



## POTHOLE DETECTION USING DEEP LEARNING

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### ABSTRACT

Techniques for identifying potholes on road surfaces aim at developing strategies for real-time or offline identification of potholes, to support real-time control of a vehicle (for driver assistance or autonomous driving) or offline data collection for road maintenance. For these reasons, research around the world has comprehensively explored strategies for the identification of potholes on roads. This paper starts with a brief review of the field; it classifies developed strategies into several categories. We, then, present our contributions to this field by implementing strategies for automatic identification of potholes. We developed and studied two techniques based on stereo-vision analysis of road environments ahead of the vehicle; we also designed two models for deep-learning-based pothole detection. An experimental

evaluation of those four designed methods is provided, and conclusions are drawn about particular benefits of these methods.

### 1.INTRODUCTION

Distracted driving, speeding or other driver errors are main causes of accidents worldwide; however, bad road conditions are also a significant cause. The condition of a road turns out to be dangerous due to number of reasons such as flooding, rain, damages caused, e.g., by overloaded big vehicles, or poor physical maintenance of the road. Road condition assessment involves identifying and analyzing distinct types of road surface distress, like potholes, cracks or texture changes as being maintenancerelevant features. Macro-scale road features are defined by being of traffic relevance. For example, speed bumps are also traffic-relevant features; they also require detection for driver assistance. A pothole is a special case of road distress. It can be an arbitrarily shaped structural defect



of a road, and a precise identification of its “border” is typically impossible. They can be vaguely outlined, but their maximum depth can be identified more precisely. Objects such as cars, persons, cyclists, dogs or cats are of specifically defined shapes (and now detected by deep learning due to appearance properties); compared to this, we can certainly claim that the detection of a pothole, being of arbitrary shape and of complex geometric structure, is a challenging object-detection task. Potholes present a grave danger to human life. As there is no online benchmark dataset available for pothole detection, we accumulated data from multiple sources, and suggest to use those five different datasets, recorded under different weather conditions, for future discussions of progress in this field of pothole detection. Contributions of this study are two different approaches of pothole detection based either on 3D scene reconstruction or on state-of-the-art deep learning techniques. The proposed strategies allow us identifications of potholes. This paper provides at first a review on techniques for pothole identification, extending brief notes on related literature in those previous conference papers.

This paper also presents (with additional material) the three previously published

methods, 2 adds one more method, and provides a comparative evaluation of all four methods. For this evaluation, we use here (first time) a more diverse set of data. Contributions of this study are two different approaches of pothole detection based either on 3D scene reconstruction or on state-of-the-art deep learning techniques. The proposed strategies allow us identifications of potholes from a distance in an accurate manner as supported by experiments. Evaluated experiments demonstrate that state-of-the-art deep learning based methods significantly outperform the conventional 3D scene reconstruction-based methods. Extensive research has been carried out for macro-scale road issues, such as for estimating the road surface (also known as road manifold estimation), detection of obstacles that are protruding from the road, recognition of traffic isles, or pothole detection. Automotive companies such as Tesla, Toyota, Ford, or BMW announced to be able to deliver autonomous cars by about 2020.. This type of systems enhances civic engagements by government, and facilitates the participation by citizens of the country. These systems use the public as sensors. The main advantage of this method is that there is no need for costly hardware or software. Citizens can report a pothole by capturing its

picture with their mobile devices and later by uploading or sending to a website or application, or by merely sending information about a pothole's location.

## 1.1APPLICATIONS

**Vibration-Based Methods** Vibration-based methods include approaches of collecting abnormal vibrations caused in the vehicles while driving over road anomalies. Vibrations of the vehicle are collected using an accelerometer; see Table II. The main drawback of the vibrationbased methods is that the vehicle has to drive over the pothole in order to measure the vibrations caused by the pothole on the road. Ghadge et al Used an accelerometer and GPS to analyze the conditions of roads to detect locations of potholes and bumps using a machine learning approach, defined by K- 3 means clustering on training data and a random-forest classifier for testing data.

The data is divided first into two clusters of “pothole” or “non-pothole”, and then a random forest classifier is used to validate the proposed result provided by the clustering algorithm. It is reported that clustering does not perform well when clusters of different size and severity are involved; size and severity of a pothole are

the major properties considered in the system.

