A review of Vision based Methods for Pothole Detection and Road Profile Analysis

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ABSTRACT: This paper is an overview of the development and application of Computer Vision for the detection of pothole, pavement distress and road profile analysis and categorisation. A brief explanation of the traditional methods for determining these factors is given, followed by a chronological description of the evolution and the challenges of using Computer Vision (CV) approaches to determine these conditions. The paper is separated into sections aligned to image capture and analysis methodologies. Qualitative evaluations and comparison of these methods have been provided along with the proposal of guidelines for new computer vision-based road analysis systems.

KEY WORDS: Computer Vision; Road Profile; Pavement distress, Potholes.

1 INTRODUCTION

A functional road network is key to the social and economic development of a nation [1]. 79% of freight transported in the UK in 2019 was by road, with 75% of commutes to work also occurring by road [2]. Despite the importance of the road network, transport infrastructure in the UK is rated as the second worst in the G7 countries [3] and has seen a reduction in maintenance budgets for road infrastructure year on year, with a current maintenance backlog of £9.3bn in the UK alone [4]. This has led to a sharp increase in pothole incidents across the UK, with ~500,000 potholes reported in 2017 compared to ~350,000 reports in 2015 [4]. The estimated cost to UK drivers in 2018 due to pothole damage was £1.7bn [5]. These reduced budgets mean that careful consideration must be given to allocation of funds. A report from the National Audit Office [6] emphasised the importance of unbiased, consistent data collection to facilitate the proper allocation of limited budgets and develop a clear picture of the current state of transport infrastructure. The prevalent method for road inspection currently is manual inspection. There are challenges in the repeatability of data from manual inspections of road profiles as they can be subjective and prone to human error [7]. This paper details the use of Computer Vision approaches to road inspection along with analysis of future trends and recommendations for future systems which can be used in conjunction with AI and autonomous vehicles.

2 ROAD PROFILE GUIDELINES AND ALTERNATIVE METHODS FOR DATA COLLECTION

There are guidelines in place for the grading of roads in order to facilitate budget management for asset owners, the methods (listed in later sections of this paper) provide the necessary information for the evaluation of road sections according to these guidelines. A brief overview of the prevalent means for grading will be presented below before the evolution of vision methods for gathering road profile data is investigated.

2.1 *Pavement Crack Analysis*

The indicator of choice for pavement crack analysis is the Pavement Condition Index (PCI). This metric involves checking a section of road for potential issues such as:

- Surface Defects
    - Ravelling
    - Flushing
- Surface Deformation
    - Rippling and Shoving
    - Wheel Track Rutting
    - Distortion
- Cracking
    - Longitudinal (Figure 1)
    - Centreline
    - Pavement Edge
    - Transverse

Figure 1. Longitudinal Cracking

2.2 *Road Profile Analysis*

The most commonly used framework for the assessment of road profile condition is the International Roughness Index (IRI) [8]. The IRI of a section of road is defined as the response of a quarter-car model to that road section. IRI can be measured with a variety of devices fitted to vehicles, such as contact profilometers, accelerometers, laser profilometers and vision-based systems. A comparison of the implementation of IRI around the world can be found in the study by [9]. Other commonly used frameworks are the Present Serviceability Rating (PSR) [10] and the Structural Condition Index (SCI) [11].

2.3 Traditional Methods for Pavement Data Collection

There are various non vision-based methods used for pavement data collection, such as manual inspection using profilometers [12] for road profile analysis and visual inspection for pothole detection, accelerometer based sensing approaches[13], [14], laser scanning [15]–[19] and hybrid sensor fusion systems [20]–[23]. These methods all have benefits such as extremely high accuracy (laser scanner, sensor fusion) or ease of setup and low cost (manual inspection, accelerometers). Drawbacks of these systems are extremely high cost (laser scanners), complex setup and synchronisation issues (hybrid systems); low accuracy for pothole detection (accelerometer), slow data collection (manual profilometer) and operator error or non-objective readings (visual inspection). In contrast to these methods, vision methods are inexpensive, easy to set up and can potentially produce accurate results in real time.

