Advances in Road Feature Detection and Vehicle Control Schemes: A Review

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***Abstract* – Road accidents are a major cause of fatalities globally. These accidents are caused by human errors, which include over speeding, drowsiness, intoxication, and loss of concentration. In an attempt to overcome these challenges, Autonomous Vehicles (AVs) have been developed and the prominence of these vehicles is rapidly growing. AVs are classified into five (5) steps ranging from no automation to full automation. For a successful operation of an AV, numerous features are put in place, one of which is Road Feature Detection and Vehicle Control. Several techniques have been adopted to ensure an effective feature detection in AVs. This paper presents a review and survey of existing techniques in lane detection and identification of road anomalies with respect to AVs. An overview of AVs and computer vision are presented, as well as the features, strengths, weaknesses of existing literature. Existing schemes were discovered to be unfit for unstructured and complex environments due to a lack of consideration for nonlinearities and an inability to perform in real-time scenarios.**

***Index Terms* – Autonomous Vehicles, Computer Vision, Lane Detection, Road Anomaly Detection, Vehicle Control.**

I. Introduction

The infrastructural decay of Nigerian roads has led to a significant setback to the Nigerian economy through the road crashes resulting to the loss of lives and properties worth millions of naira [1]. Road deficiencies such as potholes and speedbumps, which are human induced, can cause accidents when not identified early enough by drivers [2]. Due to poor construction and geographical factors, roads in Nigeria suffer from swelling, stripping, and potholing [1]. In addition, majority of speedbumps erected in Nigeria are done so indiscriminately without proper labelling or consideration for their heights and sizes [2], [3]. The prevalence of unapproved speedbumps, potholes, and poor road conditions also results in driving stress, misalignment, vehicle damage and financial burden on road users [3], [4]. The early detection of these road abnormalities will lead to effective navigation around them and the advancements in automobiles has led to the desire and need by scientists and researchers to achieve autonomy in vehicle control [5].

Autonomous Vehicles (AVs) are vehicles capable of navigating an environment with minimal human input. Also known as self-driving vehicles, AVs perceive their surroundings using sensors and utilise control schemes to generate paths and navigate the route [6]. Recently, AV research and development has seen great advancement due to advances in computer and sensor technology [7]. The advent of AVs has brought about a significant improvement in safety on roads while reducing driver workload [8] [9]. Self-driving vehicles have shown to be reliable systems for the exploration of hazardous areas and surveying unfavourable environments. Some of these areas include regions affected by oil spillage, forest fires, and polluted regions [10]. Due to their relatively low operational and deployment costs, and high endurance, AVs can provide long-term monitoring capabilities without the need for human involvement.

A major challenge with AV deployment is environment awareness [11]. The AV needs to have the ability to determine its current location (localisation), perceive its environment and determine which route to follow. Research efforts primarily focus on the use of cameras and sensors for localisation, perception, and navigation [12]. These techniques are also combined with computer vision and machine learning for improved performance.

Computer vision is a technology that allows machines to detect, interpret and comprehend video and image information. This technology has been introduced in AVs to make it easier for cars to make sense and to understand their environment [13]. Several computer vision techniques have been implemented in AVs. These techniques include edge detection, gradient and HLS thresholding, feature colour extraction, neural networks, and Hough transforms [14]–[18]. In addition, existing Machine Learning algorithms such as Convolutional Neural Networks (CNN) and You Only Look Once (YOLO) v3 have shown highly accurate results in object detection applications. These techniques do not rely solely on features such as grayscale or colour and thus, are rarely affected by light changes and image scaling, while possessing high adaptability characteristics [19].

A major aspect of AVs is lane detection, as it is a prerequisite for lane departure warning systems [20]. Lane detection is aimed at keeping the car in the right lane and avoiding accidents. Lane detection systems are usually used with cameras, sensors and Lidar [14]. A lane-keeping system's successful operation depends on vehicle speed and steering power. To maintain a reliable lane-keeping scheme, operations such as acceleration, braking and steering must be carried out effectively. For lane keeping schemes, various monitoring mechanisms have been implemented. These techniques include Lyapunov techniques [21], Model Predictive Control [22], Fuzzy control [23], Sliding Mode Control [24], and Proportional Integral Derivative (PID) control [25].

The detection of road features such as potholes, lanes, and speedbumps using computer vision in autonomous vehicles coupled with an effective vehicle control scheme significantly enhances driver and vehicle safety, reduction in the amount of

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energy consumed, reduction in pollution, and minimisation of the time taken to reach a specific destination. Due to these reasons, the need arises for the implementation of an effective road feature detection and vehicle control algorithm that will accurately identify lanes, faults, depressions, swellings, and speedbumps as well as control the vehicle to accurately navigate these features. Thus, this paper presents a review of existing road feature detection and vehicle control schemes. The rest of this paper is divided into four (4) sections. Section II provides a theoretical background on autonomous vehicles and computer vision for road feature detection while a detailed review of existing literature in road anomaly detection is presented in Section III. Section IV provides a review of related works in lane keeping and Section V provides the summary, conclusion, and directions for future research.

