

A Framework for Automated Pavement Condition Monitoring

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ABSTRACT

Pavement condition monitoring is mainly performed manually. Inspectors are driving or walking the road network bare eyed to look for irregularities. Moreover, processing the collected data for understanding the road condition is also a manual task. In this paper a framework that automates the process is presented. Video data collected from the car's parking camera is utilized to detect defects in frames. Simultaneously, elevation signals collected from accelerometers attached to the car are processed to reconstruct the profile of the road and detect defects associated with its z-axis, such as bumps. A GPS device is synchronized with the other sensors to acquire the data's geolocation. Detected defects are then classified according to their type and their severity is assessed. All information is then transferred via 4G network to a central server, where the Road Condition Index of road segments necessary to classify roads is calculated. Finally, everything is saved in a Pavement Management System. Preliminary results on the processing of video data demonstrate the frameworks' promising application. The initial identification of frames including defects produces an accuracy of 96% and approximately 97% precision. Further experiments on such frames, aiming at the detection of potholes, patches and three different types of cracks result in over 84% overall accuracy and over 85% precision.

INTRODUCTION

Road networks are very important since besides assisting mobility, they enable growth and contribute to prosperity, productivity and well-being (Cook 2011). Hence, effective road management is critical. Several countries identify the bad condition of the road network indicating the significance of road maintenance programs. The American Society of Civil Engineers have given a grade D to the US roads (ASCE 2013), with A being the best.

It is necessary that pavement condition data is accurate in order to design, plan and assist the decision-making of pavement maintenance programs in an efficient manner. The goal is to identify defective highway assets' and assess their

severity. Highway assets include the actual pavement but also the infrastructure around it, such as lamp and sign post, traffic lights etc. Specifically, the current process consists of the following steps: 1) data collection, 2) defects' detection and 3) defect's severity assessment.

There are two ways of performing data collection. Those are either automatically with the use of dedicated vehicles, or manually with visual surveys. Then, inspectors are required to digitize their findings and upload them in a central database. Such data include images of the defects along with descriptions regarding the defects' condition, the action that was made in order to fix it if that was possible or the level of urgency that the defect needs to be taken care of. It is inevitable for subjectivity to be introduced due to the level of the inspector's experience (Bianchini et al. 2010).

Dedicated vehicles are equipped with a variety of sensors, such as high definition cameras and laser scanners. The limitation with these vehicles is their high purchase (~\$800,000) and operational (~\$50/mile) costs (Werro 2013). Hence, many US states own just a few or none and operate them only once a year (MnDOT 2009), leading to the extended use of manual visual surveys (SDDOT 2009).

In this paper a framework for automating the process of pavement condition monitoring is presented. The initial motivation is to create a method that is cheap and simple. Hence, the sensors used for collecting data are a parking camera and accelerometers. The camera feed is processed to initially detect frames that potentially include highway asset related defects. The defective frame candidates are then further processed to detect specific defects. At the same time, accelerometer signals are collected to produce the road profile and detect defects related to the road's z-axis. A GPS device is synchronized with the other sensors for geo-tagging all captured data. After classifying the detected defects based on their type, their severity level is assessed. A report with all the derived information regarding the condition of the road is produced and saved in a database. This information is then used to calculate the Road Condition Index (RCI) of road segments in order to classify them based on an international standard rating system. Finally, everything is saved in a Pavement Management System (PMS).

STATE OF RESEARCH

Automating pavement condition assessment

Several research efforts have attempted to automate pavement defect detection, assessment and repair. The main focus has been on algorithmic accuracy, which in most cases has led to expensive solutions requiring the use of specialized vehicles. However, it is infeasible to maintain a whole road network in such a way.