### **Seraj et al.**

Used a support vector machine (SVM) for a machine-learning approach to classify road anomalies. The proposed system uses accelerometer, gyroscope and a Samsung galaxy as sensors for data collection; data labeling is performed manually (by a human) and then a high-pass filter is used to remove the low-frequency components caused due to turns and accelerations. Ren et al. used K-means clustering to detect potholes based on data collected by using an accelerometer and GPS. The proposed system lacks accuracy regarding the isolation of potholes from other road anomalies.

### **2D-Vision-Based Methods**

Vision-based methods use 2-dimensional (2D) image or video data, captured using a digital camera, and process this data using 2D images or video processing techniques.

The choice of the applied image processing techniques is highly dependent on the application for which 2D images are being processed.

### **Koch and Brilakis**

Proposed a method aiming at a separation of defect and non-defect regions in an image using histogram shape based threshold. The authors consider the shape of a pothole as being approximately elliptical based on a perspective view. The authors emphasize on using machine learning in future work, and claim that the proposed work already results in 86% Accuracy along with 86% Recall and 82% Precision, with the common definitions of

$$\begin{aligned} \text{Precision} &= \frac{TP}{TP + FP} \\ \text{Recall} &= \frac{TP}{TP + FN} \\ \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\ F1 &= 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \end{aligned}$$

(4) Where TP is the number of true positives, FP of false positives, TN of true negatives, and FN of false negatives.

## 1.2 PROBLEM DISCUSSION

**Data Collection:** Gathering a large and diverse dataset of pothole images representing various lighting conditions, road surfaces, and pothole sizes and severities is crucial for training deep learning models effectively.

**Accuracy and Robustness:** Ensuring the accuracy and robustness of pothole detection algorithms under various lighting conditions, road surfaces, and weather conditions is essential for reliable performance.

**Integration:** Integrating pothole detection systems into existing road infrastructure and traffic management systems requires careful consideration of communication protocols, data exchange standards, and compatibility with existing systems.

**Algorithm Development:** Developing more sophisticated deep learning algorithms that can identify and classify potholes with even higher accuracy, taking into account factors like pothole shape, texture, and surrounding road surface context.

**Multimodal Sensor Fusion:** Exploring multimodal sensor fusion techniques to combine image, video, and lidar data for comprehensive pothole detection. This approach can potentially address limitations of individual sensors and improve detection accuracy in challenging conditions.

**Pothole Depth Estimation:** Developing real-time pothole depth estimation using deep learning models to provide additional information for road maintenance

prioritization. Pothole depth is an important factor in determining the severity of the hazard and the urgency of repair.

### **Autonomous Vehicle Integration:**

Integrating pothole detection systems with autonomous vehicles for proactive road hazard avoidance. This can contribute to safer and more efficient autonomous driving by enabling vehicles to anticipate and react to potholes in real time.

## **2.LITERATURE SURVEY**

### **2.1. Public Reporting**

This type of systems enhances civic engagements by government, and facilitates the participation by citizens of the country. These systems use the public as sensors. The main advantage of this method is that there is no need for costly hardware or software. Citizens can report a pothole by capturing its picture with their mobile devices and later by uploading or sending to a website or application, or by merely sending information about a pothole's location.

#### **2.1.1. Tedeschi and Benedetto**

Recently suggested a system for automatic pavement distress recognition (ADPR) which is able to perform in real time by identifying road distress including fatigue

cracks, longitudinal and traversal cracks, and potholes. The authors used a combination of technologies of the OpenCV library and for the classification of the three different types of road distresses, three classifiers have been used based on local binary pattern (LBP) features; they achieved more than 70% for Precision, Recall, and the F1-measure. Authors discussed difficulties of defining the severity of considered kinds of road distresses. For texture classification the authors used Haralick's features based on gray level co-occurrence matrices (GLCMs) and then classified image regions using a tool from.

#### **2.1.2. Ryu et al**

Proposed a method to detect potholes both for asphalt or concrete road surfaces using 2D images collected by a mounted optical device on a survey vehicle. The system mainly works in three steps of image segmentation, candidate region extraction and decision. The system fails to detect potholes in darker images (image regions) due to shadows (e.g. of trees or cars) present in real-world road recordings. Powell and Satheesh kumar present a method for the detection of potholes by segmenting images into defected or non-defected regions. 7 After extracting the texture information from

defected regions, this texture information is compared with texture information obtained from non-defected regions. The proposed system considers shadow effects on the road and aims to remove those effects of shadows using a shadow removal algorithm.

The system is unable to perform in rainy weather. The authors concluded that the system should be further extended to perform also on video data as the system was only tested on 2D images collected using an iPhone camera with 5 megapixel image resolution.

