Pavement Distress Detection and Identification Using Structure from Motion and Digital Camera

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Abstract.

Smart City is intended to use new technologies and advanced algorithms to enhance life services and optimize resources in use. A road network in a Smart City should be available and safe at almost times. Modern sensors, Artificial Intelligence, and Machine Learning algorithms were developed to analyze data and extract meaningful information to evaluate pavement surface conditions. However, some methods cannot detect all existing damages, and others are considered very costly due to the material and effort deployed. This paper proposes a low-cost solution using a commercial digital camera and the open-source software Meshroom based on the Structure from Motion (SFM) technique. The proposed method consists of taking images of the pavement from different angles. Then, those images are transferred to a 3D model via the last stable version of Meshroom. Pavement 3D modeling obtained provides more details about road surface health, including depth information. Two case studies tested and validated the proposed approach, providing a promoted solution.

Keywords: Pavement, Structure from Motion, Meshroom, Smart City, 3D modeling

1 Introduction

According to the U.S. government website "**The World Factbook,"** there are more than sixty-three million kilometers of roads worldwide today. This vast number is increasing daily and could be explained by the significant number of vehicles worldwide (more than one and a half billion cars) and the growing population. There is a high demand for using all kinds of roads (paved and unpaved) to transport people or make logistics and supply. Inspecting those roads at less every six months makes observers walk more than one hundred twenty million kilometers yearly. For this reason and others, road visual inspection could not be used more.

Pavement Management System (PMS) aims to keep the pavement's surface healthy for as long as possible. Several approaches and tools were deployed and adapted to monitor and evaluate existing pavement-distressed areas (Nyirandayisabye et al., 2022; Benmhahe & Chentoufi, 2021; Sholevar et al., 2022; Saha et al., 2022).

Initially, PMS was based on handbooks, classical measurement tools, and human observers. Such methods are time-consuming and suffer from observers' subjectivity and tool limitations. Furthermore, methods employed to gather data cause significant downtime for the road under inspection and present danger for road users and observers.

By using Smart City concepts, PMS methods were enhanced to include more advanced materials and sensors such as UAVs (Unmanned Aerial Vehicles), digital cameras, laser scanners, and different sensors (vibration, temperature, and acoustic) to inspect the pavement surface (Tong et al., 2020; Du et al., 2021; Fan et al., 2020; Xiang et al., 2020). Furthermore, several Artificial Intelligence, Deep Learning, and Machine Learning algorithms were trained and enhanced to analyze gathered data and extract meaningful information (Liu et al., 2020; Ibragimov et al., 2022; Wang et al., 2021; Mei & Gül, 2020; Song et al., 2020).

Regarding data acquisition, it was proved that vision-based methods (images and videos) are the most flexible and cost-effective techniques (Lekshmipathy et al., 2020; Ranjbar et al., 2021; Hou et al., 2021). Other sensors, such as pressure, humidity, and vibration, were overlooked due to the limited area scanned or the higher timing needed to gather data. However, extracting damages directly from images or videos is still limited due to the need for the third dimension information.

There is no doubt that road 3D modeling using a laser scanner is the most accurate method. However, it is very costly and requires significant time to gather data while stopping the use of the road under inspection. Some studies were focused on using LiDAR (Light Detection And Ranging) and laser scanners to inspect the road surface (Yu et al., 2014), which was very costly while engaging a heavy material.

Nowadays, the Structure from Motion technique (Roberts, 2020; Shalaby et al., 2017), which consists of transforming 2D images into a 3D model based on images overlapping and cameras' poses reconstruction, has started to be used for pavement 3D modeling to detect distress and make measurements. However, this technique must be enhanced and adapted to provide more accurate details about the pavement structure. Also, pavement 3D modeling methods should be accurate, less costly, easy to deploy, and able to handle an extensive network of roads.

This paper aims to propose a new low-cost solution for pavement distress detection and identification. The proposed solution proves that digital cameras and Structure from Motion present excellent tools for pavement 3D modeling and health monitoring. Two simulations on different types of damage (pothole, rut, and crack) were conducted and compared with a reel survey. The method was compared to other techniques in terms of cost and time.