Most of the proposed methods are based on computer vision techniques that are applied on 2D images as it has been proven that such techniques can assist the automation of pavement assessment (Tsai et al. 2009). Multiple methods have focused on the defects of cracks. Those are focusing on detecting cracks (Ghanta et al. 2012;), analyzing them in real-time (Sy et al. 2008), classifying them (Moghadas Nejad and Zakeri 2011), estimating their depth (Amarasiri et al. 2009) and automatically sealing them (Kim et al. 2009). Other efforts have addressed the

detection of different pavement defects such as potholes (Jog et al. 2012; Koch et al. 2012;) or patches (Battiato et al. 2006; Radopoulou and Brilakis 2015).

The limitation of the aforementioned methods is twofold. On one hand, they don't approach the process holistically since they are restricted in the detection of one defect at a time. This isn't useful, since in order to efficiently design a maintenance plan information about all different highway asset related defects is mandatory. Additionally, since they are vision based, they are unable to capture information in relation to the z-axis of the pavement.

In order to address the limitation of vision techniques, methods that reconstruct the pavement in 3D have also been proposed. Those are capable of detecting defects such as rutting, depressions and elevations. A real-time laser scanning system has been proposed (Li et al. 2010) for that purpose, and although it is not expensive, it is manual. Stereo vision has also been used for reconstructing the pavement surface (Hou et al. 2007). However, all above methods require the use of specialized vehicles. In addition, methods that require laser scanners for data collection are restricted to elevation defects and can't detect surface defects.

Finally, the use of dynamic sensors such as accelerometers has also been tested for understanding the pavement conditions (Yu and Yu 2006). The advantage of using accelerometers is their small size, their low cost and the possibility of processing the collected data in real-time.

Sensor fusion approaches related to pavement monitoring

Currently available single sensor approaches for infrastructure monitoring cannot provide sufficiently accurate data for localizing and determining the severity of the detected defects (Attoh-Okine and Mensah 2009). For this reason, fusing data captured by a multi-sensor network in order to associate, correlate, estimate and combine information has evolved (Farrar et al. 2006).

Different sensor-fusion systems have been studied. A couple aiming at Vehicle to Vehicle and Vehicle to Infrastructure communications (Sauerwein and Smith 2011) have been proposed. Other sensor-fusion methods aim at the synchronization of pavement defect detection and geographical positioning. Such examples are the BusNet (De Zoysa et al. 2007) and Pothole Patrol (Eriksson et al. 2008) projects, both of which are combining dynamic sensors, GPS devices and mobile nodes to detect potholes. CarTel is another sensor fusion method (Hull et al. 2006) for collecting, processing, delivering and visualizing data and it isn't based on any particular application. Its main advantage is its ability to sense the environment with much finer fidelity than static sensor networks, especially in large areas.

The methods presented above show that distributed vehicle networks are in general ideal for monitoring and assessing infrastructure. Moreover, they are environmentally friendly if we consider the additional emissions that dedicated inspection vehicles produce. However, these approaches are mainly limited to detecting and localizing elevation defects without being capable of detecting surface defects. When considering comprehensive condition assessment, all types of defects need to be identified. Otherwise, the results aren't enough to efficiently decide on maintenance actions.

Based on the limitations of specialized vehicles, the current process of pavement condition monitoring and the proposed methods in the literature, the objective of this paper is to propose an automated and efficient pavement condition monitoring framework.

PROPOSED FRAMEWORK

For addressing this paper’s objective we are proposing to use the parking camera that is already installed in many vehicles. Using only one camera restrict us into acquiring only 2D information. Therefore and in order to capture all relevant information in relation to the z-axis of the road we are also proposing the use of accelerometer data. A flowchart of the proposed framework is provided in figure 1.