3 VISION BASED METHODS FOR PAVEMENT ANALYSIS

3.1 Customised Vehicle Setups for Data Collection

Early systems for pavement analysis involved the design and creation of customised vehicle with on board? computer setups that were used as inspection vehicles by asset owners. These vehicles typically employed an analogue camera to capture images of the road as the inspection vehicle travelled along the road. The images would then have to digitised for post processing and analysis. Research by Fukuhrara et al. [24] used a combination of laser scanner, oscilloscope and an analogue camera ( ) to measure cracks and road profile in vehicle that can travel up to 10 km/h.

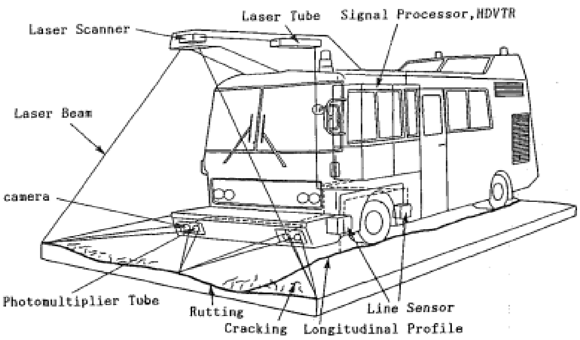

Figure 2 Monitoring setup from [24]

The authors used a shape detection system [25] for detecting cracks in the pavement from the footage captured by their camera. No detection accuracy results are shared in this study, only a detailed specification of the system which means no conclusions of system performance can be drawn. Additionally, this system only operated at night to control illumination for footage capture. A similar system was developed by [26], where a shadow moiré [27] pattern analysis system was used for detecting defects in the road surface. The moiré system in this study needed an intense light source (4 1050W lamps for a total output of 4200W) to produce accurate results, which is not practical on non-customised vehicles. Other early works in vision based pavement analysis were the studies carried out in [28] and [29]. These vehicles were expensive, cumbersome and required additional lighting systems to ensure high and consistent illumination of the pavement surface. As camera resolution and processing power has increased, more streamlined systems have become feasible.

3.2 Portable Vision based Systems

Streamlined systems for pavement condition monitoring have been explored in numerous studies where small-scale monitoring setups are attached to vehicles such as buses and cars for simpler data collection. The methodology behind these new systems has been to break down the process of pothole detection and road profile detection into several sections of code. There have been many attempts to develop a methodology for obtaining pavement condition information based on an image segmentation workflow. In [30], a beamlet transform was applied to sections of pavement images in order to reduce the effects of noise and facilitate feature extraction. If a defect, such as surface cracking or portion of a pothole, is detected in a section, that section is flagged, the next step involves connecting sections to determine crack or pothole size. The number of connected sections determine the size and type of the detected pothole. A histogram shape based-thresholding system was used for initial image segmentation in a study by [31], this method was a promising development as the initial conversion to grayscale and histogram analysis is not computationally expensive. The histogram threshold segments portions of the image based on their intensity, and as a crack or defect is usually a different colour from the road surface around it, histogram analysis can be used to potentially detect pavement distress as the pixels potentially containing the defect would be below a user-defined threshold for intensity. This means that only images that passed this first stage of processing were submitted to the classifier for further examination (in this case, shape analysis and texture comparison). This methodology was only tested on a small dataset (~120 images) and manually validated by the authors. An example of two histogram segmented images is shown in Figure 3.

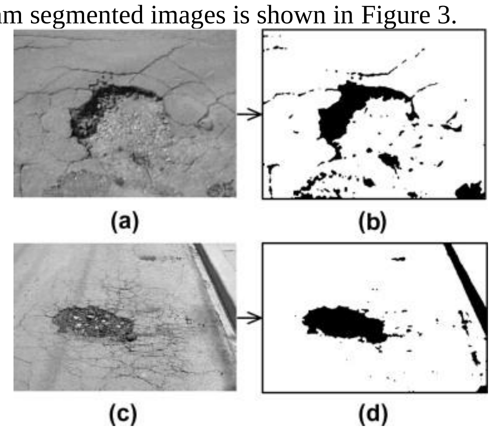

Figure 3 Result of Image segmentation from [31] (a) is a sample ppothole and (b) is the detected shade and regions, (c) is another pothole and (d) is the entire returned pothole detection