The remaining sections are organized as follows: section 2 will outline the various steps involved in implementing the proposed method, including the SFM technique, which will be used for pavement 3D modeling, a vital aspect of the proposed method. Section 3 details the materials and software used and highlights the experimental results to provide an exhaustive analysis of the findings. Finally, in section 4, the paper will be concluded, and a summary of the essential findings and future work will be provided.

2 Related works

Acosta et al. (1992) developed a system for video pavement distress analysis that identifies and classifies common types of structural pavement distress. The method was implemented mainly for asphalt concrete pavement images and can be used for Portland cement concrete pavement images. The accuracy achieved with the rule-based classification approach is close to 90 %. Distress classification, including severity and extent level, is currently limited to distress types that can be quantified by width, length, geometry, or area covered by the distress.

Ahmed et al. (2011) proved that a low-cost photogrammetric system can effectively and accurately reconstruct a detailed 3D model of pavement surface distress. The proposed solution can be used independently or integrated with existing pavement distress data systems and pavement management systems.

Research by Wai and Yuan (2017) proposed a workflow for developing a preliminary pavement distress screening system, VPADS, using video image data collected by a camera mounted in the car front. The proposed method was tested on a developed prototype using the video data collected for two low-volume roads in Northern Ontario, Canada. This method achieved an accuracy of 80.6% for the determination of distress features.

Inzerillo et al. (2018) suggest different approaches to using Structure from Motion for automated surveys of road pavements. Two approaches were analyzed and compared with the laser scan technology: An Unmanned Aerial Vehicle (UAV) SfM (UAV-SfM) and a camera SfM (N-SfM). It was proved that N-SfM provides the most realistic reconstruction compared to the laser scan and UAV-SfM technology. UAV-SfM results help understand the overall conditions of a long stretch of road pavement, identifying the critical areas of the road surface where it is necessary to carry out a more detailed analysis using the N-SfM.

Ouma (2019) presents a robust approach for cost-effecting potholes on asphalt pavements. He proposed a system for pavement surface mapping using Kinect v2.o and based on the iMMSS hardware-software system, the implementation first incorporates k-means clustering and horizontal-vertical integration as data search or filtering algorithms, followed by spatial fuzzy c-means (SPCM) segmentation for pothole and non-pothole detection.

Roberts et al. (2020) suggest a deep learning framework to continually monitor the pavement structure's health. Artificial Neural Networks were developed based on local imagery in the Sicilian region in Italy to set up a model capable of carrying out this task. The imagery was captured using a low-cost smartphone. The model identified the distress categories developed and the associated severities.

Ronald et al. (2020) demonstrated the accuracy of using imagery from mobile phones for creating 3D models of pavement and the practicality of segmenting these models to isolate pavement distresses. They used two standard mobile phones for the survey and a professional camera for the experiment's control. Then, they make a statistical analysis based on the Weibull distribution evaluation by comparing the models generated from mobile devices to those generated from a professional camera.

Kembhavi et al. (2020) proposed a computerized framework that uses image-processing procedures to evaluate pavement distress. The highest accuracy obtained was about 80%. The proposed system can identify the feature of distress, which is significant for choosing maintenance strategies. The consequences of the proposed system can be actualized in the project-level pavement management systems and also for road safety enhancement.

Khahro et al. (2021) suggest a Pavement Management System for flexible pavement maintenance. The priority ranks of the PMS indicators were made using an Analytical Network Process (ANP), and each rank was validated by a sensitivity assessment test using the Super Decision-Making tool. The indicators in the model were prioritized for low cost to make the system beneficial for developing countries. Authors recommend that this model be utilized in low-income countries where pavement management authorities face financial issues to maintain the existing road network.

Guerrieri and Parla (2022) propose a real-time algorithm for detecting and measuring road pavement damage. Data was acquired by taking top-view videos of road using a survey vehicle equipped with a front camera. After that, deep learning and the YOLOv3 algorithm were used to detect and measure flexible and stone pavement distresses. The detection rate in the pavement distress was between 91.0 % and 97.3 %, depending on the pavement and distress types.