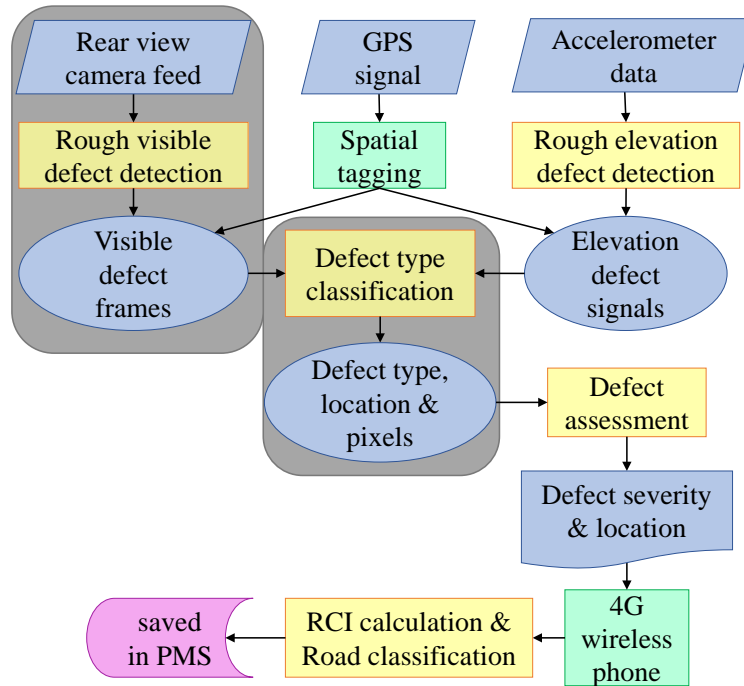


Figure 1. Proposed framework for automated pavement condition monitoring. Validated steps are highlighted.

Starting from the video feed, rough visible defect detection is initially performed using the wavelet transform to isolate frames that potentially depict defects. These are called candidate defective frames. Only these frames are then passed to the next stage of the framework, during which the supervised learning algorithm of Semantic Texton Forest (STF) (Shotton et al. 2008) is applied for detecting defects within the candidate defective frames.

Simultaneously accelerometer signals are analyzed to reconstruct the road profile which is used for the rough elevation defect detection. At this stage, signals that potentially represent defects are isolated from the rest of the profile. For the classification of these defects, a “library” of z-axis defects is used. The “library” is formed by the “signatures” of typical defects, such as depressions, sags and rutting. A “signature” is a depiction of the defect on the road profile. The candidate defects are

compared and matched with one of the “signatures” in the “library”. A GPS device that is synchronized with the other sensors provides the additional information of geographical location of the collected data.

Then follows the severity assessment of classified defects. Each type of defect has different attributes for understanding its severity level. The severity levels are low, medium and high. Each level is defined with a different range of attribute values. For example, a medium level longitudinal crack has a width between $\frac{1}{4}$ inch and $\frac{3}{4}$ inch. In addition to that, its length is also necessary for categorizing it. At this stage, each defect’s attribute(s) is measured and saved in a report.

Established wireless protocols are used to transfer this information through the 4G capability of the driver’s cellular phones to a central server. The final step of the framework is to calculate the Road Condition Index of each road segment in order to classify them based on international rating standards. Last, all information is saved in a Pavement Management System.

PRELIMINARY RESULTS

Rough visible defect detection

In order to validate the capability of the framework to roughly detect defects, pavement images were captured in Bochum, Germany. A high-speed Basler acA2040-180kc camera was used. The acquired images with a resolution of 1000x1000 pixels were analyzed using the wavelet transform method proposed by Zhou (Zhou et al. 2006). In order to allow for real-time defect detection, the wavelet transform and corresponding feature calculations were implemented on Graphics Processing Units (Georgieva et al. 2015).

A dataset consisting of 477 images was generated, whereby 305 images contained defects and the other 172 images were of a good pavement surface. Examples of the images are shown in figure 2. As proposed by Zhou (Zhou et al. 2006), the wavelet transform was applied on the images and a statistical feature was calculated, namely high-amplitude wavelet coefficient percentage (HAWCP). Based on this feature, a machine learning framework which provides implementations of multiple classification algorithms was utilized in order to classify the images into two categories, namely candidate defective frames and frames without defects. In particular, the Rotation Forest algorithm was used and tested on the sample of the 477 images. To train the algorithm and create a classification model, randomly chosen 30% of the images were manually labeled and submitted to the machine learning framework. The remaining 70% of the images were used to test the performance of the generated classification model.

