



## Speed-bump Detection using Otsu's Algorithm and Morphological Operation

C. Nelson Kennedy Babu<sup>1</sup>, W. Deva Priya<sup>2</sup>, T. Srihari<sup>3</sup> and R. Nandakumar<sup>4</sup>

<sup>1</sup>Professor, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India.

<sup>2</sup>Associate Professor, Department of Electronics and Communication Engineering, K S R Institute for Engineering and Technology Tiruchengode, Tamilnadu, India.

<sup>3</sup>Professor, Department of Electrical and Electronics Engineering, K S R Institute for Engineering and Technology Tiruchengode, Tamilnadu, India.

<sup>4</sup>Professor, Department of Electronics and Communication Engineering, K S R Institute for Engineering and Technology Tiruchengode, Tamilnadu, India.

(Corresponding author: T. Srihari)

(Received 23 March 2020, Revised 19 May 2020, Accepted 22 May 2020)

(Published by Research Trend, Website: [www.researchtrend.net](http://www.researchtrend.net))

**ABSTRACT:** Driver Assistance System (DAS) is one of the most mandatory subsystems of Intelligent Transport System (ITS). Speed Bump Detection (SBD) is a subset of DAS that supports the driver to recognise the presence of speed bump and alert the driver. Under the critical condition, it has to operate on the vehicle directly for safety. In the research work, two methods of Speed Bump Detection have proposed (i) Otsu's threshold method and (ii) Morphological Operation method. These methods are superior to the existing methods because it does not involve any network, so it is free from GPS error, network overload, delay and false alarm. It also detects the speed bump with low projected where the existing method using sensors fails. The proposed Otsu's method is straight forward, efficient and gives 74.6% accuracy for all types of road condition. The performance of Morphological or structural operation method achieves better result 85.8 % detection ratio. The two proposed methods give more than 90 % detection ratio for properly painted road and optical illusion type speed bump.

**Keywords:** Advanced Driver Assistance System, Image Processing, Morphological operation, Otsu's Algorithm, Speed-bump Detection.

**Abbreviations:** A DAS, Advanced Driver Assistance System; VELD, VisLab Embedded Lane Detector; LiDARs, Light Detection and Ranging; OBD, On-board diagnostics; ROI, Region of Interest; SVM, Support Vector Machine; RGB, Red Green Blue; GPS, Global Positioning System; GSM, Global System for Mobile Communications.

### I. INTRODUCTION

Speed-bump detection is essential because many accidents are happening due to the sudden intrusion of a speed-bump. An un-notified speed-bump on high speed is harmful to patients in transit like pregnant women [11–12]. It also leads to rapid wear and tear of tyres and even causes damages to the vehicle. The proposed system provides alert to the driver in advance about the presence of a speed-bump or provides signals to the system to work immediately to reduce the vehicle speed.

Speed breakers are built in places like accident-prone locations, sharp curves, congested residential streets, unmanned level crossings where control of speed become necessary to avoid accidents. The speed bumps are formed with various physical identities such as height, length, length of ramps etc. However, in India, it is not the case.

Challenges faced by existing systems are mobile Battery drain out as well as heat due to continuous usage of GPS. GPS error, Network overload and delay have a massive impact on real-time implementation. Involvement of more number of sensor, Processing time and the false Vibration patterns are the difficulties faced by the earlier research work.

### II. LITERATURE EXPLORATION

#### A. Speed-bump Detected using Sensor and Meter

Bret Hull *et al.*, [3] used CarTel - a mobile sensor computing system intended to gather, process, deliver, and visualise sensors data which is a part of mobile units. A CarTel is a mobile embedded processor linked with a collection of sensors. At each node, sensor readings are collected and processed locally before distributing them to a central portal, where the data stored for further analysis and visualisation. The automotive framework includes a variety of onboard and external sensors to collect data. The CarTel had been deployed on six cars, running in Boston and Seattle. It has been used mainly to analyse commute times, analyse metropolitan Wi-Fi distributions, and for automotive diagnostics. The drawback of CarTel is that they do not offer privacy.