II. THEORETICAL BACKGROUND OF THE STUDY

A. Autonomous Vehicles

It is possible to trace the origin of AVs to the early 1920s [26]. General Motors produced its first autonomous vehicle model in 1939 [27]. Between the early 1960s and early 2000s, in the United States of America, Europe, and Japan, numerous research and development projects for automated vehicles are operational. AV work was greatly influenced in 2004 by the Defense Advanced Research Projects Agency (DARPA) of the United States. This work focused on developing unmanned defense systems [26].

The levels of automation in an AV is graded on a five-step grade, these are: no automation, driver assistance, partial automation, conditional automation, high automation, and full automation [28]. These automation levels are determined by the level of human involvement in driving the vehicle. Table 1 shows the different stages of automation of the vehicle and the activities at each level.

Table 1: Levels of Automation [26], [28].

Automation Level	Level Feature	Description
Level 0	No Automation	Human driver performs all tasks.
Level 1	Function specific automation and driver assistance.	Specific functions are automated such as pre-charged braking and electronic stability control. However, the driver performs most of the driving functions.
Level 2	Combined function automation or partial automation.	At least two of the driving functions such as cruise control and steering are automated
Level 3	Limited self-driving automation or conditional automation.	The driver cedes control of driving tasks to the vehicle under certain conditions and may resume manual driving tasks with a sufficient amount of transition time.
Level 4	Full self-driving automation.	The vehicle intelligently performs all driving functions, monitors the environment, and acts accordingly.

Driverless vehicles' key aspects are classified into three main classes: perception, planning and control [29]. Perception is a feature that allows the vehicle to sense its surroundings. It includes using sensors such as ultrasonic detectors, Lidar, and cameras to provide ambient data to the vehicle [30]. This information includes barriers, speed of the vehicle, location of the vehicle, displacement and path information [29], [31]. Planning refers to the ability of the vehicle to assess and decide what action to take based on sensor data [31]. Control is the feature of the vehicle which transforms the intended motion into a movement of the actuator. This movement is done by sending the requisite control signals to the correct actuator to enable the vehicle to successfully navigate the environment [29]. Figure 1 highlights the core aspects of AVs.

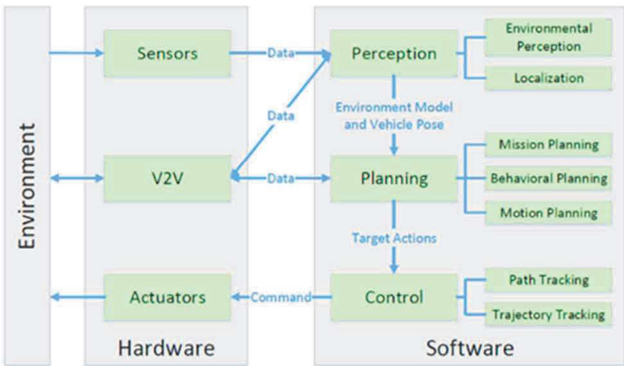

Figure 1: Core Aspects of Autonomous Vehicles [29]

B. Computer Vision for Road Feature Detection

Computer vision is a technology that detects, analyzes and recognizes the video and image content of a computer. AV researchers and developers have implemented this technology to allow cars to make sense and understand their environments [13]. In the field of road feature detection, many computer vision techniques have been introduced, these include edge detection, gradient and HLS thresholding, color extraction functions, neural networks and transformations of Hough[14]–[18]. Computer vision detection strategies usually follow these steps:

i. **Image Acquisition:** This is the first stage of the computer vision process. This is the process by which the photo or video stream from a camera is captured and stored. Normally distortions, noise, and other unwanted features affect the images captured at this point. The photo is pre-processed before it is analyzed as a result of these adverse characteristics [15].

ii. **Image Preprocessing:** In this stage, after the image is acquired, it is preprocessed before future operations. This is the method of improving the picture that has been captured and removing undesirable properties like noise. This procedure involves image smoothing by applying filters (2D, median or gaussian filters) to eliminate noise, creating a region of interest to remove unwanted areas, and enhancing image characteristics by adjusting the color scheme (RGB to grayscale, HSV to RBG, or HSI to YCbCr) and only highlighting the correct color values [20], [32].

iii. **Image Segmentation:** This stage involves the partitioning of an object into multiple classes for easier interpretation. Edge detection (Sobel, Canny, and Roberts), thresholding, and color-based segmentation are examples of segmentation techniques [32].

iv. **Feature Extraction:** In this stage, the recognition of the image's desired properties takes places. Fast Fourier Transforms, Hough transforms, color-based detection, and least square methods are common feature extraction techniques for lane detection [32].

v. **Feature Recognition:** This stage involves validating that the extracted features are the desired features. This process refers to the verification process that the extracted characteristics match a certain condition and are identical to or close to the identifying feature. This can be achieved by comparing detected features to a pre-stored value, analysing the number of occurrences, or calculating certain parameters from the detected feature.

