coming in the opposite direction. This concern might affect the stud detection accuracy of the proposed approach. In the future, we will detect the road studs at real-time nighttime for intelligent vehicles in the presence of the opposite headlights. Therefore, we will also enhance the proposed approach to improve the performance against various road environments such as rainy, day, fogy, snowy, and inside tunnel conditions based on road studs. Another future direction for this work is the detection of road studs based on live video streaming.

Data Availability

The data utilized in order to support the discoveries of this work are described in the paper and will be offered from the corresponding author upon request.

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