Choi, *et al.*, [25] develop an environment-detection and-mapping algorithm for autonomous driving for both rural and off-road real-time environments. Environment-detection-and-mapping algorithms include two parts, (1) using cameras, pedestrian crossing detection, lane detection, and speed-bump detection is implemented, and (2) using LiDARs obstacle on the road was detected. VisLab Embedded Lane Detector (VELD) and a camera are used for lane detection algorithm which returns the lane location. The position of pedestrian

crossings and speed-bumps are detected using the pedestrian crossing and speed-bump detection algorithms. The obstacle detection algorithm gets data from LiDARs. For the research purpose, a passenger car is designed with six LiDARs, three cameras, and personal computers. The algorithm mainly focuses on local obstacle map instead of using a global map for more accurate vehicle locating. From the collected information, the risk map and obstacle map is created by the model-based filter, which help the road users to know about the obstacles across the road.

Yun [24] used a camera and lidar for the speed-bump detection method. To locate the exact position of the speed bump, they used two detectors. With the support of image pattern and distance information, the speed bump is detected in the candidate area. The result provides information like the height of the speed bump, speed bump area, etc.

Kwang Ming Lion *et al.* [22] proposed a cost-effective method of speed bumps detection and height estimation by using the Microsoft Kinect Sensor. Canny edge detection is used to detect the edge of the speed bump. The system is not tested on a real-time database. Both Kinetic sensor and camera are used to detect the presence of speed bump

### B. Speed-bump Detected using a smartphone

Mohan, Prashanth, *et al.*, [6] present a system to govern road and traffic conditions. Nericell is a system established to do rich data collection by piggybacking with smartphones that people take with them. They concentrate on the sensing component, which uses the accelerometer, microphone, GSM radio, and GPS sensors in smartphone map the speed-bumps, potholes, honking, and braking. They also address many challenges like the arbitrary orientation of smartphone, honk detection and localisation in an energy-efficient manner. The effectiveness of the sensing functions using Nericell is experimented on the roads of Bangalore and produced significant results. The future scope is to work on different types of vehicles and implementing the application via machine learning to robust honk detection.

Roma Goregaonkar *et al.* [4] emphasis the safety of the driver from the advanced driver assistance system. They used three-axis accelerometer built within an Android-based smartphone to record and analyse the different environmental conditions that affect the health of the driver and the automobile. In real-time, the overall awareness regarding safety is increased for drivers by analysing and alerting about the road difficulties. For accident monitoring purpose, a wireless black box using GPS tracking and GSM module is developed. GPS coordinates system, road condition maps are created via Google Earth. Besides, for a better road anomaly detection system, multiple-axis classification method is introduced, which increase the bump and pothole classification accuracy.

### III. SPEED-BUMP DETECTION

Speed-bump detection is one of the subsystems of ADAS. Speed-bumps are constructed across the road to avoid over speed in the restricted areas. If they are constructed without proper permission, dimension and representation, it leads to accidents. Speed-bump is

classified into two types (i) marking speed-bump (ii) non-marking speed-bump. Fig 1 Shows the Block diagram Speed-bump Detection using image processing.

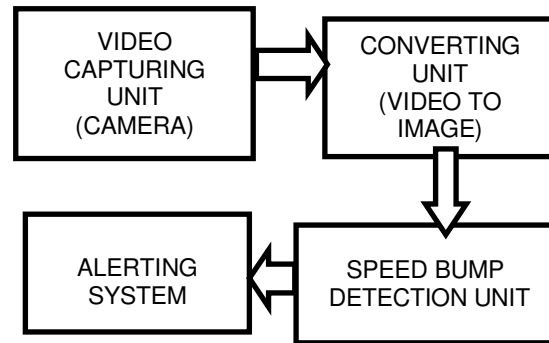


Fig. 1. Block diagram of Speed-bump Detection.

#### A. Speed-bump Detection using Otsu's Thresholding Method (SBD – OTM)

The objective of thresholding is to segregate the region of Interest (ROI) and non-ROI. In speed-bump detection, the ROI is represented by white colour and non-ROI, is represented by black. To convert a multi-valued RGB image into a black and white image, first, it should be converted to grayscale, and then by choosing a proper threshold value, it is converted to a binary image.