This research was extended to video data by [32], with accuracy versus manually verified test images of 84%. This type of measurement versus human validated images is the prevalent means of determining the accuracy of computer vision classification algorithms. Another study that used a segmentation based approach is the work by [33]. The authors used a multi scale histogram thresholding approach on a dataset of 5500 images, with an accuracy of ~95% on the images used in their trial. This method could only identify if a pothole was present in a scene, information on the profile could not be obtained using this methodology. The study by [34] performed a comparison between various methods for image segmentation including Histogram Thresholding, Edge detection, K-means clustering and Fuzzy C-means clustering. In This small-scale study,20 images were used to test the validity of each method, determined that the K-means clustering performed well in comparison to the other methods, in that K-means returned results faster and with greater accuracy compared to the other methods on the test dataset. While this study is interesting, a rerun of this trial with a larger image dataset for testing would be beneficial to truly determine the superior method for image segmentation. A real-time method for segmented pavement analysis based on thresholding and segmentation was performed by [35], this method was able to accurately detect potholes at approximately 33 fps, which would allow for a monitoring vehicle to move at a reasonable speed and also reduce the effects of image blur. This approach is promising; however, the results are only manually validated, and no determination of pothole profile is performed. Another study with manual validation was the work by [36], where a Raspberry Pi microcomputer was used to detect potholes on an onboard, real time image analysis setup. This type of embedded system allows for simple and inexpensive monitoring. These initial thresholding steps are an essential component of any system for pavement condition analysis, and barring the invention of an equivalent low-cost high-accuracy method (potentially new laser technology) that it should be implemented into future systems for pothole detection from captured images.

3.3 Stereo Vision Studies

Stereo vision-based systems can provide additional insight on road condition due to their ability to provide depth on the road which facilitates pothole and crack detection and road profile analysis. Stereo vision obtains depth information by calculating the disparity between images captured by two cameras whose parameters (location, focal length etc.) have been obtained by a process of stereo calibration. This usually involves capturing images of a patterned object with both cameras and using a feature extraction process to determine the location of points in the view frame of each camera, as can be seen in Figure 4. These known locations can then be converted from image to physical coordinates and used to determine the position of the cameras in relation to each other.

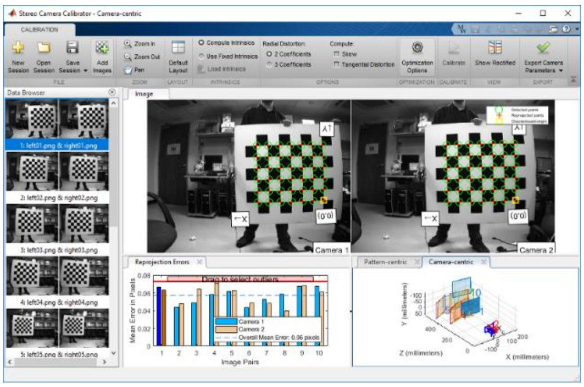

Figure 4. Stereo Camera Calibration Process [37]