The Rotation Forest algorithm classified correctly 96% of the test images and achieved a precision and recall of 97%. The time required to execute the wavelet transform on an image and calculate the HAWCP value was 0.17 milliseconds, which enables real-time pavement defect detection.

Defect type classification

For this part of the framework, data was collected from the local streets of Cambridge, UK. Two different cameras were used for that reason; an HP Elite

Webcam (colored videos) and a Point Grey (PG) Blackfly (monochrome videos). The first one provides an image of 640x480 and has a lens with 50° horizontal angle of view. Data was collected with such a low resolution camera to test its applicability to the specific problem. The second camera has a resolution of 0.5MP and a 133° horizontal angle of view. This was chosen based on the characteristics of parking cameras currently available in the market. The camera was positioned at the rear of the vehicle on the

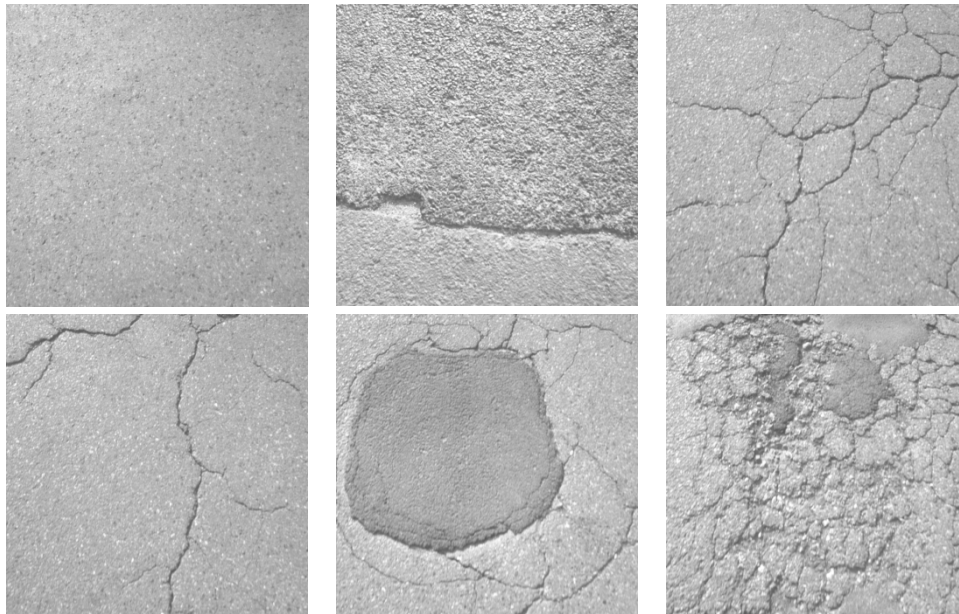


Figure 2. Examples of pavement images

same spot that parking cameras are found. This is approximately in the middle of the car; just below or above the license plate.

Assuming that the rough visible defect detection was performed, the defective frames were manually isolated from the healthy ones and were used for training and validating the algorithm. Two datasets were created; one using the colored video collected with the HP camera consisting of 211 images and another one using the video collected with the PG camera consisting of 517 images. In both datasets, half of the images were used for training and the rest for testing.

Six categories were used for preparing the ground truth, necessary to train the algorithm, each of which was marked with a different color. The first dataset, included images that contained all six categories. The second one included images that contained only four of them. The colors used to mark each category were red for longitudinal cracks, blue for traverse cracks, green for alligator cracks, yellow for patches, pink for potholes and grey for healthy pavement (examples can be seen in column b of fig.2).