The input image is fed to the speed-bump detection stage, as shown in Fig 2. Speed-bump detection includes pre-processing and Otsu's thresholding. Pre-processing contains resizing and converting of RGB image into a grayscale image

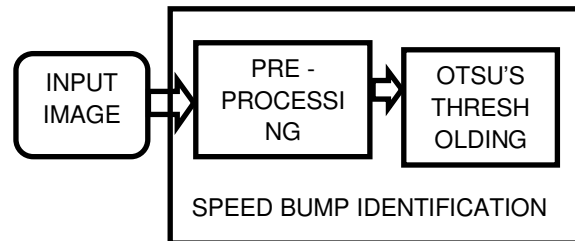


Fig. 2. Block diagram of SBD – OTM.

#### (i) Pre-processing, Resizing, Converting RGB to Gray Scale Image:

Image pre-processing is the methodology to formulate the image before doing the actual computational process. It includes resizing and RGB to grayscale conversion. All the input images are resized to 250×350 size. After resizing, the RGB image is converted to a grayscale image by using three different methods using lightness, average, and luminosity. Luminosity is calculated using the formula given in equation (1)

$$L(x, y) = 0.21R(x, y) + 0.72G(x, y) + 0.07B(x, y) \quad (1)$$

Where R – Red component of the image

G – Green Component of the image

B – Blue component of the image

x, y – position of a pixel.

#### (ii) Otsu's algorithm

Otsu's method converts the grayscale image to a binary image by performing the following steps

Step 1. Read the grayscale image.

Step 2. Compute image histogram.  
 Step 3. Select a threshold value and compute foreground variance and background variance  
 Step 4. Compute within Class variance  $\sigma_w^2$  using the equation (2)

$$\sigma_w^2 = W_b \sigma_b^2 + W_f \sigma_f^2 \quad (2)$$

where  $W_b, W_f$  and  $\sigma_b, \sigma_f$  are the weights and variances of background and foreground.

Step 5. Repeat steps 3 and 4 for different threshold values  $T = 2, 3, 4, \dots$

Step 6. For each Within-class variance choose a threshold value (T)

Step 7. If grayscale pixel value  $> T$ , assign 255 (white) else assign 0 (black)

For the different threshold value,  $T = 2, 3$  and 4 otsu's method is applied. Among these, the threshold value  $T = 2$  gives proper segmentation. This method is suitable only for the roads in good condition. The main advantage of this method is less computation time, but it is suitable only for dust and damage free roads.

### B. Speed-bump Detection using Morphological Operation (SBI-MO)

In the proposed method SBD – MO, the input image is pre-processed to enhance or make the image ready for further processing is shown in Fig 3. The second step is to convert a grayscale image to a binary image. The third process is a morphological operation which helps to identify the speed-bump using opening, area opening and filling operation.

The grayscale image is transformed to black and white image using the threshold concept. The range of threshold value is chosen at a higher value between 190 to 255 because our focus is to separate the white region (255) and the black region(0). If the input image pixel value is above the threshold, the value is replaced as 255 to the corresponding location. For the pixel value below the threshold is replaced with 0 as given in equation (3).

$$\text{If } P(x, y) > 200, \text{ then } Q(x, y) = 255 \quad (3)$$

$$\text{Else } Q(x, y) = 0$$

where  $P(x,y)$  refer the input pixel value at the location  $x,y$

$Q(x,y)$  refer the output pixel value at the location  $x,y$

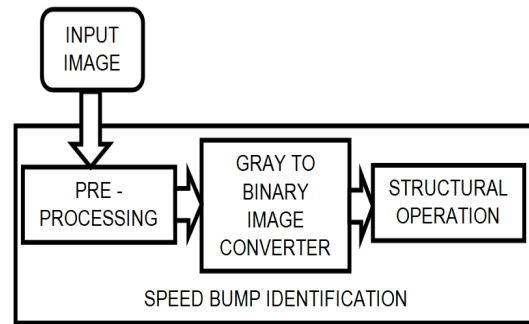


Fig. 3. Speed-bump Detection using Morphological operation

(i) **Structural Operation:** Morphological image processing is a set of operators that transform images according to the size, shape, connectivity using the concept of set theory and other functions. This stage includes the following (a) Opening (b) Area opening (c) Filling.