III. REVIEW OF ROAD ANOMALY DETECTION TECHNIQUES

Several studies have been carried out in the area of road anomaly detection. In [33], a crowd sensing application for estimation of road conditions was developed. The system uses acceleration data from mobile phones of road users to estimate the location of potholes and speedbumps. The application, called CRATER, had a success rate of 90% and 95% in the identification of potholes and speedbumps respectively. However, the application had a false detection rate of 10% and 5% for potholes and speedbumps respectively. In addition, there was no navigation or control scheme to manoeuvre around the road anomalies.

A machine learning approach for assessment of road surface anomalies using a smartphone's sensors was developed in [34]. The system focused of the classification of smooth road, potholes, and deep traverse cracks. A deep neural network was used for the classification of road conditions with and without explicit feature extraction. Although the results showed an improved classification technique using machine-learning models, the small size of the dataset caused loss of accuracy and precision. Additionally, no control or navigation scheme was implemented to avoid the road anomalies.

In [35], an asphalt pavement potholes and cracks detection system was developed using multispectral imagery on unmanned aerial vehicles. The technique presented spatial and spectral features of road anomalies and machine learning algorithms such as support vector machines, neural networks and random forest were used for classification between normal pavements and pavements with damages. The results showed a 98.3% accuracy in classification, however, spatial resolution limitations of the UAV pavement images was a major limitation, and this led to the system's inability to capture cracks less than 13.54 mm in width.

In addition, a road quality detection method based on the Mahalanobis-Tagushi System (MTS) was developed in [36]. The technique provided a pothole detection error rate of 3.26% compared to other techniques such as classification regression tree and support vector machines. The MTS method also had a false positive rate of 5.72% and speedbump detection error rate of 0.01%. The system, however, provided no navigation and control technique for avoiding the road anomalies.

A speed bump detection technique using accelerometric features and genetic algorithm was developed in [2]. The model exhibited an accuracy of 0.9714 with a false positive rate of less than 0.018. Although the system successfully detected speedbumps, no control scheme was implemented or proposed to aid navigation.

In the area of pothole avoidance and speed bump manoeuvring, there exists several literature. A graph theoretic approach for detecting and avoiding potholes was presented in [37]. The system uses laser sensors and pressure sensors to detect potholes and evaluate their depths. The location of the anomalies is kept in a centralised server and based on that data, a route with least number of potholes is computed. The results showed the algorithm provides damage level data and provides optimum paths for travel. However, it does not provide information on real time applications, as the system relies on existing data. This technique will not be effective in areas where the layout is unknown.

In [38], an intelligent smartphone technology was developed for the detection of speed bumps and reducing car speed. The system uses a gravity sensor to detect speedbumps and speed reduction is achieved using third equation of motion. Data was obtained through crowd sources and numerous vehicles. Although the system presented satisfactory results, the lack of an intelligent technique, nonlinear control scheme, or consideration of the depth and width of holes and bumps respectively, are limitations associated with this work.

A detection and avoidance system of simulated potholes for autonomous vehicle navigation in unstructured environments was developed in [39]. The system uses cameras, imaging board, and a vehicle control algorithm were used for the implementation of this system. The technique implements image processing methods such as histogram calculation, thresholding, and edge detection to identify potholes. However, no information was provided on the effect of the system in real time scenarios, pothole avoidance, and vehicle navigation.

Additionally, several works exist in the area of anomaly and obstacle avoidance for AVs. [40] designed an obstacle detection algorithm in an indoor environment using a mobile camera to aid visually impaired people. The algorithm measured the mean square error between the detected image and a pre-stored floor image and then compared the error to a threshold value. Although the algorithm worked in real time and has a 96% accuracy rate, it is unsuitable for dynamic environments, autonomous vehicles and outdoor scenarios.

Also, [41] developed an obstacle detection method for outside environments based on infrared and depth fusion. The infrared sensor tackled the problem of light intensity affecting the accuracy of the recognition algorithm. However, the range of the infrared sensor used was 0.5 m – 8 m, which makes it unfit for autonomous vehicle navigation.

Similarly, [42] developed an obstacle detection technique based on infrared sensor application. The technique used inputs from the infrared sensor and pre-timed delays to detect and avoid obstacles. The limitation of this technique is that it cannot be applied in a dynamic environment of autonomous vehicles due to the low infrared range and unsuitability of timed delays in a dynamic environment.