## 2.2. 3D Scene Reconstruction-Based Methods

3D scene reconstruction is the method of capturing the shape, depth, and appearance of objects in the real world; it relies on 3D surface reconstruction which typically demands more computations than 2D vision. Rendering of surface elevations helps to understand accuracy during the design of 3D vision systems. 3D scene reconstruction can be based on using various types of sensors, such as Kinect stereovision cameras, or a 3D laser. Kinect sensors are mainly used in fields of (indoor) robotics or gaming. 3D lasers define an advanced road-survey technology; compared to camera-based systems it still comes with higher costs;

report survey cycles of (usually) once in four years. A 3D laser uses a laser source to illuminate the surface and a scan camera for capturing the created light patterns. Applied the common laser-line projection; the recorded laser line deforms when it strikes an obstacle (and supports thus the 3D reconstruction), but does not work well, e.g., on wet roads or potholes filled with water. Stereo-vision cameras are considered to be cost-effective as compared to other sensors

## 3. SYSTEM DESIGN

System design is transition from a user oriented document to programmers or data base personnel. The design is a solution, how to approach to the creation of a new system. This is composed of several steps. It provides the understanding and procedural details necessary for implementing the system recommended in the feasibility study. Designing goes through logical and physical stages of development, logical design reviews the present physical system, prepare input and output specification, details of implementation plan and prepare a logical design walkthrough. The database tables are designed by analyzing functions involved in the system and format of the fields is also designed. The fields in the database tables should define their role in

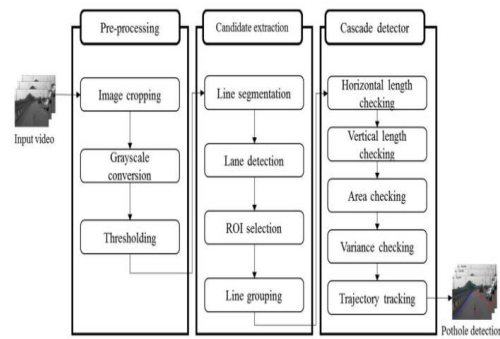
the system. The unnecessary fields should be avoided because it affects the storage areas of the system. Then in the input and output screen design, the design should be made user friendly. The menu should be precise and compact.

## SOFTWARE DESIGN

In designing the software following principles are followed:

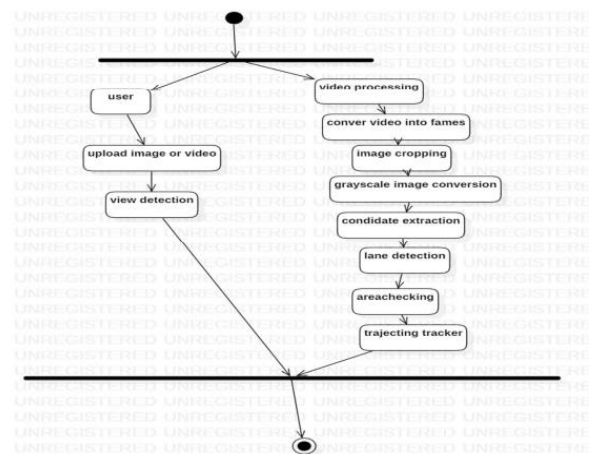
1. **Modularity and partitioning:** software is designed such that, each system should consists of hierarchy of modules and serve to partition into separate function.
2. **Coupling:** modules should have little dependence on other modules of a system.
3. **Cohesion:** modules should carry out in a single processing function.
4. **Shared use:** avoid duplication by allowing a single module be called by other that need the function it provide.

### 3.1 SYSTEM ARCHITECTURE:



System Architecture

**3.2 ACTIVITY DIAGRAM:** Activity diagrams are graphical representations of Workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