(a) **Opening:** The opening is a structural operation which performs the erosion operation followed by dilation, as shown in Equation 4. This function helps to remove the region, which is smaller than the structure element B and preserves the wider area region. The shape of the structure element B is considered as 'square' and size as '10' as it gives a better result.

$$A \circ B = (A \ominus B) \oplus B \quad (4)$$

where

A - Input Binary image

B - Structure element

$\circ$  - Opening notation

$\ominus$  - Erosion notation

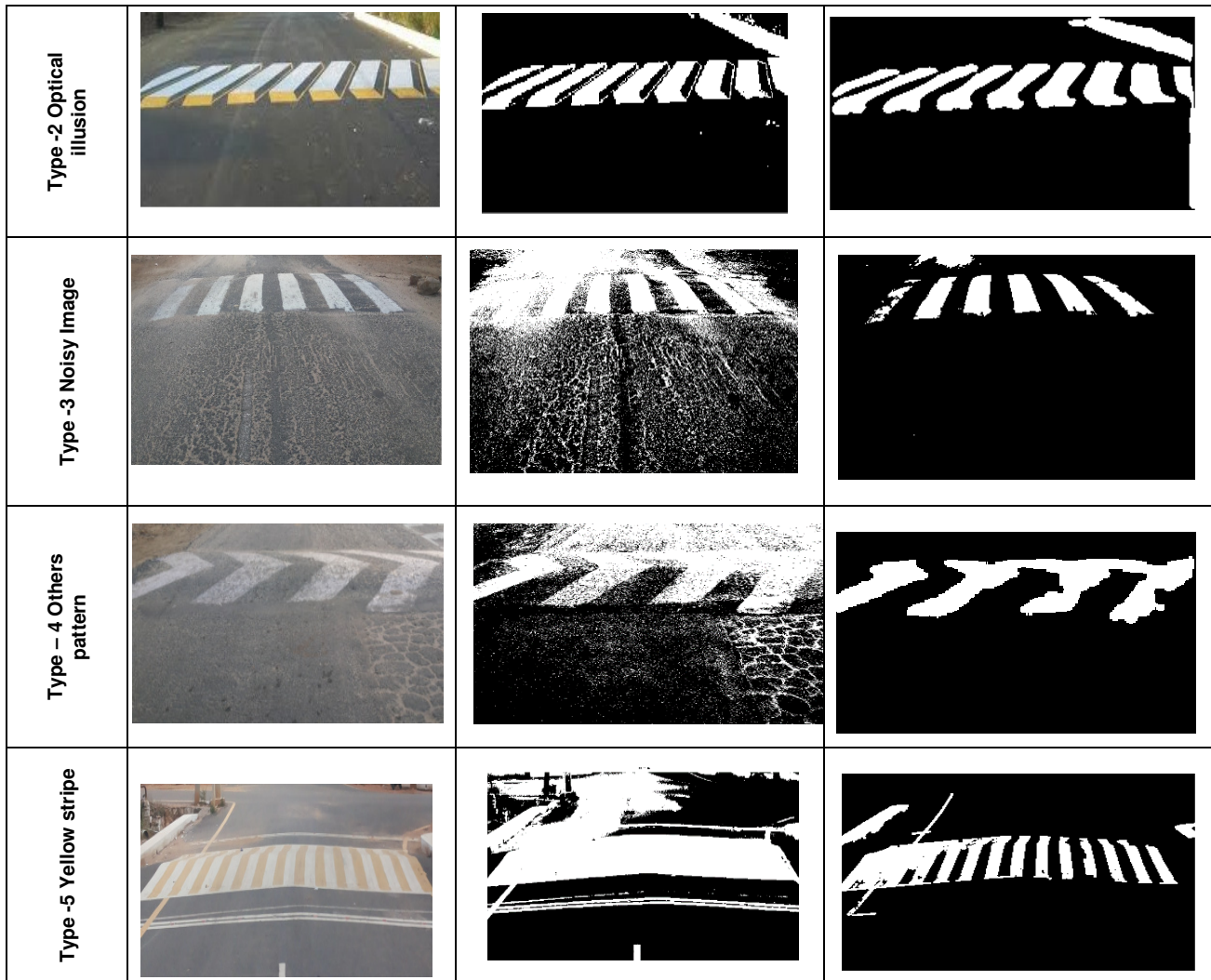
$\oplus$  - Dilation notation

(b) **Area opening:** This stage is a refining process which helps to remove further few noises that are left by opening operation and concentrate on the speed-bump area.

(c) **Filling:** After completing the opening operation, the next stage is filling process. It is a process of filling the gap in the white region of speed-bumps evenly because in real-time, most of the white regions are not perfectly painted.

Table 1: Comparison of Output proposed method.