Martinelli et al. (2022) suggest a low-cost system for real-time monitoring of road pavement health based on data provided by on-car accelerometers. They performed a short Fourier analysis on the acceleration signal to extract the signal energy information from the time-frequency domain. They tested the three supervised machine learning algorithms: Decision Tree (DT), Support Vector Machine (SVM), and k-nearest Neighbor (kNN). The SVM classifier was the most accurate (97%).

Qiu et al. (2023) developed a multi-sensor solution for pavement distress segmentation. They created and annotated a multi-sensor dataset consisting of aligned IR, RGB, and depth images and then evaluated four popular deep-learning methods for pavement distress segmentation. ConvNext demonstrated the most effective segmentation performance. The method limitation is that the results of deep learning segmentation strongly depend on the accuracy of the manual annotations.

3 Method

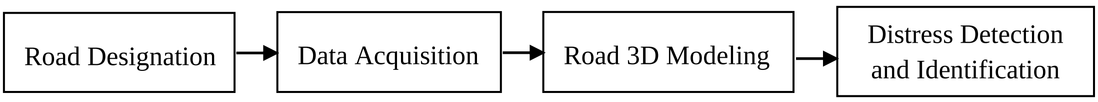
This paper proposes a novel pavement distress detection and identification method based on a digital commercial camera and the Structure from Motion technique. After the designation of the road area to be inspected, data acquisition is conducted to take images of the selected area from different angles. Then, those images are converted to a 3D model based on a personalized version of the software Meshroom. Distress detection and identification are made by comparing models created with reel damages.

3.1 Flow chart of the study

The proposed method consists of four steps, as illustrated in Fig. 1:

- **Road designation**: The first step concerns the definition of the road surface to be inspected by identifying the coordinates and limitations of borders.
- **Data acquisition**: This step aims to take pictures of the road surface to be inspected from different angles. Images should be clear and cover all views. An overlap of images between 50% and 70 % is highly recommended not to lose data.
- **Road 3D modeling**: In this step, images captured are transformed into a 3D model using the software Meshroom, an efficient tool based on the Structure from Motion technique.
- **Distress detection**: It is concluded by extracting all Points Cloud from the 3D model and identifying those points representing damages, then comparing it with the real distress identified during the survey.

Figure 1: Flow chart of the study



3.2 Material

The EOS 450D camera will be used for taking images of the pavement surface. EOS 450D (Fig. 2) is a digital camera manufactured by Canon. This device provides a resolution of 12.2 MP and disposes of a CMOS sensor that has a size of 22.2 mm.

Figure 2: EOS 450D Canon camera

3.3 Structure from Motion

Photogrammetry is the technique of extracting information and measurement from images. It is an old technique used in geology, mapping, and agriculture (Shalaby et al., 2017; An et al., 2021). Structure from Motion (Schönberger et al., 2016) is a photogrammetry process that provides 3D models using overlapping images acquired from different perspectives with standard cameras, including Smartphone cameras, and geo-referencing information. SFM is recovering the 3D structure of a stationary scene from a set of projective measurements, represented as a collection of 2D images, via the motion estimation of the cameras corresponding to these images. SFM employs multiple algorithms developed from computer vision, traditional photogrammetry, and more conventional survey techniques.

SFM technique involves three main steps: (1) Extraction of features in an image such as points of interest, lines, and corners, and matching these features between images. (2) Camera motion estimation using relative pairwise camera positions estimated from the extracted features. (3) Recovery of the 3D structure using the estimated motion and features.