Early exploration of stereo vision for road analysis focussed on correctly identifying the road surface, such as the works by [38]–[40]. Once the road surface area could be correctly identified focus could shift to pavement distress and road profile analysis. The work by [41] used stereo vision to obtain longitudinal profile estimation of road sections via a v-disparity map calculation. The results obtained were not compared to any means of accuracy verification in the study meaning no concrete conclusions about the applicability of this study for field deployment could be made. A study by [42] used 4 cameras to monitor a 4-metre wide section of road for the purposes of road profile calculation with each camera responsible for 2 metres of pavement, unfortunately this study also had no means of verification for captured data. The study in [43] used an enhanced v-disparity map to calculate the longitudinal profile of road sections, but the familiar pitfall applies in that no concrete results are supplied with the study so it is in effect a purely theoretical implementation. A road profile calculation study that did provide verifiable results was the work by [44], where a RANSAC [45] approach was used to obtain prediction accuracy of 80% when compared to the KITTI [46] road image dataset. Another study which used the KITTI dataset as a comparator was the study by [47], where the ground geometry of road sections was determined by use of a point cloud creation system based on calculated disparity maps. While this study did obtain promising results, (~80% compared to KITTI), the use of point cloud calculation adds a significant computing overhead to the system, meaning it may not be deployable on embedded devices for road profile monitoring. The authors of [48] broke from the common assumption that a road surface should be treated as a planar surface, instead opting to represent the calculated profile as a Kalman filtered B-spline curve. This resulted in improved accuracy on road sections where there was a gradual incline or decline on the road profile, as previously this would have caused disparity map calculation to fail. A study that did not assume any preconceived ideas for road surface shape was the work presented in [49]. This study detected the road surface based on a non-parametric depth-based algorithm. Their method outperformed the work by [41] on three separate image datasets. A real time method for stereo road profile analysis was presented in [50]. This method performs a perspective transformation before bilateral filtering of the calculated disparity map, which reduces processing time and opens the possibility of real time operation. The bilateral filtering is a time consuming step and could be replaced by an anisotropic or permutohedral filter in order to reduce processing time and allow deployment on embedded microcomputer with stereo camera setups similar to the one shown in Figure 5.

Figure 5 ZED Stereo Camera and Jetson Nano microcomputer.

In the area of pavement distress, research by [51] used dense stereo maps to detect obstacles in the road such as traffic isles with an accuracy rating of between 93-99% for differing obstacle types. This principle of dense stereo matching could prove viable if applied to pavement distress detection. This is proven in the work by [52], where any areas on the calculated planar disparity map that have an increased depth (0.04mm below the road surface) are assumed to be potholes. This also allows for the size and volume of potholes to be identified. The authors claim a high level of accuracy for their results, but no numbers are published in this study. The suitability of the Microsoft Kinect[53] stereo camera sensor for pavement data collection is explored in [54], this type of pre-calibrated specialised camera like the Kinect or ZED stereo camera removes a potential source of error from poor calibration procedures that can reduce accuracy on dual camera setups. The research by [55] also treats any pixels in the disparity map that are below a threshold as possible potholes, a secondary method then analyses the potential potholes to determine depth and volume. While no results are formally published in this study, the method of initial detection based on disparity map depth calculation is a valid approach and should be considered for inclusion in any stereo based pavement distress detection system. Another multi-step approach was detailed in [56]. The methodology in this work involved first calculating a high threshold based disparity map that detected the edges of potholes, then reducing the threshold for key point matching in order to detect the interior of the pothole in a second pass where the Region of Interest (ROI) for the matching algorithm was focused on the pothole interior. A sample frame from this matching process is shown in Figure 6.

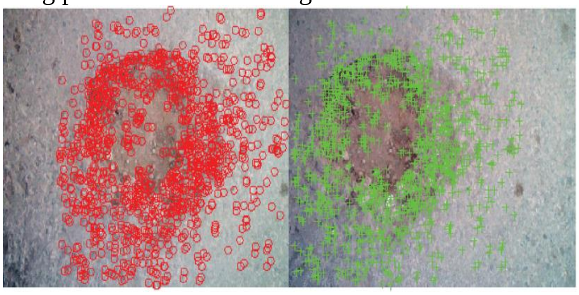

Figure 6 Matched Keypoints from Secondary disparity map calculation in [56]

This was done because the surface textures inside a pothole are typically less distinct than the edges, meaning they would be discarded by the initial pass. A final block matching approach was then applied to ensure the pothole interior is mapped as accurately as possible. This method was then tested on both static images and images captured from a moving vehicle by a dual camera setup. It was found that the dynamic images suffered a drop in performance, this is potentially due to the frame rate of the cameras being too low resulting in image blur as the vehicle approaches cruising speed. The static image trials did however yield satisfactory results (within 3mm of ground truth for pothole size), meaning with some improvements to the algorithm to enhance processing time and changes to the hardware setup, this method or a similar multi-step approach could be used to accurately detect potholes from a moving vehicle without disruption to other road traffic.