Types of speed bumps	Input Image	Output Image of SBD-OTM	Output Image of SBD - MO
Type-1 Only White stripe			



#### IV. RESULTS ANALYSIS

Computer vision method, Local neighbourhood and canny edge detection are existing image processing methods. In the above methods, the detection ratio is very less. Detection ratio is the ratio between the number of images correctly detected to the total number of images. In Otsu's thresholding method performance is slightly higher than the local neighbourhood whereas Morphological method has shown a better performance.

The output obtained for various types of images using Otsu's thresholding, Morphological operation is shown in Table 1.

**Table 2: Average Detectionratio Comparison.**

Method	Existing Method			Proposed Method	
	Computer vision	Local neighbour	Canny edge	SBD - OTM	SBD - MO
Average Detection ratio	50%	56%	65%	74.6%	85.8%

Otsu's method is well suited for the Optical illusion type speed-bump and noise-free roads. But it finds difficulty

in differentiating yellow and white colour painting on a speed-bump. Thus the performance of the system is reduced. The morphological operation gives excellent performance for all type of roads. It handles noisy roads easily and yellow type marking to some extent. The Detection ratio of speed-bump using morphological operation is very much improved.

For the analysis purpose, the Speed-bumps are categorised into 5 types, namely Type 1, 2, 3, 4 and Type 5, as shown in Table 2. The most common type of speed-bump is type 1, which contains only white stripes. Type 2 is an 'Optical illusion' which is a 3D illusion of speed-bumps launched to fake the drivers to slow down on roads. This is a future type of speed-bump. Type 3 is a kind of speed-bump similar to type 1 but with a noisy environment. Type 4 includes all the other pattern other than stripes like arrow shape, chessboard shape. Type 5 category has white with yellow marking on them.

For specific speed-bump category, several real-time images are captured in and around Indian roadside the analysis. Table 3 and 4 gives the Detection ratio attained by the two proposed methods. It also contains a total number of samples, the number of speed-bump detected correctly, count of speed-bump missed, and the Success rate in percentage is given for comparison. The variation of speed-bump is seen in terms of their

pattern, colour, length, width and height. In this work, categorisation of speed-bump is done only based on colour and pattern irrespective to their dimensionality.

**Table 3: Detection ratio comparison of various types of speed bumps using Otsu's Thresholding Method (SBD – OTM).**

Image Type	Nature of speed Bump	Total No. of input images	No. of speed bumps detected correctly	No. of speed bumps missed	Detection Ratio %
Type 1	Only White stripe	884	835	49	94.45
Type 2	Optical illusion	50	48	2	96.00
Type 3	Noisy Image	446	307	139	68.83
Type 4	Others pattern	254	134	120	52.76
Type 5	Yellow stripe	214	130	84	60.75

**Table 4: Detection ratio comparison of various types of speed bumps using morphological operation (SBD - MO).**

Image Type	Nature of speed Bump	Total No. of input images	No. of speed bumps detected correctly	No. of speed bumps missed	Detection ratio %
Type 1	Only White stripe	884	852	32	96.38
Type 2	3D	50	49	1	98.00
Type 3	Noisy Image	446	334	112	74.89
Type 4	Others pattern	254	198	56	77.95
Type5	Yellow stripe	214	176	38	82.24

## V. CONCLUSION

In ADAS, Speed-bump Detection is a critical subsystem. In this paper, speed-bump is detected using Otsu's Threshold Method and Morphological operation method. Compare to Otsu's method; the morphological method gives a better result. The above system is suitable for the road which is properly maintained but fails for improperly maintained roads. The method is straightforward to implement and gives the required result in less processing time.

## VI. FUTURE SCOPE

The future scope of the proposed work is to implement the speed bump detection using deep learning & neural network algorithm by increasing the database size. In real-time, the speed-bump detection needs a higher-end processor. Working on unmarked speed-bump is another open research area.

## ACKNOWLEDGEMENTS

Funding not involved in this work.

**Conflict of Interest.** The Author(s) declare(s) that there is no conflict of interest.

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**How to cite this article:** Nelson Kennedy Babu, C., Divya Priya, W., Srihari, T. and Nandakumar, R. (2020). Speed-bump Detection using Otsu's Algorithm and Morphological Operation. *International Journal on Emerging Technologies*, 11(3): 989–994.