3.4 Meshroom

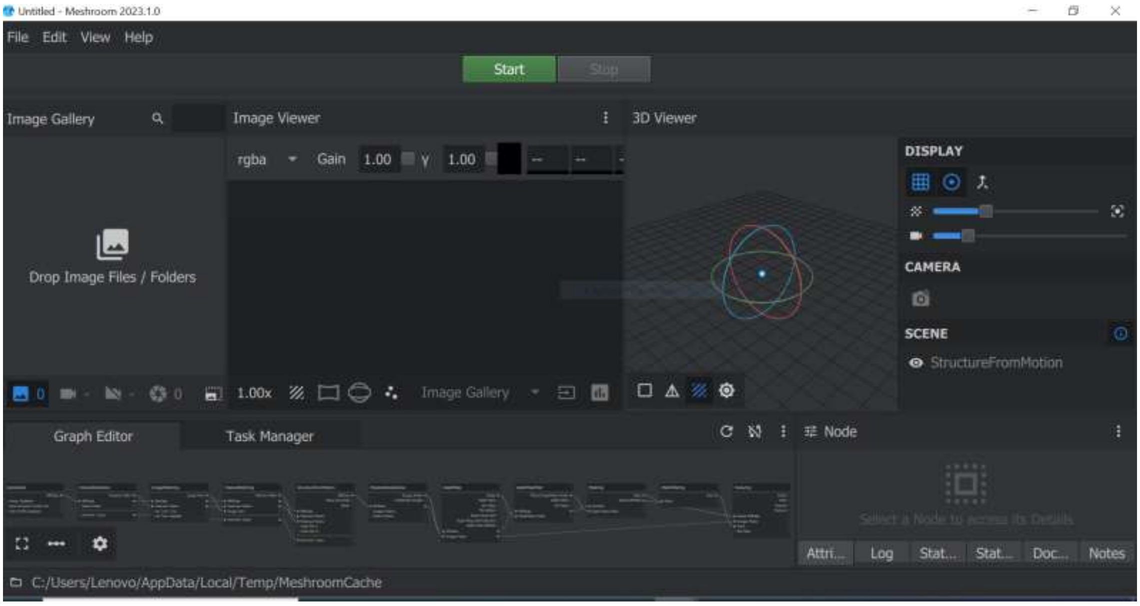
Meshroom is an open-source, free 3D reconstruction software based on the AliceVision framework (AliceVision | Meshroom, 2023). It will be adapted and used to create pavement 3D modeling. It is available for the three operating systems: Windows X64, Linux, and macOS. Meshroom is based on the SFM techniques and employs other algorithms and methods such as SIFT (Scale Invariant Feature Transform), RANSAC (RANdom SAmple Consensus), Accelerated KAZE, and CCTAG. This tool uses nodes to control the reconstruction, as illustrated in Fig. 3. A node represents a particular task to be executed, which could require input from other nodes and provides output to others. The software could be personalized to enhance the quality of the reconstruction.

3.5 Road 3D modeling

Road 3D modeling is the most critical step of the proposed method because its accuracy highly impacts the next steps for measuring and identifying distress. This step will be conducted via the software Meshroom and consists of eight sub-steps, as illustrated in Fig. 4:

- **Camera Initialization**: Images metadata and sensor information are extracted. It creates groups of intrinsic data: Focal length, camera model based on a database, and the serial number of the de device.

Figure 3: Meshroom interface Windows



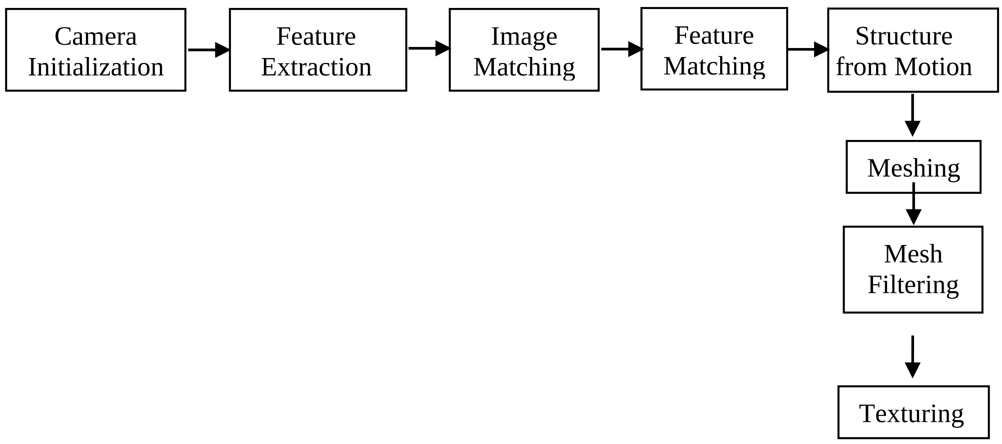
- **Feature Extraction**: Features and descriptors are extracted from the images using SIFT (Scale Invariant Feature Transform).
- **Image Matching**: A preprocessing step determines which images make sense to match each other. The objective is to find images looking at the same areas of the scene. This sub-step uses the 'Sequential And Vocabulary Tree' method, which combines a sequential approach with Vocabulary Tree to enable connections between keyframes at different times.
- **Feature Matching**: It finds the correspondence between the images using feature descriptors. This sub-step aims to match all features between candidate image pairs using SIFT and RANSAC techniques.
- **Structure from Motion**: It aims to understand the geometric relationship behind all the observations provided by the input images and infer the rigid scene structure (3D