Activity Diagram

## 4. OUTPUT SCREEN

```

C:\Windows\System32\cmd.exe
! synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
np.uint8 = np.dtype([('uint8', np.uint8, 1)])
C:\Users\krant\AppData\Local\Programs\Python\Python7110\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:543: FutureWarning: Passing (type, 1) synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
np.uint16 = np.dtype([('uint16', np.uint16, 1)])
C:\Users\krant\AppData\Local\Programs\Python\Python7110\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:544: FutureWarning: Passing (type, 1) synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
np.uint32 = np.dtype([('uint32', np.uint32, 1)])
C:\Users\krant\AppData\Local\Programs\Python\Python7110\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545: FutureWarning: Passing (type, 1) synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
np.resource = np.dtype([('resource', np.dtype, 1)])
2020-03-09 17:13:14.617721: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this TensorFlow binary was not compiled to support: AVX512
WARNING:tensorflow: From C:\Users\krant\AppData\Local\Programs\Python\Python7110\site-packages\keras\backend\tensorflow_backend.py:4876: The name tf.nn.conv2d is deprecated. Please use tf.nn.conv2d instead.
WARNING:tensorflow: From E:\potholes-detection-master\potholes-detection-master\backend.py:43: The name tf.space_to_depth is deprecated. Please use tf.nn.space_to_depth instead.
(13, 13)
Node: 'Model_2'
-----
Layer (type)                   Output Shape         Param #         Connected to
-----
input_1 (InputLayer)          (None, 416, 416, 3)  0
-----
model_0 (Model)               (None, 13, 13, 1624) 5854708         input_1[0][0]
-----
detection_layer (Conv2D)      (None, 13, 13, 38)  38758          model_1[1][0]
-----
reshape_1 (Reshape)          (None, 13, 13, 5, 0) 0
-----
input_2 (InputLayer)         (None, 1, 1, 1, 38, 8)
-----
lambda_2 (Lambda)            (None, 13, 13, 5, 0) 0
-----
Total params: 58,578,686
Trainable params: 38,758,814
Non-trainable params: 20,819
  
```

Screen 1: loading for detect pothole

The script is loading a pre-trained model to detect potholes and then running it on the video.



Screen 2: image detection

The image shows a pothole on a wet road is detected. The pothole is large and deep, and it is filled with water.



Screen 3: video detection

The potholes in the image are detected by using the bond boxing method This pothole is a hazard to drivers and pedestrians, and it could cause serious damage to vehicles or injuries to people. It is important to avoid driving over potholes, and to report them to the appropriate authorities so that they can be repaired.

## 5. CONCLUSION

The gravity of pothole related accidents can be understood by increased numbers of accidents around the world due to potholes. In this research, four different techniques are proposed and tested against each other. Each technique has its own benefits and can provide different pathways to a number of applications. The LM1 model can identify a pothole under challenging weather conditions with good precision and recall whereas the LM2 model is capable of real-time pothole identification. The SV2



approach can identify potholes and road manifolds with very high accuracy when used with stereo-vision cameras. The SV2 approach can also be used to track a pothole from one frame to another, and is relatively easy to implement. The findings that we have presented here suggest that it is very difficult to define the irregular shape of a pothole which further makes it difficult to annotate ground truth. This, in turn, causes a complex process of matching results with ground truth. To date, there is no platform or benchmark available for pothole identification. As a result of conducting this research, we also put forward six datasets specifically for pothole identification, and discussed applications of two different areas of research such as computer vision and deep learning. It would be fruitful to pursue further research in order to combining the output of LM1 for annotating pothole data and to use it to train more LM2-type models in order to increase detection accuracy for real-time purposes.

## 6. FUTURE ENHANCEMENT

Deep learning has revolutionized pothole detection, offering remarkable accuracy and efficiency compared to traditional methods. As technology advances, several promising enhancements are poised to further elevate

pothole detection capabilities. One key area for improvement lies in enhancing the accuracy and robustness of deep learning models. By training models on larger and more diverse datasets, encompassing images from varying lighting conditions, road types, and geographical regions, their ability to accurately detect potholes under diverse conditions will significantly improve. Real-time detection is another critical area for advancement. By optimizing deep learning models for real-time performance, pothole detection can be achieved on-the-fly, enabling integration into autonomous vehicles and road maintenance systems. This real-time capability will facilitate immediate alerts and timely repairs, ensuring road safety. Depth estimation, a crucial aspect of pothole assessment, can also be enhanced through deep learning. By training models to estimate pothole depth, road maintenance authorities can prioritize repairs based on severity, optimizing resource allocation and improving road infrastructure. Multi-sensor fusion, combining deep learning with other sensing modalities like LiDAR and radar, holds immense potential. By integrating data from multiple sensors, a more comprehensive understanding of road conditions can be obtained, leading to improved pothole detection accuracy and the

ability to detect other road hazards. Transfer learning and domain adaptation techniques can further accelerate model development. By leveraging knowledge from similar domains, such as image classification or object detection, and fine-tuning it for pothole detection, the need for large amounts of labeled pothole data can be reduced, improving model performance and efficiency.

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