Additionally, the images of the second database were cropped in order to isolate the application of STF to the part of the image that is useful to do so. This corresponds to the area that depicts the road lane only, while considering the size of defects that inspectors are looking for. The calculation was made using the principles of inverse perspective mapping that correlate the World Coordinate system with the

Image Coordinate system (Tapia-Espinoza and Torres-Torriti 2013), along with the fact that the minimum width of a crack that has to be detected is $\frac{1}{4}$ inch. The result was that the upper 193 rows of the images weren't useful (examples can be seen in the 3rd and 4th rows of fig.3).

Several are the parameters that affect the performance of STF. Two of those are the box size and the maximum tree depth. The former refers to the number of pixels that surround the pixel in question (meaning the pixel that is being categorized during the testing phase) and the latter refers to how deep a tree can grow (how many levels it can include) during the training phase. Different combinations of these two parameters were tested, the details of which can be found in table 1. There, the overall and average accuracies of each combination can also be seen. Table 2 shows the average precision and area under curve (the one formed when precision vs recall is plotted) of each defect separately. Visual results are depicted in column c of figure3.

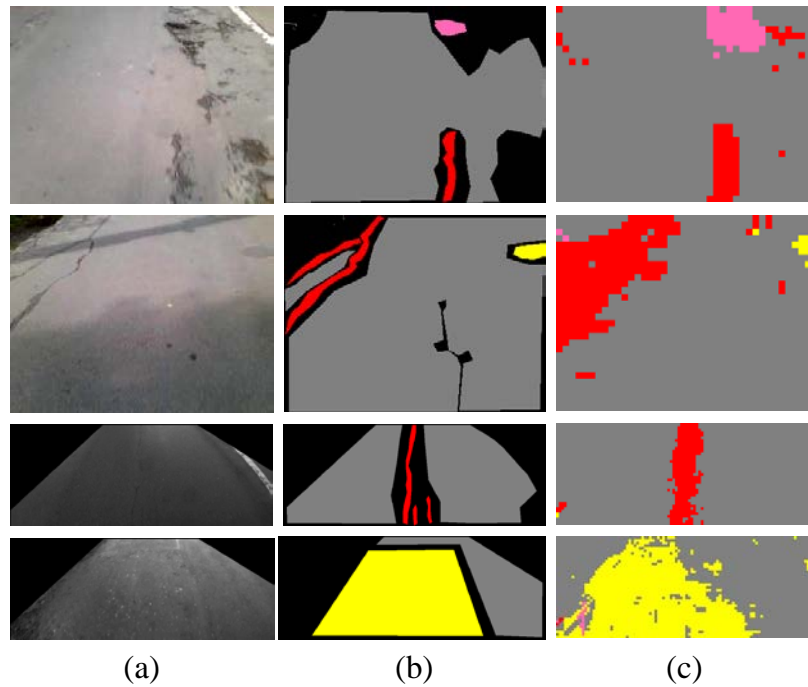


Figure 3. Examples of ground truth data (b) along with the original video frame (a) and the STF result (c).

CONCLUSIONS

The current process of pavement condition assessment is predominantly performed manually which is laborious, time-consuming, subjective and not frequent enough. Therefore, poor road condition still remains a problem for every day commuters. Research efforts have attempted automating the detection, assessment or repair of pavement related defects. However, none of these methods approaches the problem holistically. All proposed methods are focusing on one or a couple of defects and this isn't enough to acquire a complete report of information for the road condition. Additionally, since most are aiming at algorithmic accuracy, the solutions

they provide are quite expensive and aren't appropriate for being applied to a national scale. Some studies have shown that sensor fusion approaches would be ideal for monitoring infrastructure.