points) with the pose (position and orientation) and internal calibration of all cameras. The incremental pipeline is a growing reconstruction process.

It first computes an initial two-view reconstruction that is iteratively extended by adding new views by using SIFT technique.

- **Meshing**: It creates a dense geometric surface representation of the scene. The mesh can also be simplified to reduce unnecessary vertices.
- **Mesh Filtering**: It applies a Laplacian filter to remove local defects from the raw Meshing cut.
- **Texturing**: It computes the texturing on the mesh.

Figure 4: Road 3D modeling



4 Results And Discussion

4.1 Data acquisition

Data was collected near Ibn Tofail University, Kenitra City, Morocco, on the 31st of January 2023, between 3 pm and 4 pm, to have more visibility and clear images. During the survey, the temperature was 19°C, and the wind speed was 13 Km/h Nord – Est. The EOS 450D camera was used in the automatic mode; it automatically adjusts all necessary parameters. Distances between the camera lens and the pavement surface were around 1 m.

Two case studies were conducted to evaluate the proposed method (Fig. 5):

a) First case study combines pothole and rut connected. Ten pictures were taken for this case (Fig. 5 (a)).

b) Second case study consists of a crack with a noise in the background (dust and oil). Seven images were captured for this case (Fig. 5 (b)).

Figure 5: Images taken during the survey a) Ten images for the first case study b) Seven images for the second case study

a) *b)*

4.2 Simulation

The 3D model of the road was created by importing the images taken during the data acquisition step to the personalized version of Meshroom with the configuration explained in paragraph 2.5. The computer used for the simulation was Lenovo ThinkPad T460 (Intel® Core i7 – 66000U CPU @ 2.60GHz 2.81 GHz) with 8GB RAM and a 64-bit Operating System.

For the first case study, it took 27 minutes to upload the ten images and generate the 3D model illustrated in Fig. 6. Fig. 6(a) shows camera poses, and Fig. 6(b) illustrates the 3D model shape. However, the second case took only 11 minutes to upload the seven images and generate the 3D pavement model, as illustrated in Fig. 7. Fig. 7(a) shows camera poses, and Fig. 7(b) illustrates the 3D model shape.

Figure 6: First case study simulation a) camera' poses reconstruction b) Pavement 3D modeling

a) b)

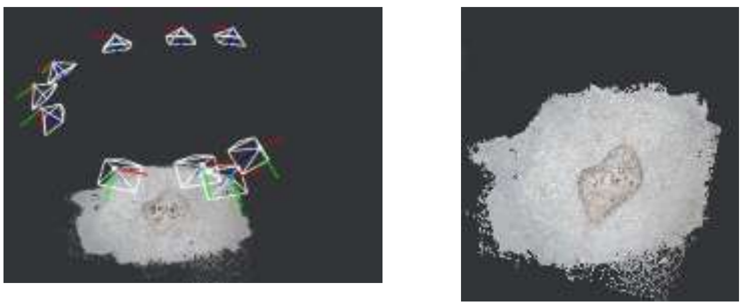
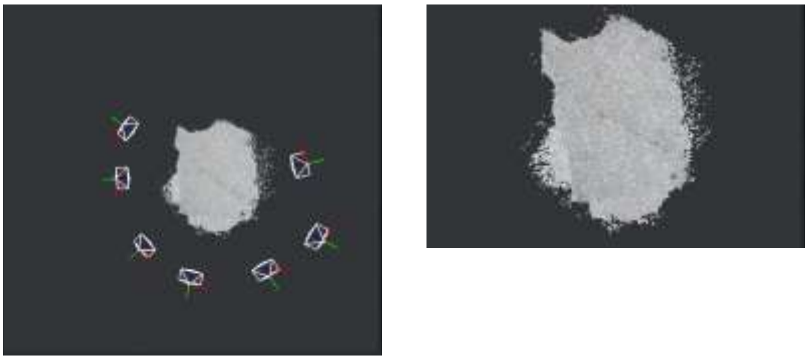