[43] implemented a LiDAR based obstacle detection and tracking algorithm for an autonomous vehicle. The technique used a 3-dimensional LiDAR to detect the obstacle and a Kalman filter to improve the tracking of the obstacle. The algorithm had a detection rate of 100% for roadside obstacles and 63.47% for moving obstacles. However, the technique could not deal with situations in which the obstacles are close to others and the detection rate for moving obstacles requires improvement.

IV. Review of related works in lane keeping systems

In the area of lane identification, lane management and steering control, several studies have been conducted. [44] developed an autonomous vehicle steering controller using a tracking algorithm based on geometry. A Proportional-Integral-Derivative (PID) controller with dead band compensation was used to implement this steering control system. The tests showed a good quality route monitoring. Nevertheless, due to the dead band, the steering control output was reduced, and the control system performance depended on the parameters of the road. The control system also introduced a linear control structure (PID) to address a nonlinear issue and ignored external disturbance effects.

A skid steering and differential steering control system for an electric vehicle was also developed [45]. On the one hand, the results indicated that in terms of robustness and control of the yaw rate and slip angle, the differential steering controller provided a better performance than the skid steering controller. On the other hand, because of the large differential drive torque needed, the skid steering control system was not feasible for practical use. However, the external vehicle yaw moment and the additional steering angle produced by the differential steering controller in practice reduces the controller quality.

Furthermore, a steering and braking control technique was developed using Nonlinear Model Predictive Control (NMPC) [46]. The NMPC's performance was compared with a Velocity Ratio Control (VRC) technique performance. The results showed that the performance of the NMPC was faster than the VRC, and the NMPC had adequate control effects on steering and braking. The NMPC control criterion was based on the definition of the lane, which makes it difficult to apply the technique with different lane features in real time. The approach also focuses solely on straight roads and does not provide data on the quality of the curved roads technique.

Similarly, [47] developed a system focused on line segment detection (LSD) lane-keeping assistance. The technique involved using reverse perspective mapping and LSD to introduce an algorithm for real-time lane detection. The system also showed driver direction arrows if deviation from the edge of the lane was observed. However, the system did not have an automated lane-keeping control technique.

A lane-keeping control system for vehicles under crosswind impact was built in [25]. This technique was based on visual navigation and was used to detect the road lanes by Hough transforms. The lane deviation was measured and compared to a predefined road map, and to correct the deviation error, a Proportional-Integral-Derivative (PID) controller was set up. While the method showed precise tracking and lane detection capabilities, it is not feasible in practice to use a predefined road map as the map may not always be available. In fact, only a straight line was considered by the technique.

[48] introduced a differential torque-based lane departure avoidance system. Using a front-facing camera, the device collected road information and identified routes using artificial vison methods. The lane-keeping system was designed using a technique of PID-based gain scheduling in compliance with guidelines for optimum h-infinity. Results showed that the machine was able to maintain a good lane with total error values of 0.9 m for deliberate lane departures and 0.35 m for accidental lane departures. This strategy, however, focuses only on straight roads.

In addition, [22] established an integrated lane support system with switchable modes of assistance. This methodology applied a predictive control method focused on the learning system to account for the model's inaccuracies. The results indicated that, especially in terms of switching and robustness, the controller was efficient. The methodology, however, had drawbacks such as difficulty in implementing the algorithm in embedded processors, and the parameters tested for the method were based on intuition and experience alone. Such shortcomings make the technique unsuitable for application in real time.

An adaptive multivariable super-twisting controller has been built in [24] for lane keeping in autonomous vehicles. Using a high fidelity simulation of CarSim-Simulink, the system was tested, and results showed that the system was successful and stable. The simulations were carried out using a reference trajectory, however, and it was not possible to verify the real-time performance..

V. Conclusion, summary, and future research directions

This paper presented a review on existing road feature detection and vehicle control techniques. A theoretical background on autonomous vehicles and computer vision was presented. In addition, the authors reviewed existing literature in the area of road anomaly detection as well as lane keeping and identification.

The review of existing works indicated that in the road anomaly detection systems, a major limitation was the absence of a control scheme to manoeuvre around the anomalies. In the aspect of lane keeping schemes, however, the review showed that although control schemes were implemented to carry out lane keeping operations, the effectiveness of these schemes could not be verified due to the unsuitability of the techniques for real time operations. This is as a result of the availability of only simulation data, absence of field-testing results, and the use of a reference tracking model, which makes it difficult for real time implementation.

Due to the aforementioned salient limitations of the reviewed literature, which includes unsuitability of the existing schemes for unstructured and dynamic environments, future research works will focus on the development of not only a road anomaly detection scheme, but also a suitable navigation technique to manoeuvre around the detected anomalies in real time. In addition, this review will aid researchers in their quest to develop effective and efficient autonomous vehicle perception and navigation techniques.

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