Table 1. Tested parameter combinations and general results

Colored video frames						
Test #	1	2	3	4	5	6
Box Size	9	11	13	13	13	15
Max tree depth	10&14	10&14	10&14	11&13	12&16	10&14
Overall accuracy	0.87	0.87	0.89	0.89	0.86	0.84
Average accuracy	0.6	0.65	0.56	0.6	0.58	0.64
Monochrome video frames						
Box Size	9	9	11	13	15	15
Max tree depth	10&14	11&13	10&14	10&14	10&14	11&13
Overall accuracy	0.88	0.86	0.87	0.87	0.88	0.86
Average accuracy	0.85	0.83	0.82	0.84	0.86	0.86

Table 2. Validation results per defect

Colored video frames							
Test #		1	2	3	4	5	6
Alligator crack	Av. Pr.	0.89	0.93	0.84	0.94	1	1
	AuC	0.99	0.99	0.99	0.99	1	1
Longitudinal crack	Av. Pr.	0.86	0.94	0.96	0.98	0.94	0.96
	AuC	0.56	0.76	0.85	0.85	0.75	0.83
Traverse crack	Av. Pr.	0.53	0.77	0.77	0.78	0.04	1
	AuC	0.96	0.97	0.97	0.98	0.69	1
Patch	Av. Pr.	0.75	0.86	0.81	0.79	0.72	0.75
	AuC	0.82	0.93	0.89	0.89	0.83	0.85
Pothole	Av. Pr.	0.96	0.76	0.98	0.99	1	1
	AuC	0.99	0.94	0.99	0.99	1	1
Healthy pavement	Av. Pr.	0.98	0.99	0.98	0.98	0.96	0.97
	AuC	0.19	0.6	0.21	0.43	0.1	0.07
Monochrome video frames							
Longitudinal crack	Av. Pr.	0.97	0.92	0.93	0.91	0.97	0.93
	AuC	0.9	0.97	0.98	0.97	0.99	0.95
Patch	Av. Pr.	0.95	0.99	0.95	0.94	0.96	0.97
	AuC	0.87	0.96	0.86	0.91	0.89	0.91
Pothole	Av. Pr.	0.84	0.84	0.89	0.91	0.93	0.82
	AuC	0.98	0.98	0.98	0.99	0.99	0.97
Healthy pavement	Av. Pr.	0.94	0.95	0.94	0.97	0.95	0.96
	AuC	0.52	0.53	0.5	0.67	0.63	0.65

Thus, this paper proposed a framework that automated the process of pavement condition monitoring while keeping the cost low for doing that. It is a solution that could potentially transform every day road users to ubiquitous pavement monitoring reporters. The sensors used are the parking camera, accelerometers, a GPS device and the driver's mobile phone. The parking camera feed is processed to detect candidate defective frames, which are then processed to detect surface defects. The accelerometer signal helps in detecting defects related to the z-axis of the pavement. After assessing the severity of the defects, the RCI of road segments is calculated to classify roads based on international rating standards. Finally, all information is saved in a PMS, which is used for designing maintenance actions.

To validate the rough detection of defects, the wavelet transform was applied on images with a resolution of 1000x1000 elements. Based on the high-amplitude wavelet coefficient percentage of the frames, the frames were classified by the Rotation Forest algorithm as candidate defective frames or good surface frames with a precision of 97%. An HP Elite Webcam and a Point Grey Blackfly camera were used for collecting data to validate the step of detecting defects in candidate defective frames. Several combinations of two parameters that affect the performance of the utilized machine learning algorithm were tested. All tests resulted in overall accuracies above 84%. The best average accuracy was produced in the colored video frames and it was 89%. Regarding the performance of detecting each defect individually, the algorithm performed better in the second database where the results were always above 85%.

The experiments described in this paper helped us derive preliminary results for validating part of the framework. Hence, in our future work, we are interested into performing more experiments using the same equipment and data for both steps of rough visible defect detection and classification. Such a validation will demonstrate the reliability of the proposed framework and algorithms. Additionally, we aim at creating the "library" of elevation defects by studying their "signatures" in road profiles. Once this task is ready, data will be collected for validating and testing the performance of detecting elevation defects.

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