Figure 7: Second case study simulation a) camera' poses reconstruction b) Pavement 3D modeling

a) b)



4.3 Results and discussion

4.3.1 Results

The proposed approach presents a quick, low-cost, and simple-to-deploy solution for pavement distress detection and identification. The system comprises a commercial camera and the open-source software Meshroom, which can be run on a personal laptop. One operator could handle the global system and have short waiting times for obtaining data.

The presented approach was tested on two cases of study. In the first case study, which presents a pothole connected to a rut, it was observed that damages are identified with the same shape and dimension compared to reality. However, the distress is visible in the second case, which is a crack but unclear. Tab. 1 and 2 illustrate the results captured and the computer's performances during the two simulations. Results obtained are excellent while engaging cheaper material in a short period. The 3D model created by Meshroom could be cleaned and processed to cluster 3D points in distressed and non-distressed areas. The solution is straightforward and can be used by local authorities as a pavement management system or a friendly application in cars by drivers while presenting excellent results.

However, the method presented is limited by its poor quality regarding minor damages such as cracks. The enhancement of the quality of the 3D model could be conducted by modifying the open-source code of Meshroom and applying noise filters to eliminate non-significant data. It could also be enhanced by using more advanced cameras and UAVs (Unmanned Aerial Vehicles). This method must also be automated while permitting detection, measurement, and classification of damaged areas.

Table 1: Summary of simulations' results

Case Study	Distress Types	Number of Pictures	Number of Points Cloud	Quality of Detection	Simulation Time (s)
First	Pothole & Rut	10	29,410	Very good	27
Second	Crack	7	14,121	Poor	11

Table 2: Parameters of computer during simulations

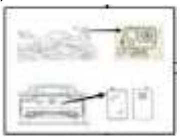
Road 3D modelling Sub-steps	1st case		2nd case	
	CPU (%)	RAM (%)	CPU (%)	RAM (%)
Camera Initialization	46	70	35	60
Feature Extraction	90	85	80	75
Image Matching	98	60	80	55
Feature Matching	99	60	90	55
Structure from Motion	95	62	88	55
6) Meshing	97	60	90	55
7) Mesh Filtering	60	60	75	55
8) Texturing	96	60	76	55

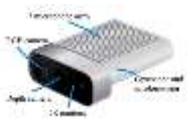
4.3.2 Comparison with other methods

Despite its high accuracy, laser scanning is costly and requires more time during scanning. Other methods, such as UAVs (Unmanned Aerial Vehicles) and smartphones, are more costly than digital cameras while presenting the same data quality. Many associated applications and software involve wired sensors, which present difficulties for deployment, given their fixed nature. Also, commercial applications such as Road AI, ARAN, and Pavement AI are costly and cannot be considered by public administration.

A deep comparison between the proposed approach and ten low-cost solutions on the pavement distress detection and identification field has been conducted as described in Tab. 3. During the comparison; it was observed that the nature of the material engaged, the software development, and the integration efforts. In some studies, the type of material used was not mentioned, so an estimation of the cost for each material category has been adopted: drone (~1 000 $), smartphone (~200$), and digital camera (~300$). Also, some studies have used a car or a bike to conduct the scanning. The car service and bike service estimations were 5/hour and 4$/hour, respectively. Estimating the cost of such effort for the development is challenging. However, it could be a considerable amount that will be increased if multiple software enhancements and upgrades are required to maintain the system. The evaluation of the estimated cost and the equipment and software engaged for each method confirmed that the proposed solution is the least costly and the easiest to deploy.