3.4 Neural Network based Approaches

The recent rise of neural networks as a tool for computer vision has seen large image datasets and convolutional neural networks be implemented for many challenges including that of road profile analysis. Convolutional neural networks (CNNs) are a system that learns by being shown thousands or millions of labelled images in order to correctly classify these images into categories. The accuracy of CNNs is determined by their classification accuracy on a test image dataset, this may be collected by the authors or there are also several image datasets available online for the purposes of comparison. Research by [57] was one of the early attempts at using neural networks to classify pavement cracks. The images used in this trial were obtained from the NCHRP 1-27 program [58]. The methodology used to obtain these images is not publicly available, but it can be assumed that a similar approach to the ones detailed above was used. For analysis, the authors used fuzzy thresholding to obtain a binary image of captured pavement cracks, followed by classification according to a moment-based approach. The authors obtained highly accurate results when compared to their own test dataset, but they had a very small dataset for training and testing so there is the possibility of overfitting (this is a source of error in neural networks where the network becomes very good at analysing the images it has been trained on, but cannot extend this performance to images it has never seen) as the testing set was made up of augmented images of the training set. This work was continued in [59] but the relatively small dataset (hundreds of images compared to the thousands required to train a truly accurate convolutional neural network) mean that this approach is not totally valid for all crack detection scenarios. The massively increased availability of data storage and the increase in processing power of Graphical Processing Units (GPUs) has led to a surge in the accuracy of trained neural networks in recent years. This has been reflected in the area of pavement condition analysis, such as the work by [60], which used a technique known as *transfer learning* to train a network to detect road surfaces. Transfer learning is a deep learning principle where a network that has been trained for one purpose is retooled to accomplish a different task. Another study in the application of CNN structures to road surface detection is [61], which uses a patch based convolutional network to detect road surface accurately (87% accuracy on the KITTI dataset).
[62] used a weightless neural network based on pattern recognition in tandem with transfer learning to detect pavement distress in a small dataset (78 images). The authors report accurate results (86% accuracy on their dataset); however, the small dataset size and the lack of comparison to existing methods for road analysis mean that their system cannot be considered to be truly validated for widespread use. The issue of small datasets also hinders the otherwise promising work by [63], where pixel level accuracy of ~85% is obtained on the dataset used in the trial of their method for pavement distress detection. A study that does have a reasonable size dataset for testing(~45,000 images) is the work by [64], where accuracy of ~93% was obtained using a semi-supervised training approach for a neural network. The ease of deployment of CNN architecture onto embedded computers mean that these

implementations can be adapted for use on inspection vehicles without any requirements for large or cumbersome monitoring setups.

4 CONCLUSIONS AND RECOMMENDATIONS

The application of computer vision methods to the challenge of road surface analysis has been explored by many researchers with some purported accurate results from a variety of approaches although some have not been validated with real data. From the review of the state of the art carried out for this paper, it is the opinion of the authors that the future systems should consist of the following components for road profile analysis:

1) The system should be a stereo based system as the additional information provided by depth calculation from disparity map generation is extremely useful for generating accurate road profiles.
2) The system should not attempt to constrain the road surface points into a planar or precalculated surface, a flexible nonparametric system such as the one found in [49] will be more adaptable to varying gradient found in real world scenarios.
3) If obstacle detection (traffic islands, etc) is desired during road profile analysis, the use of a CNN would speed up processing time and enable detection and classification of objects in the scene view. It should be noted that sourcing and labelling data for training a CNN is a time-consuming process, so this should be considered.

For the area of pothole detection:

1) The system should implement an initial coarse grained pothole detection algorithm where defects of all type are detected, the images obtained from this could then be passed to a more detailed classifier to determine volume of detected potholes.
2) The system should also be a stereo vision-based system as obtaining depth information on detected pavement distress would enable prioritisation of repairs for governing bodies.
3) CNN architectures are a promising development for pothole analysis with deep learning architectures obtaining superior results on the comparative datasets used in these works, however the same issue regarding obtaining training data is applicable here.

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