Table 3: Comparison between the proposed method and other low-cost solutions

Method	Material	Software & algorithms	Estimated Cost
The proposed method	EOS 450D Canon camera 	*SFM *Meshroom	*Camera: 300$. *Software development: very low.
Acosta et al. (1992)	A developed system PAVEment		*Hardware: 30 000$. *Software development.
Wai and Yuan (2017)	Consumer-grade video camera mounted in the car front	A developed system (VPADS) : *Canny Edges *Hough *Transform *RANSAC *DBSCAN	*Camera: ~ 200 $. *Car service: ~ 5$/hour. *Software development.
Inzerillo et al. (2018)	Drone equipped with GoPro hero 3  Faro focus3D Scanner 	*SFM *MeshLab *PhotoScan *Rhinoceros CAD	*Drone: ~ 1 000 $. *GoPro hero 3: 400 $. *Faro focus3D: 6 000$. *Software development.
Ouma (2019)	iMMSS hardware-software system based on : *k-means clustering *Spatial fuzzy c-means (SPCM) *Edge ellipse fitting 		*Kinect v2.0: 200$. *Other hardware. *Software development.
Roberts et al. (2020)	Smartphone Google Pixel 2XL 	*MyCityReport *LabelImg *Faster R-CNN *SSD Inception *SSD Mobilenet	*Smartphone: 210$. *Car service: 5$/hour. *Software development.
Ronald et al. (2020)	Huawei P20 Pro  Samsung Galaxy S9  Nikon D5200 	*SFM *RANSAC *CloudCompare *'Fit' Algorithm *Weibull distribution	*Huawei P20 Pro: 440$. *Galaxy S9: 340$. *Nikon D5200: 730$. *Software development.
Kembhavi et al. (2020)	Smarthphone fixed on a vehicle (Gopro) camera fixed on a bike 	*Fuzzy-C-Means (FCM) *Spectral Theory algorithm *Matlab2016Ra	*Smartphone: ~ 200$. *Gopro camera: ~ 300$. *Car service: ~ 5$/hour. *Bike service: ~ 4$/hour. *Software development.

Guerrieri and Parla (2022)	Vehicle equipped with a front camera 	*Darknet-53 *YOLOv3	*Camera: ~ 300$. *Car service: 5$/hour. *Software development.
Martinelli et al. (2022)	Acceleration sensor on a car  (a) Sensor placed on the car's dashboard; (b) Sensor placed on the car's floorboard.	*Fourier analysis *Decision Tree *SVM *k-nearest Neighbor (kNN)	*Acceleration sensor: ~ 20$. *Car service: 5$/hour. *Software development.
Qiu et al. (2023)	Azure Kinect DK  	*ConvNext *Unet *SegFormer *ResNeSt	*Azure Kinect DK: 400$. *Car service: ~5$/hour. *Software development.

5 Conclusion and future work

This paper proved that 3D modeling using a digital camera and the Structure from Motion technique presents good data quality, permitting the detection and identification of pavement distress. The EOS 450D commercial camera manufactured by Canon was used to take images of the pavement from different views, then 3D modeling was created by the open-source software Meshroom based on the Structure from Motion. Two case studies were conducted to evaluate the proposed method, and the 3D models show a high similarity with the existing damages on the road surface while permitting access to depth information.

The proposed method presents a lower-cost solution than the laser scanning technique. Also, it is easy to deploy quickly. Unmanned Aerial Vehicles are the most flexible; however, the gathered data provide a general idea about pavement health. Furthermore, UAVs are restricted by authorization for use in some countries.

The proposed approach is quick, low-cost, and can be initiated only by one operator. It could be used as a part of a Pavement Management System to help with road condition evaluation and assess the safety driven.

Future works will focus on using more sophisticated cameras and enhancing the pavement 3D modeling quality based on the Structure from Motion technique. Noise filters and the 3D Points neighbor-based techniques will be applied to enhance the 3D model. Machine Learning and Artificial Intelligence algorithms will be developed to automate pavement distress detection, measurement, and classification.

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